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MULTI-SCALE ANALYSIS OF URBAN WETLAND CHANGES USING SATELLITE REMOTE SENSING TECHNIQUES

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by
DZINGIRAI MURAMBADORO

B.S., University of Zimbabwe, 1994
M.S., University of Zimbabwe, 1999

Kansas City, Missouri
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Dzingirai Murambadoro, Candidate for the Doctor of Philosophy Degree
University of Missouri - Kansas City, 2011

ABSTRACT

This study investigates urban wetland-cover changes in the Kansas City metropolitan area with analyses at various spatial and temporal scales. Not many studies fully addressed multi-scale urban wetland-cover dynamics in both the temporal and spatial dimension. The objective was to understand how major driving factors - human disturbances and climate variation - impacted urban wetlands as determined by the scale effects of observing land-cover changes. To address this objective, multi-year and multi-season SPOT satellite images were acquired and digitally classified to generate wetland and related land-cover data over various temporal ranges. To detect long term changes of urban wetland, the study examined the landscape changes between 1992 and 2008. Furthermore, for a short term analysis over a period between 2008 and 2010, the study analyzed seasonal land-cover variation among the autumn, spring, and summer. These multi-temporal land-cover data were analyzed at various spatial scales – the metropolitan region, watersheds, sub-watersheds, specific wetland areas, and particular urban development zones. The results show that over the 16-year period, both wetland and impervious surfaces gained in area at the metropolitan level. However, the wetland change patterns were varied at other spatial scales of analysis, which were related to the dominant site-specific development activities. Further, the wetland change patterns differed if large surface water bodies (> 8ha) were excluded from the class of wetlands. The study also revealed that the seasonal change patterns of urban wetlands were likely correlated with short term precipitation conditions; but this effect may be varied depending on sampling area sizes. The study suggests that the effects of spatial and temporal scales should be considered in remote sensing detection of urban wetlands as they influence the interpretation of remotely sensed land-cover changes and correlation of driving factors. In conclusion, understanding the complex human-climate coupling factors affecting urban wetland-cover requires a multi-scale and multi-faceted analysis.

The faculty listed below, appointed by the Dean of the School of Graduate Studies, have examined a dissertation titled "Multi-Scale Analysis of Urban Wetland Changes Using Satellite Remote Sensing Techniques", presented by Dzingirai Murambadoro, candidate for the Doctor of Philosophy degree, and hereby certify that in their opinion it is worthy of acceptance.

Supervisory Committee

Wei Ji, Ph.D., Committee Chair and Research Advisor
Department of Geosciences

Jimmy O. Adegoke, Ph.D.
Department of Geosciences

Jejung Lee, Ph.D.
Department of Geosciences

Yugyung Lee, Ph.D.
Department of Computer Science and Electrical Engineering

Vijay Kumar, Ph.D.
Department of Computer Science and Electrical Engineering

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LIST OF ABBREVIATIONS

APM	Automatic Point Matching
CART	Classification and Regression Tree Analysis
CMAP	CPC merged analysis of precipitation
COE	Army Corps of Engineers
CPC	Climate Prediction Center
COM	Component Object Model
CWA	Clean Water Act
DEM	Digital Elevation Model
DTs	Decision Trees
EPA	United States Environmental Protection Agency
ERSI	Environmental Systems Research Institute
EVALUWET	European valuation and assessment tools supporting wetland ecosystem legislation
FGDC	Federal Geographic Data Committee
FWS	Fish and Wildlife Services
GIS	Geographic Information Systems
GPI	Global Prediction Index
GUI	Graphic User Interface
IBI	Index of Biotic Integrity
IUCN	International Union for Conservation of Nature
LULC	Land Use Land Cover

MLC	Maximum Likelihood Classifier
NAD83	North American Datum 1983
NCEP	National Centers for Environmental Prediction
NDVI	Normalized Difference Vegetation Index
NRSC	Natural Resources Conservation Services
NOAA	National Oceanic and Atmospheric Administration
NWI	National Wetland Inventory
OOP	Object Oriented Programming
OPI	OLR (Outgoing Long-wave Radiation) Prediction Center
RMSE	Root Mean Square Error
RS	Remote Sensing
SCS	Soil Conservation Services
SQL	Structured Query Language
SPOT	Satellite Pour l'Observation de la Terre
SSM/I	Special Sensor Microwave Imager
SVM	Support Vector Machines
TMU	Target Mapping Unit
UTM	Universal Transverse Mercator
WCMC	World Conservation Monitoring Centre
WGS84	World Geodetic System 1984
WFD	Water Framework Directive
USGS	United States Geological Survey
USFWS	United States Fish and Wildlife Service

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CHAPTER 1

INTRODUCTION

Many areas around the world are experiencing an increase in impervious land-cover due to urban sprawl. Urban sprawl is characterized by rapid urban development out of the city into the fringes and country-side of the community (Woosley 2006). Urban development has received a lot of attention, and one focus has been on the increasing impervious surface footprint. An increase in the amount of impervious land-cover correlates to an increase in runoff, and therefore a possible increase in flooding and non-point source pollution (Pryor 2005). Impervious surfaces can be defined as any material that prevents the infiltration of water into the soil. While roads and rooftops are the most prevalent and easily identified types of impervious surfaces, other types include sidewalks, patios, bedrock outcrops, and compacted soil (Arnold and Gibbons 1996). Impervious surfaces can have a deleterious effect on water resources and stream water quality. The studies completed in the United States nationally and particularly in Delaware over the last ten years show an increasingly significant correlation between impervious surface coverage and stream water quality and habitat (Kauffman and Brant 2000).

However, researchers have paid little attention to wetland-cover dynamics as related to urban development processes. This has resulted in an incomplete understanding of urban landscape changes and associated driving factors. The need to fill this information gap has motivated this study on urban wetland changes. The study is mainly based on the following considerations:

(1) Urban wetlands could be more sensitive to human disturbances and climate change than impervious surfaces. Through their modifications (disappearance or emergence), urban wetlands may indicate the quality and sustainability of urban development as determined by wetland health. In addition, during urban area development, urban wetlands could reveal subtle human disturbances such as changing amounts of water and incoming sediment, increased amounts of toxic contaminants, and fragmenting habitats, among others. These impacts would affect the distribution and abundance of birds, mammals, and plants that are closely associated with wetlands.

(2) Complex factors could affect urban wetland-cover dynamics. Urban wetlands are affected by precipitation in similar ways as non-urban wetlands, but the difference could be that the expansion of urban wetlands might be extremely exaggerated due to reduced water infiltration in urban areas owing to a large impervious surface area that results in large stream water flows. Conversely, urban wetland-cover might rapidly decrease as water is drained out of the wetlands, directly or indirectly, for agricultural, industrial, or domestic uses. According to the U.S. Environmental Protection Agency (1997 & 1998), the region, in which the Kansas City metropolitan area lies, has experienced a significant increase of precipitation since the 19th century. However, few studies have been conducted to examine how the increased precipitation has affected urban wetland areas.

The above considerations were supported by some previous studies. For example, according to (Wolter, Johnston and Niemi 2006), the volume of storm water runoff increased in concert with expanding development. Using aerial photographs from 1937 and 1995, Wegener (2001) studied changes in impervious surface area and found increases in urban area (formerly farmland) were responsible for a 69% increase in the volume of storm water runoff. He determined that a 7.6 cm (3 inch) rainfall event in 1995 resulted in a 65% greater rise in lake levels than was the case in 1937 from the same volume of precipitation. On the other hand, urban wetland loss or modifications can ensue as wetlands give way to new urban developments.

The scale issue has been a concern in planning this study. In many previous urban wetland studies, researchers focused only on regional spatial scales that may not adequately reveal wetland-cover change details at small spatial extents: watershed or sub-watershed scales. A watershed is a discrete area of land bounded by drainage divides that drains to a specific point on a stream or a lake or wetland; watersheds are based on topography and the observation that water flows downslope because of gravity (Hunsaker and Levine 1995). Watersheds provide the natural boundaries to guide the land planning decisions that affect stream water quality; after all, watersheds know no political boundaries (Kauffman and Brant 2000). Thus, in this study, the analysis is watershed-based.

Specifically, the study is designed to focus on a multi-scale analysis of the Kansas City metropolitan area land-cover/land-use employing varying spatial and temporal dimensions to achieve a better understanding of urban wetland dynamics. The spatial dimension can reveal how urban wetland-cover changes relative to other land-cover classes affects decisions that can be made at each spatial extent. The spatial extents used in the project are based on hydrologic unit levels; for example, the watershed to sub-watershed level. Watershed-based spatial analysis considers that the impacts of hydrological processes affecting a particular watershed are naturally confined to the watershed area in which they exist.

Many researchers have stressed the importance of hydrological unit level land cover/land use studies for management and planning purposes, but not many have carried out a multi-scale spatial analysis to determine the effect of landscape variability as area extents are varied. A detailed discussion on the importance of watersheds as critical functional and ecological management units is given in (Diana, Allan and Infante 2006) and (Hollenhorst, et al. 2007). Advocating for the watershed-based analysis, the Environmental Systems Research Institute (ESRI), along with key state, national, and international contributors, developed the ArcHydro data model (Maidment and Morehouse 2002) to better manage and process watershed information and watershed delineation methods (Hollenhorst, et al. 2007). In landscape analysis, many investigators have used sub-basin (8-digit hydrologic unit) or larger 'watershed' areas. In one study 67 equal-area hexagons of a Kansas landscape, each 2560 km^2 in area were used (Griffth, Martinko and Price 2000); in another study 1200 and 1800 km^2 equal-area sub-units were used in the Chesapeake Bay and Tennessee River basins (Cain, Riitters and Orvis 1997). Out of the few researchers that carried out multi-scale land use analysis, the majority did not incorporate the temporal dimension. In addition to the use of 8-digit hydrologic units catchment areas some researchers used small sub-catchments averaging 43 km^2 in area (Cifaldi, et al. 2004) because these constituted the spatial scale at which much stream assessment and management as well as watershed planning took place.

Though not as integrated as the approach designed for this study, landscape phenomena have been studied at various spatial and temporal scales using coarse to high resolution images acquired by various sensors. Mostly, medium spatial resolution imagery has been used in projects of various spatial extents in land resource studies. Where the spatial extents or temporal scales used were not appropriate, results would be less relevant, resulting in inappropriate recommendations. In some cases, land-use planners would experience challenges in applying the findings to some applications or extrapolating the results to different spatial extents. Under heterogeneous landscape conditions, some researchers would mistakenly directly apply analysis results from one spatial scale to another, which might not be appropriate.

In order to address the challenges posed by heterogeneous landscapes, this study sought to analyze land-use/land-cover resource data for a variety of spatial extents to demonstrate how land cover classification results are affected by both spatial and temporal scale. It also sought to find out the relevance of landscape analysis results as they are extrapolated to various spatial scales. For instance, would reporting a wetland-cover decrease at state level (e.g., state of Missouri) be telling enough to a watershed level planner located somewhere else in the same state? This observation questions the extrapolation of analysis results from one spatial or temporal scale to another or whether there is a recommended spatial extent or image spatial resolution that should be used to study land resources for particular applications.

In line with the discussion above, researchers have also questioned extrapolation of analysis results across spatial scales. In a study to explore landscape pattern variability at a finer spatial scale to investigate pattern, process, and management opportunities within individual watersheds, researchers found that for both theoretical and practical reasons, analyses often are carried out using large landscape units. However, land use planning and the activities of management agencies typically take place at the local level to address issues related to land use/cover over relatively small spatial extents (Cifaldi, et al. 2004). The investigators also queried whether pattern indicators and unique dimensions of patterns, identified in analyses of larger landscape units were also meaningful for more finely sub-divided landscapes. In concurrence with my goal in this study, research has shown that not all aspects of pattern are the same in studies that differ in data resolution and diversity of landscapes (Riitters, et al. 1995). Many landscape metrics are sensitive to changes in the spatial resolution (grain size) of the data or the area (extent) of the landscape (Wickham and Riitters 1995), and numerous correlations occur among landscape indices. The down-scaling and up-scaling of landscape metrics, as functional and structural landscape indicators at different scales, remains a challenge (Mander, Muller and Wrbka 2005).

In this study, analysis in the temporal dimension was an assessment of urban wetlands change over time, and the study applied this in both the short term (seasonal) and the long term (multi-year) periods. The long term analysis assessed urban wetland dynamics for about two decades, while the short term assessment evaluated seasonal urban wetland dynamics. The study highlights the precipitation pattern prior to imaging dates to address questions like:

- Would it be enough for researchers to only emphasize the use of cloud free and anniversary images and ignore the precipitation activity immediately prior to the imaging dates?
- In the event of extremely different precipitation amounts received before imaging dates, would the use of anniversary images still be valid to produce acceptable results for temporal analysis applications?
- What would be the effect of large variations of precipitation amounts on the wetland-cover expression on an image?
- Would not such a wetland footprint be misleading in image classification given that many wetlands could rapidly swell with large amounts of rainfall and rapidly decline

as soon as rainfall ceases? Comparatively, other land-cover types do not change that fast.

- Furthermore, based on historical precipitation data, which years in particular – dry or wet - should be used to study wetlands?

In many previous studies, the tendency was to use freely available images which might not adequately meet research goals.

Unique to this study is an attempt to address urban wetland dynamics, in light of the above issues, in five ways: (1) using long term temporal image analysis, (2) using short term analysis to study the effect of seasonal changes on wetland (surface water) cover dynamics at various spatial scales, (3) utilizing different hydrologic unit-based (e.g., watershed) spatial extents, (4) integrating both remotely sensed wetland-cover (surface water) analysis, hydric soils, and impervious surfaces to assess wetland loss, and (5) assessing wetland-cover change without the influence of major rivers and large water bodies (e.g., lakes) using different hydrologic unit scales.

For the land-cover classification analysis, the study used the SPOT satellite imagery, a medium spatial resolution dataset, instead of high spatial resolution images because, for this purpose, the benefits of using medium resolution imagery outweigh the advantages of using high spatial resolution datasets in achieving the results, as discussed in the literature review section.

The outline of the next sections of this research are as follows: the methodology section details the approach used to study wetland-cover change, in both the spatial and temporal dimensions, as the spatial extents and study period are varied. In the temporal dimension, the study used the period 1992 to 2010 to study wetland-cover changes; in the spatial dimension, it studied how the Kansas City metropolitan area's urban wetland changed relative to other land-cover classes as the spatial extents were varied. Furthermore, this study incorporated the effect of precipitation change on urban wetland-cover by studying Kansas City's lake level variations and stream flow changes over time in addition to using station-based precipitation records. The results and discussion section presents how wetlands varied spatially and temporally in both the long and short terms. Also the effect of hydric soils and the influence of major rivers and large water bodies on wetland-cover changes are illustrated.

Research Objectives

This research applied a multi-scale approach to understand urban wetland-cover dynamics in the Kansas City metropolitan area between 1992 and 2010 using remote sensing and GIS techniques to acquire and manipulate data and apply these data for urban wetland change assessments. The wetland-cover change assessment was conducted both in the multi-temporal and multi-spatial dimensions. In addition, the impact of precipitation on urban wetland-cover change was studied.

The specific objectives were as follows:

- Use SPOT multi-spectral images to derive land use/land-cover information for the Kansas City metropolitan area over the past two decades.
- Identify and quantify urban wetland-cover changes as they are impacted by impervious surface development and precipitation variation in the same period.
- Investigate the changes in urban wetland-cover at two temporal scales: the long term (1992-2008) and short term or seasonal (2008-2010).
- Investigate wetland-cover changes using multi-scale spatial analysis at various watershed levels.

- Use a multi-faceted approach to understand the historical precipitation variation and its impact on wetland-cover changes in the Kansas City metropolitan area.
- Use hydric soils to quantify urban wetlands that cannot be detected by optical sensors. The quantified wetland data are augmented to the urban wetland-cover obtained using optical sensors.
- Study precipitation changes in the Kansas City metropolitan area as they affect wetland-cover expression. This included assessing the influence of large water bodies such as major rivers and lakes on the wetland-cover dynamics in the study area.
- Design a geo-processing model for assessing urban wetland-cover dynamics.

Study Area

The Kansas City metropolitan area is located in the central United States and is centered along the eastern boundary of Kansas and the western boundary of Missouri. Rolling hills and open plains characterize the general topography of the area. The predominant land-cover is vegetation that primarily consists of grasslands, forests and cropland. The metropolitan area covers 7 counties that include more than 10 major cities. The area witnessed significant population and economic growth for the past century, especially in the recent decades.

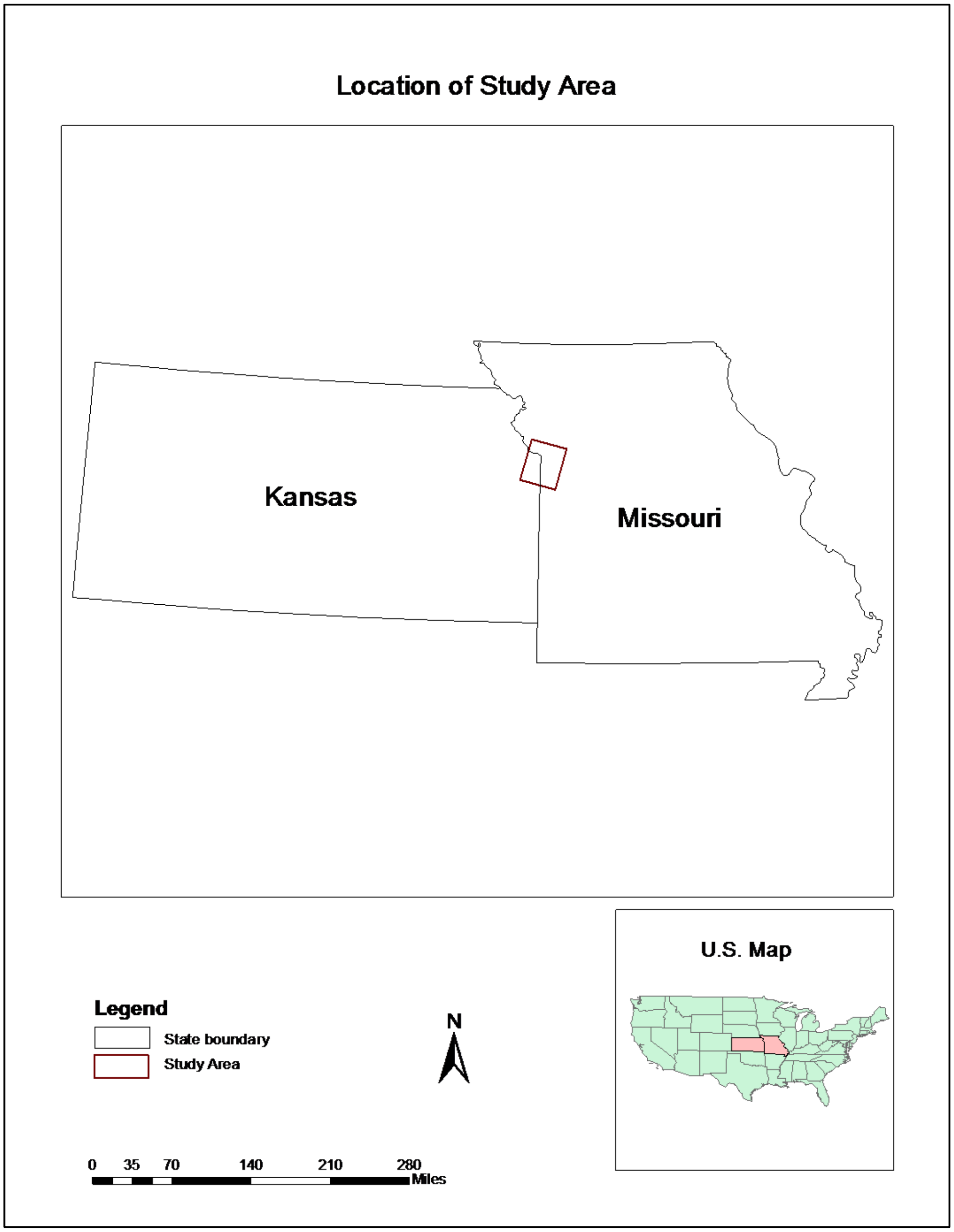


Figure 1-1: Location of the Kansas City metropolitan used as the study area.

Kansas City has a humid continental, bordering on a humid subtropical climate, with moderate precipitation and extremes of hot and cold. Summers can be very humid, with moist air riding up from the Gulf of Mexico, and during the months of July and August, daytime highs can reach into the triple digits, doing so on an average of five days per year, and surpassing 32.2 °C (90 °F) 44 days per year. Winters vary from mild to bitterly cold, with lows dipping below (0 °F) −17.8 °C for around four nights a year (Wikipedia 2011). The study area has experienced significant urban sprawl in the past decades as identified by previous studies (Ji., et al. 2006).

CHAPTER 2

LITERATURE REVIEW

Extensive studies have been carried out on both wetland and impervious surface dynamics in various parts of the world. In the U.S., researchers have studied changes in wetland-cover and functions and found that over the past 200 years, wetland-cover has decreased by about 50%. Impervious surfaces are defined as the sum of roads, parking lots, sidewalks, rooftops, and other impermeable *barriers in* the urban landscape (Barrios 2000). Over the same 200-year period, urbanization in the U.S. also significantly increased resulting in large areas of impervious surfaces.

Wetlands play critical roles in our environment. According to the U.S. Environmental Protection Agency (EPA), wetlands are important in that they store and release water over time, helping to maintain water flow in streams in dry periods; they provide habitats for various species of fish and wildlife and also serve as filters as they are able to degrade pollutants and improve water quality. Wetlands are also vital in recharging aquifers, which are important water sources in different parts of the country.

Wetlands are well known as important ecosystems to maintain the biological diversity and the natural resources, and as storage sites of pollutants (Ikingura and Akagi 2003). The landscape patterns of wetlands are the results of the combined effects of different ecological processes, climate change, land use/cover change and changes in biological diversity (Zhang, et al. 2000)

In urban areas, wetlands have undergone various changes ranging from modification to disappearance. The scarcity of land in urban areas often drives the destruction of small wetlands because they are within the few undeveloped areas remaining or are among the least expensive sites to develop (Hall, Rosenberg and Wiens 1998). These wetlands are impacted by clearing, land use changes, and overall fragmentation of the landscape that comes with development (Azous and Horner 2001). As urbanization of natural landscapes occurs, some or all of the functions and values of wetlands may be affected. Some may be impacted by direct activities such as filling, draining, or outlet modification, while others may be affected by secondary impacts, including increased or decreased quantity and reduced quality of inflow water (Azous and Horner 2001).

What are Wetlands?

Wetlands are natural ecosystems subject to permanent or periodic inundation or prolonged soil saturation sufficient for the establishment of hydrophytes and/or the development of hydric soils or substrates unless the environmental conditions are such that they prevent them from forming (Cowardin, et al. 1979). The U.S. Environmental Protection Agency (EPA) and U.S. Army Corps of Engineers define wetlands as "... those areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions". The U.S. Fish and Wildlife Services (USFWS) define wetlands as:

> 'lands transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is covered by shallow water. For purposes of this classification wetlands must have one or more of the following three attributes (1) at least periodically, the land supports predominantly hydrophytes (2) the substrate is predominantly un-drained hydric soil (3) the substrate is non-soil and is saturated

with water or covered by shallow water at some time during the growing season of year’.

Outside the United States, each country has, or does not have, its own definition of a wetland. Canada, a nation with large amounts of arctic and subarctic wetlands, uses the Canadian Wetland Classification System which separates wetlands into various classes, forms, and types (Wetland Wiki 2009).

Internationally, the Convention on Wetlands, Ramsar, defines wetland types individually, (e.g. bog, fen, inland wetland, coastal wetland) rather than identifying characteristics common to them all. Under the Convention on Wetlands (Ramsar, Iran, 1971), “wetlands" are defined by Article 1.1 as follows: “"… areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six metres."” This definition included open water in addition to the other mentioned types of wetlands (Mauverney 1996).

International Wetland Management Initiatives

In Europe, the Water Framework Directive (WFD) embodies many of the existing directives that have implications for wetlands (European Union 2000). EVALUWET (European valuation and assessment tools supporting wetland ecosystem legislation) is a research project supported by the European Commission under the Fifth Framework program. It is a collaborative project involving 10 partner organizations in seven countries. Its aim is to improve the management of wetlands within Europe by facilitating their integration into river basin management as defined in the Water Framework Directive (WFD). Within the project a wetland evaluation decision support system is developed to support European policy objectives. A multidisciplinary approach is adopted combining expertise from natural and social scientists. The system is applied in nine European catchments.

In Africa, the World Conservation Monitoring Centre (WCMC) and International Union for Conservation of Nature (IUCN) estimated the location and extent of the wetlands in Africa. A group of experts delineated wetlands boundaries by generalizing information on inundated areas, rivers, lakes, and topography from the 1:1 million Operational Navigation Charts (World Resources Institute 2000). However, because of the small scale used in the Operational Navigation Charts, the extent of wetlands are under-estimated, particularly seasonal wetlands, flooded forests, and wetlands in valley bottoms, such as dambos (“"valley meadowlands"” in southern Africa), which are important for agricultural production, food security, and habitat.

Wetland Classification in the United States of America

The U.S. Fish and Wildlife Service (USFWS) conducted an inventory of the wetlands of the United States (Shaw 1956) in 1954 and another wetland inventory was conducted in the 1980s. It was noticed that wetlands have undergone and are still experiencing considerable change, both natural and man related, and their characteristics and natural values have become better defined and more widely known than before the 1980s. Numerous classifications of wetlands and deep water habitats have been developed (Stewart and Kantrud 1971), but most of these are regional systems, and none would fully satisfy the national needs of the United States. Research has found that there is no single, correct, indisputable, ecologically sound definition for wetlands, primarily because of the diversity of wetlands and because the demarcation between dry and wet environments lies along a continuum (Cowardin, et al. 1979).

The USFWS also reports that, in general terms, wetlands are lands where saturation with water is the dominant factor determining the nature of soil development and the types of plant and animal communities living in the soil and on its surface. The single feature that most wetlands share is soil or substrate that is at least periodically saturated with or covered by water. Due to the complex nature of wetland characteristics, the term wetland includes a variety of areas that fall into one of five categories: (1) areas with hydrophytes and hydric soils, such as those commonly known as marshes, swamps, and bogs; (2) areas without hydrophytes but with hydric soils, for example, flats where drastic fluctuation in water level, wave action, turbidity, or high concentration of salts may prevent the growth of hydrophytes; (3) areas with hydrophytes but non-hydric soils, such as margins of impoundments or excavations where hydrophytes have become established, but hydric soils have not yet developed; (4) areas without soils but with hydrophytes such as the seaweed-covered portion of rocky shores; and (5) wetlands without soil and without hydrophytes such as gravel beaches or rocky shores without vegetation. Drained hydric soils that are no longer capable of supporting hydrophytes because of a change in water regime are not considered wetlands by EPA’s definition. These drained hydric soils furnish a valuable record of historic wetlands, as well as an indication of areas that may be suitable for restoration.

According to Cowardin et al. (1979), wetlands include lands that are identified under other categories in some land-use classifications. For example, wetlands and farmlands are not necessarily exclusive. Many wetlands are farmed during dry periods, but if they are not tilled or planted to crops, a practice that destroys the natural vegetation, they will support hydrophytes. The authors defined four major wetland systems, namely: the estuarine, riverine, lacustrine and palustrine systems. These wetlands are defined as follows: the estuarine system consists of deep-water tidal habitats and adjacent tidal wetlands that are usually semi-enclosed by land but have open, partly obstructed, or sporadic access to the open ocean, and in which ocean water is at least occasionally diluted by freshwater runoff from the land. The riverine system includes all wetlands and deep water habitats contained within a channel, with two exceptions: (1) wetlands dominated by trees, shrubs, persistent emergents, emergent mosses, or lichens; and (2) habitats with water containing ocean-derived salts in excess of 0.5 %. The lacustrine system includes wetlands and deep water habitats with all of the following characteristics: (1) situated in a topographic depression or a dammed river channel; (2) lacking trees, shrubs, persistent emergents, emergent mosses or lichens with greater than 30% areal coverage; and (3) total area exceeds 8ha (20 acres). The palustrine system includes all non-tidal wetlands dominated by trees, shrubs, persistent emergents, emergent mosses, or lichens, and all such wetlands that occur in tidal areas where salinity due to ocean-derived salts is below 0.5%.

The following are examples of wetland classes as given by Cowardin et al. (1979). The moss-lichen wetland class includes areas where mosses or lichens cover substrates other than rock and where emergents, shrubs, or trees make up less than 30% of the areal cover. The only water regime is saturated. The emergent wetland class is characterized by erect, rooted, herbaceous hydrophytes, excluding mosses and lichens. This vegetation is present for most of the growing season in most years, and these wetlands are usually dominated by perennial plants. The class scrub-shrub wetland includes areas dominated by woody vegetation less than 6 m (20 feet) tall. The species include true shrubs, young trees, and trees or shrubs that are small or stunted because of environmental conditions. All water regimes except sub-tidal are included. The class forested wetland is characterized by woody vegetation that is 6 m tall or taller. All water regimes are included except sub-tidal. This classification system was designed for use over an extremely broad geographic area and for use by individuals and organizations with varied interests and objectives. The classification employs five system names, eight subsystem names, 11 class names, 28 subclass names, and an unspecified number of dominance types. It is important to note that various wetland classification systems are used in different states of the U.S. to suit the types of wetlands available in the relevant states. Many countries also have their classification systems that address the types of wetlands peculiar to them.

Why Urban Wetlands?

Wetlands play a vital role in our social and economic well-being. They provide services such as improved water quality, groundwater recharging, shoreline anchoring, and natural flood control, and support a diverse variety of fish, wildlife, and plants (National Research Council 1995).

The growth of urban and suburban areas has been a dominant demographic characteristic of the 20th century. During this time urban population has increased ten-fold, and the proportion of the human population living in urban areas has risen from 14 to over 50% (Platt 1994). The result is a land use/land-cover (LULC) change which indicates changing human demographics, natural resource uses, agricultural technologies, economic priorities, and land tenure systems (Wolter, Johnston and Niemi 2006). Such changes, especially in built-up areas, have an impact on the hydrological processes in an area. According to Wolter, Johnston and Niemi (2006), the volume of storm water runoff increased in concert with expanding development. Using aerial photographs from 1937 and 1995, Wegener (2001) studied changes in impervious surface area and found increases in urban area (formerly farmland) were responsible for a 69% increase in the volume of storm water runoff. He determined that a 7.62 cm (3 inch) rainfall event in 1995 resulted in a 65% greater rise in lake level than was the case in 1937 from the same volume of precipitation.

Many researchers have used impervious surface development as an indicator of human impacts in urban areas. However, urban wetlands are more sensitive to human disturbances than impervious surfaces. The use of urban wetlands as indicators of human impacts in urban areas, which is the focus of this research, has not been fully studied. Impervious surfaces are a mere expression of area changes, but wetland disappearance or emergence can indicate the nature of urban development with regards to the health of the watersheds in which the development is taking place.

Urbanization impacts wetlands in numerous ways, both directly and indirectly. For example, construction reportedly impacts wetlands by causing direct habitat loss, suspended solids additions, hydrologic changes, and altered water quality (Darnell 1976). Indirect impacts, including changes in hydrology, eutrophication, and sedimentation, can alter wetlands more than direct impacts, such as drainage and filling (Keddy 1983). Urbanization may affect wetlands on the landscape level through loss of extensive areas; at the wetland complex level through drainage or modification of some of the units in a group of closely spaced wetlands; and at the level of the individual wetland, through modification or fragmentation (Weller 1988). In addition, wetlands can reveal even subtle human disturbances such as changing amounts of water in a wetland, changing amounts of sediment coming into a wetland, increasing amounts of toxic contaminants to the wetland, and fragmenting wetland habitats during urban area development. These impacts affect distribution and abundance of plants, birds, and mammals that are closely associated with wetlands.

Wetland Policy

The U.S. has a long history of Federal involvement in wetland issues using various policies. Several acts were enacted; for example, the Swamp Act of 1849 was intended to aid states in constructing levees and drains to reclaim swamp and overflowed land; the Rivers and Harbors Act involved dredging and filling of navigable waters by the Corps of Engineers; the Clean Water Act (1972) governed water pollution; the 1977 Presidential Executive Order on protecting wetlands was announced; the Swampbuster provision of Food Security Act (1985) declared that persons converting wetlands to agriculture would be denied agricultural loans; the 1988 National Wetland Policy Forum recommended a single definition of wetlands and also the “no net loss” policy of the federal government. In 1989, a federal “wetlands” manual was published by four agencies working together: the Soil Conservation Services (SCS), the Environmental Protection Agency (EPA), the Army Corps of Engineers (COE), and the Fish and Wildlife Services (FWS). This process also involved court cases that led to revision of wetland definitions.

The Clean Water Act (CWA), passed in 1972, gave the U.S. government - specifically the Environmental Protection Agency - control of setting water quality and effluent standards (Fennesy 2011). Section 404 of this act required land owners to get a site-specific permit from the Army Corps of Engineers before filling activities or dredging of any navigable waters, including wetlands (Weems and Canter 1995, Kelly 2001). In 1986, President George W. Bush, Sr. promised to achieve "no net loss of wetlands” in response to an outcry by the organization, Ducks Unlimited, about the decline in duck population

(Searchinger 1992). In order to achieve "no net loss" of wetlands, mitigation became a viable policy option for replacing destroyed wetlands. Mitigation consists of the restoration or creation of a wetland. In theory, this mitigation project should be executed in a similar landscape position to the original wetland, morphology should resemble the original wetland as closely as possible, and water should be able to be held in the system (Weems and Canter 1995).

Executive Order 11990 requires that Natural Resources Conservation Service “take action to minimize the destruction, loss, or degradation of wetlands and to preserve and enhance the beneficial functions of wetlands when ‘providing federally undertaken, financed or assisted construction and improvements’” (Montana NRCS 2011).

Wetland Mapping Standard

In the U.S., a Wetland Mapping Standard was designed to direct the current and future digital mapping of wetlands. The Federal Geographic Data Committee (FGDC) endorsed this standard in July 2009; the purpose of the standard is to support accurate mapping and classification of wetlands, while ensuring mechanisms for their revisions and updates (Federal Geographic Data Committee 2009). The wetland mapping standard would be used for all wetland mapping nationally. This included mapping by Federal Agencies, States, and Tribes, especially if that mapping data would be uploaded into NWI/The National Map as a data layer. Stakeholder representation from the Federal, State, and local government, non-profit, and private sectors was included in the development of this Standard to ensure that the end-user information requirements would be reflected in the final product. The classification accuracy of the final map product should be measured by the target mapping unit (TMU) and producer’s accuracy (PA) metrics. During the time of writing, the structure of the FWS Wetlands Geo-database was a mosaic of best available wetlands data. The standard provides specification of the minimum data quality components for wetlands inventory mapping needed to support inclusion of the data into the national spatial data infrastructure (NSDI), particularly when these activities are funded or conducted by the Federal government.

Importance of Watershed Scale Analysis

Many researchers have stressed the importance of watershed level studies for management and planning purposes. A detailed discussion on the importance of watersheds as critical functional and ecological management units (Diana, Allan and Infante 2006) had been given by many researchers. In a related development, the Environmental Systems Research Institute (ESRI), along with key state, national, and international contributors, developed the ArcHydro data model (Maidment and Morehouse 2002) to better manage and process watershed information and watershed delineation methods (Hollenhorst, et al. 2007).

In landscape analysis, many researchers used large watersheds with an 8-digit hydrologic unit code or larger in area. For example, some 67 equal-area hexagons of a Kansas landscape, each 2560 km^2 in area, were used one analysis (Griffth, Martinko and Price 2000); in another study, 1200 and 1800 km^2 equal-area sub-units were used to study the Chesapeake Bay and Tennessee River basins (Cain, Riitters and Orvis 1997). Some researchers used multi-scale watershed analysis, but only in the spatial dimension, not the temporal. In addition to the use of 8-digit watersheds, (Cifaldi, et al. 2004) used small sub-catchments averaging 43 km^2 in area because these constituted the spatial scale at which much stream assessment and management, as well as watershed planning, takes place.

Researchers also compared fish index of biotic integrity (IBI) scores in a stream buffer with the scores found at a watershed scale (Fitzpatrick, et al. 2001). They found that fish IBI scores seemed most sensitive to land-cover in the entire stream network buffer, more so than watershed-scale land-cover and segment or riparian vegetation width. This followed conflicting research studies regarding the interactions between physical and chemical characteristics at various spatial and temporal scales. Figure 2-1 below shows the hydrologic unit hierarchy that uses the standard hydrologic unit code system. The hydrologic units are shown starting from region (level 1) through sub-basin (level 4) plus levels 5 (watershed) and level 6 (sub-watershed).

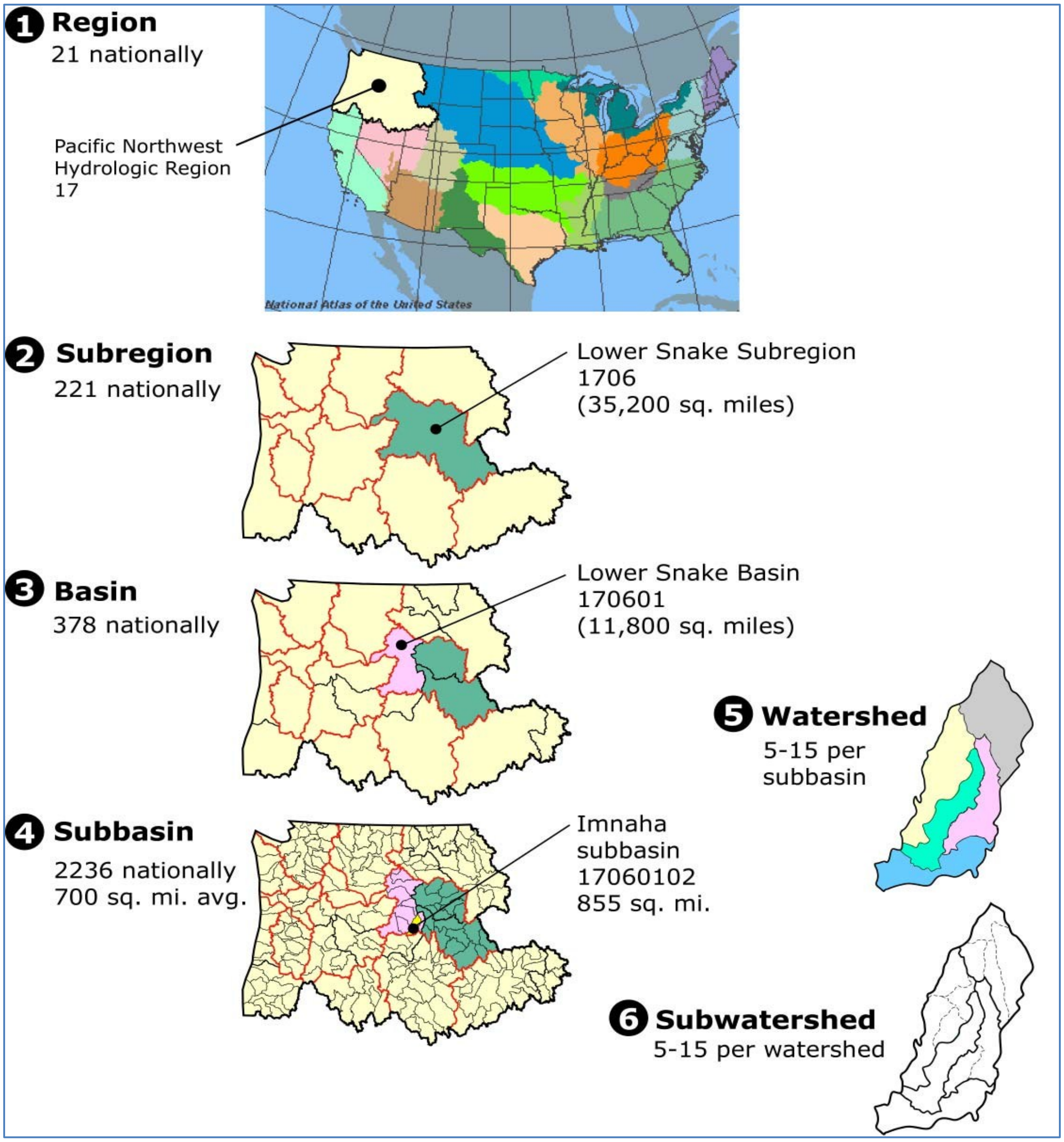


Figure 2-1: Hydrologic unit hierarchy which uses the standardized hydrologic unit code system. (Source: Bruce McCammon, U.S. Forest Service)

In this research, the focus was on the watershed and sub-watershed levels that were used to study wetland dynamics in the Kansas City metropolitan area.

Geospatial Methods for Wetland Mapping: Remote Sensing and GIS

The importance of satellite technology in remote sensing has found use in many land resource applications, including urban wetland change studies. Remote sensing allows large-scale measurements over a large region within a very short period of time. Continuous and repeatable measurements are indispensable features of remote sensing (Makkeasorn 2007). Remote sensing can provide abundant spatial data covering large areas, such as watersheds, in multiple time scales, such as monthly, seasonal, annual and decadal. GIS can offer the power for storing, manipulating, analyzing and visualizing a variety of spatial and non-spatial data such as topographical, wetlands and land-use/land-cover data in a watershed. Geospatial technologies including remote sensing and geographic information systems (GIS) may provide an effective and economical method for evaluating watershed condition related to disturbance from human and natural stresses.

Satellite data provides regular overpass intervals that enable the monitoring of wetland changes seasonally and over longer time periods. Nearly every sensor has been tested and utilized for wetlands identification and wetlands-related research (Ozesmi and Bauer 2002). Each sensor has advantages and limitations often related to their associated resolutions: spatial, temporal, radiometric, and spectral (Torbick, Lawrence and Czajkowski 2008). Research has shown that using aerial photography and field-collected data, classification accuracies improved from 69% for single-season to 88% for two season imagery. A variety of classification techniques have been executed using multi-spectral data and these range from visual interpretation to expert systems. Torbick, Lawrence and Czajkowski (2008), define the term “expert system” as a general descriptor for a variety of organizational frameworks such as intelligent systems, artificial neural networks, or knowledge-based systems. These frameworks, in some situations, are improvements to the regularly used per-pixel image classification.

Although the importance of wetlands is becoming more widely recognized, many wetlands have been destroyed or degraded, historically through agricultural drainage and more recently through urban expansion (Dahl and Johnson 1991). Recent research has shown that the continuing loss and degradation of wetlands is of ongoing concern to the Ramsar Convention, which has been seen through the convention's involvement in recent remote sensing initiatives (Fernandez, Delibes and Palomares 2007). Assessments have confirmed that the extent of wetland mapping and inventory was inadequate. It was found that the most recent estimates of wetland extents were under-estimated, with significant gaps regionally and for various types of wetlands.

Various methods have been used to map wetlands. Advancements in Earth Observation coupled with ground analyses have provided opportunities for identifying, describing, and mapping the distribution of wetlands at a range of scales from local to global (Sahagian & Melack, 1996); Lehner and Do¨ll, 2004; Fernandez-Prieto et al., 2006). Remote sensing and Geographic Information Systems (GIS) have been the major techniques used in mapping land resources data, including wetlands and impervious surfaces. Remote sensing involves classifying image features using two main methods: (1) the per-pixel (spectral) classification and (2) the object-based (feature extraction) classification. Object-based classifications take into consideration not only the spectral values of the pixels but they also look for other characteristics that include texture, pattern, and relative location to each other (Repaka, et al. 2004). Research has also found that object based classifications were far superior to spectral based classifications (Blaschke and Strobl 2001). The object-oriented approach offers new possibilities that exceed the traditional visual interpretation of aerial photography. The former approach allowed for quantitative analysis of change detection and GIS-implementation using an automatic feature extraction. (Willhauck 2000).

A discrete map unit mapping approach, using aerial photo interpretation, was compared with the continuous mapping approach, which derived a depth-to-water value for each pixel from a DEM and hydrographic data using a new GIS-based algorithm developed recently at the University of New Bunswick (Murphy, et al. 2007). The authors criticized the discrete mapping approach, arguing that it made wetlands appear as isolated units rather than as a part of the continuous landscape hydrologic system that connects wetlands.

Recent research has found that use of higher and higher spatial resolution imagery may not be a panacea for wetlands detection analyses. Increasing spatial resolution does not make the “mixed pixels” phenomenon disappear. The percentage of “real mixed pixels” falling between two adjacent fields decreases, but at the same time, a new problem appears: areas that are relatively homogeneous at a 30 m resolution (Landsat TM) exhibit variation at 4 m resolution (multi-spectral IKONOS). Suddenly gaps within a natural forest appear because small islands in the coverage are now represented by several pixels (Blaschke and Strobl 2001). As spatial resolution interacts with the fabric of urban landscapes, a special problem of mixed pixels is created because several land-use/land-cover (LULC) types are contained in one pixel. For example, buildings, lawns, concrete, and asphalt can occur in one pixel (Weng and Lu 2008). Airborne hyper-spectral imagery with high spatial and spectral resolution has not been substantially used to map or discriminate wetlands or impervious surfaces. A few researchers have used it to discriminate vegetation types; for example, salt marsh species (Underwood, Ustin and DiPietro 2003, Artigas and Yang 2004).

Image Spatial Resolution Issues in LULC Classification

Land resources satellite data, ranging from low to high resolution, have been used in land-use and land-cover studies. In the recent decade, researchers have advocated the use of high spatial resolution images (better than 5 m spatial resolution), such as IKONOS and Quickbird, for land-use/land-cover and impervious surface mapping in urban areas (Sugumaran, Zerr and Prato 2002, Goetz, et al. 2003, Van der Sande, de Jong and de Roo 2003). A major advantage of high spatial resolution images is that such data greatly reduces the mixed-pixel problem by providing greater potential to extract much more detailed information in land-cover structures than medium or coarse spatial resolution data (Lu., Scott and Emilio 2010). However, some new problems associated with the high spatial resolution images emerge, notably the shadows caused by topography, tall buildings, and trees (Asner and Warner 2003) and the high spectral variation within the same land-cover class. These disadvantages may lower classification accuracy if the classification procedure cannot effectively handle the mixed-pixels (Irons, et al. 1985, Cushnie 1987).

Though this may compromise on the spatial detail, use of medium resolution images such as SPOT 5 data avoids the challenges that associated with spectral variation brought about by high spatial resolution imagery. Also with high resolution imagery, shadows from tall buildings reduce the spectral values of true land-cover under shadows resulting in poor land-cover classification. For this reason, this research used SPOT satellite imagery with a medium spatial resolution.

Researchers have also found some methods of improving image classification accuracy. A combination of texture and spectral features improved classification accuracy by about 9 to 17 percent compared to results obtained based solely on spectral features (Shaban and Dikshit 2001). However, identification of suitable textures involves the determination of a texture measure, image band, the size of the moving window, and other parameters (Franklin, Wulder and Lavigne 1996). The difficulty in identifying suitable textures and the computation cost for calculating textures limits extensive use of textures in image classification.

In the event of high spectral variability within the same land-cover type, object-oriented classification procedures have had an upper hand over per-pixel classification methods. Because per-pixel spectral-based methods cannot effectively solve the high spectral variation problem within the same land-cover, object-oriented classification methods have been regarded as a good choice to reduce this problem (Thomas, Hendrix and Congalton 2003). Two stages are involved in object-oriented classification: image segmentation and image classification (Jensen 2004). Image segmentation merges pixels into objects, and a classification is then implemented based on those objects instead of the individual pixels. In the process of creating objects, scale determines the occurrence or absence of an object class, and the size of an object affects a classification result (Jensen 2004).

Classification Algorithm

To identify the various land-cover classes from satellite data, various image classification methods are used, such as decision trees (DTs), support vector machines (SVM), and the likelihood classifiers. A decision tree classifier is a non-parametric classifier that does not require any a priori statistical assumptions to be made regarding the distribution of data. The process of building the decision tree is presented in (Quinlan 1993). The support vector machines (SVM) are a set of related learning algorithms used for classification and regression. Like the DTs classifiers, the SVM are also non-parametric classifiers. The theory of the SVM was originally proposed by Vapnik and Chervonenkis (1971) and later discussed in detail by Vapnik (1999). The success of the SVM depends on how well the process is trained.

As used in this study, the maximum likelihood classifier (MLC) is a parametric classifier that assumes normal or near normal spectral distribution for each feature of interest. The algorithm for computing the weighted distance or likelihood D of unknown measurement vector X, belongs to one of the known classes Mc, is based on the Bayesian equation (ERDAS 1999).

$$D=\ln(ac)-[0.5\ \ln(|covc|)]-[0.5(X-Mc)T(covc-1)(X-Mc)]$$

Where:
c= a particular class
M_c= the mean vector of the sample of class c
a_c= percent probability that any candidate pixel is a member of class c
(defaults to 1.0, or is entered from a priori knowledge)
Cov_c= the covariance matrix of the pixels in the sample of class c
$|Cov_c|$= determinant of Cov_c (matrix algebra)
Cov_c-1= inverse of Cov_c (matrix algebra)
ln= natural logarithm function
T= transposition function (matrix algebra)

The unknown measurement vector is assigned to the class in which it has the highest probability of belonging. It assumes an equal prior probability among classes and the classifier is based on the probability that a pixel belongs to a particular class. This classifier takes the variability of classes into account by using the covariance matrix. Therefore, MLC requires a sufficient number of representative training samples for each class to accurately estimate the mean vector and covariance matrix needed by the classification algorithm (Chen, Stow and Gong 2004, Landgrebe 2003, Hubert-Moy, et al. 2001, Mather 2004) . When the training samples are limited or non-representative, inaccurate estimation of the mean vector and covariance matrix often results in poor classification results. A detailed description of

MLC can be found in many textbooks e.g., Richards and Jia, 1999; Lillesand and Kiefer, 2000; Jensen, 2004. MLC may be the most common classifier used in practice because of its sound theory and its ubiquitous nature in commercial image processing software.

Relevance of Spatial Extent for Landscape Analysis

Although geo-spatial analysis may be carried out at various scales, some spatial scales are more useful for practical purposes than others. In a study to explore landscape pattern variability at finer spatial scale to investigate pattern, process and management opportunities within individual watersheds, research found that for both theoretical and practical reasons, analyses often are carried out using large landscape units. However, land use planning and the activities of management agencies typically take place at the local level and address issues related to land use/cover over relatively small spatial extents (Cifaldi, et al. 2004). These researchers also queried whether pattern indicators and unique dimensions of pattern identified in analyses of larger landscape units were also meaningful for more finely subdivided landscapes. Furthermore, research has shown that not all aspects of pattern are the same in studies that differ in data resolution and diversity of landscapes (Riitters, et al. 1995).

Attempts at Finding Suitable Spatial Scales for Studying Landscapes

Although developing indicators of the ecosystem condition was a priority in the Great Lakes, little was known about appropriate spatial scales to characterize disturbance or response for most indicators (Brazner, et al. 2007). These researchers assessed the responsiveness of 66 candidate indicators to human disturbance (agriculture, urban development, and point source contaminants) characterized at multiple spatial scales (100, 500, 1,000, and 5,000 m buffers and whole watersheds) using classification and regression tree analysis (CART). The authors concluded that identifying the appropriate scale to characterize disturbance will be necessary for many indicators, especially when urban development is the primary disturbance.

The use of various spatial scales to provide summaries for a variety of anthropogenic stressors within the Great Lakes at different watershed-based spatial scales was demonstrated by (Hollenhorst, et al. 2007). They used three general approaches: 1) segmentation of the shoreline at point's midway between adjacent streams and delineation of a watershed for each segment; 2) specific watershed delineations for sampled sites; and 3) a Great Lakes basin-wide, high-resolution approach wherein sub-basins could be agglomerated into larger basins for specific portions of the coast. The third method shows that the authors realized that various spatial levels are needed to better understand anthropogenic stressors.

Attempts were made by some researchers to determine the most effective spatial scale for predicting occurrences of anuran species (Price, et al. 2004). They used habitat variables measured within 100, 500, 1000, and 3000 m of sampling points at 63 coastal wetlands along the U.S. shores of Lake Michigan and Lake Huron. Their results would provide meaningful information for anuran conservation efforts and would help wetland managers interpret the significance of amphibian population changes in the Great Lakes coastal region. They concluded that, in general, variables associated with larger geographic scales (particularly 500 and 3000 m from the survey point) predicted the occurrence of anurans better than the local scale variables measured within 100 m of the survey point in Great Lakes coastal areas. This is a case where large spatial extents give a better picture than smaller spatial extents. No clear cut spatial scales have been defined to study various land resources data.

Spatio-Temporal Analysis Studies Using LULC Data

Some researchers used a spatial multi-scale approach in the form of buffer areas along a shoreline. For example, (Wolter, Johnston and Niemi 2006) used LULC change by buffer class as a percentage of watershed-level changes quantified for each LULC change category used in the study. The 0-1, 1-5, 5-10, 0-10 km buffer classes from the Great Lakes shoreline were the four spatial scales used in their study. Seto and Fragkias (2005) also calculated and analyzed landscape metrics spatio-temporally across four buffer zones.

In recent decades, researchers have used landscape metrics to characterize landscape patterns. The term “landscape metrics” mostly refers to indices developed for categorical map patterns (McGarigal, et al. 2002), but it is sometimes also used for topographic measures (Vivoni, et al. 2005) that characterize landscape. It may also refer to some combination of several characteristics that are important to a particular species (Schils 2006, Fernandez, Delibes and Palomares 2007). Many metrics are sensitive to changes in the spatial resolution (grain size) of the data or the area (extent) of the landscape (Wickham and Riitters 1995), and numerous correlations occur among landscape indices (Riitters, et al. 1995). The down-scaling and up-scaling of landscape metrics as functional and structural landscape indicators at different scales still remains a challenge (Mander, Muller and Wrbka 2005).

From works cited in this document, it is evident that wetland mapping was not adequately done in many landscapes, including urban areas. Many institutions are using estimated wetland-cover data. Involvement by local and international organizations stresses the importance of understanding wetland dynamics. Though geospatial technologies have been extensively used in wetland studies, multi-scale urban wetland-cover dynamics at various spatial and temporal scales was not fully addressed in an urban area environment.

CHAPTER 3

METHODOLOGY

The research approach involved identifying urban wetland land-cover types using satellite remote sensing and geographic information systems; quantifying urban wetlands and impervious surfaces using geospatial techniques, using hydric soils as surrogates for optically hidden wetlands; determining urban wetland-cover changes at various spatial and temporal scales, and determining the impact of precipitation changes on urban wetland-cover dynamics. The following is a flow chart of the procedure used in this study.

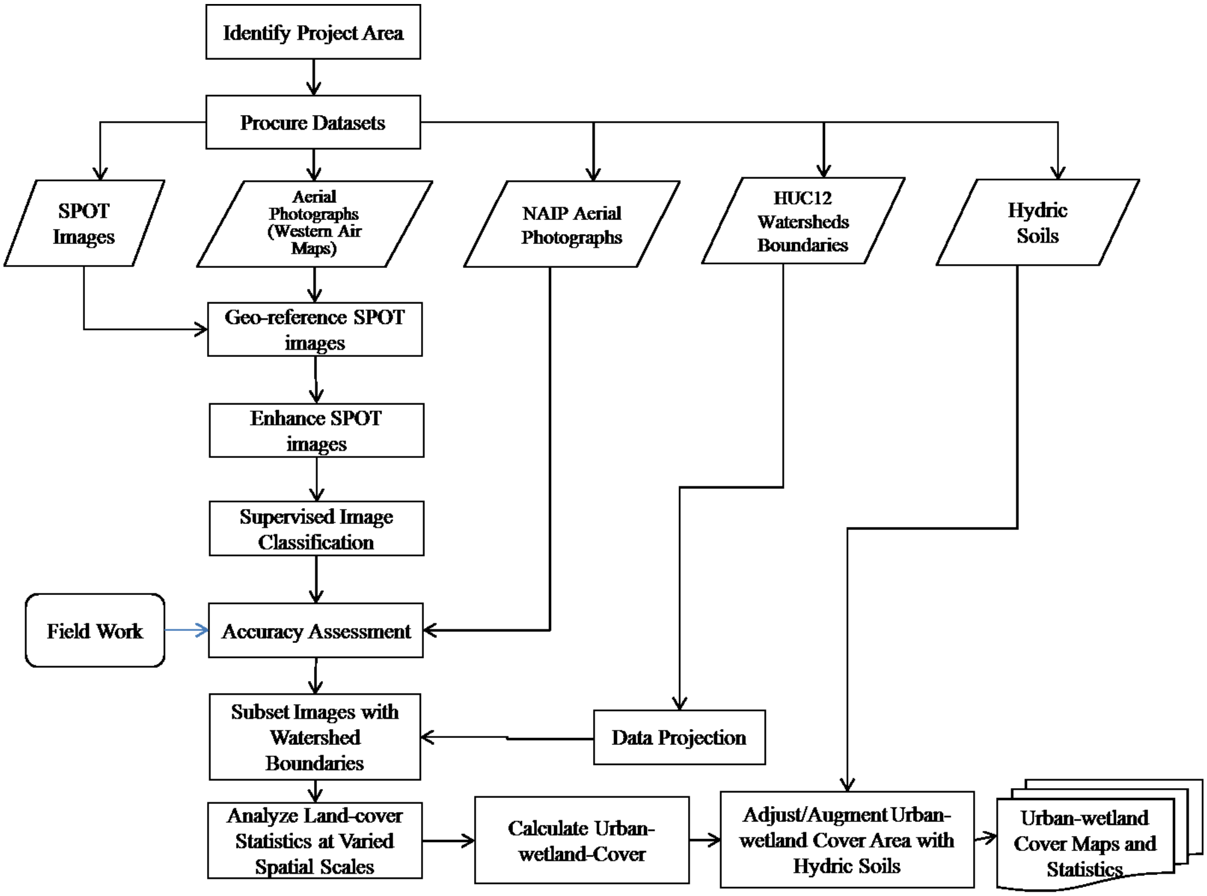


Figure 3-1: Flow chart of the major tasks carried out in the study

Data

SPOT images for 1992 and 2008 were procured from the SPOT Image Corporation, Virginia, USA and aerial photographs were procured from Western Air Incorporated. Five SPOT satellite images were used in this study. These included two SPOT2 1992 images with 20 m spatial resolution. One 1992 image covered the northern part of the Kansas City metropolitan area and other covered the southern part. A mosaic of these two images was used in this research. In addition, three 10 m spatial resolution SPOT5 images acquired in 2008, 2009, and 2010 were used. The 1992 images had 3 spectral bands and the 2008-2010 images had four bands: three multi-spectral and one panchromatic band. The fused SPOT images were used for the land-use/land-cover classification. The 1992 and 2008 SPOT images were geo-referenced, enhanced, and then subjected to supervised classification. The study conducted accuracy assessment using the entire images and then extracted the study area thematic maps based on watershed boundaries for wetland-cover change analyses. For analysis purposes, all data were projected to the same coordinate system.

For geo-referencing the SPOT images, this research used aerial photographs of the Kansas City metropolitan area with 0.625m spatial resolution. The aerial photographs supplied by Western Air Incorporated, included single tiles (0.625 m spatial resolution) and a mosaic (1.8 m spatial resolution) of the same tiles covering the entire Kansas City metropolitan area. Aerial photographs served as reference images for geo-referencing the SPOT images. The study used watershed boundaries (shapefiles) acquired from the Missouri Natural Resources Conservation Service State Office. Further, this research used the National

Agriculture Imagery Program (NAIP) aerial photographs (0.6m spatial resolution) in the accuracy assessment procedure and as a guide in identifying the features of interest. Tables 3-1 and 3-2 below show the characteristics of the SPOT images and the aerial photographs used in this study, respectively.

Table 3-1: Characteristics of SPOT images

Sensor	Orbit	Date	Time	Spectral mode	No. of bands
SPOT 2	587-272	29-Jan-92	17:23:19	XS	3
SPOT 2	587-271	29-Jan-92	17:23:11	XS	3
SPOT 5	586-271	8-Oct-08	17:06:42	J	4
SPOT 5	586-271	23-Apr-09	17:20:47	J	4
SPOT 5	586-271	11-Aug-10	17:12:31	J	4

The spectral mode XS means 20 m spatial resolution multi-spectral and J stands for 10 m spatial resolution multi-spectral mode. The orbit is made up of two numbers, separated by a dash, representing the satellite path and row.

Table 3-2: Characteristics of the aerial photographs used to augment the ground truth exercise

Type	Year	Area covered	Source
Air photo	2005	Kansas City metro	Western Air Maps Inc.
NAIP	2007	Kansas City metro*	Missouri Spatial Data Information Services
NAIP	2009	Kansas City metro*	Missouri Spatial Data Information Services

*Different NAIP photographs were used for each county since no one photograph covered the entire study area.

Table 3-3: Vector data and other ancillary datasets used in this study

Data	Source
Watersheds boundaries	Missouri Natural Resources Conservation Service State Office
Hydric soils	NRSC
Stream flow discharge	USGS Water Services
Lake inflows	Army Corps of Engineers (COE)
CPC merged analysis of precipitation data	NOAA website

To understand the impact of precipitation changes on wetland-cover dynamics, precipitation data, stream flow discharge and lake-inflow, variations data were used. Precipitation was analyzed using both station-based data and regional CPC merged analysis of precipitation data. Watershed and sub-watershed vector boundaries were used to extract watershed areas from classified satellite images, thereby facilitating watershed-based urban wetland-cover analysis.

Geo-referencing Procedure Using the ERDAS™ Imagine Autosync Module

ERDAS™ Imagine's Auto sync module was used for geo-referencing the SPOT™ images using a 2005 aerial photograph as a reference image. This research used the geo-referencing wizard module, which requires that the user specify both the input image and the reference image. The difference in the spatial resolution of these images must not exceed a factor of six (6) and at least a 40% overlap of the images was required in order to achieve acceptable results. The images used in this research met the above criteria with respect to the reference aerial photograph.

Next, the analyst specified the parameters of the Automatic Point Matching (APM) strategy, which included selecting the layers to use for generating tie points, blunder removal, and maximum number of iterations, among other things. In all cases, the geometric model was set to a second degree polynomial as the images were not significantly distorted to warrant the rigorous high-order polynomial rectification procedures. The map projection of the output image was set to be the same as the reference image: UTM with WGS84 as the datum. The geo-referencing procedure involved specifying the (1) APM strategy parameters (2) geometric model for the output image (3) projection for the output image, and (4) the geo-correction method (e.g., resample/calibrate). Following this, I reduced the error threshold to less than 0.3, deleting Ground Control Points (GCPs) with error values greater than the threshold value and reviewing the points till an acceptable RMSE error was achieved. More than 100 GCPs or tie points were used for each image, and all were fairly well distributed within the image area. This was followed by running the calibrate/resample function to generate the output image. The registration procedure achieved an accuracy of less than 0.5 pixel root mean square error (RMSE) for each image used. Finally, the analyst used the swipe/blend or flicker functions to perform visual verification on the output image to check the correctness of the geo-referencing process.

Determination of a Classification Scheme

This research assessed the long- and short term land-cover changes in the Kansas City metropolitan area focusing on wetland-cover changes using five different spatial scales, namely: regional (metropolitan), watershed and sub-watersheds, specific wetland areas, and particular urban development zones exhibiting rapid wetland or impervious land-cover changes. The study performed a land-use/cover classification to determine areas covered by the various land-cover classes in the Kansas City metropolitan area. A suitable classification scheme is required before implementing a land-cover classification. Many factors may affect the determination of a classification scheme, but the major concerns are research objectives, user's needs, characteristics of the study area, and selected remote sensing data (Lu and Weng 2007). In this research, the selected classification system included the following land-use/land-cover classes: surface water (SW), farmland/grassland (FG), impervious surfaces (IS) and forestland (F).

Table 3-4 below shows the classification scheme used in this research. Note that the main idea was to emphasize wetlands and impervious surfaces though forested-wetlands or wetlands under vegetation that could not be easily identified using optical remote sensing classification techniques. Hydric soils were used in later in this study as indicators of "optically hidden" wetlands.

Table 3-4: The land-cover classification scheme

Class name	Description
Surface Water	Rivers, lakes, ponds
Farmland/Grassland	Cultivated land, grasslands, golf courses, lawns
Impervious surfaces	Built up areas (buildings, roads, paved walk-ways etc.)
Forestland	Trees and shrubs

Of the four land-cover classes, impervious surfaces were the most complex, followed by farmlands. Different impervious surfaces such as roads, building roofs, and parking lots may have similar or different spectral signatures. These impervious surfaces could be confused and mis-classified with other land-cover types such as bare soils, surface water, wetland, and crop residues due to similar spectral signatures (Lu., Scott and Emilio 2010). Shadows affect classification of features by reducing the spectral values of true land-cover under shadows. In this research, the shadow effect was prominent in down town Kansas City area, where some features under shadow were classified as surface water. The presence of clouds also affects land-cover classification: clouds on one portion of the 2009 SPOT image were classified as impervious surfaces and their shadows were classified as surface water (wetland). The watershed that was contaminated with clouds was not used for other spatial analyses that required the use of cloud-free images. The urban wetland-cover class was unique in that it was composed of both surface water and vegetated-wetlands. Unlike surface water, vegetated wetlands could not be detected by optical sensors hence I had to use hydric soils as a surrogate for these “hidden” wetlands.

Image Classification Approach

The maximum likelihood algorithm was used for the supervised classification. This study used the maximum likelihood classifier (MLC) which is a parametric classifier that assumes normal or near normal spectral distribution for each feature of interest in the target image. As discussed above, it assumes an equal prior probability among classes, and the classifier is based on the probability that a pixel belongs to a particular class.

More than 80 signatures were used in order to capture, as much as possible, the different spectral manifestations of the target land-cover classes. A supervised classification was conducted on the 1992, 2008, 2009 and 2010 SPOT™ images. After the classification, all signatures were examined to detect those that were misclassified and assign them to correct classes. To achieve this, the study used a high spatial resolution (60 cm) National Agriculture Imagery Program (NAIP) aerial photograph as a guide in identifying the features of interest. The classified image was re-coded according to the classification scheme in Erdas Imagine using the “Recode” function. This was followed by conducting an accuracy assessment for each image used. For all images, at least four classification runs were conducted to obtain the most representative classified layers that had both a high accuracy assessment percentage and a high visual compliance with the detailed features on the aerial photograph.

Field Visits for Ground Truthing

A ground truthing exercise was conducted in October 2009 to check for classification authenticity or confusion in some parts of the study area. Challenging areas to classify were mainly some wet farming areas that classified as wetlands. Figure 3.2 below shows crop-land that classified as surface water.

(a) – Soy bean field

(b) – Harvested soy bean field

Figure 3-2: Wet crop-land that presented challenges in wetland cover identification during satellite image classification.

On visiting the sites, it was realized that cropland that was imaged soon after the rains (Figure 3-2 above) had surface water, which caused the fields to give a wetland signature; hence the spectral confusion. The information gathered in this exercise was useful in refining the supervised classification, especially for the 2008 image.

Of note was the fact that some impervious surfaces manifested different signatures depending on the surface material that was used to construct them. A case in point was the use of asphalt and concrete in surfacing parking areas and highways, resulting in these areas manifesting different spectral signatures depending on the material that was used for surfacing. Shadows from tall buildings also classified as wetlands because the radiation reflectance of shadow was close to that of water bodies. For each image, I performed an accuracy assessment to generate error matrices showing the producer's accuracy, user's accuracy, and overall accuracy, as well as Kappa coefficients.

Accuracy Assessment

Accuracy assessment is often required for evaluating the quality of land-cover classification results or for identifying a suitable classification method by comparing different classification results in a study area. The error matrix approach is most frequently used in accuracy assessment (Foody 2002). Other important accuracy assessment elements, such as overall classification accuracy, producer's accuracy, user's accuracy, and Kappa coefficient, can be derived from the error matrix (Lu., Scott and Emilio 2010). In this research, 200-250 test samples were examined for each of the four SPOT™ images used.

Effect of Temporal Scale

To determine the effect of temporal scale, this research conducted a long and a short term land-cover data analysis using thematic datasets obtained after classifying the SPOT images. The long term analysis covered a period of 16 years between 1992 and 2008, and the short term analysis covered the period from 2008 to 2010. For the long term analysis, the study compared the land-cover class areas which were obtained using the SPOT™ 1992 classified image with the related areas on the SPOT 2008 classified image. The objective was to assess how urban wetland-cover changed within that period of time. The comparison also sought to find out if there were any related change trends based on land-cover statistics data. For example, impervious surfaces may increase at the expense of wetlands or farmland or any other land-cover class. Noteworthy was the fact that not all wetland types could be identified using optical remote sensing. Therefore, in an attempt to address the challenge of hidden wetlands (wetlands that are not easy to identify using optical remote sensors, e.g., SPOT™ sensors) we used hydric soils and digital elevation models as proxies for such wetlands.

For the short term period, the study used three satellite images acquired in different seasons of the year. The first image was acquired in October 2008 (autumn), the second in April 2009 (spring) and the third image was an August 2010 (summer) image. The intention was to use four cloud-free images acquired at the peak of the four seasons experienced in the Kansas City metropolitan area; that is, summer, autumn, winter and spring. However, this was not possible due to satellite programming issues and low chances of having cloud-free days in Kansas City.

Effect of Spatial Scale

To study the effect of spatial scales in assessing urban wetland changes, the study conducted image analyses at 5 spatial scales/levels namely: regional (metropolitan), watershed, sub-watersheds, specific wetland areas, and particular urban development zones. The metropolitan level presents the big picture of urban wetland changes as they are affected by impervious surface developments; the watershed and sub-watershed level studies reveal the effects of urbanization developments on particular watersheds. Sub-watershed wetland changes may not be accurately determined at regional scale and also analysis results obtained at the watershed or sub-watershed scales may not be extrapolated to regional scales when dealing with heterogeneous landscape scenarios. The first part of this research focused more on surface water cover changes and the latter part includes wetlands that could not be mapped using optical remote sensors. Specific wetland-cover areas were studied to capture rapid urban wetland-cover changes that might not be addressed at the above scales. Particular urban development zones were chosen to reveal areas that have experienced rapid changes in wetland-cover or rapid urbanization.

The second part of the study also compared urban surface water cover changes obtained solely using remote sensing procedures and the changes obtained using both the remote sensing procedure and hydric soils analysis. Analysis results from the two different approaches were analyzed to find out pros and cons for each and then determine and recommend how urban wetland-cover change should be evaluated. The results were also used to adjust wetland-cover changes where the two methods were complementary.

The Geo-Processing Model Tool for Watershed Based Wetland-Cover Analysis

To aid land use planners who would want to find urban wetland cover change for any watershed of interest using thematic maps and watersheds vector datasets for the study area, the project developed a tool in ArcGIS™ ModelBuilder and Python™ that facilitates the procedure. The land-cover datasets and watershed and sub-watershed boundaries were stored in a geo-database from which the tool would extract the input datasets based on user specified hydrological unit (watershed or sub-watershed area). The tool would calculate land-cover areas for any watershed level, regardless of the spatial resolution of the input classified image data.

Conclusion

Studying wetland-cover change is a complex process which requires the use of various data sets, techniques, and tools, since wetland expression is affected by various factors that are both natural and human induced. Some of these factors are direct and others indirect; hence, there is a need to identify appropriate approaches necessary to discover the wetland-cover trends over time and at various spatial scales.

CHAPTER 4

REMOTE SENSING ANALYSIS

The remote sensing analysis involved geo-referencing, mosaicking and supervised-classification of satellite images. This was followed by ground-truthing, conducting accuracy assessments and sub-setting watershed-based focus areas from the thematic maps generated after image classification. Land cover statistics were then compared among the various watersheds and sub-watersheds used in this study in both the long term and the short term periods.

The overall classification accuracy for all images used was over 90% for the four target land-cover classes: Surface water (SW), farmland/grassland (FG), impervious surfaces (IS), and forestland (F). At least four classification runs were conducted for each image, using ERDAS™ Imagine software, with the subsequent selection of the best outputs for each year based on high accuracy assessment values and how best the thematic maps represented the features under study. A summary of accuracy assessment results for the two SPOT images used in the long term analysis is shown in Table 4-1.

Table 4-1: Accuracy assessment results showing the producer's and user's accuracies for each land-cover class, as well as land-cover percent area for 1992 and 2008.

	1992			2008		
	Cover	Accuracy assessment		Cover	Accuracy assessment	
Land cover class	percent	Producer’s	User’s	percent	Producer’s	User’s
Surface water	1.67	96.15	100.00	1.61	100.00	100.00
Farmland/Grassland	52.61	88.64	96.30	42.14	86.96	95.24
Impervious surfaces	11.95	96.43	87.10	14.59	94.87	97.37
Forestland	33.78	94.83	87.30	41.65	97.01	87.84
Total	100.00	92.5		100.00	93.5	

Overall classification results were fairly high even for the 1992 image, because the bulk of the image cover was mainly farmlands and vegetation which could be clearly identified. In all images, water bodies had a clearly distinct signature; hence, they were easy to classify.

Long Term Temporal Scale Analysis at Varying Spatial Scales

In this analysis, the study used three different spatial scales: regional (metropolitan), watershed and sub-watershed scales to study wetland-cover dynamics over the 16-year period.

Long Term Urban Wetland Change Analysis – Regional Scale

At the Kansas City metropolitan scale, this research involved extraction of watershed-based subsets of the study area from both the 1992 SPOT-2 and 2008 SPOT-5 images. The extracted images were used to calculate the land-cover class area changes over the 16-year study period. Classification results revealed substantial increases in forestland (trees and shrubs) and impervious surfaces at the expense of mainly farmland/grasslands. However, it should be noted that the comparison was between the January 1992 and the October 2008 images that were acquired in different seasons. Therefore the results may be subject to minor seasonal differences that may, however, be important at the local level or large scales. Figures 4-1 and 4-2 below show the study areas extracted from each of the two classified images. This was the area of overlap between the source images.

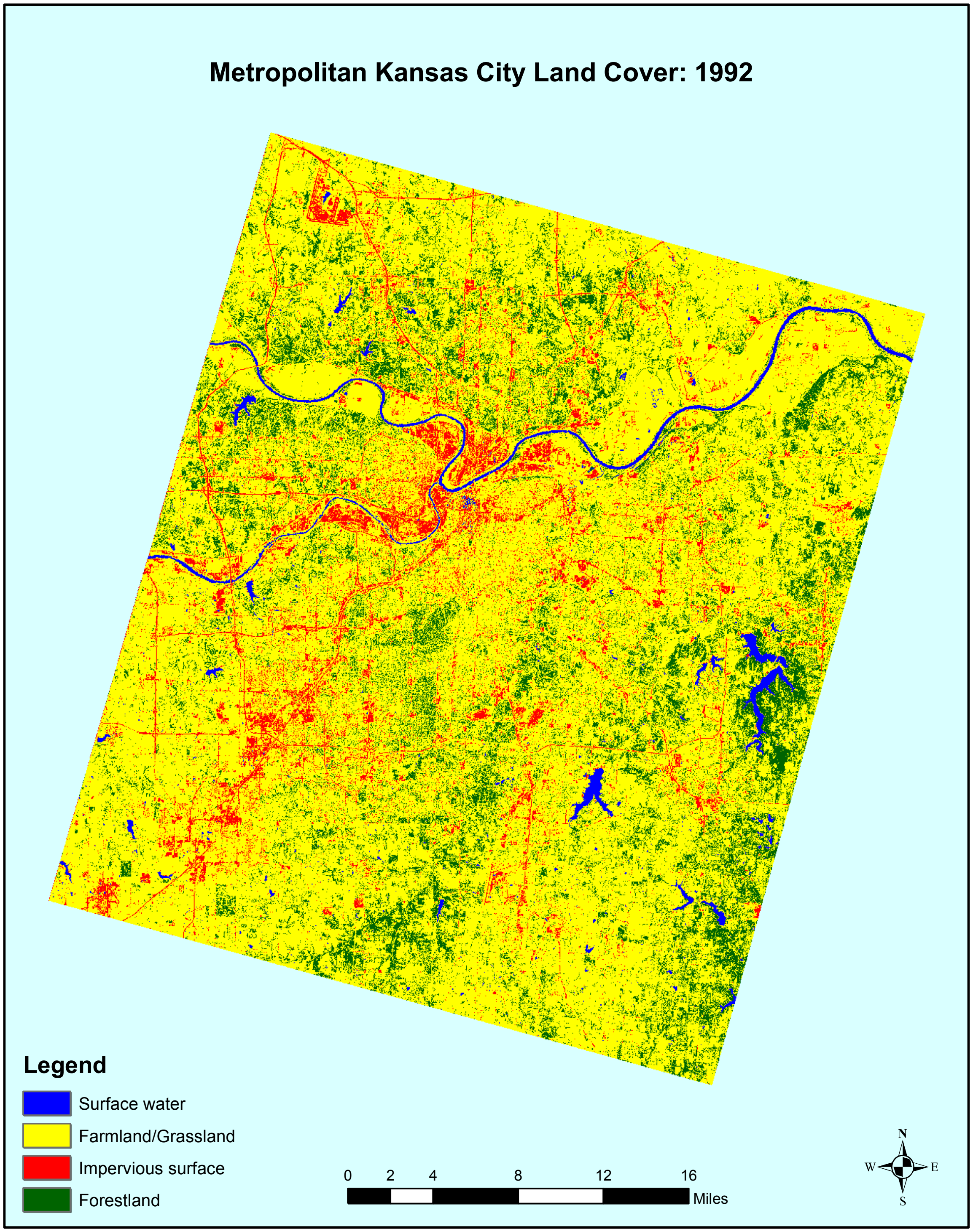


Figure 4-1: Kansas City metropolitan land cover in 1992

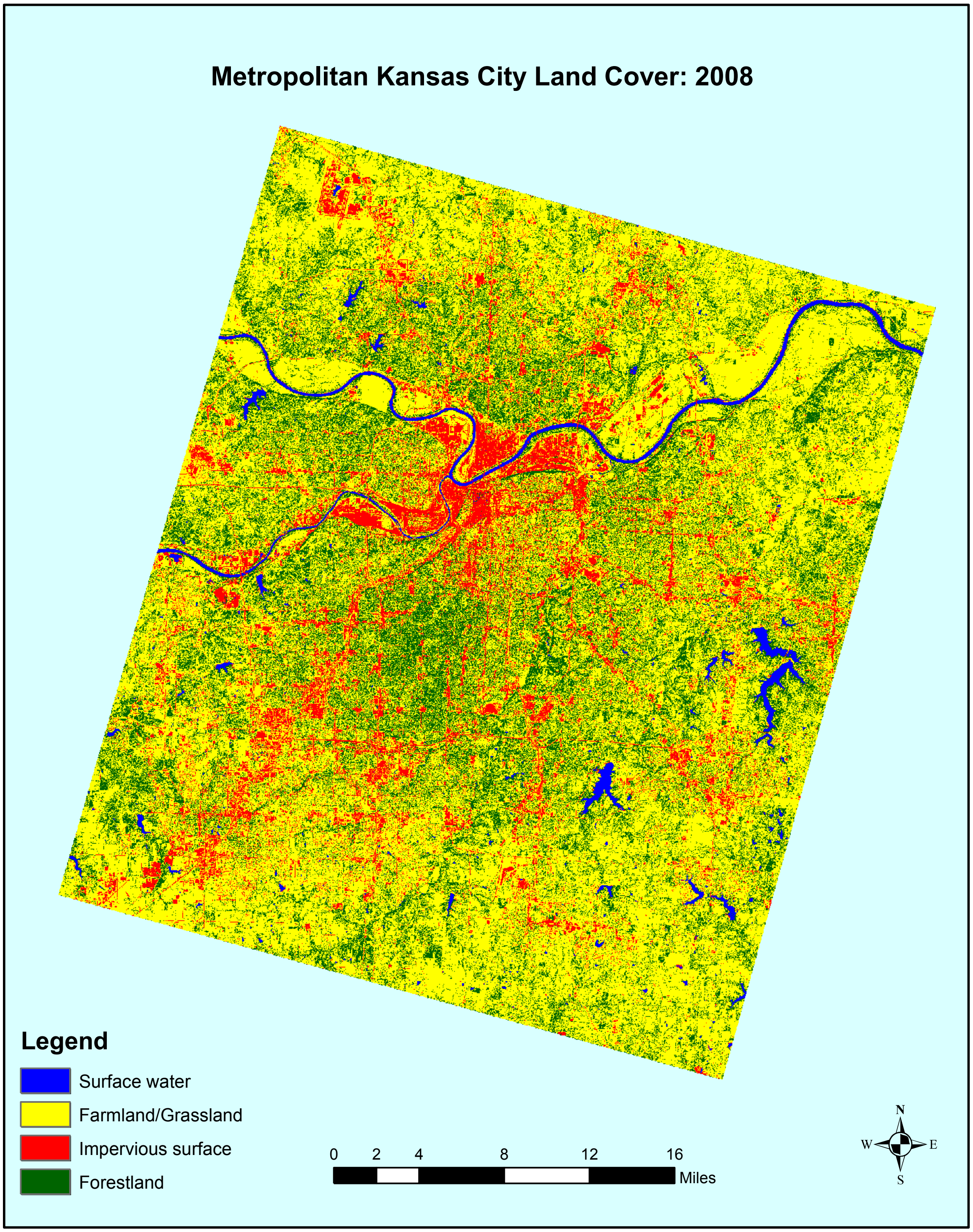


Figure 4-2: Kansas City metropolitan land cover in 2008.

Note the increase in impervious surfaces (red) between 1992 and 2008 in Figures 4-1 and 4-2 above. This was due to an increase in the built-up areas, including road networks, in the Kansas City metropolitan area. The increase in tree canopy, augmented by planting of trees in suburban areas, contributed to a pseudo-increase in forestland cover. The study also compared surface water cover changes between 1992 and 2008 in relation to other land-cover classes at the Kansas City metropolitan area scale. The classification results are shown in Table 4-2 below, and they are based on the four land-cover classes in the classification scheme: Surface water, Farmland/Grassland, Impervious Surface, and Forestland.

Table 4-2: A comparison of area and percent land-cover changes in the Kansas City metropolitan area between 1992 and 2008.

	1992		2008		
Land cover type	Area (sq. km)	Cover percent	Area (sq. km)	Cover percent	Relative percent cover change
Surface water	49.60	1.60	50.90	1.64	+2.47
Farmland/Grassland	2415.90	77.74	1996.42	64.18	-17.44
Impervious surface	222.80	7.16	333.01	10.71	+49.5
Forestland	419.26	13.49	730.1	23.47	+74.14

Note the percentage cover increase for wetland, impervious surface, and forestland (trees) areas. Percent land-cover data for 1992 and 2008 are shown in Figure 4-3 below. The four land-cover classes are represented in the chart as follows: Surface water (SW), Farmland/Grassland (FG), Impervious Surface (IS), and Forestland (F).

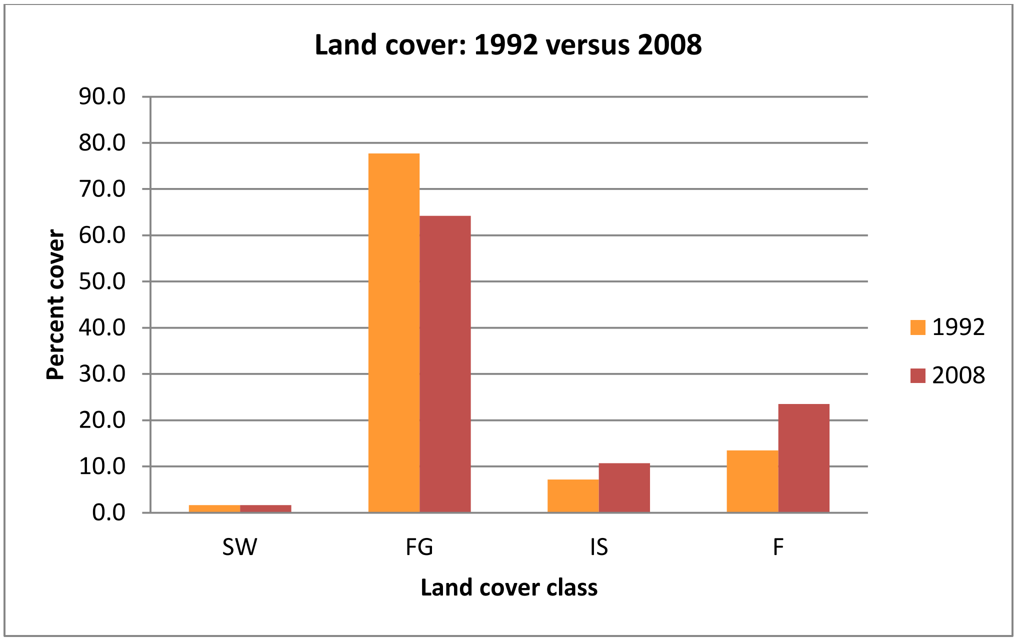


Figure 4-3: Land-cover/use comparison between 1992 and 2008 for the Kansas City metropolitan study area.

At the metropolitan scale, surface water slightly increased. Significant increases were noticed in impervious surfaces and forestland (trees), but farmland/grassland cover decreased, giving way to built-up areas, mostly in suburban areas.

The analysis conducted so far gave an overview of the land-cover/use changes at a regional (metropolitan) scale or entire study area. However, such an analysis may not be representative of areas of smaller spatial extents such as hydrological units within the metropolitan area. Therefore this study narrowed down the analysis of urban surface water cover dynamics to watershed and sub-watershed levels, as well as some selected areas experiencing rapid urbanization.

Long Term Urban Wetland Change Analysis – Watershed Scale

At the watershed scale, this research focused on the three major watersheds from the study area in order to understand the surface water cover dynamics at this spatial level. The watersheds selected had over 80% of their area within the study area. However, none was completely contained in the study area boundary due to limited image coverage. These watersheds were the Blue River, Little Blue River, and Shoal Creek-Missouri River. The Little Blue River watershed had the largest water bodies and, comparatively, less urbanization than the Blue River watershed. The Shoal Creek Missouri River watershed contained the bulk of the downtown Kansas City metropolitan area which has a relatively large concentration of impervious surfaces. The three watersheds are shown in Figures 4-4 and 4-5 below on both the 1992 and 2008 classified images.

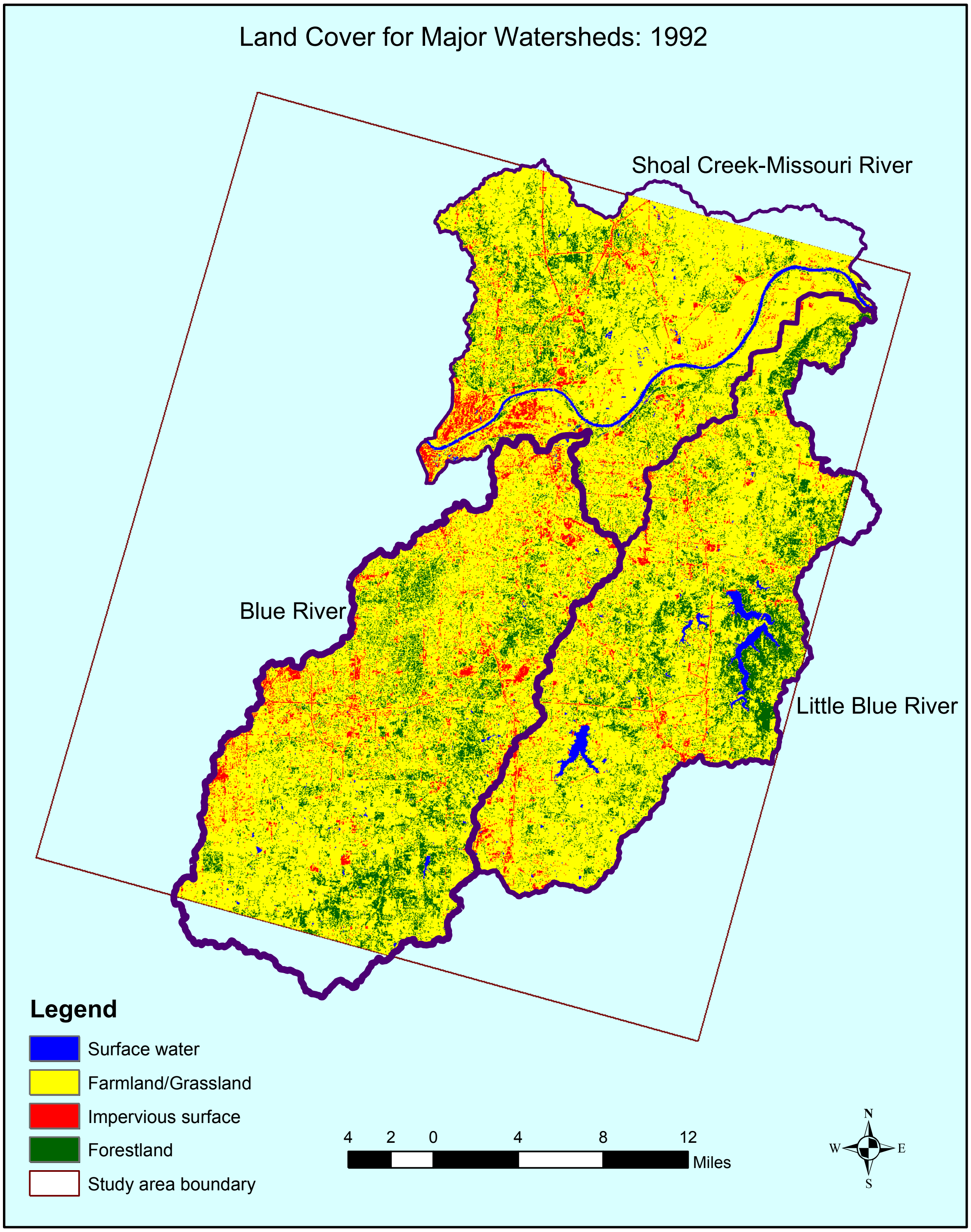


Figure 4-4: Watersheds selected for analysis of land-cover in 1992.

In Figure 4-4 above, the brown rectangular boundary shows the entire study area. The three major watersheds selected that are almost contained within the study area are the Blue River, the Little Blue River, and the Shoal Creek-Missouri River.

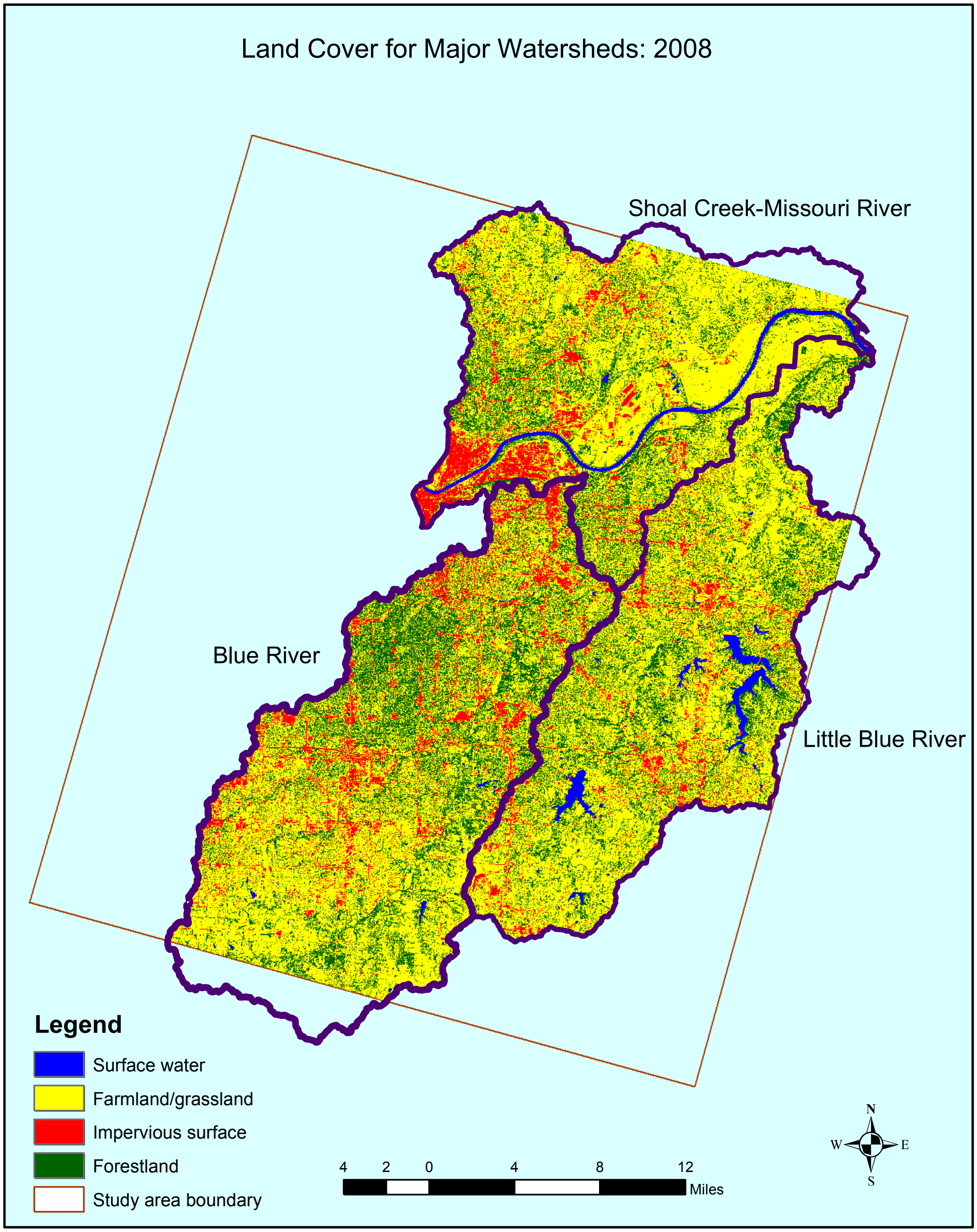


Figure 4-5: Watersheds selected for land-cover analysis in 2008.

The Blue River, the Little Blue River, and the Shoal Creek-Missouri River watersheds, used in 1992, were also used for the 2008 surface water cover analysis. Analysis results for the two years were compared. It should be emphasized that these results were based only on the segments of the watersheds contained within the study area. It would have been ideal to carry out a complete watershed-based analysis, but the study was limited to the available images then. The study compared the analysis results for both 1992 and 2008 in order to capture the land-cover change dynamics. Tables 4-3 and 4-4 below show the results of the land use/cover analysis based on the three major watersheds for 1992 and 2008.

Table 4-3: Land-cover area and percentage cover for the watersheds used in 1992.

	Watershed: 1992					
	Blue River		Little Blue River		Shoal Creek MO River	
Land cover type	Area (sq. km)	Cover Percent	Area (sq. km)	Cover Percent	Area (sq. km)	Cover Percent
Surface water	2.5	0.38	13.3	2.31	12.2	2.47
Farmland/Grassland	511.1	77.82	436.1	76.10	390.9	79.29
Impervious surface	46.2	7.03	26.6	4.65	37.1	7.53
Forestland	97.0	14.77	97.1	16.94	52.8	10.70
Total area	656.8		573.1		493.0	

Land-cover class areas for the different land-cover types are in square kilometers and are also represented as percent areas of the portions of the watersheds used.

Table 4-4: Land-cover area and percentage cover for the watersheds used in 2008

	Watershed: 2008					
	Blue River		Little Blue River		Shoal Creek Missouri River	
Land cover type	Area (sq. km)	Cover Percent	Area (sq. km)	Cover Percent	Area (sq. km)	Cover Percent
Surface water	2.3	0.36	13.3	2.32	12.7	2.58
Farmland/Grassland	392.8	59.81	377.2	65.83	315.9	64.12
Impervious surfaces	86.8	13.21	43.6	7.61	59.6	12.10
Forestland	174.9	26.63	138.9	24.24	104.4	21.20
Total	656.8		572.9		492.7	

The two tables above show that wetland area decreased in the Blue River watershed, remained almost constant in the Little Blue watershed, and increased in the Shoal Creek Missouri River watershed. The watershed scale analysis gives a slightly different picture from the general increase in surface water cover area that was obtained at the metropolitan scale. In all three watersheds, farmland decreased giving way to built-up areas as revealed by the substantial increase in impervious surface area over the 16-year period. This result points in the same direction as the outcome of the analysis at the metropolitan level but it reveals watershed specific information that could not be deduced at the metropolitan scale.

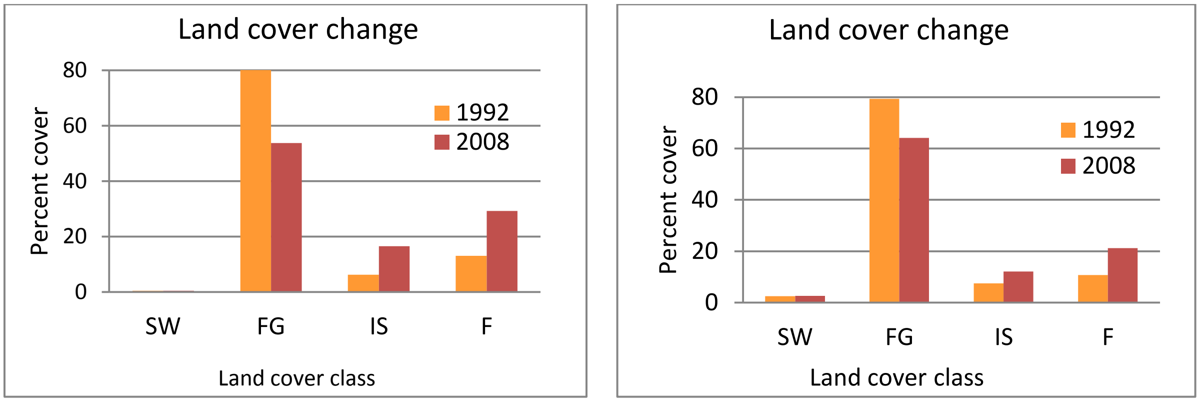
A seeming increase in forestland (trees) over the 16-year period under study was observed for the three watersheds. This is explained by the loss of farmland through conversion to built-up areas, especially residential areas. Residential areas, in most cases, are in turn eventually vegetated as residents plant trees in their land parcels. It is this tree signature that confusingly classifies as forestland. The spectral signature of these trees is similar to that of forestland, which presents challenges in separating the two using optical remote sensing. At the regional (metropolitan) scale as well as for the Shoal Creek Missouri watershed, surface water cover areas have increased, which appears somewhat counter intuitive, as one would expect some wetland areas to be replaced by impervious surfaces as cities grow. This can be attributed to the environmental policies championed by the Environmental Protection Agency (EPA), which are geared at preserving and recovering wetland and surface water resources. Table 4-5 below shows the relative percent changes of land-cover classes between 1992 and 2008 for the three watersheds used in this analysis.

Table 4-5: Relative percent changes of watershed land-cover classes between 1992 and 2008.

	Relative watershed percent land-cover change between 1992 and 2008		
	Blue River	Little Blue River	Shoal Creek MO River
Land cover type			
Surface water	-8	0	4.1
Farmland/Grassland	-23.1	-13.5	-19.2
Impervious surface	87.9	63.9	60.6
Forestland	80.3	43.0	94.8

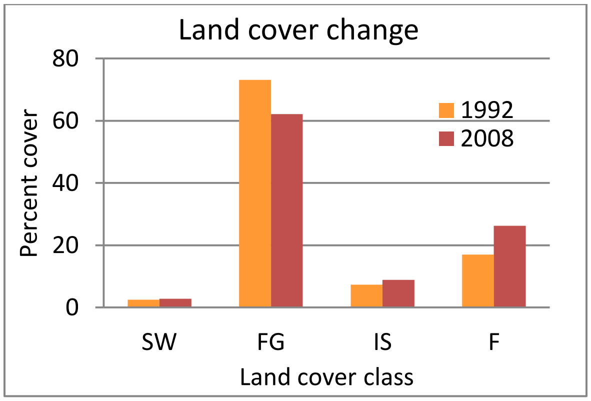
The relative percent changes of land-cover classes are more informative to a watershed level planner than regional scale analysis results. This shows that classification results may not be extrapolated to different scales when dealing with heterogeneous landscapes.

Figure 4-6 shows a comparison of land-cover/use class percentages for the major watersheds in 1992 and 2008.



(a) Blue River watershed

(b) Little Blue River watershed



(c) Brush Creek-Missouri River

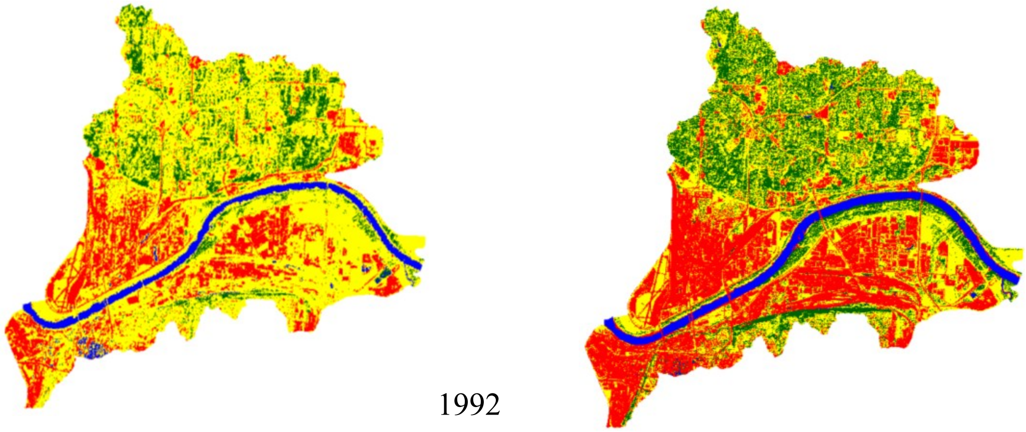
Figure 4-6: Land use/cover change comparison between 1992 and 2008 for the studied watersheds.

The Blue River watershed experienced the most decline in farmland/grassland and correspondingly the highest increase in both impervious surfaces and forestland (trees) compared to the Little Blue River and Shoal Creek MO River watersheds.

However, the watershed scale may be too large to use for local planning, so this research went further to find out if the sub-watershed level would yield more information that may not be clearly revealed at the watershed level. The sub-watershed scale is often used for planning purposes at city level.

Long term Urban Wetland Change Analysis – Sub-Watershed Scale

At the sub-watershed level, the study used sub-watersheds that demonstrated rapid changes in urbanization or surface water cover. For example, the Buckeye Creek Missouri River and the Headwaters Indian Creek sub-watersheds show areas that underwent rapid urban development. In addition, the Headwaters Indian Creek sub-watershed also experienced an increase in tree cover owing to suburban area expansion (Figure 4-7).

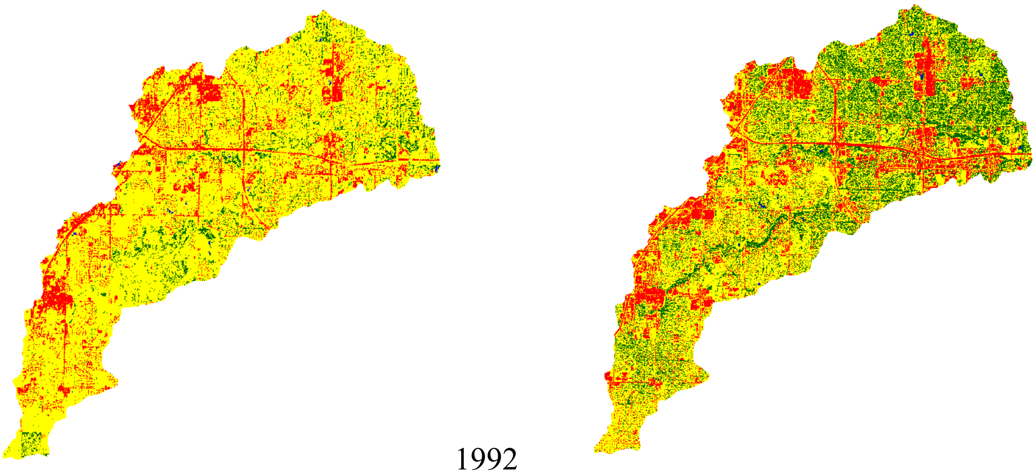


1992 2008

Percent land-cover change**:** SW: 2% FG: (- 39.7%) IS: 68.8% F: 118.1%

Figure 4-7: Land-cover change in the Buckeye Missouri sub-watershed between 1992 and 2008.

Note a significant increase in impervious surfaces (built-up area) at the expense of farming and grassland areas. Forestland seemingly increased owing to trees planted in residential areas, and it is also important to keep in mind that the 1992 image was acquired during off-leaf season. Negative percent values in brackets, for example, for farmland/grassland cover class denotes a decline in cover area.

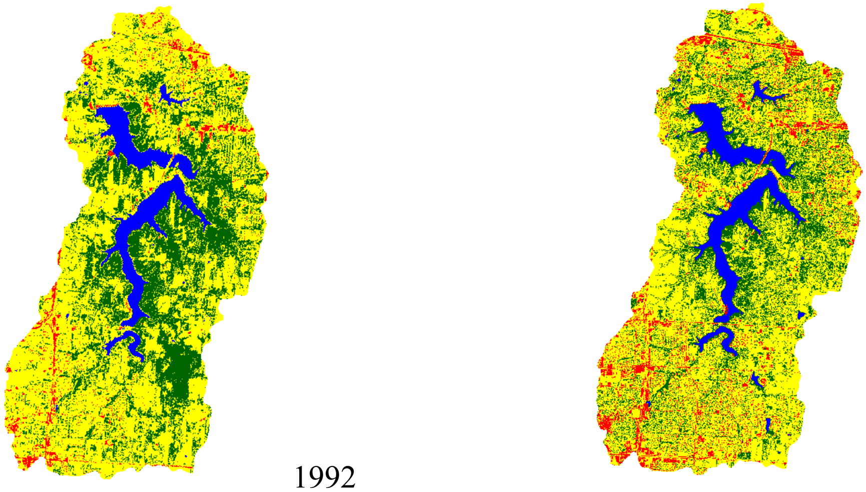


1992 2008

Percent land-cover change: SW: (- 23.0%) FG: (- 26.4%) IS: 28.0% F: 255.0%

Figure 4-8: Land-cover change in Headwaters Blue River sub-watershed between 1992 and 2008.

The Headwaters Blue River sub-watershed experienced a 23% decrease in surface water, which would be a cause for concern for local land resources planners at this spatial extent. In this sub-watershed, impervious surfaces increased significantly similar to the Buckeye Creek Missouri sub-watershed, but surface water as well as farming/grassland areas decreased. This raised a flag for further investigations. In the East Fork-Little Blue River sub-watersheds as shown in Figures 4-9 and 4-10 below, surface water cover gained despite a phenomenal increase in impervious surfaces that could have been at the expense of forestland.



1992

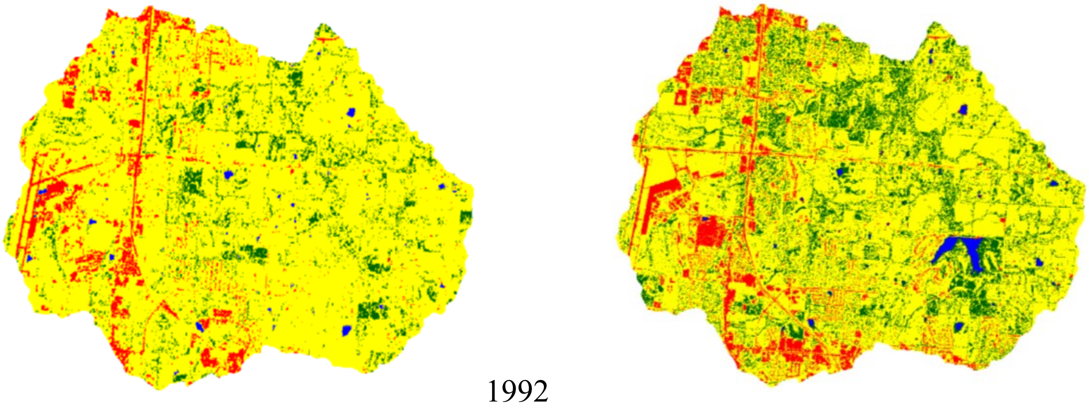
2008

Percent land-cover change: SW: 2.1% FG: 0.9% IS: 145.4% F: (- 19.0%)

Figure 4-9: Land-cover change in East Fork-Little Blue River sub-watershed between 1992 and 2008.

The East Fork-Little Blue River sub-watershed experienced a significant increase in impervious surfaces in the southern part and a general increase in wetlands (surface water).

Figure 4-10 below shows that development of residential areas in Headwaters - Little Blue River sub-watershed was accompanied by construction of water reservoirs to service these areas; hence, there was an increase in the wetland signature in the lower left portion of this sub-watershed.



1992

2008

Percent land-cover change: SW: 60.5% FG: (- 14.5%) IS: 33.3% F:132.8%

Figure 4-10: Land-cover change in Headwaters - Little Blue River sub-watershed between 1992 and 2008.

The Headwaters - Little Blue River sub-watershed experienced a significant increase in surface water. This was, to a large extent, attributed to the construction of a dam that shows in the 2008 image. Impervious surfaces and forestland-cover also increased at the expense of farmland/grassland land-cover, which decreased in area.

In the long-term assessment, the study used images acquired in different seasons and in the following assessment I sought to assess whether there would be significant surface water cover changes with seasons. In this case, the research used 2008, 2009, and 2010 images because cloud-free satellite images acquired in one year and that were also representative of the four seasons were not available. Satellite programming was also a challenge in acquiring the ideal images.

Short Term Temporal Scale Analysis at Varying Spatial Scales

The metropolitan scale analysis was not conducted in the short term because some of the satellite images that were supposed to be used for this analysis, specifically the 2009

SPOT image, had cloud contamination in some areas. Consequently, watersheds that were contaminated by clouds were excluded in the watershed scale analysis. It should be mentioned that cloud contamination was a factor in reducing the scope of the analysis in some areas.

Short Term Urban Wetland Change Analysis – Watershed Scale

For the short term urban surface water cover analysis, this research used the period 2008 - 2010. In this case, the aim was to assess how surface water cover area changed with seasons and thus the satellite images acquired in the spring (April), summer (August) and autumn (October) were used. An image of comparative spatial resolution was not available for the winter season; hence, the winter image was not used.

This research also considered the precipitation activity during the 31 days before the satellite imaging date for each image because the precipitation amounts received prior to the imaging date might have had a bearing on the expression of the surface water footprint on the target satellite image. For each image used, there was no flooding activity that occurred a few months before the satellite image acquisition dates. As shown in Table 4-6 below, the spring image had 4.47 inches of rainfall received 31 days before its acquisition date; the summer image had 2.88 inches, and the autumn image had 7.15 inches of precipitation. The 1992 imaging date was included only for comparison purposes and it represents winter precipitation for that year.

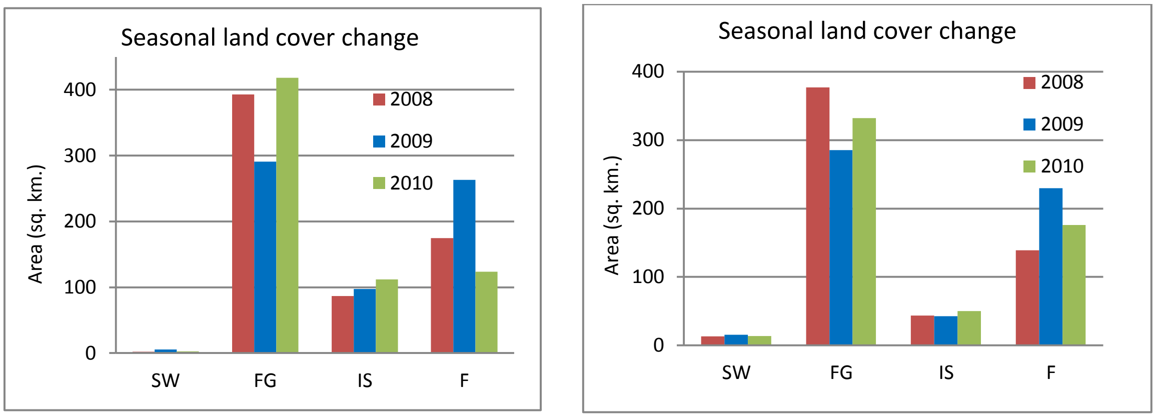
Table 4-6: Precipitation activity during the 31 days prior to SPOT satellite imaging dates.

Cumulative Precipitation (inches)

Days before image acquisition date	Image acquisition dates			
	1/29/1992	10/8/2008	4/23/2009	8/11/2010
0	0	0.08	0	0.04
1	0	0.5	0	0
2	0	0.5	0	0
3	0	0.5	0	0
4	0	0.5	0.25	0
5	0	0.5	0.25	0
10	0.13	0.62	0.83	0
15	0.13	1.32	1.37	1.43
20	0.47	1.32	2.13	1.45
25	0.85	4.57	2.38	2.08
30	1.32	6.95	4.4	2.84
31	1.32	7.15	4.47	2.88

Comparatively higher precipitation amounts were received prior to the 2008 (7.15 inches) and 2009 (4.47 inches) imaging dates. Relatively higher precipitation amounts have the effect of swelling larger water bodies for a comparatively longer period of time than it would for smaller water bodies. Water that accumulates in some of the smaller water bodies would eventually drain into the larger water bodies hence maintaining the swell of the latter a little longer. Evaporation effect, which varies with seasons, has not been taken into account in this analysis.

For this analysis, the Blue River and the Little Blue River watersheds were used. The Shoal Creek Missouri watershed had some cloud contamination that would negatively affect the outcome of the analysis hence was excluded in the analysis. Figure 4-11 shows land-cover area variations for the selected land classes in the different seasons used in this research. It is evident that at the watershed scale, surface water cover did not vary significantly, but major variations were experienced in farmland/grassland and forestland (tree) cover. These are the land-cover classes that are strongly affected by seasonal variations in terms of their manifestations.



Blue River watershed

Little Blue River watershed

Figure 4-11: Land cover change from October 2008 (autumn), April 2009 (spring) and August 2010 (summer) in both the Blue River and the Little Blue River watersheds.

The spring images, especially for the Little Blue River watershed, showed an increase in surface water cover. This could be explained by the water accumulated in the ground as snow melted during the winter season. Evapo-transpiration would also be low during the winter season; hence, soil moisture tends to be high in the spring, resulting in a larger wetland signature on the images. The research also analyzed land-cover changes for selected sub-watersheds that either exhibited rapid urban development or rapid surface water changes or both and the results are shown in Figure 4-12 below.

Short Term Urban Wetland Change Analysis – Sub-watershed Scale

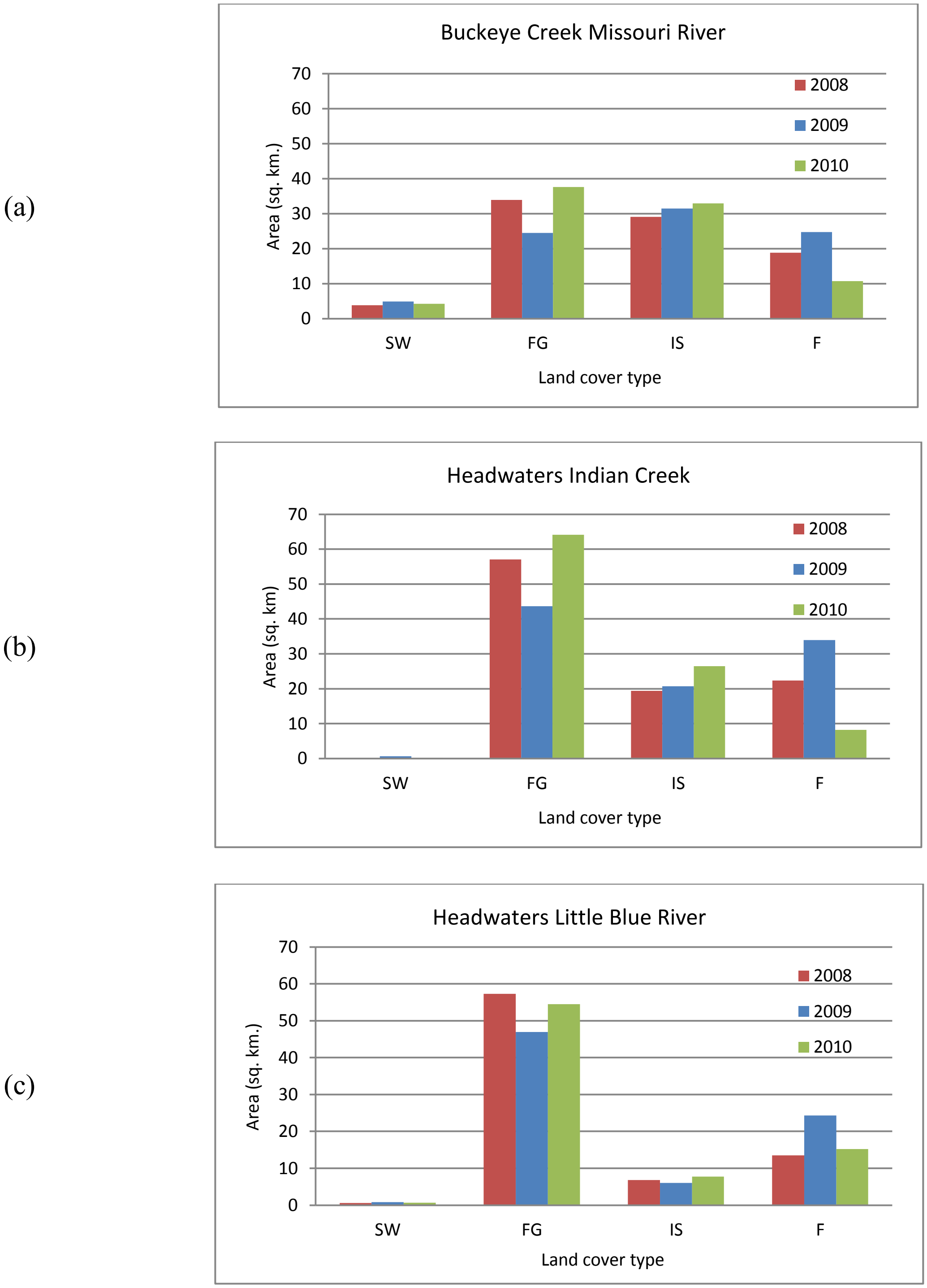


Figure 4-12: Seasonal (short term) surface water cover variations in selected sub-watersheds.

In Figure 4-12 above, surface water cover is higher in the spring as shown in charts (a) and (c). The effect of seasonal variations is prominent in all sub-watersheds especially on land-cover classes that are strongly affected by season changes: farmland/grassland and forestland (trees). The 2009 (spring) land-cover classification shows a higher forestland to farmland/grassland ratio than the 2010 classification result. In 2010 (spring), grassland/farmland cover is more prominent than forestland cover: this is the leaf-off period for deciduous trees; hence, most of the grass cover was captured. Comparatively, there is little variability in water bodies and impervious surfaces.

Changes in water bodies between 1992 and 2008 might not be clear due to the influence of large water bodies and major rivers. When these large water bodies are modified, for example, through dredging or related activities by the Army Corps of Engineers, the effect may be so significant as to mask natural changes associated with urban surface water cover dynamics. In the following section, the study compared water bodies that existed in 1992 and 2008 after eliminating all water bodies greater than 8 hectares (ha) (80000 square meters) in size. The Ramsar wetland convention uses 8ha as the upper area limit for water bodies designated as ponds.

Changes in Water Bodies without the Influence of Major Rivers and Lakes

Large rivers such as the Missouri and Kansas rivers and major lakes such as Lake Jacomo found in the Little Blue River watershed were removed in the analysis to find out how the surface water cover change results would be different than when such large bodies were included in the analysis. The procedure involved conversion through vectorizing of watershed-based thematic image maps into ArcInfo coverage files for each studied watershed. The coverage files were converted to shapefiles using the “Import to shapefiles (multiple)" function in ArcGIS™. Next was the extraction of areas that represented water bodies using the "Select by Attributes" procedure in ArcMap™. The selected water bodies were saved as new shapefiles using the "Export Data" function in ArcMap™. From these files, I eliminated all water bodies with an area greater than 80000 square meters – the upper area limit for pond size according to the Ramsar convention. At the time of writing, the difference between a pond and a lake was still fuzzy from the perspective of various wetland stakeholders as explained in the excerpt below. I therefore adapted the Ramsar Convention on Wetlands' wetland sizes because of their international recognition.

> The international Ramsar Convention on Wetlands sets the upper limit for pond size as 8 hectares (19.768 acres or *80 000 square meters*), but biologists have not universally adopted this convention. Researchers for the British charity Pond Conservation have defined a *pond* to be 'a man-made or natural water body which is between 1 m^2 and 20,000 m^2 (~2 ha or ~5 acres), in area which holds water for four months of the year or more.' Other European biologists have set the upper size limit at 5 ha (12.355 acres or *50000 square meters*). (Wikipedia 2011).

I used the Structured Query Language (SQL) in ArcMap™ to extract water bodies from the feature classes as well as extracting water bodies with areas under 8ha. The SQL expressions used to select water bodies from watershed shapefiles was as follows:

SELECT * FROM *watershed_name* WHERE GRID_CODE = 1.

GRID_CODE "1" represented surface water in the shapefiles generated from classified SPOT images. The resultant shapefiles were exported to a file geodatabase so that new feature classes would be created. The new feature classes had the new “Shape_Area” field which contained the re-calculated or updated areas for the water body features.

The SQL expression for selecting water bodies, from water body feature classes extracted in the previous procedure, with areas below the upper size limit for ponds was as follows:

SELECT * FROM *watershed_name_SW* WHERE Shape_Area <= 80000.

Major rivers and large lakes receive and retain more water than small water bodies such as ponds. Some of the water in these large water bodies might have come from areas upstream outside the study area. In this part of the study, I eliminated the influence of these large water bodies to the surface water cover in the Kansas City metropolitan area. This resulted in having two classes for surface water: (1) major rivers and lakes (> 8ha) and (2) ponds (<= 8ha) as shown in Figure 4.13 below.

Furthermore, during the post-classification of the satellite images used in this study, it was noticed that shadow from tall buildings, especially in the downtown Kansas City area classified as surface water, thereby inflating the surface water cover. In 1992, shadow from tall buildings in this was accountable for an area of about 299736.0 sq. m. (0.3 sq. km.). In 2008, shadow contributed an area of 57072.5 sq. m. (0.06 sq. km). The shadow values for 1992 and 2008 periods are counter-intuitive because one would expect more shadow in 2008 owing to an increase in high-rise buildings in downtown Kansas City. This could also be explained by the spatial resolution differences between the two images used. This misclassification was corrected with the aid of aerial photographs. Shadow areas for the two years were subtracted from corresponding surface water areas and were added to the impervious surface cover for each respective year.

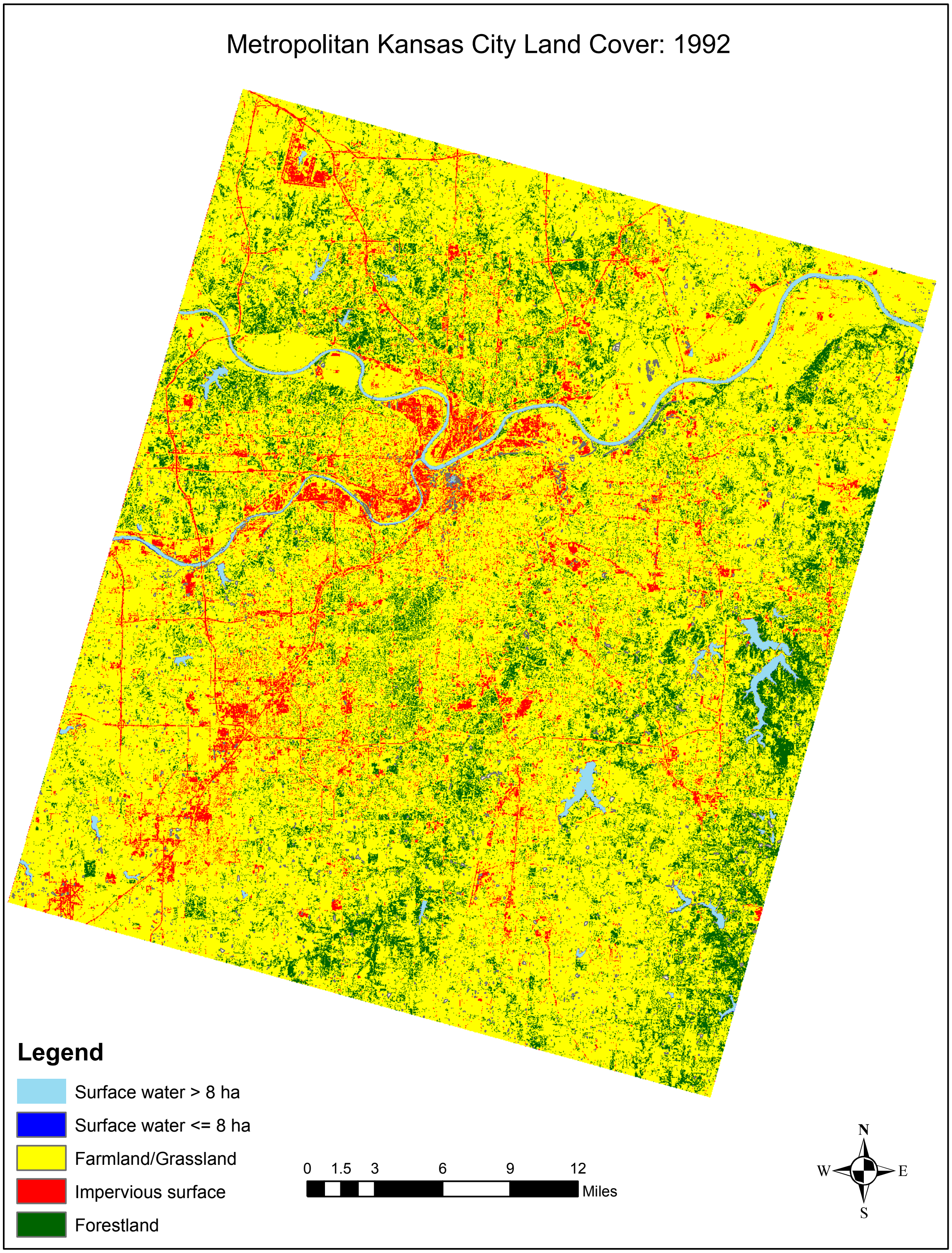


Figure 4-13: Land cover in 1992 with surface water separated into (1) major rivers and lakes and (2) water bodies less or equal to 8ha.

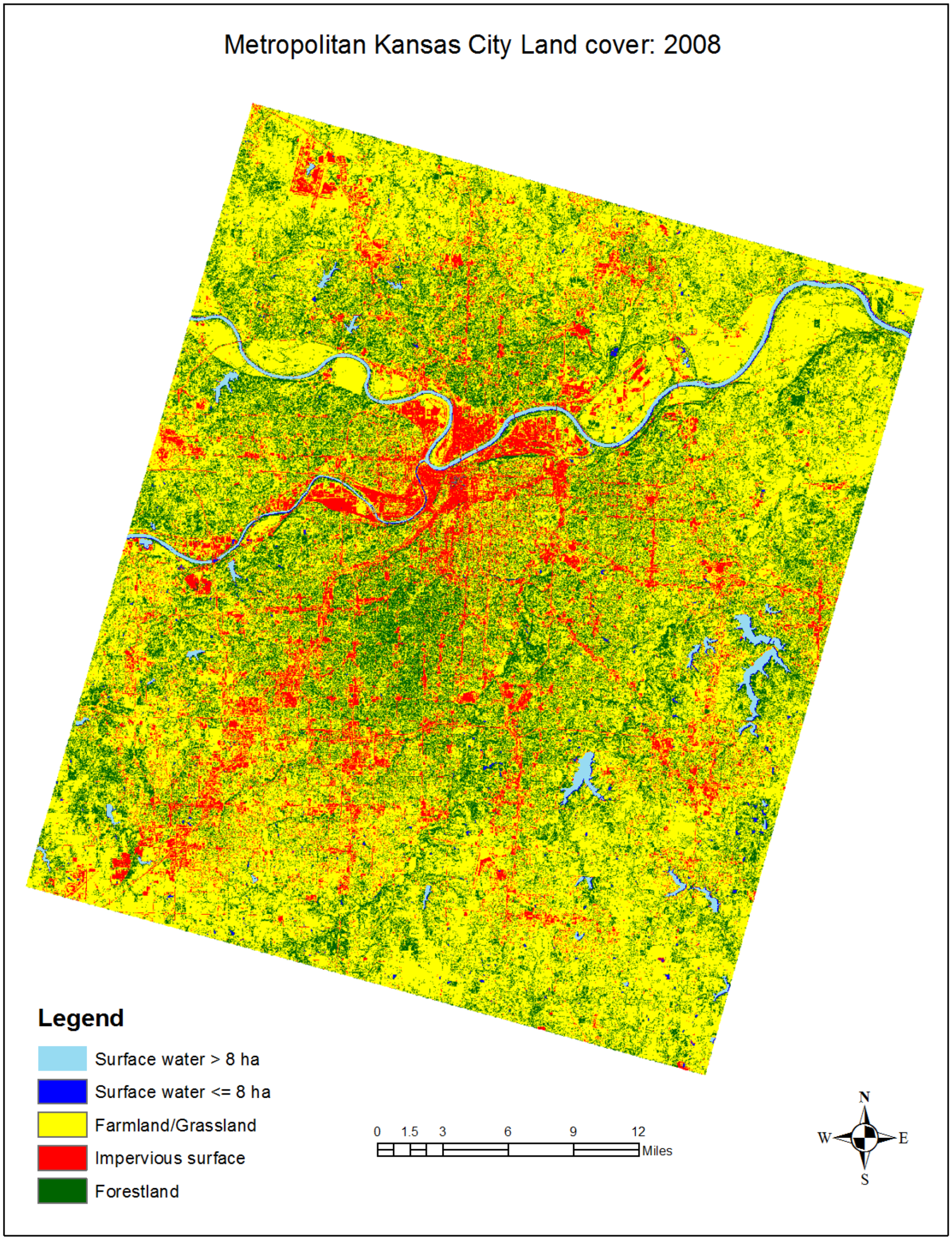


Figure 4-14: Land cover in 2008 with surface water separated into (1) major rivers and lakes and (2) water bodies less or equal to 8ha.

The adjusted surface water cover area for water bodies less or equal to 8ha in area at the Kansas City metropolitan scale in 1992 was 10110991 sq. m. (10.11 sq. km.) and the adjusted surface water for 2008 was 8511617.4 sq. m. (8.51 sq. km). This result showed a decline in surface water area with time. However, surface water cover contributed by water bodies larger than 8ha in area (major rivers and lakes) increased from 39531673 (39.53 sq. km.) in 1992 to 42042939 sq. m. (42.04 sq. km.). After correcting for the shadow effect in the downtown Kansas City area, the combined surface water cover areas still exhibited an upward trend, rising from 49642664 sq. m. (49.64 sq. km.) to 50901228 sq. m. (50.90 sq. km.). At the metropolitan scale, the results showed that inclusion of large water bodies could inflate surface water cover area. This could be due to construction of new lakes or reservoirs or, for example, opening the flood gates in major river systems could result in an unrepresentative increase in the surface water foot print thereby giving a false impression that surface water increased in a watershed area. Another reason for the exaggerated increase in surface water cover in major rivers could be the effect of rainfall activity happening outside the study area. An example is the flooding of the Missouri river in mid-2011 due to upstream precipitation outside the Kansas City area. This resulted in inundation of farms and properties along the precincts of the Missouri river.

Figure 4-15 below shows the analysis of the different surface water categories; that is, water bodies =< 8ha in area, water bodies > 8ha and the combined surface water bodies between 1992 and 2008 at the metropolitan scale.

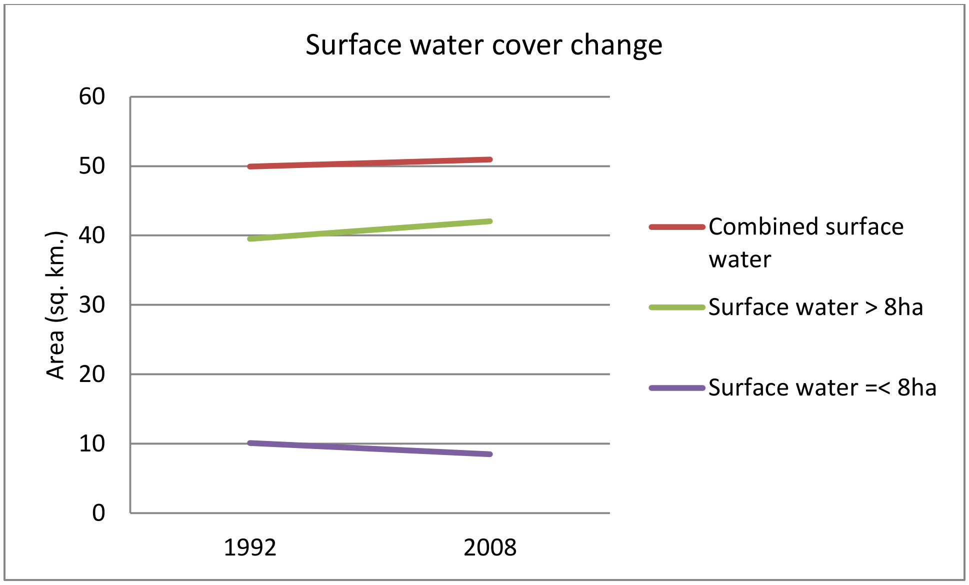


Figure 4-15: Surface water cover change by category at the Kansas City metropolitan scale.

This figure reveals that the overall increase in surface water at the metropolitan scale was attributed to activities taking place in large water bodies. Small water bodies were actually decreasing due mainly to human activities. This gives the planner a rough idea of where to focus regarding loss of surface water bodies. However, at this scale it would not be clear as to where exactly the activities responsible for depleting surface water bodies are concentrated; hence, there is a need to assess the trends at smaller hydrological units.

Figure 4-16 below shows the water bodies (in cyan), for each major watershed, that were selected using a similar SQL expression used to extract surface water cover at the metropolitan scale.

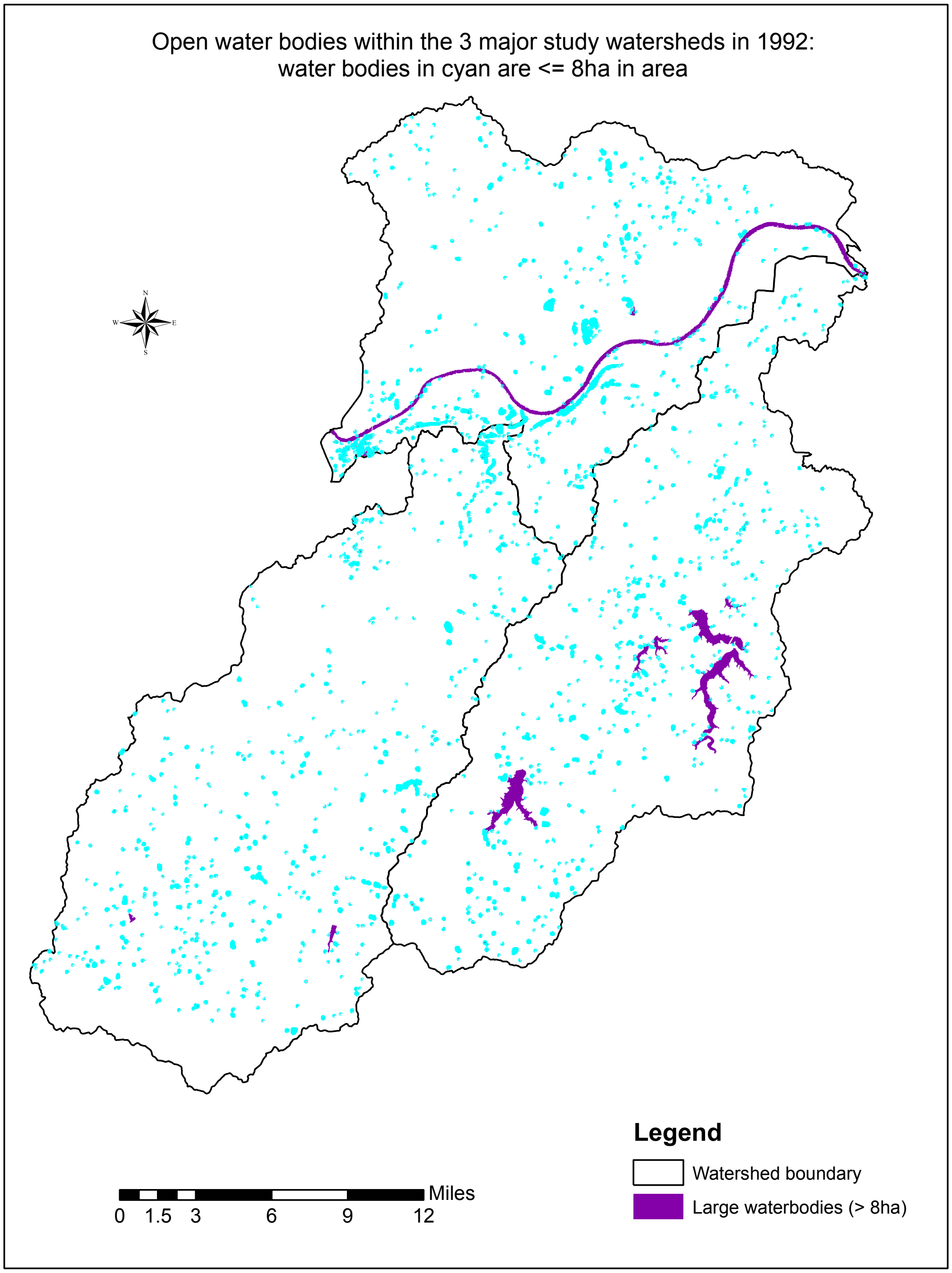


Figure 4-16: Distribution of large (> 8ha) and small (<= 8ha) water bodies (cyan) within the three watersheds in 1992.

Similarly, the distribution of large and small water bodies for 2008 is shown in Figure 4-17 below.

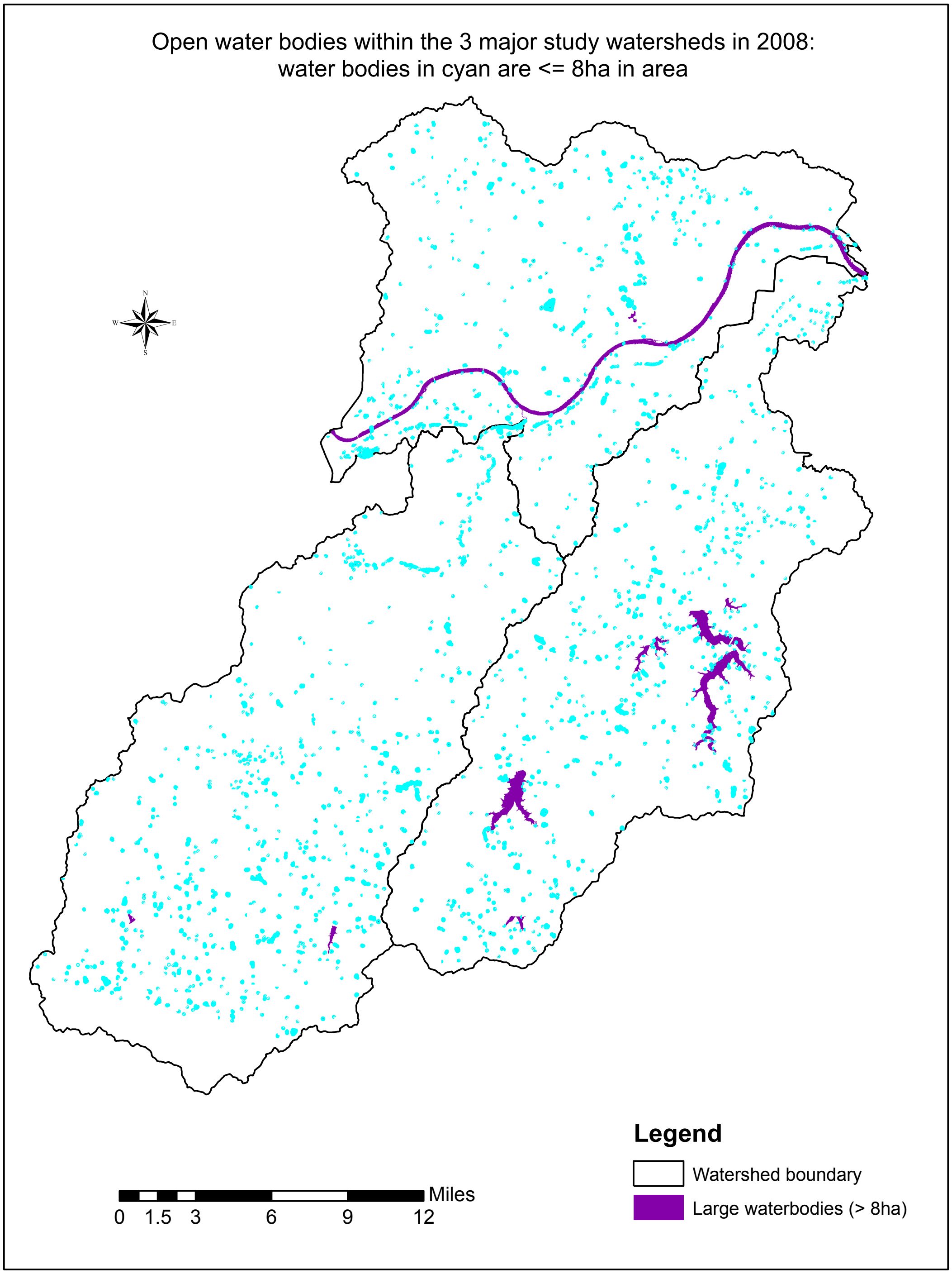


Figure 4-17: Distribution of large (> 8ha) and small (<= 8ha) water bodies with the 3 watersheds in 2008.

Relative differences in surface water cover areas, for water bodies of size less or equal to 8ha, were compared for 1992 and 2008 and results are shown in Figure 4-18 below.

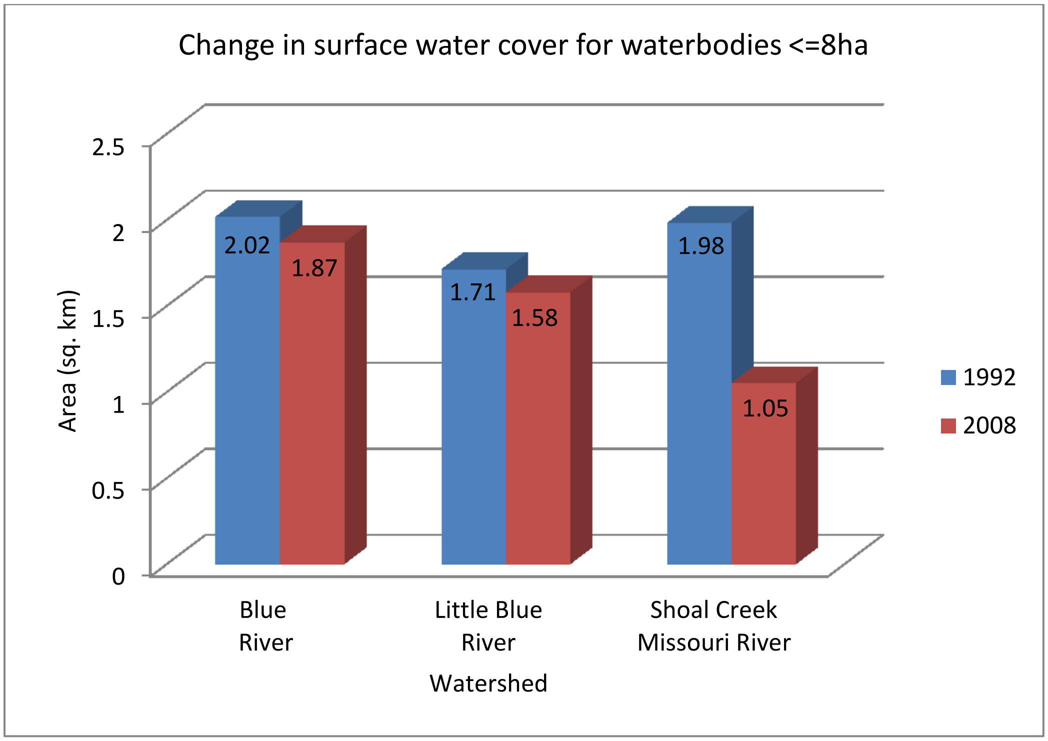


Figure 4-18: Surface water cover change for water bodies equal or less than 8ha at the watershed scale.

The results show that without the influence of large water bodies, all three study watersheds registered a decline in surface water cover. Based on the SPOT data used, the three watersheds lost surface water cover by the following percentages: Blue River (-7.4%), Little Blue River (-7.6%), and Shoal Creek Missouri River watershed (- 46.9%). The Shoal Creek Missouri River watershed is made up of a large portion of downtown Kansas City area; hence, a large surface water cover loss was attributed to a comparatively rapid urbanization that was taking place in this watershed.

Figure 4-19 below confirms the overall decline in surface water cover mainly due to depletion of smaller water bodies. Surface water cover by larger water bodies did not change much. The Little Blue River watershed showed a slight increase in surface water cover due to large water bodies. Interestingly, the Shoal Creek Missouri River watershed showed a substantial decrease in smaller bodies and a substantial increase in surface water cover due to larger water bodies. This watershed showed a net increase in combined surface water cover between 1992 and 2008.

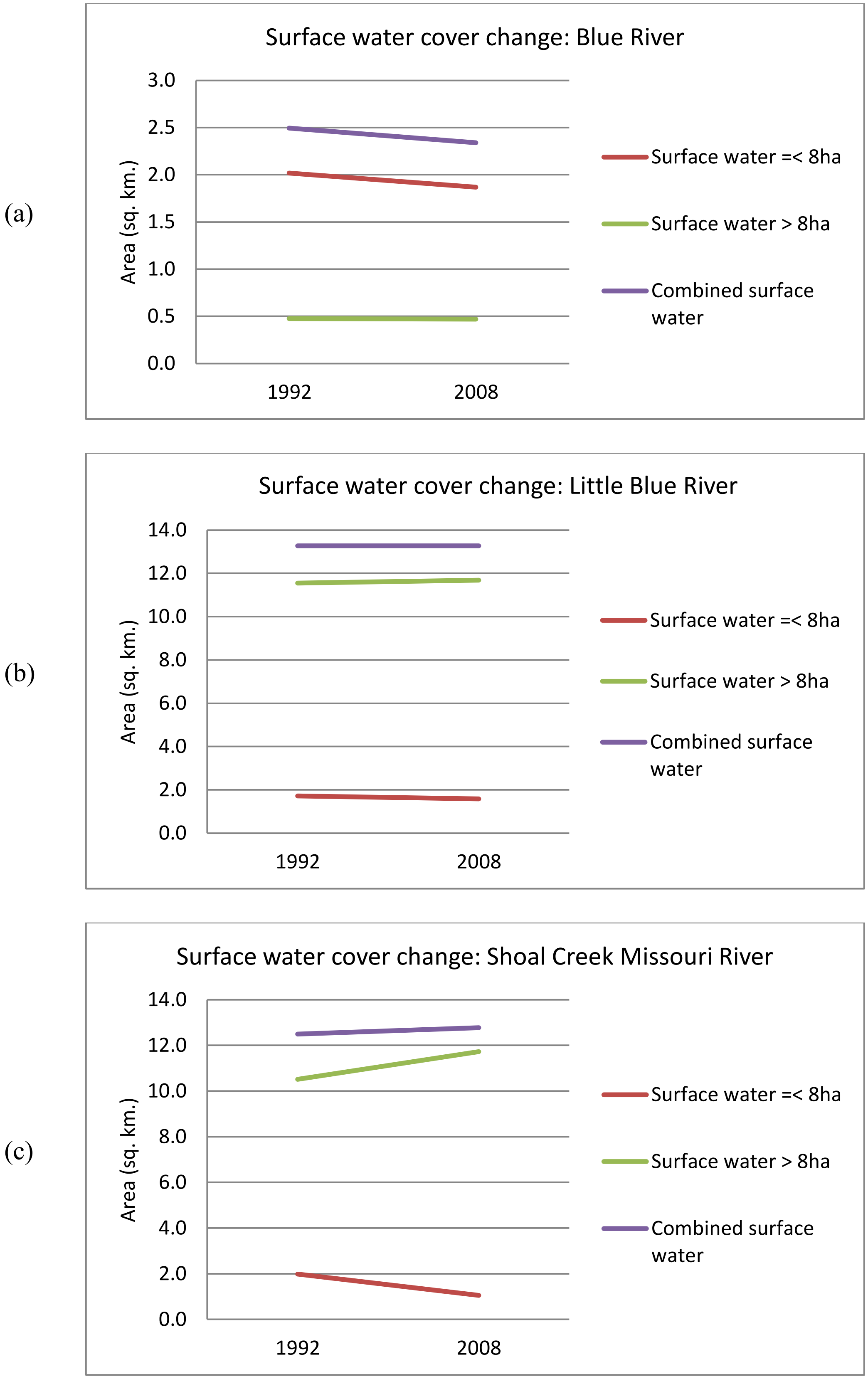


Figure 4-19: Surface water cover change for the major watersheds between 1992 and 2008

Furthermore, the study analyzed the changes in surface water cover at the sub-watershed scale starting with the three sub-watersheds that exhibited rapid surface water and urbanization changes as shown in Figure 4-20 below. The sub-watersheds are: Buckeye Creek Missouri River, Headwaters Indian Creek, and Headwaters Little Blue River.

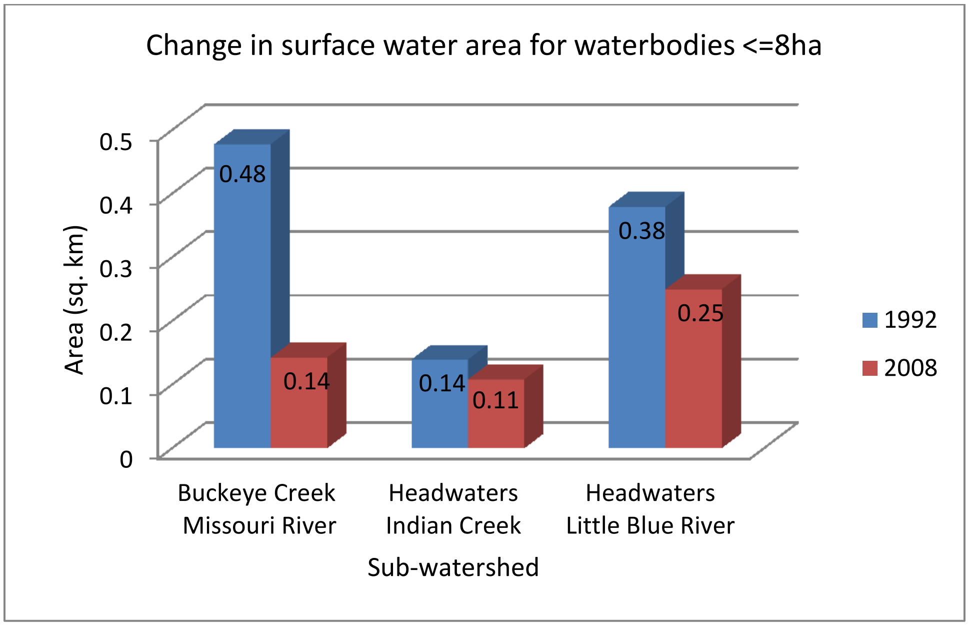
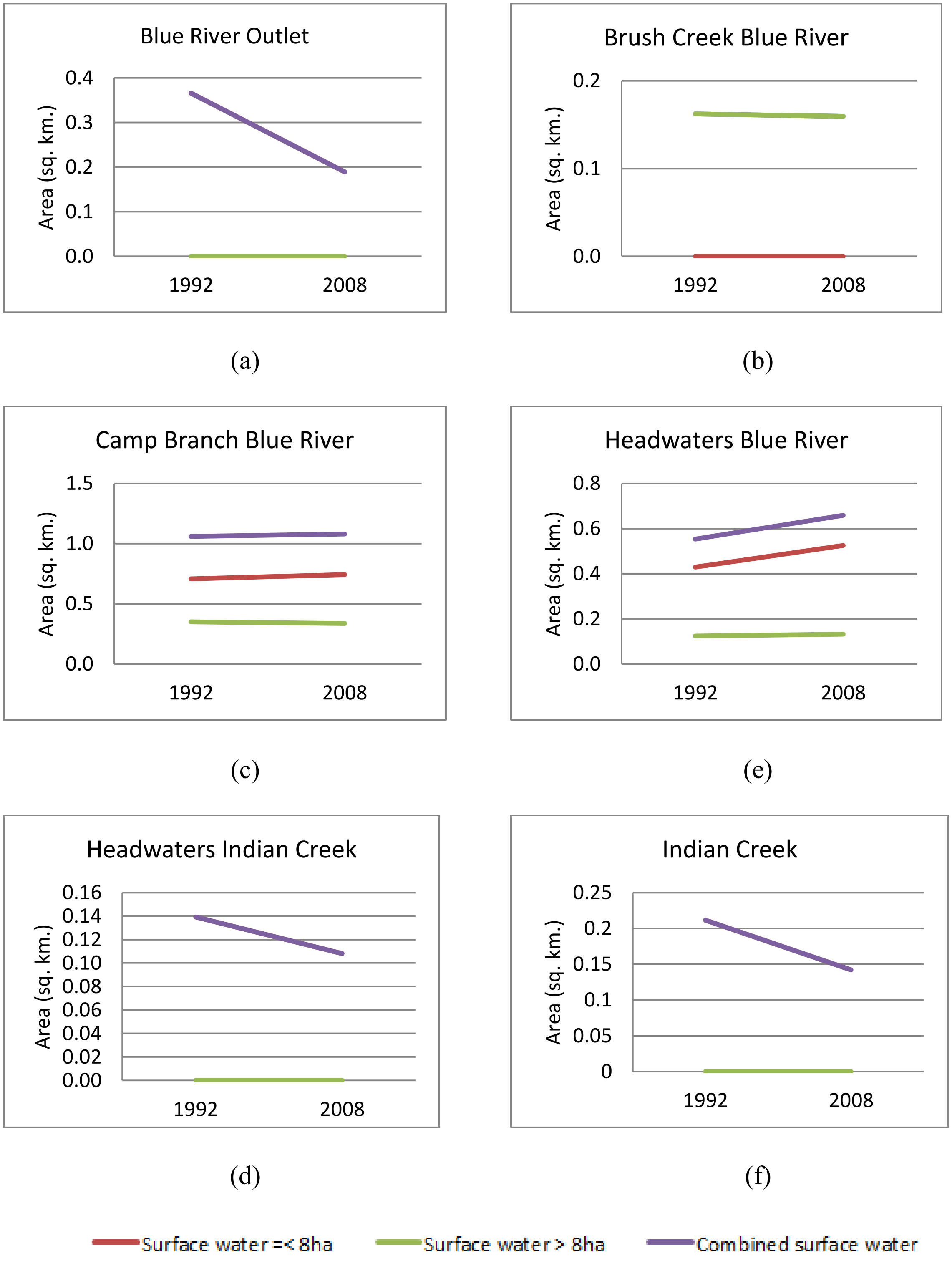


Figure 4-20: Surface water cover change for water bodies equal or less than 8ha at sub-watershed scale.

As with the watershed scale, generally surface water cover decreased for all the sub-watersheds studied. Between 1992 and 2008 these sub-watersheds lost surface water cover by the following percentages: Buckeye Creek Missouri River (-70.8%), Headwaters Indian Creek (- 21.4%), and Headwaters Little Blue River (-34.2%). A significant decrease in surface water cover was identified in the Buckeye Creek Missouri River sub-watershed due to rapid urbanization. This sub-watershed belongs to the Shoal Creek Missouri River watershed, in which lies part of downtown Kansas City. However, as the scale of analysis changes, different magnitudes of urban surface water cover change are observed which emphasizes the need for a multi-scale analysis of land cover/use change. Another observation from this analysis was that changes in surface water area of large water bodies tend to either mask surface water cover changes from smaller water bodies or influence the overall trend of urban surface water cover change. The results also suggest that precipitation effects are more noticeable in large water bodies than smaller ones.

The study analyzed surface water change in all sub-watersheds used in this study to determine the trend in changes between surface water cover in small and large water bodies. The charts for the sub-watershed are grouped according to the watershed to which they belong and are shown in Figures 4-21, 4-22 and 4-23 below.

I. Surface Water Cover Change: Blue River Sub-watersheds



(a) (b)

(c) (e)

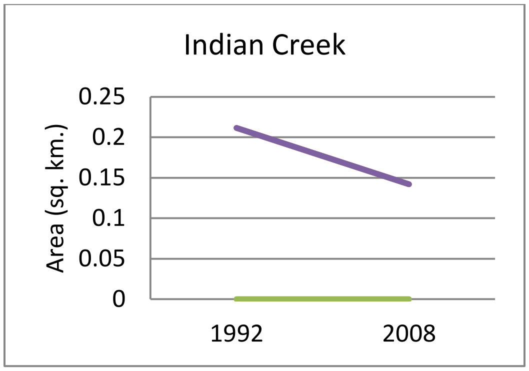
(d) (f)

Figure 4-21: Surface water cover change for Blue River sub-watersheds between 1992 and 2008.

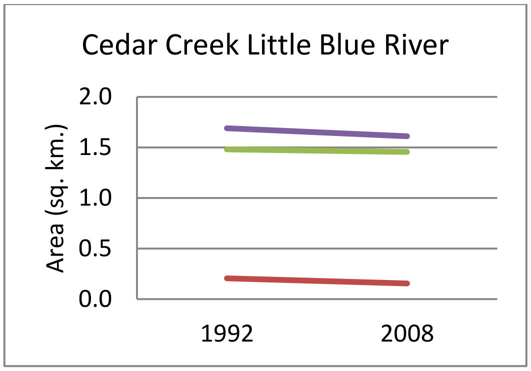
At the watershed scale, the Blue River watershed exhibited a decline in surface water from small water bodies with no significant change in water bodies greater than 8ha in area. However, the sub-watershed scale reveals more information as to which sub-watersheds are responsible for the general decline reported at the watershed scale. Most of the sub-watersheds showed a decline in surface water cover from small water bodies. The Blue River Outlet (a), the Headwaters Indian Creek (d), and Indian Creek (f) sub-watersheds were largely accountable for the decline in surface water from water bodies equal or less than 8ha; Brush Creek Blue River (b) watershed did not register a significant change in surface water cover between 1992 and 2008. The Headwaters Blue River (e) and Camp Branch Blue River (c) actually showed an increase in surface water cover. Sub-watershed scale results are particularly important because this is the spatial scale that is used by most cities for land resources planning purposes.

The following are results of the analysis of the sub-watershed of the Little Blue River watershed. At the watershed scale, this watershed showed a decline in water bodies of size equal or less than 8ha. However the combined surface water cover area went up between 1992 and 2008 owing mainly to the influence of large water bodies. Figure 4-22 shows the analysis results obtained at the sub-watershed scale for this watershed.

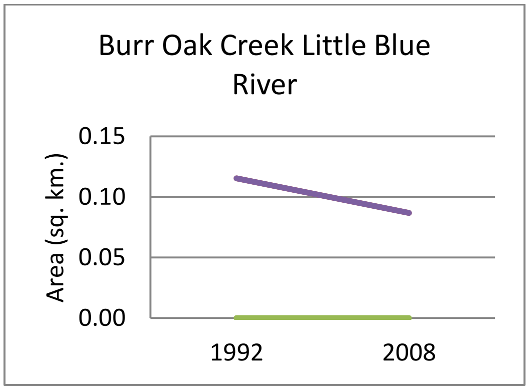
II. Surface Water Cover Change: Little Blue River Sub-watersheds



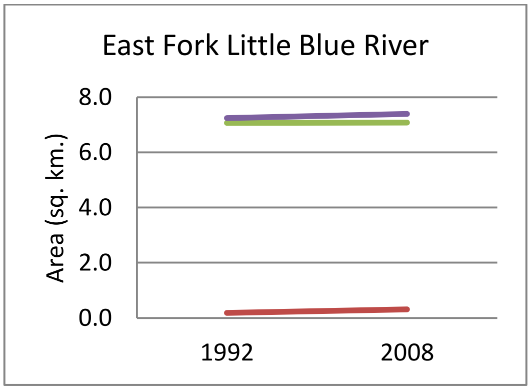
(a)



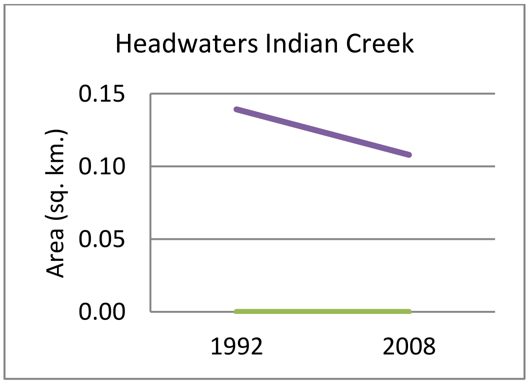
(b)



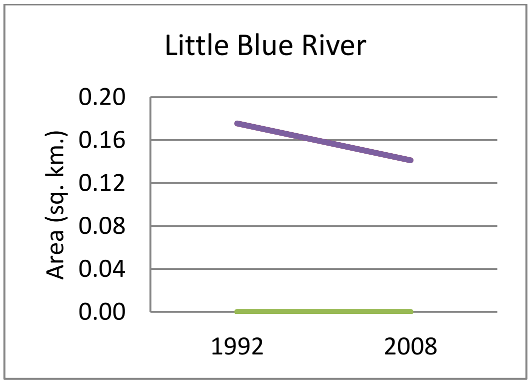
(c)



(d)

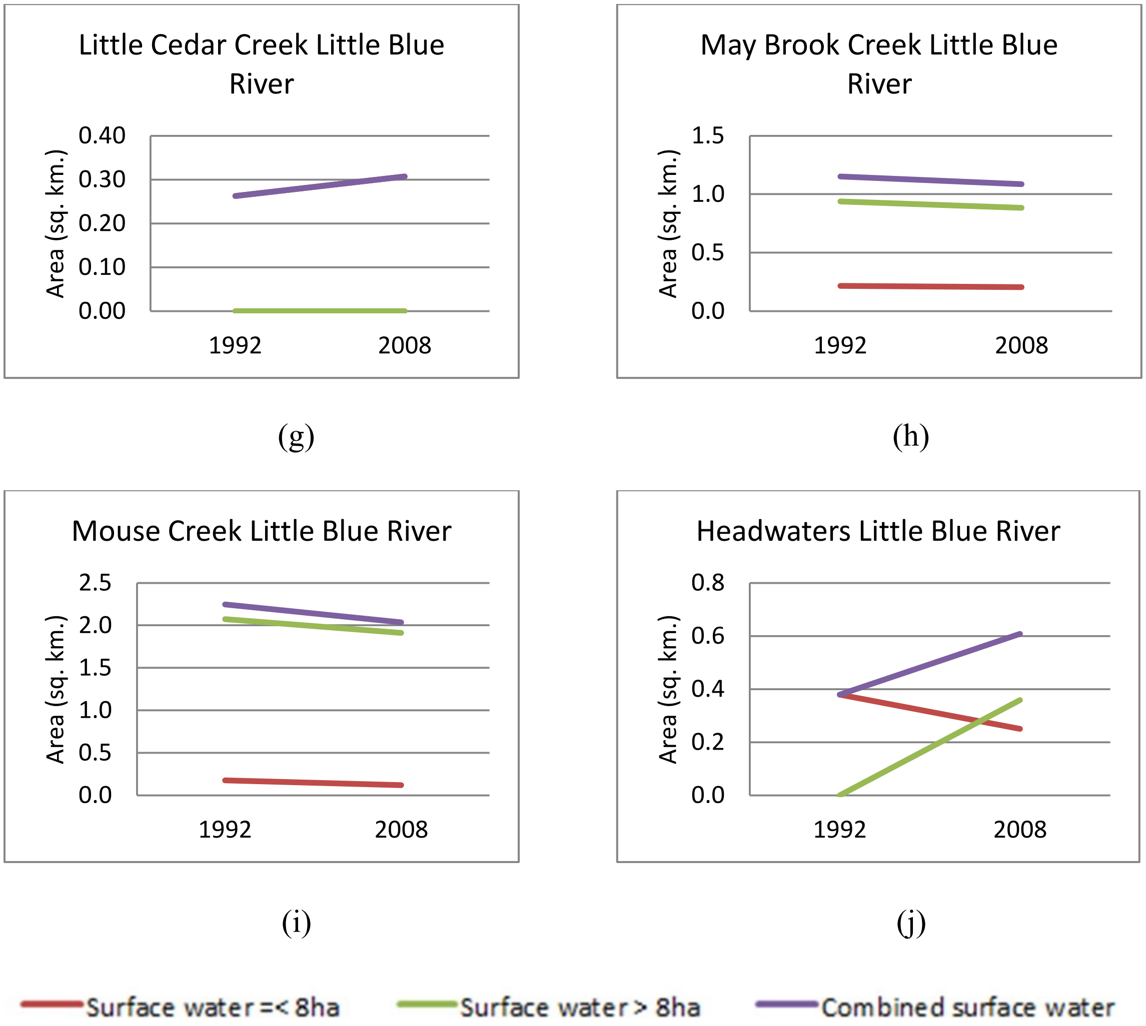


(e)



(f)

II. Surface Water Cover Change: Little Blue River Sub-watersheds



(g) (h)

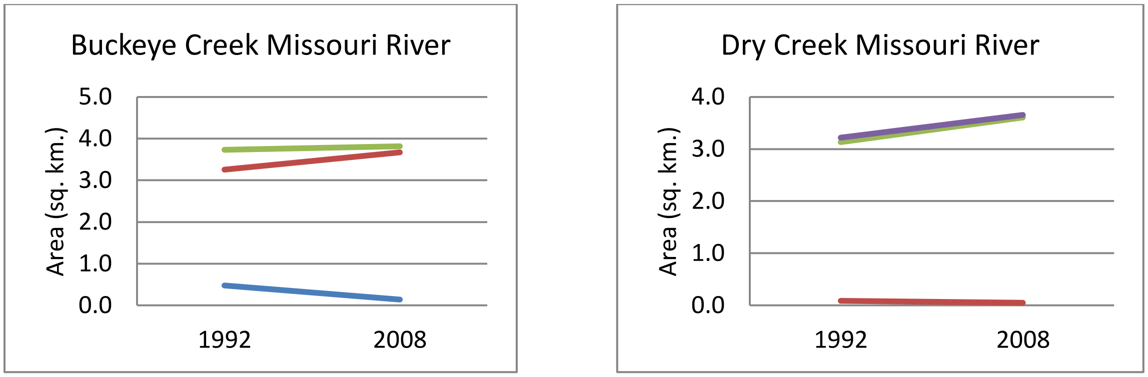
(i) (j)

Figure 4-22: Surface water cover change for Little Blue River sub-watersheds between 1992 and 2008.

At the sub-watershed scale, surface water from small water bodies declined in the following sub-watersheds: Burr Oak Creek Little Blue River (c), Headwaters Indian Creek (e), Little Blue River (f), Cedar Creek Little Blue River (b), Mouse Creek Little Blue River (i), and the Headwaters Little Blue River (j). The Indian Creek, Burr Oak Creek Little Blue River, Headwaters Indian Creek, Little Blue River, and Little Cedar Creek Blue River watersheds did not have large water bodies; hence, they are represented by a single line implying that surface water cover from small water bodies also serves as the total surface water cover for these sub-watersheds. The influence of large water bodies is evident in the Headwaters Little Blue River watershed which resulted in the overall increase in the combined surface water cover due to a dam that was constructed in this sub-watershed. This influence could mask the decline in surface water bodies from this sub-watershed if there were no separation between the two types of water bodies in the analysis. Note that this information could not be revealed at the metropolitan or watershed scale analysis, but the sub-watershed scale.

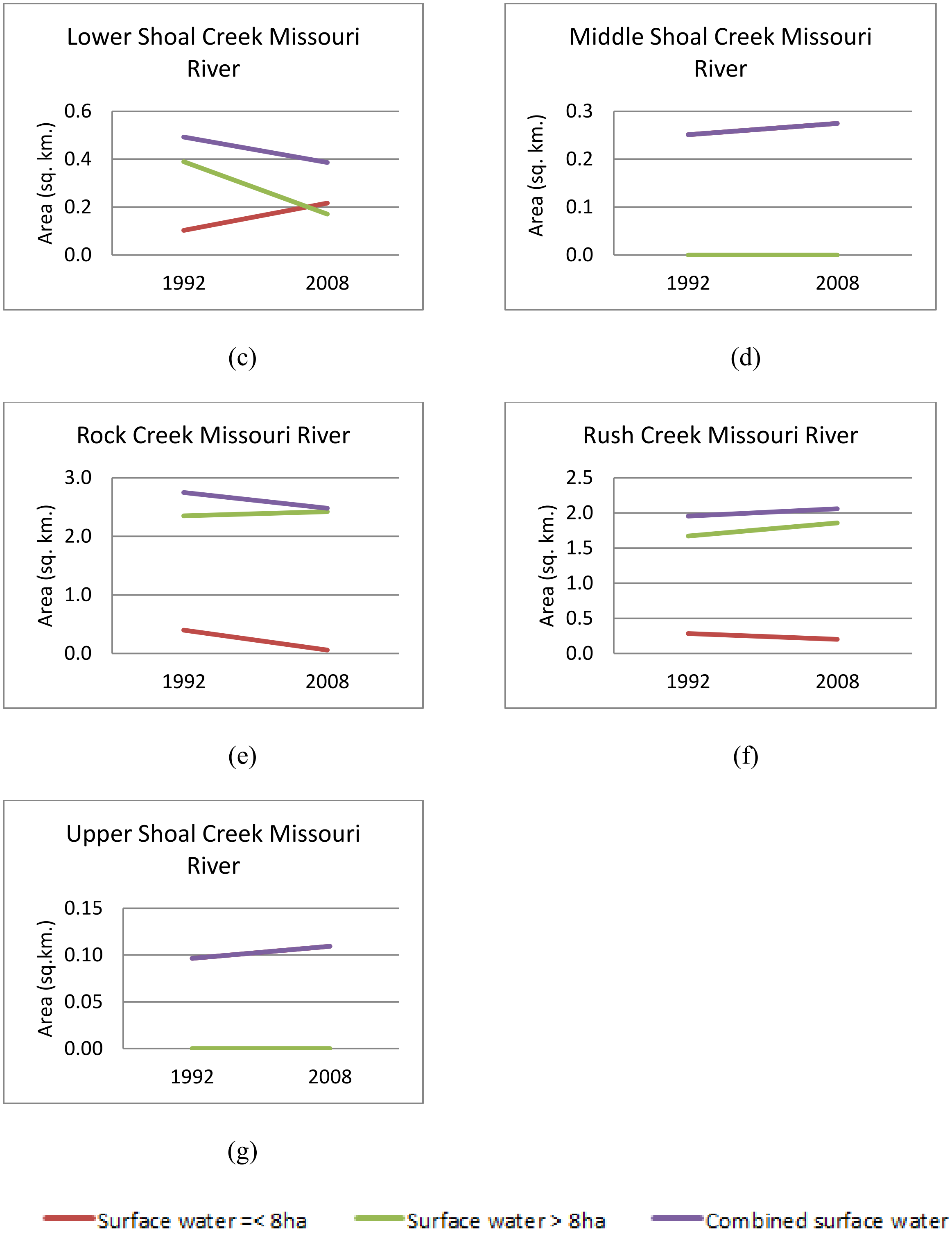
A similar kind of analysis was conducted for the Shoal Creek Missouri River sub-watersheds. The Shoal Creek Missouri River watershed showed a decline in the surface water due to small water bodies; an increase in surface water cover for large water bodies and an overall increase in the combined surface water cover. The results of this analysis are shown in Figure 4-23 below.

III. Surface Water Cover Change: Shoal Creek Missouri River Sub-watersheds



(a) (b)

III. Surface Water Cover Change: Shoal Creek Missouri River Sub-watersheds



(c) (d)

(e) (f)

(g)

Figure 4-23: Surface water cover change for Blue River sub-watersheds between 1992 and 2008.

After subjecting this watershed to sub-watershed scale analysis, it was found that the following sub-watersheds were accountable for a decline in surface water cover for water bodies =< 8ha: Buckeye Creek Missouri River (a), Lower Shoal Creek Missouri River (c), Rock Creek Missouri River (e), and Rush Creek Missouri River. Sub-watersheds responsible for an increase in surface water due to large water bodies were: Dry Creek (b), Middle Shoal Creek Missouri River (d), Rock Creek Missouri River (e), Rush Creek Missouri River and Upper Shoal Creek (g). The Middle Shoal Creek Missouri River and the Upper Shoal Creek Missouri River sub-watershed had no large water bodies.

So far, the surface water cover analysis was based on results obtained solely from remotely sensed image data analysis. But the wetland definition also encompasses wetland types like marshes and ferns which are not easy to detect using optical sensors. To address these wetlands, the study used hydric soils as indicators of such wetlands. Analysis results obtained from remotely sensed data and hydric soils were combined to give a better picture of wetland variations at various spatial and temporal scales in the study area.

Hydric Soils as Surrogates for Wetlands Hidden to Optical Sensors

Hydric soils are indicators of wetlands or where wetlands existed in an area. By overlaying impervious surface maps over hydric soil maps, one can identify wetland areas that have been lost to the development of impervious surfaces due to human built-up activities. Extracting and quantifying the overlap areas between hydric soils and impervious surfaces yields wetland area lost to impervious surface development. Applying the same technique to a different time period, one can also get the wetland cover area lost to such development. The difference in wetland cover areas between the two time periods is the surface water cover area lost over that particular period under study.

Remote Sensing and Hydric Soils Analysis: Long Term Watershed Scale

The spatial distribution of hydric soils in the Blue River, Little Blue River, and Shoal Creek Missouri watersheds was mapped in Figure 4-24 below. The Little Blue River watershed had the highest concentration of hydric soils, followed by the Blue River watershed. In these two watersheds, there are high chances that future build-up activities would likely be sitting on wetlands.

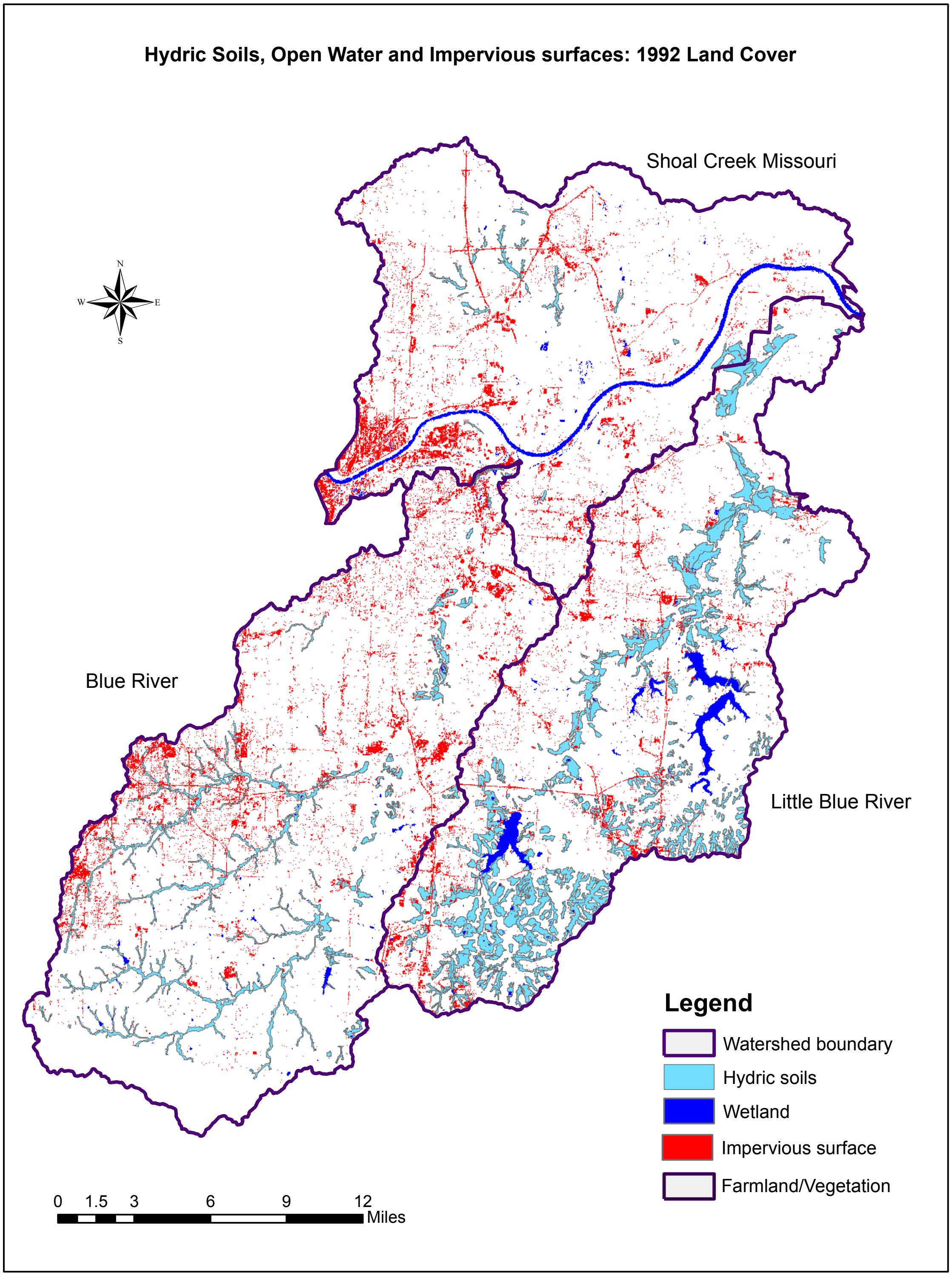


Figure 4-24: Spatial distribution of hydric soils, surface water and impervious surfaces in the Blue River, Little Blue River and Shoal Creek Missouri River watersheds in 1992.

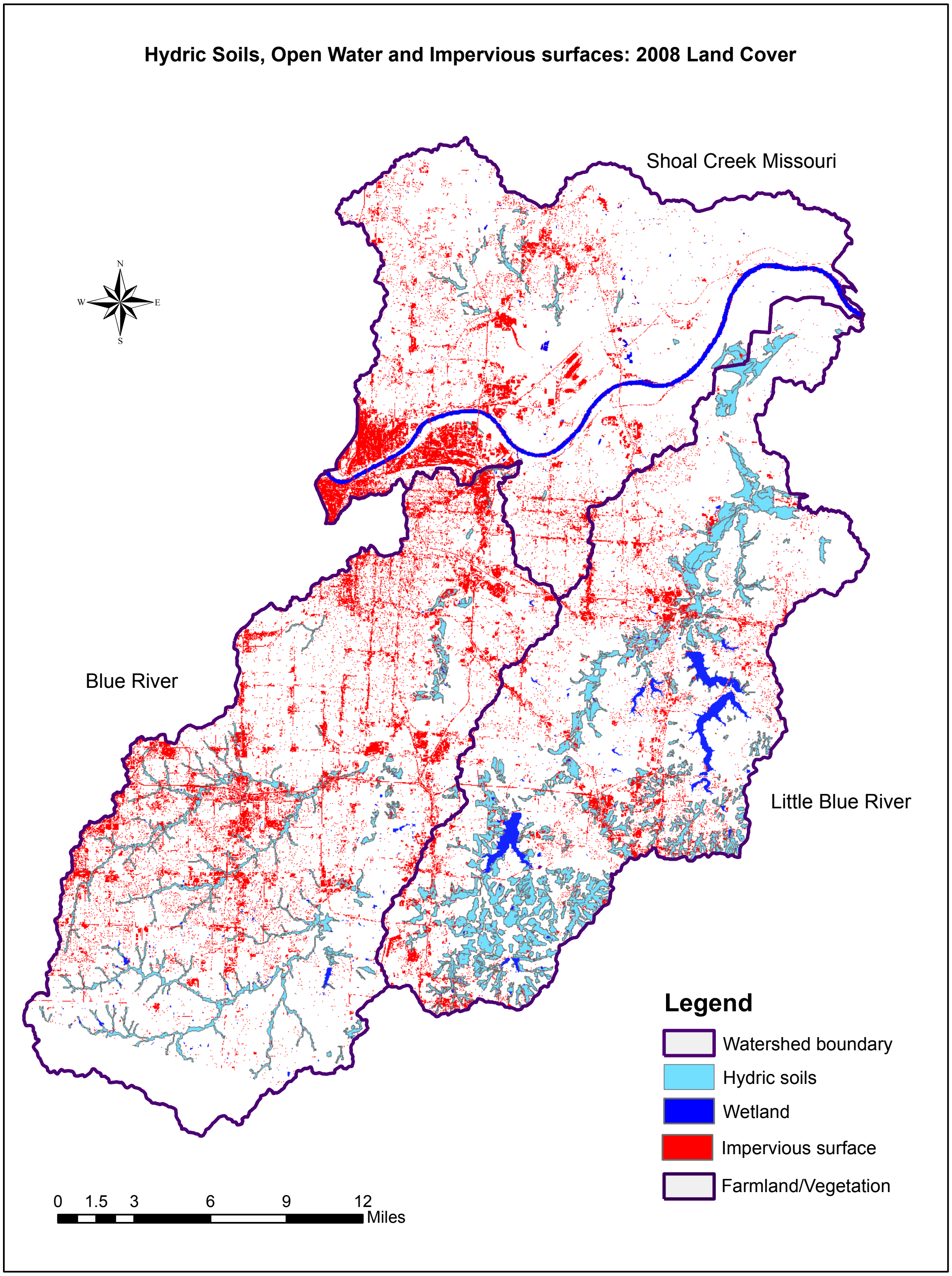


Figure 4-25: Spatial distribution of hydric soils, surface water and impervious surfaces in the Blue River, Little Blue River and Shoal Creek Missouri River watersheds in 2008.

The hydric soils, surface water, and impervious surfaces were used to obtain the urban wetland cover area lost to impervious surface development between 1992 and 2008 using the procedure detailed below.

1. Extract watershed area off the classified image using the watershed boundary as the area of interest. This is accomplished by using the subset procedure in the ERDAS Imagine™'s "Data Preparation" module.
2. Extract impervious surface cover class from the watershed thematic image; vectorize watershed image to an ArcInfo coverage file using ERDAS Imagine™'s "Raster to Vector" function in the Vector module; convert coverage file to shapefile. (Or select features from a coverage file in ArcMap™ using ArcGIS™ software; save the feature selection as a layer; export data and save output as a shapefile).
3. Delete the surrounding background area of the resultant shapefile using ArcMap™'s editing tools. The "Dissolve" function merged the land cover/land use classes based on their class values.
4. Using the "Intersect" tool, create a shapefile made up of the overlap area between the hydric soils and impervious surfaces shapefiles. The area represents the surface water cover that was lost to built-up areas. (The shapefiles must have the same coordinate system).
5. Import the resultant shapefile into a geo-database so that an updated area field (shape_area) is created based on the coordinate system. This import procedure creates a new output feature class in the geo-database.

6. Calculate the area of this feature class by summarizing the shape_area field values: the result is the area of urban surface water cover lost to impervious surface development.
7. Repeat steps 1 – 6 for a different time period – this research used the 1992 and 2008 images.
8. Subtract the urban surface water cover area obtained in 1992 analysis from the area obtained in 2008. The result in this study was the urban surface water cover area lost between 1992 and 2008.

The same procedure was used to find urban surface water cover lost in at both watershed and sub-watershed scales.

Based on the above procedure, Figure 4-26 below shows the urban wetland area lost to the three major watersheds used in this study.

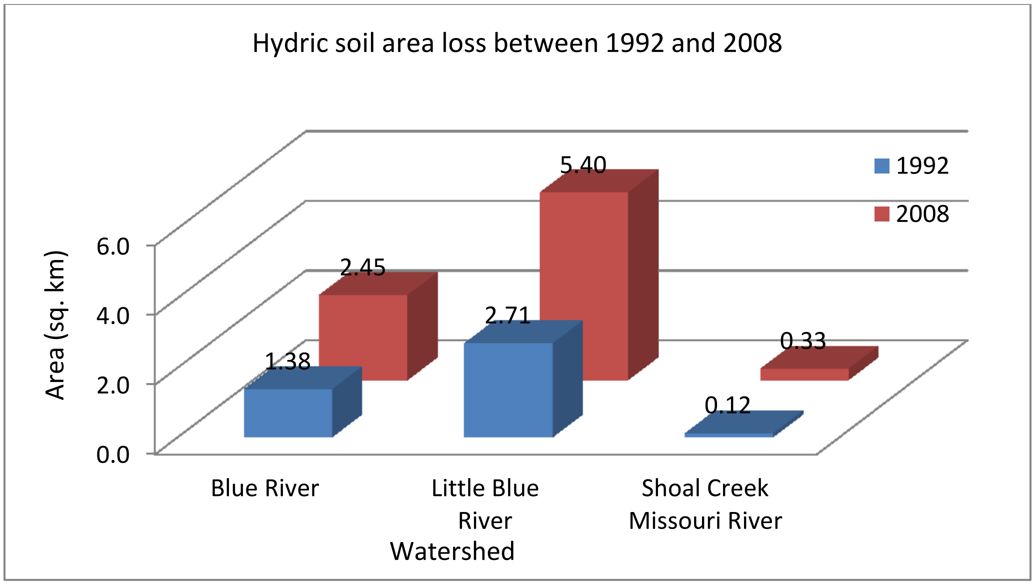


Figure 4-26: Hydric soil area lost to impervious surface development between 1992 and 2008 in major watersheds.

Note that although the Shoal Creek Missouri River watershed had the least hydric soil area (0.21 sq. km) lost to impervious surface development, it had the highest relative percent loss of 173% between 1992 and 2008. Relative percent hydric soil (wetland-cover) losses for the Blue River and Little Blue River watersheds were 77.1% and 99.3% respectively. The largest wetland-cover loss (2.7 sq. km.) however took place in the Little Blue River watershed.

Table 4-7 below compares the hydric soil (wetland-cover) losses for three watersheds obtained using solely remotely sensed image data analysis with a procedure that combines hydric soil data analysis as well as remotely sensed image data analysis.

Table 4-7: Watershed urban wetland-cover change between 1992 and 2008 using two procedures: remotely sensed image data analysis versus a combination of the former and hydric soils analysis.

Watershed	Remote sensing only	Remote sensing with hydric soil analysis
	Area lost/gained (sq. km.)	
Blue River	-0.2	-1.1
Little Blue River	0	-2.7
Shoal Creek Missouri River	0.3	-0.2

Incorporating ancillary data such as hydric soils yielded more information on the trend of urban wetland loss than solely using satellite remote sensing techniques. Remote sensing techniques are good at mapping surface water but not optically hidden wetlands. The hidden wetlands that are represented by hydric soils are the areas that are candidates for wetland restoration currently advocated by the Environmental Protection Agency (EPA) through mitigation banks. This analysis was extended to selected sub-watersheds within the three major watersheds used above in the following section.

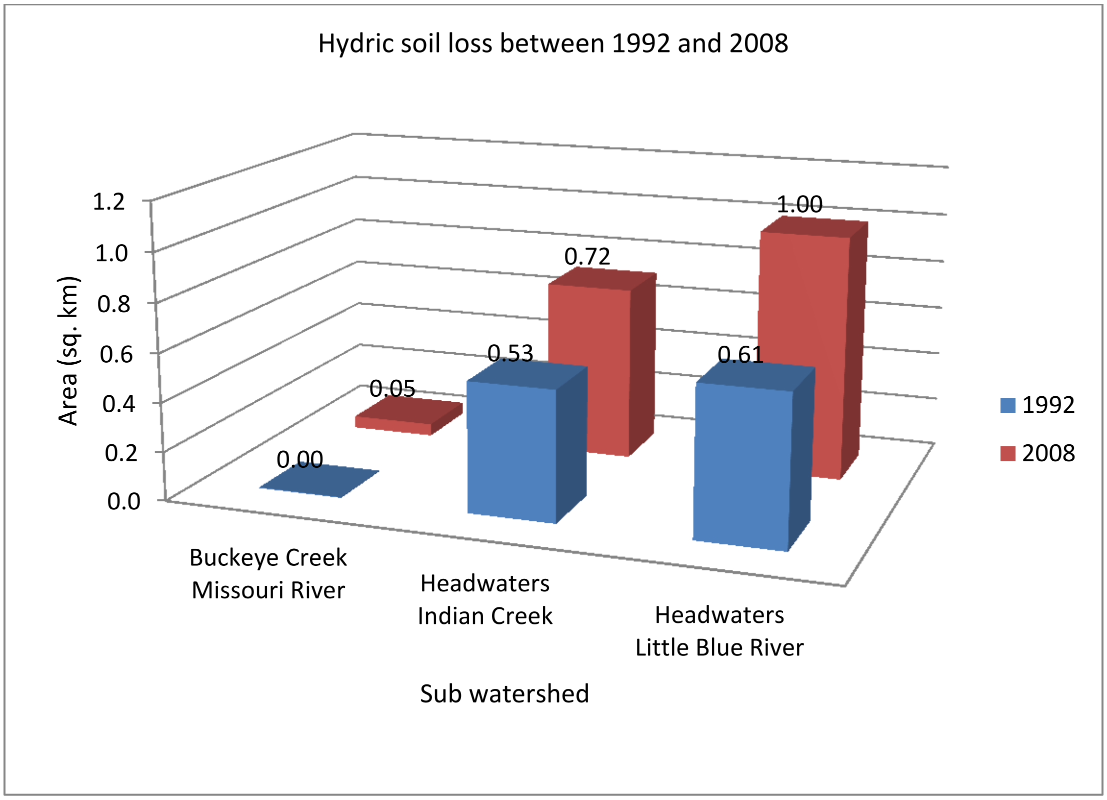


Figure 4-27: Hydric soil lost to impervious surface development between 1992 and 2008 in selected sub-watersheds.

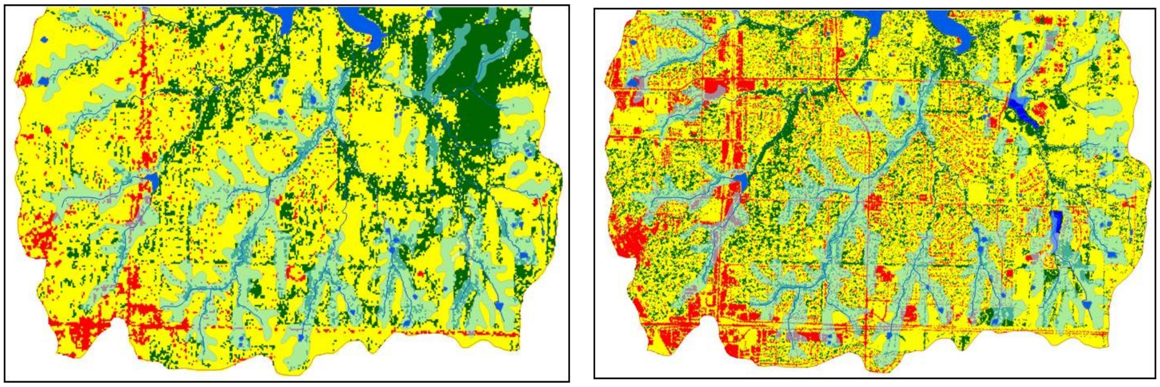
Although the Buckeye Creek Missouri River sub-watershed experienced the least hydric soil area (0.21 sq. km) loss to impervious surface development, it had the highest relative percent loss of 1809.8% between 1992 and 2008. Part of this sub-watershed is located in the downtown Kansas City area, which experiences more rapid urbanization than surrounding areas. Relative percent hydric soil area (wetland-cover) losses for the Headwaters Indian Creek and Headwaters Little Blue River sub-watersheds were 35.0% and 63.8% respectively. The largest wetland-cover loss (0.39 sq. km.), however, took place in the

Headwaters Little Blue River watershed. This sub-watershed is located in the Little Blue River watershed, which is characterized by large areas of both hydric soils and large surface water bodies (lakes). Table 4-8 below shows a comparison of wetland-cover loss obtained using a combination of remote sensing analysis and hydric soil analysis procedures for watersheds selected on the basis that they were experiencing rapid wetland changes or rapid urbanization.

Table 4-8: Sub-watershed urban wetland-cover change between 1992 and 2008 using two procedures: remote sensing only versus remote sensing with hydric soils.

Watershed	Remote sensing only	Remote sensing with hydric soil analysis
	Area lost/gained (sq. km.)	
Headwaters Indian Creek	-0.03	-0.19
Headwaters Little Blue River	0.23	-0.39
Buckeye Missouri	0.08	-0.05
East Fork Little Blue River	0.15	-0.87

The East Fork sub-watershed of the Little Blue River was selected for this analysis because it is composed of more water bodies (surface water) and hydric soils than any other sub-watershed in the study area. The hydric soils area lost to impervious surface development in this sub-watershed was 401072.13 sq. m. (0.40 sq. km.) as of 1992 and by 2008 the area lost rose to 1277239.3 sq. m. (1.28 sq. km.). This translates to a net wetland-cover loss of 876167.2 sq. m. (0.87sq. km.) or an increase of 218.5% in impervious surfaces replacing wetlands over the 16-year period. Contrast this percent value with a 2.1 % gain in wetland-cover (surface water) reported earlier using remote sensing analysis. Figure 4-28 below shows the spatial distribution of hydric soils in the southern portion of the East Fork sub-watershed with respect to impervious surface cover on the supervised classified SPOT images.



1992 2008

Figure 4-28: Impervious surface cover substantially increased and covered more hydric soils in 2008 (right) than in 1992.

Sub-watershed level analysis is more informative at the local planning level as it can reveal areas where rapid loss of urban wetlands took or is taking place. This information is particularly important for planners and policy makers so that they take necessary measures for sustainable development of their cities.

It is still a challenge to map hidden wetlands using optical remote sensing techniques. Better methods should be able to detect wetlands that are under vegetation and should also be able to identify sub-surface wetlands connectedness so that the units that seem individual on the surface would not be treated as separate from each other. Mapping hydric soils would be a closer solution to this challenge. Techniques such as LiDAR mapping could also improve wetlands detection by better representing topography and facilitating ease of identifying low lying areas which are usually associated with wetlands. It should, however, be noted that not all low lying areas that are usually associated with wetlands as shown in Figure 4-29 below. The figure shows an overlay of hydric soils and water bodies on a 10 m digital elevation model (DEM) of the southern part of the East Fork sub-watershed in the Little Blue River watershed. However, with exception of mostly large man-made water bodies, many water bodies lie within hydric soils areas. It should be noted that this is not a DEM generated from LiDAR data.

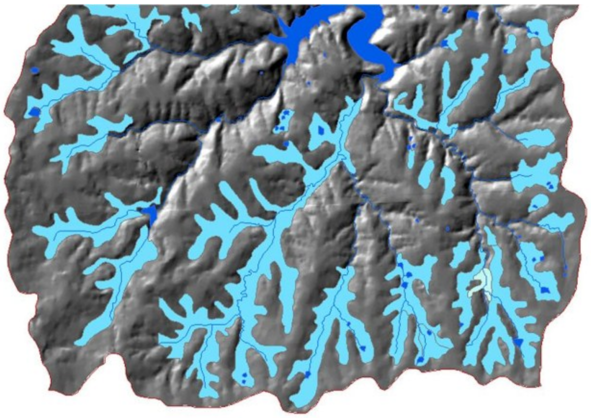


Figure 4-29: A DEM of the southern East Fork sub-watershed showing hydric soils (cyan) and surface water (blue) distribution.

With LiDAR technology, mapping of hidden wetlands could be improved but not completely, since LiDAR pulses cannot penetrate vegetation especially in densely vegetated areas. A better timing for such mapping should therefore be during the leaf-off period of the year.

Precipitation Trends in the Kansas City Metropolitan Area

Another factor that can affect wetland-cover expression is the amount of precipitation received in an area. This study assessed the precipitation pattern in the Kansas City metropolitan area from 1889 – 2008. The goal was to determine if there were changes in the amounts of precipitation received that could affect urban surface water cover expression. An increase in precipitation would result in increase in surface water cover while a decline would result in reduced surface water cover in spite of any on-going human build-up activities. The precipitation chart for the Kansas City metropolitan area is shown in Figure 4-30 below.

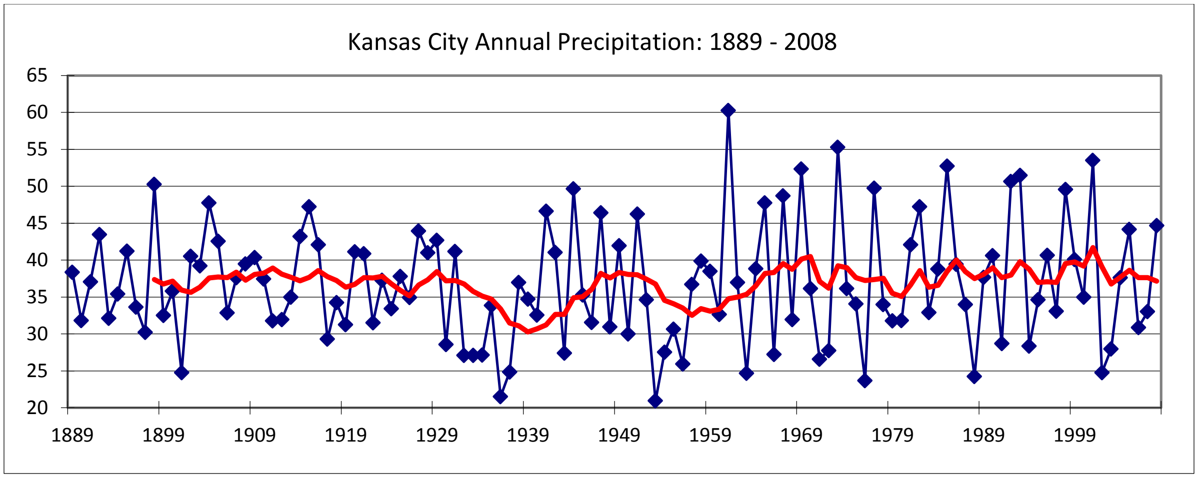
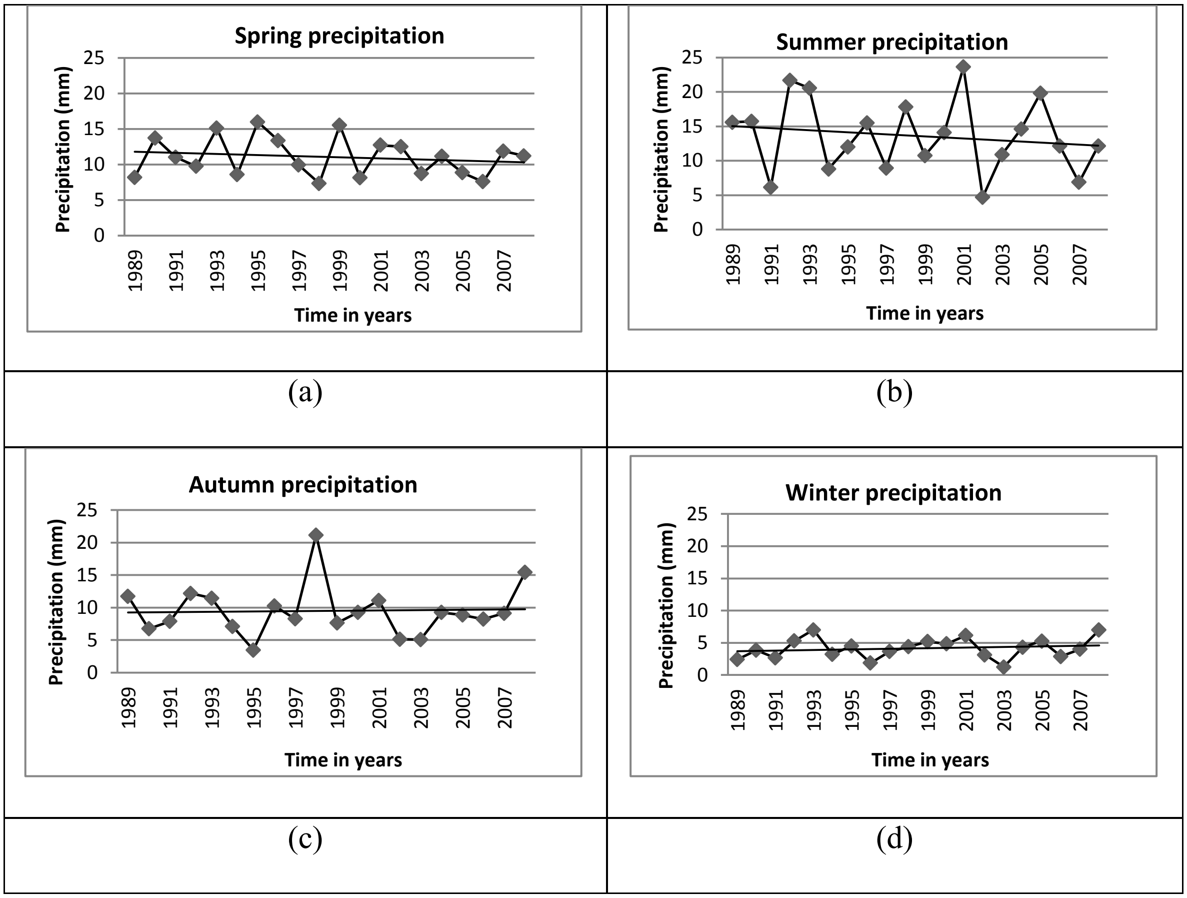


Figure 4-30: Total precipitation (inches) for the Kansas City downtown area for the period 1889 - 2008. (Source: NOAA)

Precipitation generally showed a rising trend from the 1960s onwards, compared to the period before as shown by the moving average graph line (red).This could have the effect of increasing wetlands-cover in the Kansas City metropolitan area. Total annual precipitation received for each year was used in the analysis. Figure 4-31 below shows a seasonal break-down of precipitation to give an insight as to how the precipitation trend changed over the spring, summer, autumn and winter periods in the Kansas City area over the period 1989 – 2008.



(a) (b)

(c) (d)

Figure 4-31: Seasonal precipitation trends for Kansas City area in the period 1989 – 2008.

Figure 4-31 shows that both the spring (a) and summer (b) precipitation exhibited a declining trend while autumn (c) and winter (d) precipitation gradually increased. Since most of the precipitation is received in the spring and summer seasons, precipitation data in Figure 4-31, above, might suggest a decline in net precipitation. Note that this data is based on point or station data collected from the Kansas City International Airport. A regional precipitation data analysis that takes into account several rain gauges in the study area would give a better precipitation picture. Therefore, to achieve more representative precipitation data coverage, this study used the CPC merged analysis of precipitation (CMAP) data obtained from the NOAA website. The data is made up of monthly averaged precipitation rate values which come in two formats: the standard and the enhanced data values. The standard data values are obtained from 5 kinds of satellite estimates (GPI, OPI, SSM/I scattering, SSM/I emission, and MSU). In addition to the satellite estimates, the enhanced data also includes blended NCEP/NCAR Reanalysis Precipitation values. The data was downloaded as a NetCDF file that was converted to a table in ArcGIS using the "MakeNetCDF Feature Layer" tool in ArcToolbox. To show the spatial extent and the grid sizes of the focus area, this research used the "MakeNetCDF Raster Layer" tool to generate the raster data file. The raster file was overlaid with the state map of the U.S. Midwest as shown in Figure 4-32. The pixelated area of this figure also shows the area from which the data was extracted.

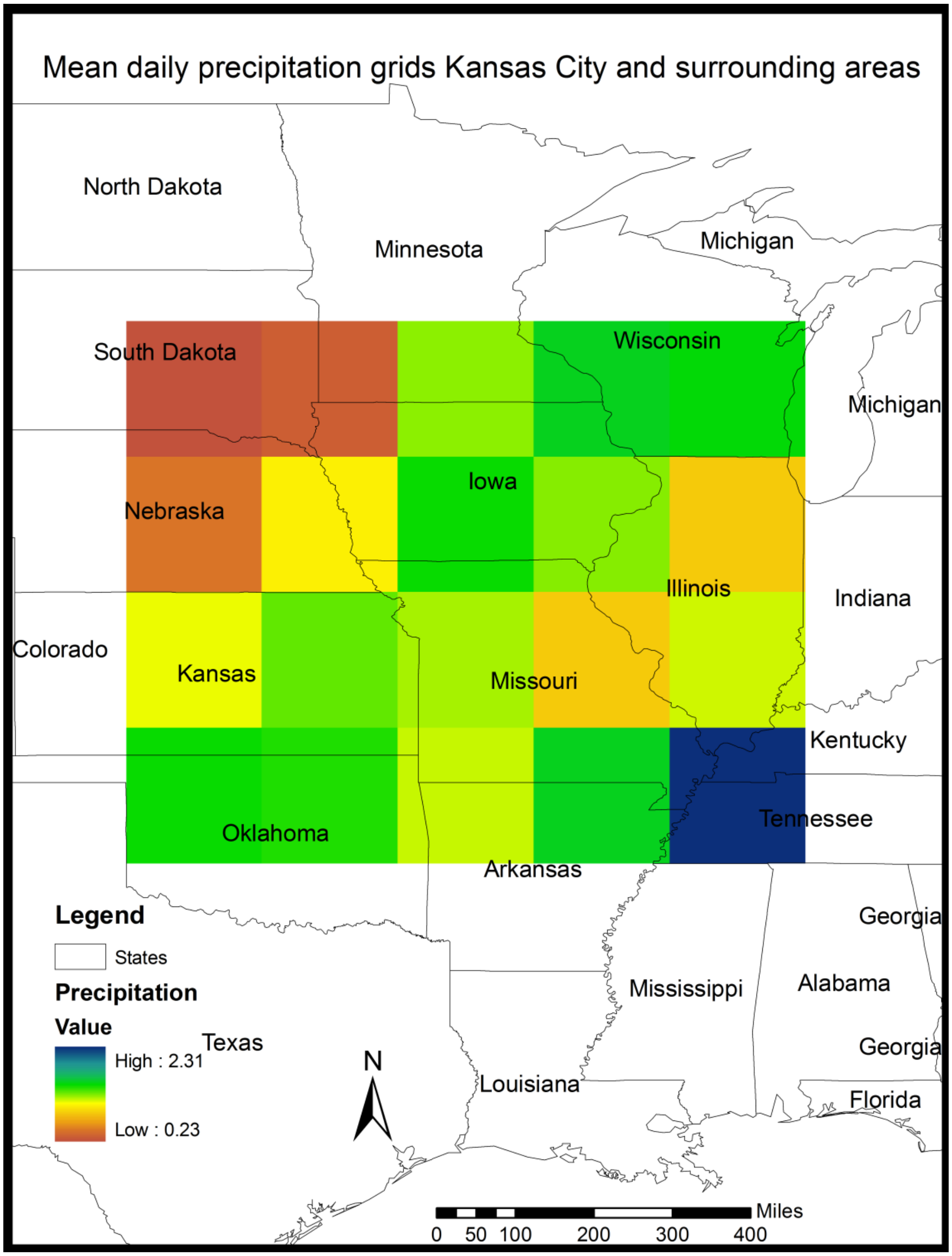
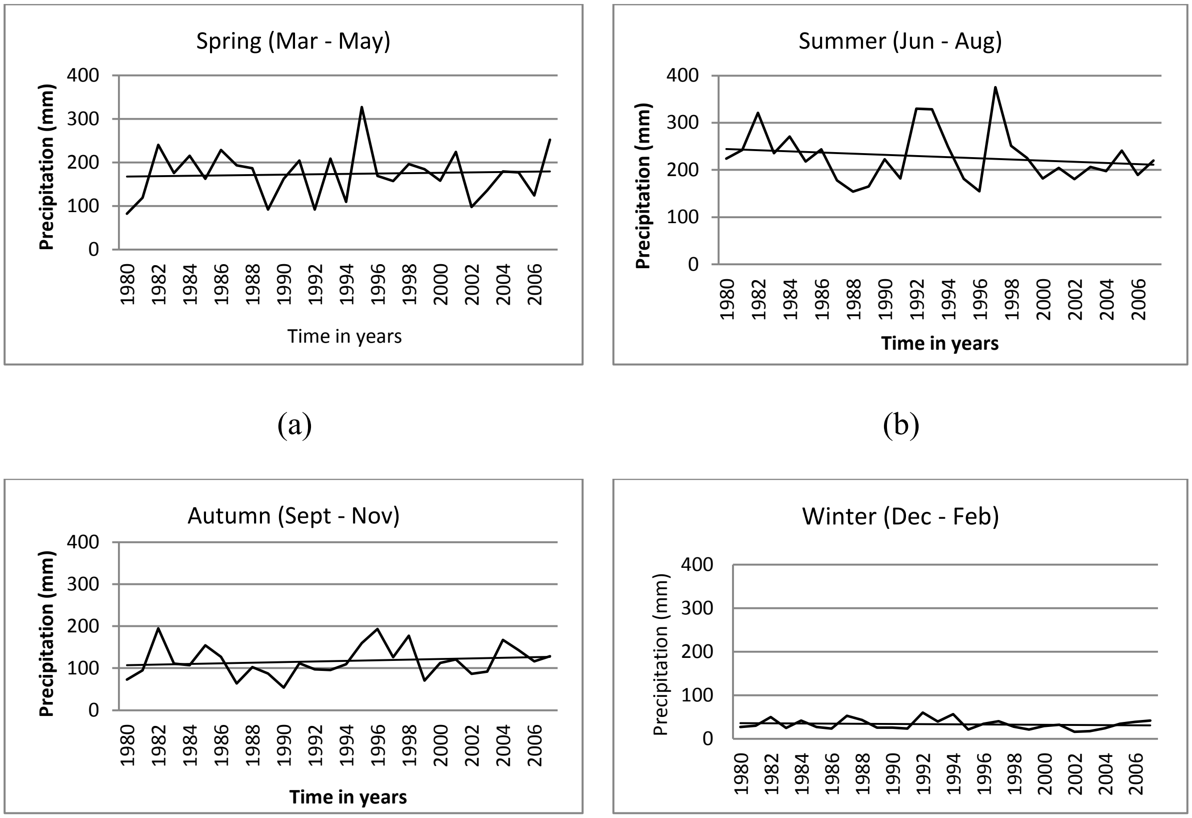


Figure 4-32: CMAP mean precipitation grid for the Midwest in which the Kansas City metropolitan area lies.

Kansas City is located at the tip of the vertical border line between the states of Kansas and Missouri. The area shown covers most of the U.S. Midwest, which has a strong influence on the precipitation pattern of the study area. The CMAP enhanced data values were used to produce the charts shown in Figure 4-33 below.



(a) (b)

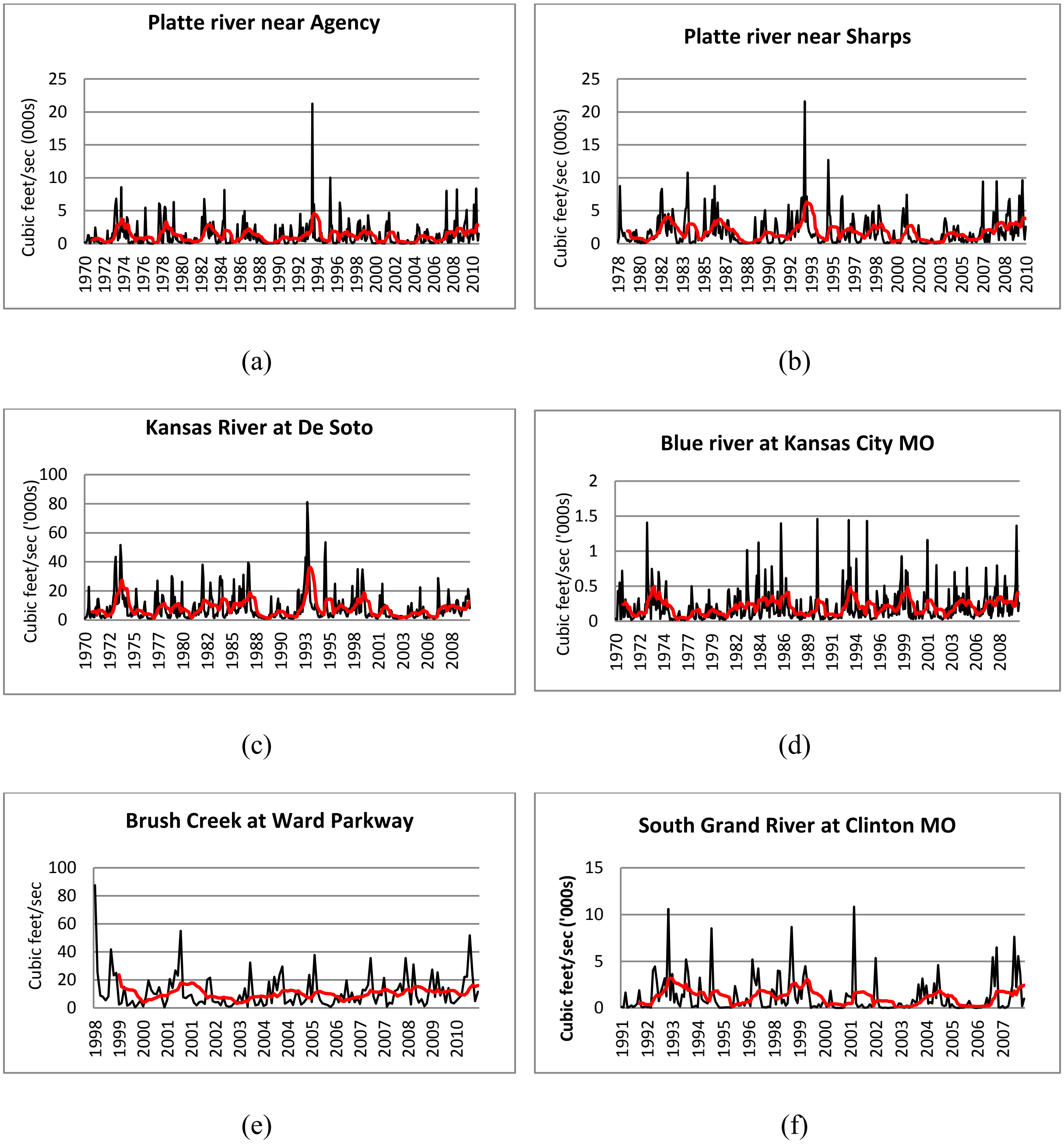
(c) (d)

Figure 4-33: Total seasonal precipitation for the U.S. Midwest.

In this figure, total precipitation for the spring (a) and autumn (c) seasons generally increased but declined in summer (b) and winter (d) seasons. Despite this decline in precipitation for both the summer and winter seasons, there was a general rise in precipitation in the decade before 2008.

To further understand the precipitation variations in the study area, the study analyzed the mean stream flow discharge data of selected uncontrolled streams/rivers in the Kansas

City metropolitan area. Stream flow discharge data were provided by the United States Geological Survey (USGS) water resources department serving the Kansas City area. This research analyzed the mean stream discharge (measured in cubic feet/second) for the following rivers: Platte River near Agency (Missouri), Platte River near De Soto (Kansas), Blue River at Kansas City (Missouri), Brush Creek Ward Parkway (Missouri), and South Grand River near Clinton (Missouri). Though South Grand River is somewhat outside the study area, it was chosen because it is an uncontrolled stream which is fairly close to the study area. Stream flow discharge can be used as an indicator of precipitation changes in an area but, unlike station data, it is representative of the "watershed" area behind the gaging station. Stream discharge accounts for both surface and some sub-surface water flow; thus this study chose to use it as an indicator of precipitation variations in the studied watersheds. Figure 4-34 below shows mean stream discharge data for the selected rivers in the study area.


Platte river near Agency

Platte river near Sharps

(a)

(b)

Kansas River at De Soto

Blue river at Kansas City MO

(c)

(d)

Brush Creek at Ward Parkway

South Grand River at Clinton MO

(e)

(f)

Figure 4-34: Mean monthly stream discharge for selected uncontrolled streams in and around the Kansas City metro area

In Figure 4-34 above, the data covers the period 1970 - 2010 except for gaging stations (b), (e) and (f) for which data were not collected as early as the 1970s. Generally, there is an increase in mean stream flow discharge for rivers represented in charts (a), (b) and (d).

To further check precipitation trend in the study area, the study used lake level variation data that was sourced from the Army Corps of Engineers. Appendix A shows the data charts used to show lake inflow data variation. The data was provided by the Army Corps of Engineers, Kansas City District. Based on the data and charts, Clinton Lake shows an increase in water inflow from the year 2000 to 2009. For Long Branch Lake, there was an increase in water inflow in the past 3 – 4 years and its 2009 inflow far exceeded its historic mean monthly inflows in 10 out of 12 months. There was a general increase in lake inflow for Pomme De Terre in the last decade. All this indicates a rise in precipitation in the Kansas City area, which consequently increases wetland-cover areas for both natural and artificial wetland types. Figure 4-35 below shows the location of the uncontrolled lakes used in this research.

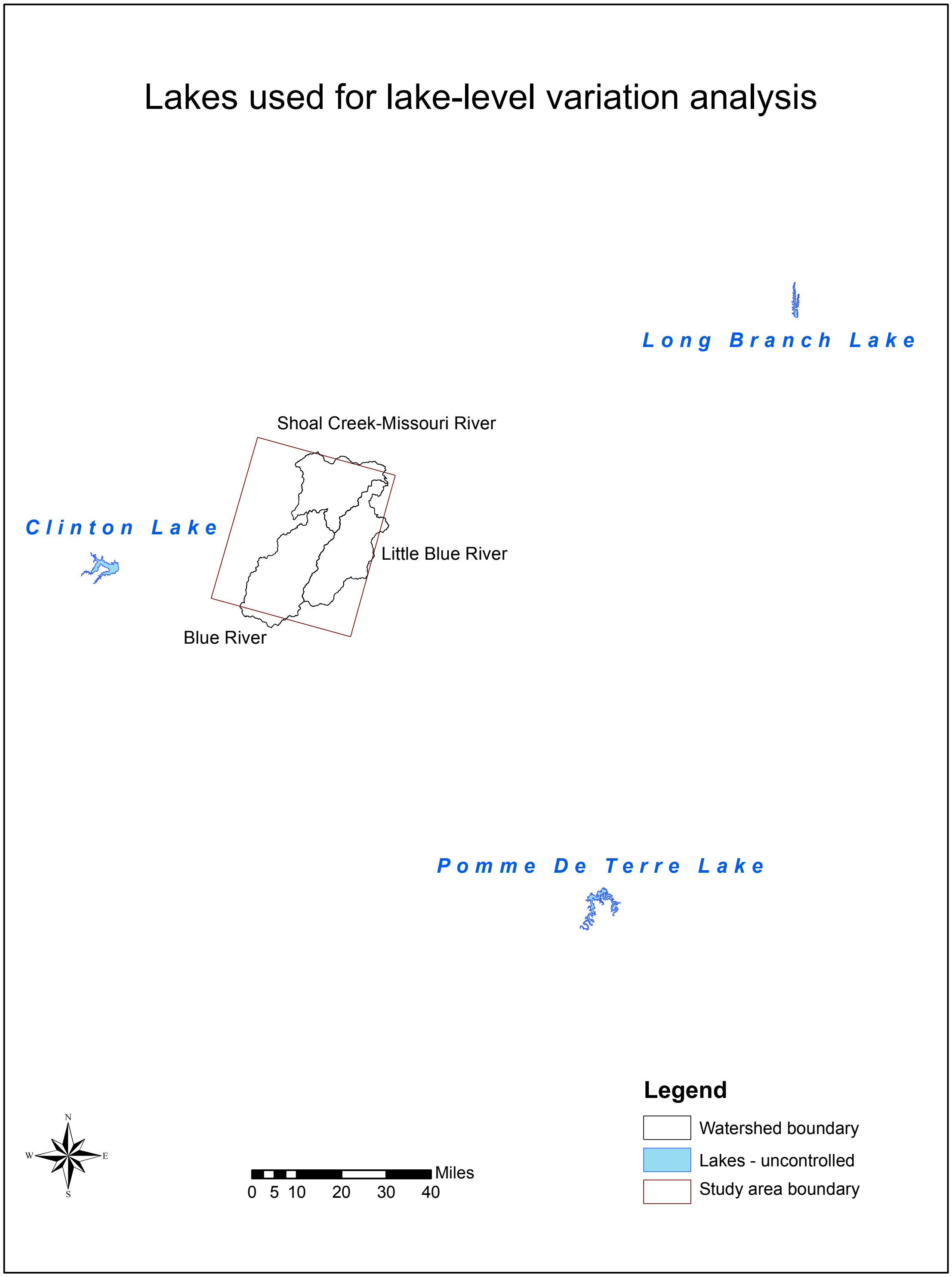


Figure 4-35: Use of lake-level variation as an indicator of precipitation changes over time. Clinton, Long Branch and Pomme De Terre lakes were selected because they were not controlled upstream.

Population Growth Trend in the Kansas City Metropolitan Area

The study area experienced a conspicuous increase in open artificial wetlands. This followed the construction of dams or reservoirs to service the emerging suburban or industrial areas that came with urbanization. In some cases, dams would be constructed over existing natural wetlands, thereby changing, to a considerable extent, the natural wetland functions. The result would be a change in faunal and floral composition in the resulting artificial wetlands. In a study of natural versus artificial wetlands, researchers found that eight of nine faunal species under that study exclusively used natural wetlands while one species occurred only on artificial wetlands (Bellio, Kingsford and Kotagama 2009). In this study, it was found that wetlands' landscape patterns are strongly affected by human build-up activities, especially through development of suburban and industrial areas while modifying urban wetlands in the process.

The census data for the Kansas City metropolitan area shows a continued increase in human population, which further threatens urban wetland-cover due to human activities. Population has been spreading out of the Kansas City downtown area, resulting in urban sprawl. Figure 4-25 below shows population dynamics in the counties that are located in the three study watersheds from the year 1980 to 2000.

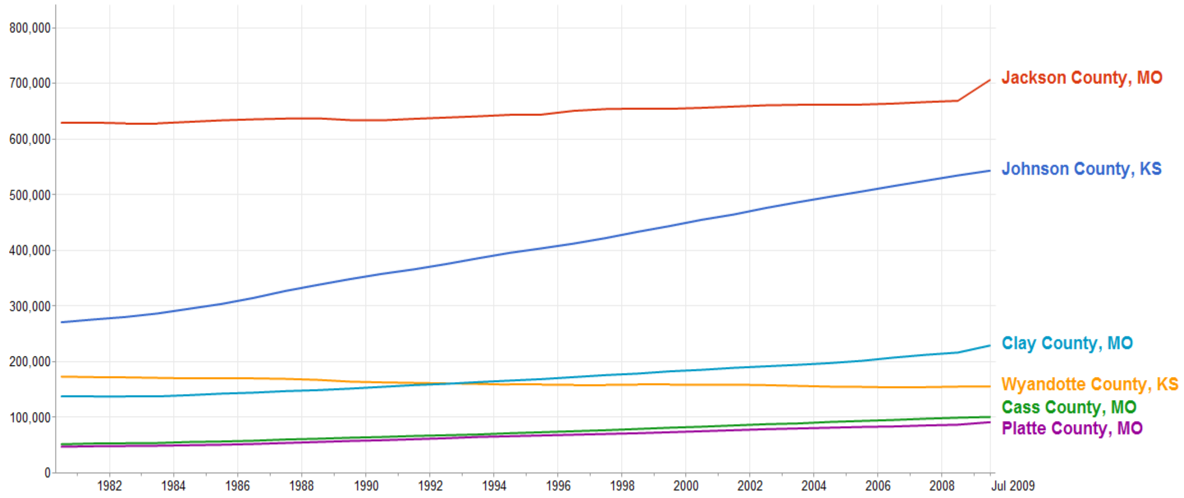


Figure 4-36: Estimates of the resident population growth trends for counties in the study area (Source: U.S. Census Bureau, Population Division).

The bulk of the Little Blue River watershed lies in Jackson County, Missouri; Johnson County largely falls in the Blue River watershed and Shoal Creek Missouri River watershed lies in Clay County, Missouri. The phenomenal increase in Johnson County, Kansas, population is consequently associated with increased urban development. This development may threaten urban wetland-cover unless such development is planned with wetlands protection and preservation in mind.

Discussion and conclusion

To understand urban wetland-cover dynamics, a multi-scale and multi-faceted approach would be required as revealed in this research. Many factors affect changes in wetland-cover and these include natural (e.g., precipitation) and human induced changes (e.g. land use) changes. Wetlands manifest in different forms, and some forms cannot be detected by optical satellite remote sensing; hence, some wetlands are still hidden to this technology. There is therefore a need to incorporate surrogate datasets (e.g., hydric soils) as well as ancillary data that can serve as wetland indicators. No one spatial scale of analysis can adequately address the identification of wetlands, which is why there are still challenges in adequately mapping wetlands in different parts of the world. This again points to the need for multi-scale and multi-faceted approaches.

CHAPTER 5

QUANTIFYING LAND COVER DATA USING GEOSPATIAL MODELING

Introduction

Building models using the ModelBuilder module allows for automating the geo-processing workflow because models help one manage the complex combination of assumptions, tools, datasets, and other factors associated with their analysis. Models update dynamically, and therefore changes to one part of the model are automatically carried through to the rest of the model. In ModelBuilder, models are represented as flow charts with distinct symbols for input data, spatial operations, and output data. This makes it easy to see the model's scope and understand how it works. Models allow one to add complexity by assembling simple and complex processes into one geo-processing tool. For complex processes, one can create separate models that can be added as "sub-models" to primary models. This allows one to incorporate components developed by experts in various disciplines (adapted from ERSI’s Geo-processing Virtual Training Campus course for ArcGIS 9.3).

Watershed Spatial Data Used in Modeling Analysis

The data set shown in Figure 5-2 below was extracted from a complete digital hydrologic unit layer of the entire United States whose smallest hydrologic unit is the sub-watershed. The sub-watershed marks the 6th level of hydrologic unit classification and is represented by a 12-digit code. This data set consists of geo-referenced digital data and associated attributes created in accordance with the FGDC Proposal version 1.0. Polygons are attributed with hydrologic unit codes for 4th level sub-basins, 5th level watersheds, 6th level sub-watersheds, name, size, downstream hydrologic unit, and type of watershed, among other attributes. The watershed and sub-watershed hydrologic unit boundaries provide a uniquely identified and uniform method of subdividing large drainage areas. The sub-watersheds are useful for numerous application programs supported by a variety of local, State, and Federal Agencies. This data set is intended to be used as a tool for water-resource management and planning activities, particularly for site-specific and localized studies requiring a level of detail provided by large-scale map information (NRCS 2011).

Highlighted below are the three major watersheds used in this study, together with rectangular boundary of the study area which represents the area covered by satellite data that were used in this research.

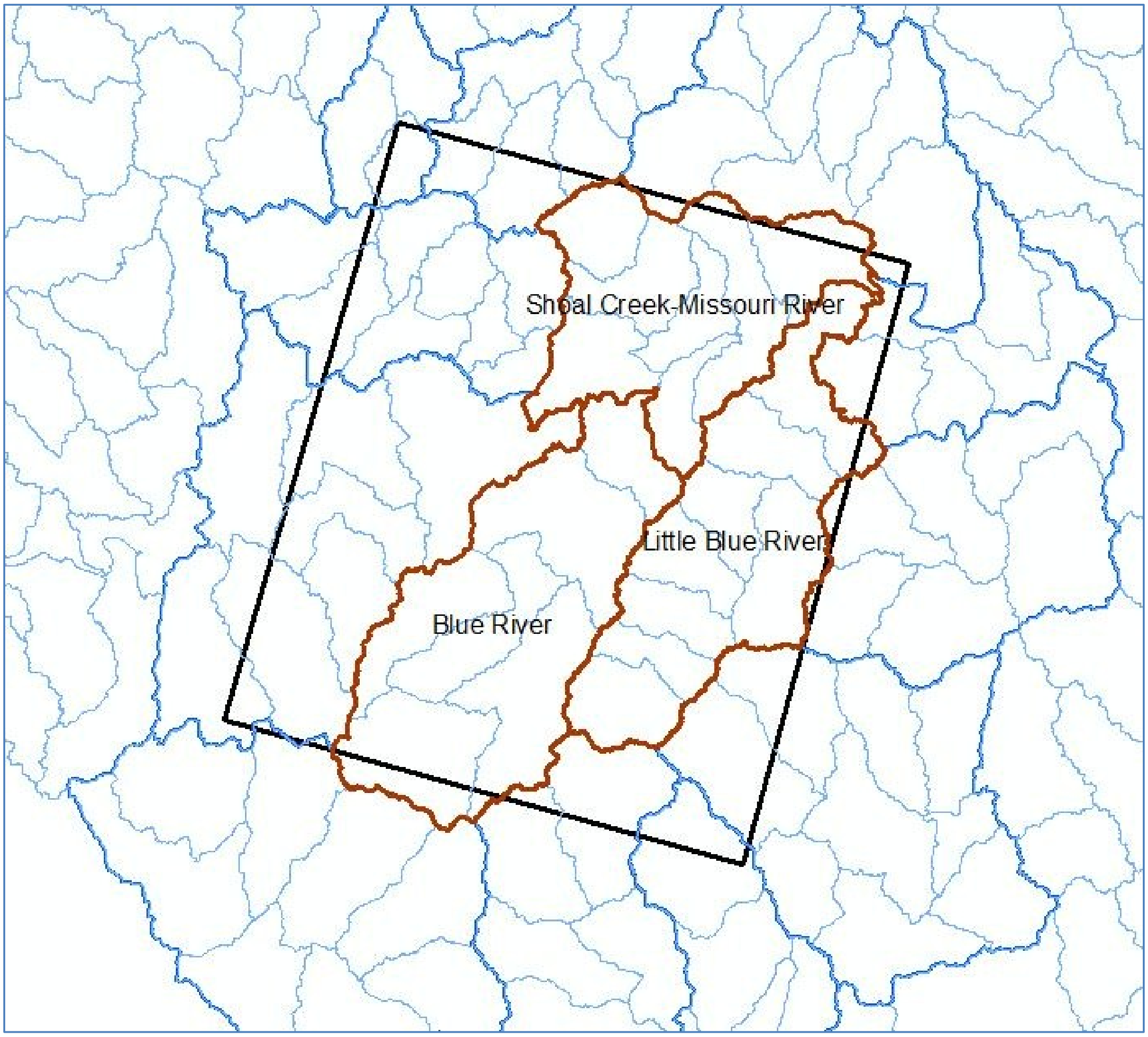


Figure 5-1: Watersheds and sub-watersheds of the Kansas City metropolitan area.

This study used these hydrological unit data as input to the geospatial model that was developed for use in quantifying land-cover class data.

Model for Extracting and Quantifying Land-Cover Class Areas

Since most land resources planning activities take place at the local or sub-watershed scale, a model was developed that could be used by land resources managers to extract sub-watersheds (or watersheds) from a classified satellite image and calculate areas of land cover types represented in the thematic maps of interest. The model was developed using the

Model Builder module and was enhanced using Python scripts. Both the watershed (hydrologic units) feature classes and classified satellite images were stored in file geo-databases. The ModelBuilder's "Select Data" function was used to select child data elements (individual images or watershed feature classes) for use in quantifying land cover classes. Land cover classes are represented in the raster thematic map's value field found in the map's attribute table. If a different field should be used, the user should specify it in the structured query language (SQL) expression in the interface that exposes model parameters.

In this research, the complete model was broken down into two models using the concept of sub-models. The first model (Figure 5-2) was incorporated in the second (Figure 5-4) as a sub-model, mainly to avoid clutter and to make the model easy to understand. Examples of the required and optional parameters the user needs to provide for the models used in this research are shown by ellipses with the letter "P" (for parameter) next to them in Figure 5-2 below.

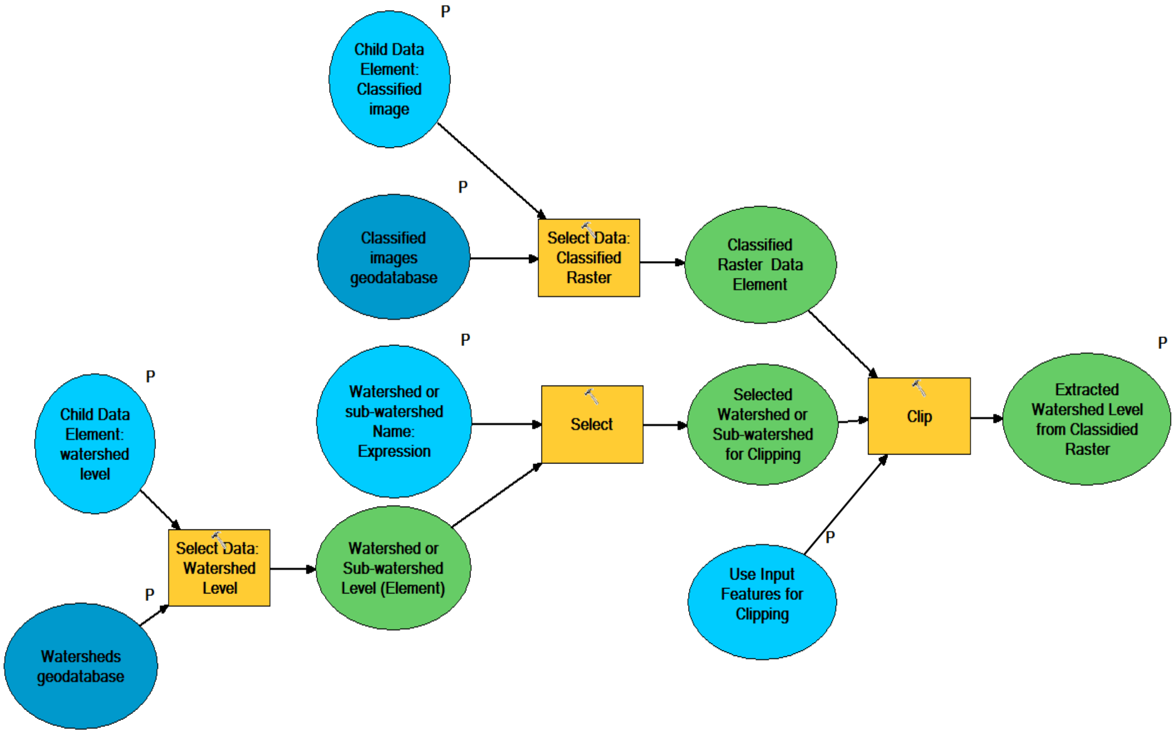
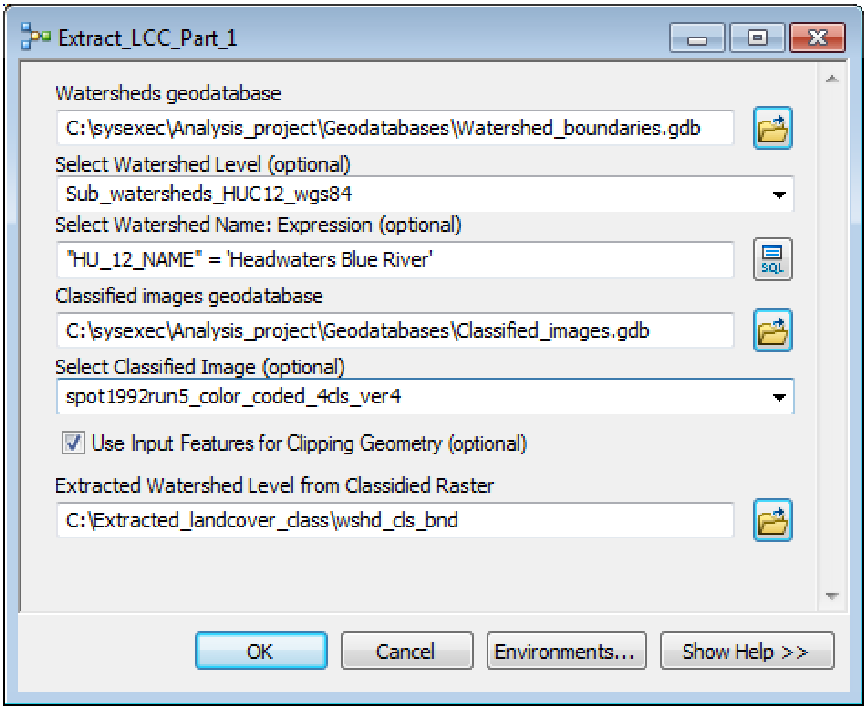


Figure 5-2: A model to extract watershed-based thematic maps using watershed boundaries and classified satellite images

In the above model, the dark blue ellipses represent input data; the light blue ones are child data elements, SQL expressions, or variables. The boxes represent the geo-processing functions or tools. This model has an associated interface that exposes the model parameters which allows for user-defined inputs. Using this interface, the user can select input data, specify names of output data as well as specifying inputs to the SQL expressions. The exposed parameters for this model are shown in Figure 5-3 below.



Watersheds geodatabase
C:\sysexec\Analysis_project\Geodatabases\Watershed_boundaries.gdb

Select Watershed Level (optional)
Sub_watersheds_HUC12_wgs84

Select Watershed Name: Expression (optional)
"HU_12_NAME" = 'Headwaters Blue River'

Classified images geodatabase
C:\sysexec\Analysis_project\Geodatabases\Classified_images.gdb

Select Classified Image (optional)
spot1992run5_color_coded_4cls_ver4

☑ Use Input Features for Clipping Geometry (optional)

Extracted Watershed Level from Classidied Raster
C:\Extracted_landcover_class\wshd_cls_bnd

Figure 5-3: Model interface for specifying input parameters.

The model also calculates areas for a given land-cover class regardless of spatial resolution of the input image/thematic map. The spatial datasets used should however be of the same spatial reference or coordinate system.

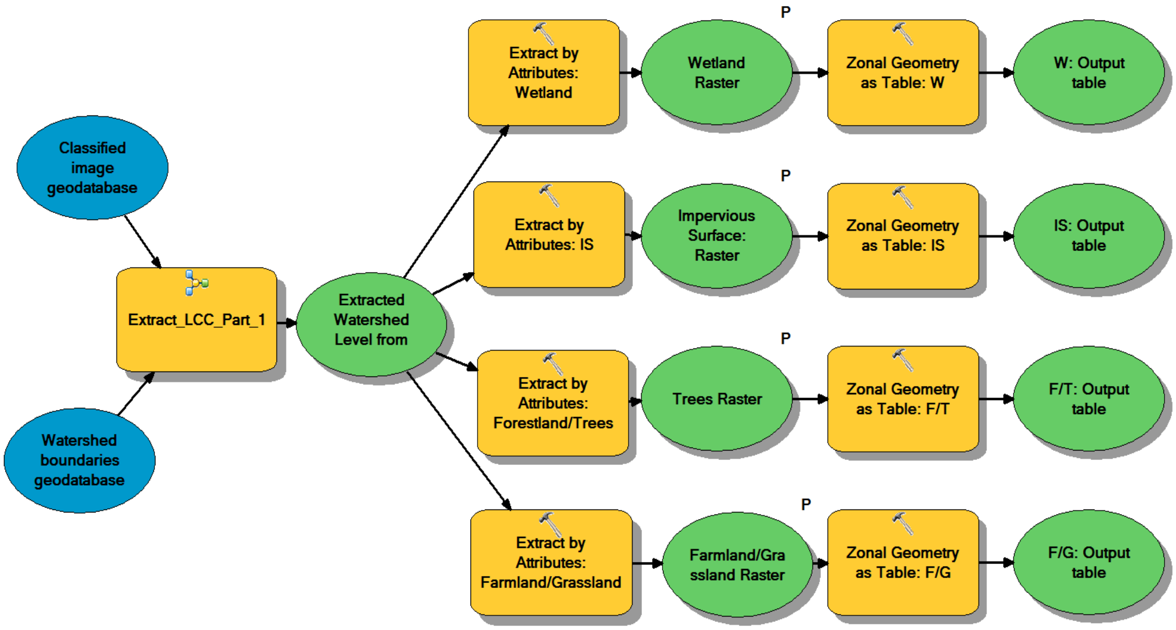
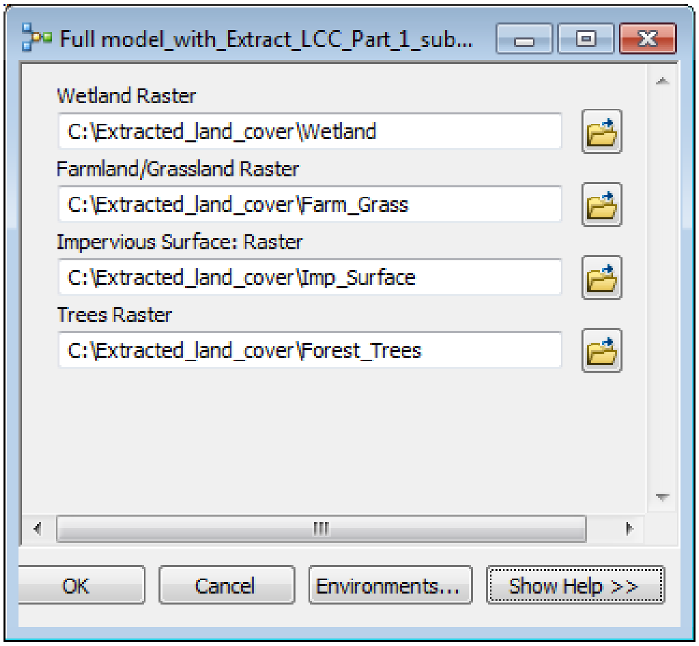


Figure 5-4: Full model with tools to extract and calculate areas for particular land-cover classes selected.

Note that in this model, the first model (Figure 5-2) is represented as a sub-model in the first model process. The model's associated interface shown in figure 5-5 below provides for the user to specify land cover classes of interest using query expressions as well as entering the names of output datasets.



Wetland Raster
C:\Extracted_land_cover\Wetland

Farmland/Grassland Raster
C:\Extracted_land_cover\Farm_Grass

Impervious Surface: Raster
C:\Extracted_land_cover\Imp_Surface

Trees Raster
C:\Extracted_land_cover\Forest_Trees

Figure 5-5: Interface for specifying land cover class output tables. The tables contain an area field for a particular land cover class.

Conclusion

In addition to enhancing functionality and adding complexity of geo-processing capability in ArcGIS™, use of models and scripts facilitates indirect and friendly use of complex processes by land resource managers who may not necessarily have to learn the technical aspects of geospatial software. The model developed in this would also enable users to extract more information from classified images. Such images may be lying idle in various organizations. Model parameters and methodology can be quickly adjusted, and one can run such a model as many times as they wish various classified images.

CHAPTER 6

DISCUSSION AND CONCLUSION

Assessment of wetland-cover dynamics requires a multi-faceted approach since there are several factors that affect wetland-cover change over time. Use of SPOT multi-spectral images to derive land cover data was helpful in this research in that it enabled me to identify and discriminate my target land classes. However, optical images such as SPOT satellite data could not be used to detect vegetated or forested wetlands. In this research, I had to use ancillary data such as hydric soils, which served as indicators of wetlands that are hidden to optical sensors. The spatial resolution of SPOT images would naturally be limited when dealing with small features that contributed to rapid impervious surface or wetland-cover changes. An example would be water bodies smaller than the pixel dimension.

For successful implementation of multi-scale analysis, it is suggested that spatial extents should change in tandem with image resolution. Large spatial scale analysis would require finer resolution images, but the image classification challenge that comes with such spatial resolutions could be a deterrent on its own – target classes would be broken down into sub-classes, thereby introducing complexity to the classification process. A solution would probably be to use data acquired using different satellite sensors; however, the results would not be comparable in most cases.

For the four land cover classes used in this research, use of medium spatial resolution SPOT images to discriminate and quantify target land cover classes yielded thematic maps with acceptable accuracy assessment percentages. Land cover changes between 1992 and 2008 were clearly detected after analyzing SPOT images acquired in these two years. Though the two images were captured in two different seasons, the analysis results revealed the major changes in urban land cover classes, especially surface water. Such changes could have been difficult to assess in a rural area setting because major changes take a long time to show, such that a 16-year period may be too short for this kind of research. Due to the limited spatial resolution, some small ponds and streams could not be detected in the watersheds of study. This implies that, in this research, the open-water (wetland) cover class did not include water from relatively narrow streams. Higher spatial resolution image datasets together with appropriate classification algorithms could be used to capture such wetland features.

The influence of large water bodies (major rivers and lakes) is usually overlooked in many studies. In this study, it was revealed that separating large water bodies from small water bodies would, in almost all cases, give a different picture of results altogether. Small water bodies are easier to destroy in urbanizing environments. Urbanizing environments may be associated with modifications of large water bodies for recreation or dredging purposes. In such cases, determining wetland-cover changes would need separation of major water bodies from small water bodies. Surface water cover of large water bodies tends to mask the change trends in small water bodies if the two are combined in determining surface water cover trends in hydrologic units of interest.

Seasonal wetland-cover analysis (2008 – 2010) using SPOT images revealed changes in land cover classes that are sensitive to seasonal variations such as farmland/grassland and forestland. Higher spatial resolution images (less than 1 meter) could be used in the future focusing solely on water bodies to avoid the complexity that would be associated with the inclusion of all land cover classes.

Land cover analyses that focus on particular hydrological units (watershed or sub-watershed) are necessary because watersheds are affected by activities that take place within their confines. This is even more the case for wetland-cover analysis. The impact of watershed processes defies political boundaries; hence, any land resource management activities should involve stakeholders resident in the target watershed or sub-watershed. For example, in the case of water pollution from non-point sources, downstream areas are affected without regard to political jurisdictions. The sub-watershed level coincides in most cases with spatial extents that are usually used for planning purposes by local authorities. As was revealed in this research, different land cover analysis results were produced at each spatial scale of analysis. This emphasizes the fact that under heterogeneous environments, analysis results from one hydrologic unit may not be applied to another, let alone across different hydrologic unit scales.

Precipitation received just before image acquisition can adversely affect wetland expression on an image and that may invalidate the use of anniversary images for land cover detection analysis, especially wetland-cover, because wetlands swell or shrink rapidly with changes in precipitation amounts. When studying precipitation changes in a hydrologic unit such as a watershed, use of station-based precipitation data may not be adequate. Precipitation data with a regional dimension would be appropriate, as these data can capture aerial precipitation variability; thus in this study used long term precipitation data, stream flow data and lake level data from uncontrolled streams, as well as satellite-based CPC merged analysis precipitation data to understand precipitation dynamics. Results from analysis of these data pointed towards an increase in precipitation for the Kansas City metropolitan area. However, it should be noted that the increase registered at the time of this study was not significant enough to recover the wetlands lost in the study area based on historical wetland loss reports. This was also exacerbated by the fact that the Kansas City metropolitan area was still losing wetlands due to continued impervious surfaces development.

Use of hydric soils is important in assessing wetland-cover changes because these soils represent areas where wetland exists or once existed. At the time of this research, these soils were targeted for recovering lost wetlands in the U.S. by the Environmental Protection Agency because the hydric soil areas could easily be converted back to wetlands. Combining hydric soils data analysis and remote sensing analysis yielded a declining trend in urban wetland-cover, even in watersheds where use of remote sensing analysis alone suggested increases in surface water cover.

According to the findings of this research, human activities rank topmost in wetland-cover disturbances, both directly and indirectly. Wetlands are destroyed through their conversion to other land uses such as urbanization or farmlands. Some wetlands, such as open-water reservoirs, are introduced in cities and suburban areas to service industries and suburbs in their localities. Anthropogenic activities also result in climate changes, such as global warming, that can affect the weather system of an area. Consequences of such disturbances could increase or decrease precipitation amounts received in an area.

Multi-scale spatio-temporal image analysis yields more information than studying land resources data, especially wetlands, in a single dimension. Short term seasonal wetland changes may be challenging to understand because of significant land-cover changes that take place from one season to another. It is also difficult to find images that were acquired on the most representative date or time for a particular season. Land resources planning should be based on local scale analysis in a heterogeneous environment, and regional scales should serve solely to give a general picture of land-cover/use change in an area. In spite of that, local scale findings should also not be directly extrapolated to regional level planning in heterogonous landscapes.

There are also some indicators that some dried up wetlands may be restored and that destruction of wetlands would be under some control. This is encouraged by a potentially increasing precipitation trend as revealed in this analysis, as well as in EPA policies aimed to protect and restore wetlands. An example of such policies is the promotion of mitigation banks, which is championed by both the EPA and the Army Corps. of Engineers. The U.S. government's "No net loss" wetland policy enforces replacement of wetlands in the event of conversion of wetland area for any use. The effect of such polices could result in a net increase of both surface water and "hidden" wetland-cover in the Kansas City metropolitan area.

It was also noted that precipitation data received just before an imaging date may have a strong bearing on the wetland footprint expressed on a satellite image; hence care should be exercised when using anniversary images for wetland change detection analysis. As a recommendation, the study suggests the analysis of wetland-cover data using increasing image spatial (pixel) resolutions; for example, use of SPOT 2 (20 m), SPOT 5(10 m), and SPOT 5 (5 m) for different hydrologic unit scales, where higher spatial resolutions are applied to small hydrologic units such as the sub-watershed level.

Geo-processing models can bring about added functionality that would be unique to manipulating an organization's datasets. Such functionality helps to bridge the gap between the user and the data by removing technical complexities that may be a hindrance to maximum utilization of an organization's datasets. This will result in increased productivity as more useful information may be extracted from the organization's image datasets.

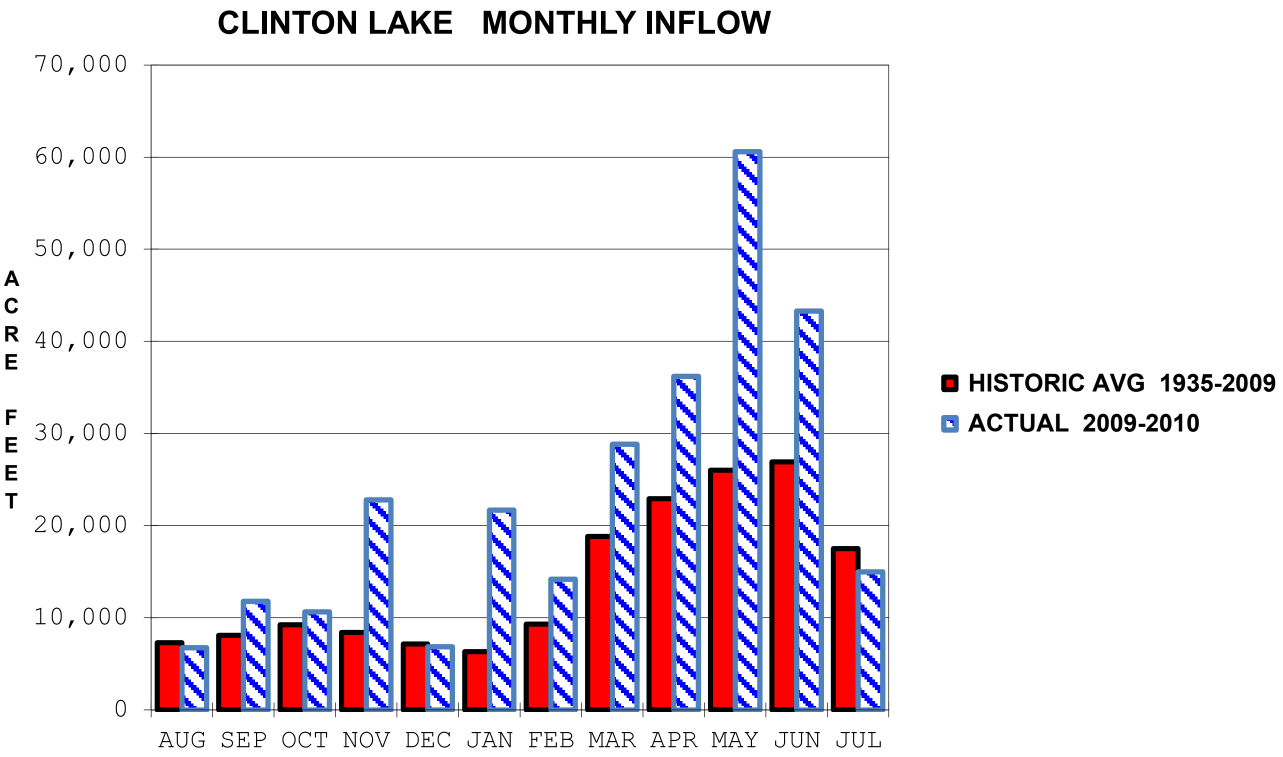
In summary, multi-scale analysis of urban wetlands in both the spatial and temporal dimension is important to understanding wetland-cover dynamics. Identifying wetlands using optical sensors is still a challenge and should be augmented by ancillary data such as hydric soils and precipitation. An increase in precipitation can result in an increase in urban wetland-cover in some areas, while in some locations increasing impervious surface causes wetland-cover loss. Human activities can increase (e.g., mitigation banks, constructed reservoirs) or decrease (e.g., impervious surfaces) wetland areas. The impact of these activities is noticeable more at the local level than on the regional scale; thus there is a need to analyze the impacts at appropriate spatial extents. Understanding the complex human-climate coupling factors affecting urban wetland-cover requires a multi-faceted or multi-disciplinary approach.

APPENDIX A

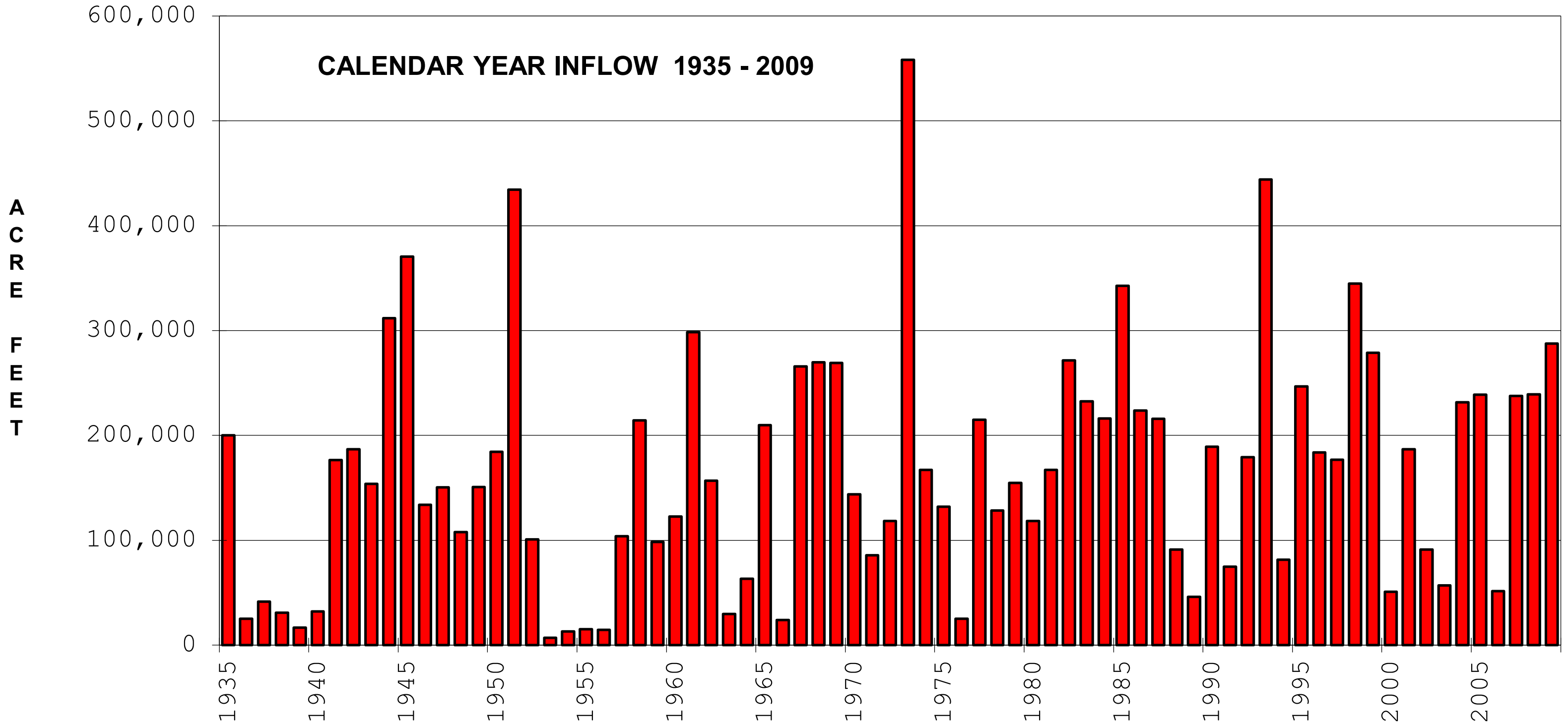
LAKE INFLOWS: HISTORICAL AND ACTUAL

HISTORIC AND ACTUAL INFLOW FOR CLINTON LAKE

	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul
Historical Avg 1990-99	7276	8084	9217	8390	7149	6332	9301	18806	22929	26026	26927	17511
Actual	6754	11502	10641	22830	6873	21709	14212	28869	36228	60615	43299	14995

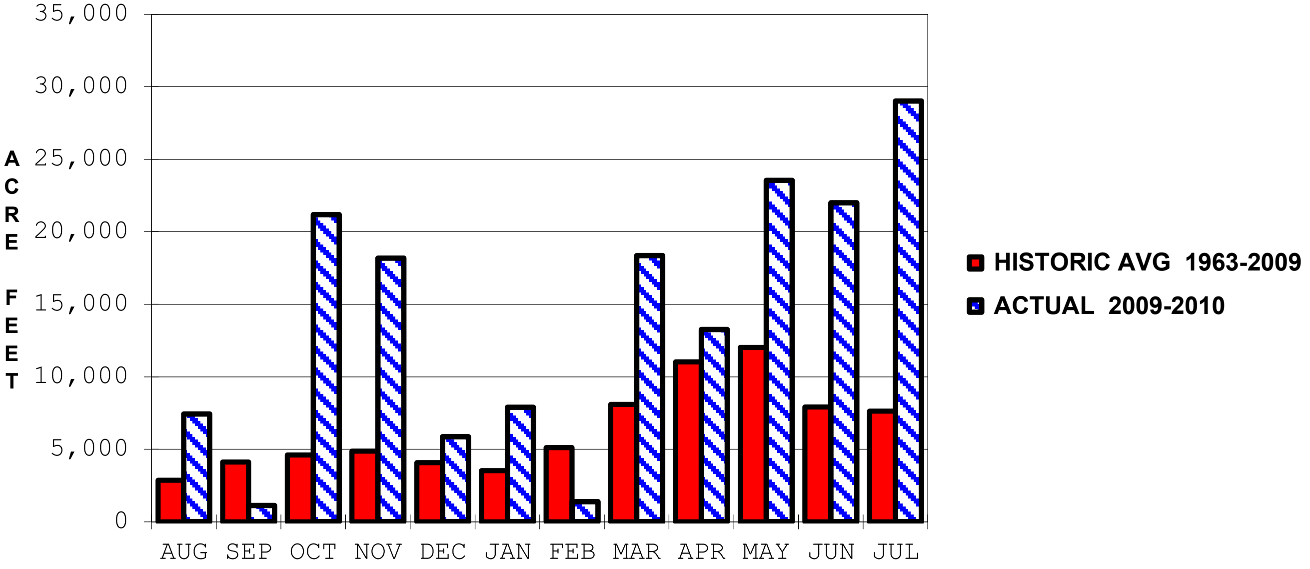


CLINTON LAKE ANNUAL INFLOW



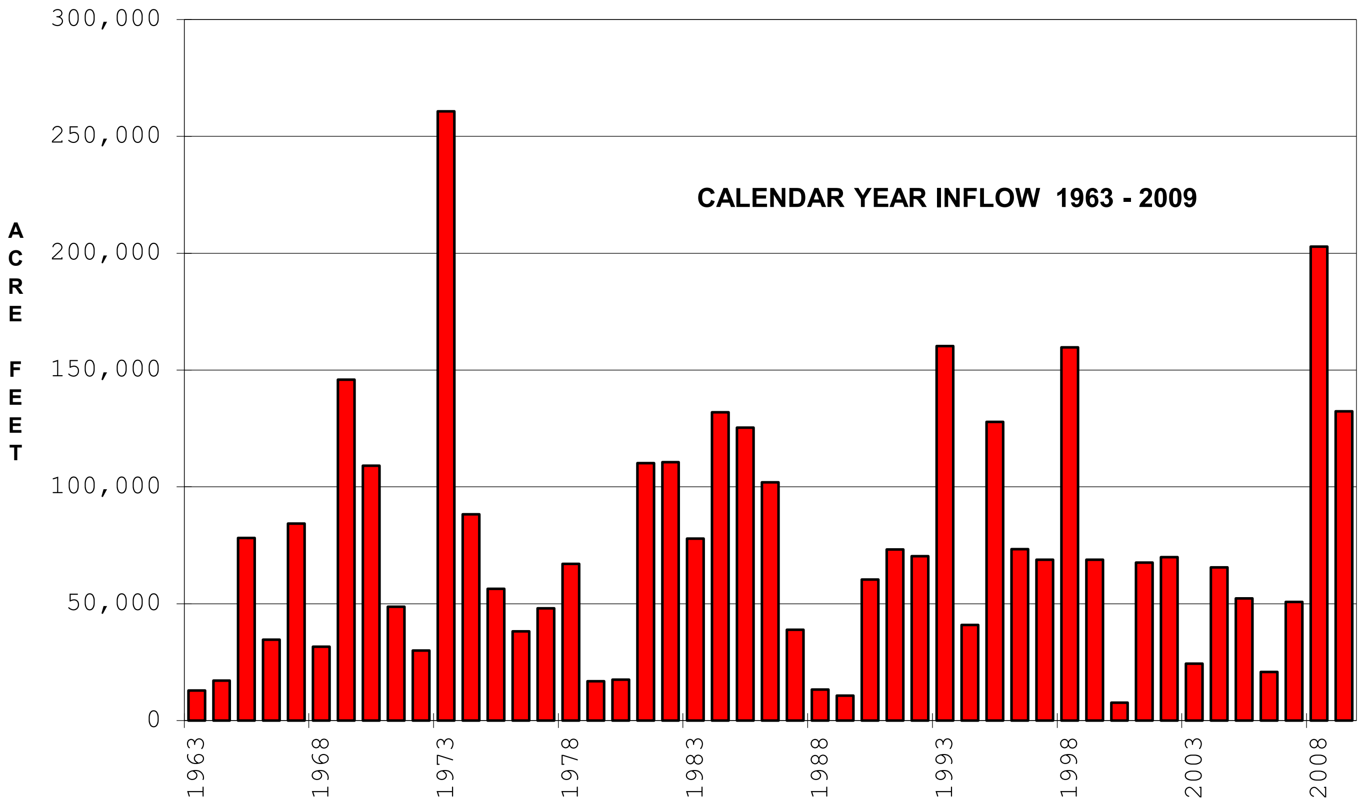
HISTORIC AND ACTUAL INFLOW FOR LONG BRANCH LAKE

	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul
Historical Avg 1990-99	10336	18103	24551	31629	30330	31812	39001	59528	61576	60758	36195	19375
Actual	18198	18268	163854	55101	27878	60059	59316	77802	37160	147897	9689	15501



LONG BRANCH LAKE MONTHLY INFLOW

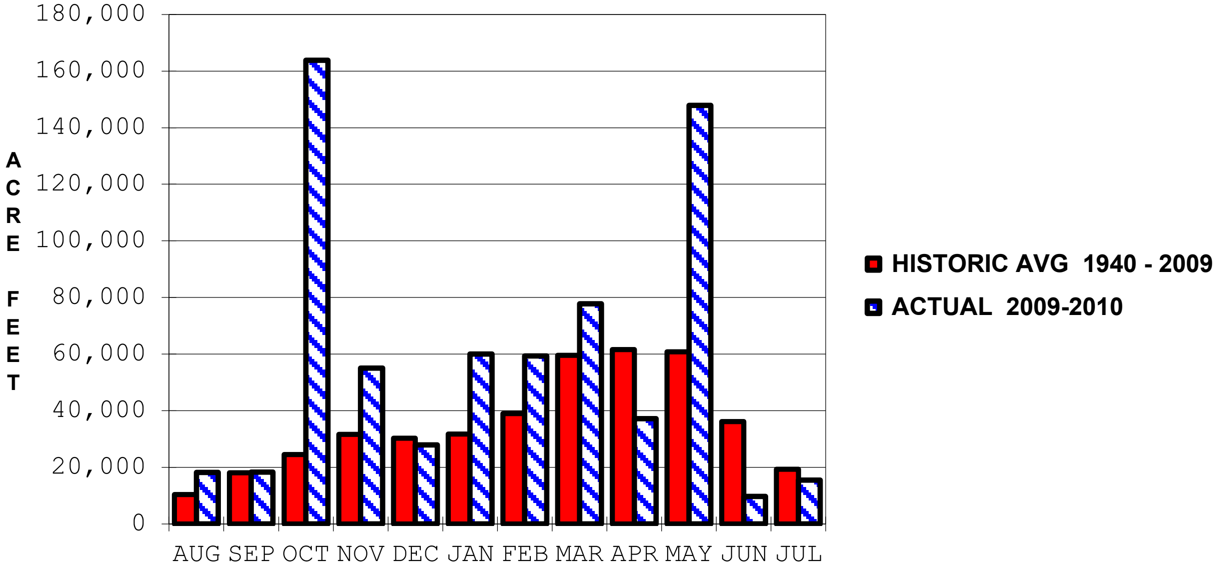
LONG BRANCH LAKE   ANNUAL INFLOW



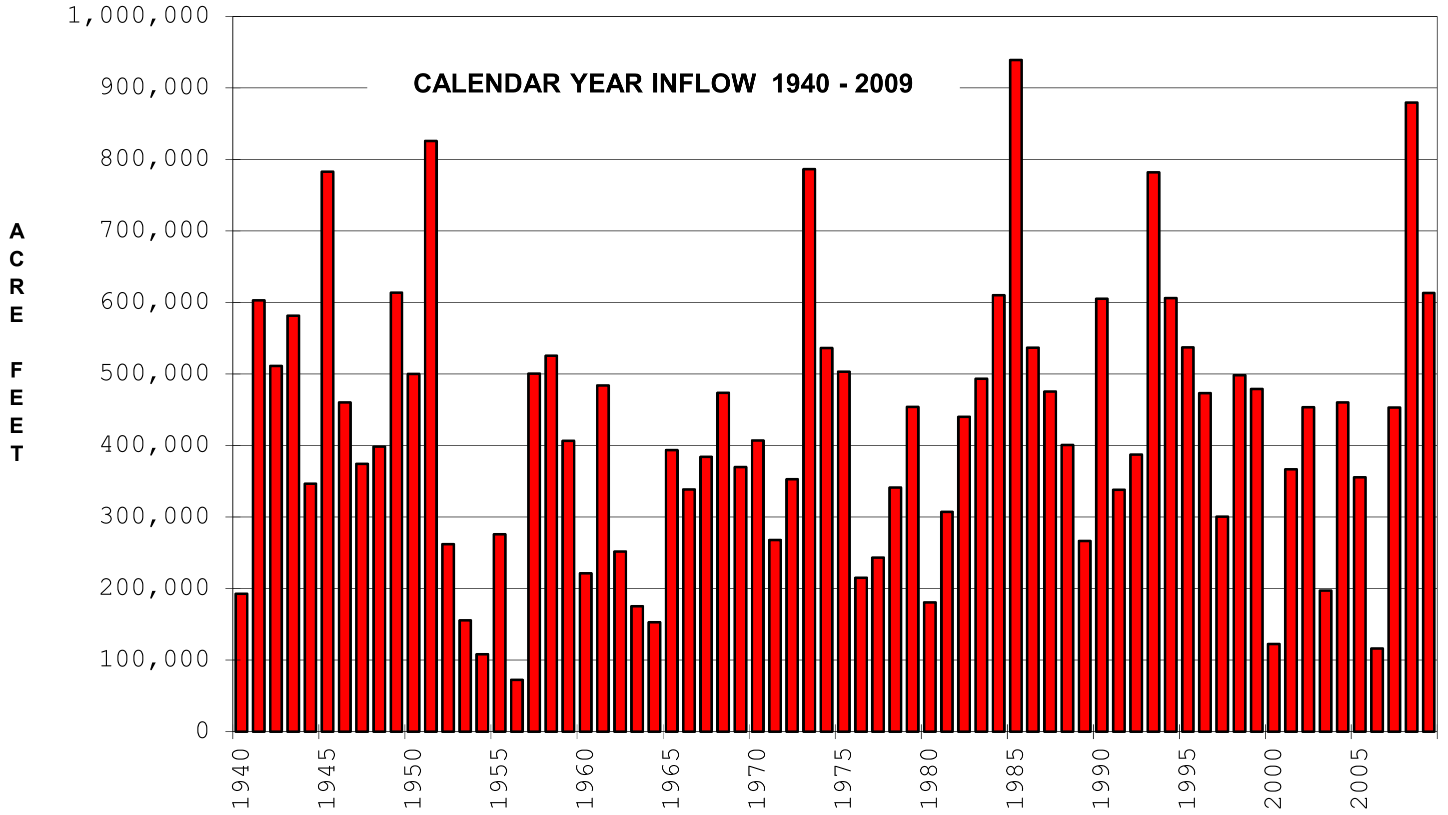
HISTORIC AND ACTUAL INFLOW FOR POMME DE TERRE LAKE

	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul
Historical Avg 1990-99	2866	4130	4599	4859	4079	3527	5108	8091	11023	12014	7921	7625
Actual	7428	1111	21174	18169	5871	7894	1388	18343	13250	23534	21987	29018

POMME DE TERRE LAKE   MONTHLY INFLOW



POMME DE TERRE LAKE   ANNUAL INFLOW



APPENDIX B

SOURCE CODE FOR THE GEO-PROCESSING MODEL

Python source code for extracting watershed areas from a thematic classified raster layer based on watershed or sub-watershed boundaries. The source code below is as it appears in Python editor.

```
# Extract_LandCover_Class.py created by Dzingirai Murambadoro
# Created on: 2011-06-10 14:15
#   (generated by ArcGIS/ModelBuilder   and modified in Python)
# Usage: Extract_LandCover_Class <Child_Data_Element__watershed_level>
<Child_Data_Element__2_> \
# <Watershed_or_sub-watershed_Name__Expression>
<Use_Input_Features_for_Clipping_Geometry> <Wetland_Raster> \
# <Impervious_Surface__Raster> <Trees_Raster> <Farmland_Grassland_Raster>

#--------------------------------------------------------------------------
This script extracts user-defined watersheds or hydrological units (HU) from a raster
thematic layer and calculates the areas of various land-cover classes for a watershed or sub-
watershed. The land-cover based thematic maps are generated after classifying land resources
satellite images. All the data used in this script use the UTM WGS 84 projection.  A
watershed or sub-watershed feature-class is selected from a geo-database. From this feature
class, a particular watershed (or sub-watershed) polygon is selected based on the hydrologic
unit (HU)'s name field; the selected polygon is used to clip out a corresponding area in the
classified image. Various land-cover classes are extracted from the output raster based on the
class value found in the 'value' field. For each of these land-cover classes, areas are
calculated using the 'Zonal Geometry as Table' tool. For each land-cover class, the resultant
tables are displayed in the ArcMap table of contents and can be opened to view the areas.
# -------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")
#***********************************
# Script arguments
# These user inputs are required; they can entered as sys.arg() in Python

Child_Data_Element__watershed_level = arcpy.GetParameterAsText(0) # watershed level

Child_Data_Element__2_ = arcpy.GetParameterAsText(1)

Watershed_or_sub-watershed_Name__Expression = arcpy.GetParameterAsText(2)

Use_Input_Features_for_Clipping_Geometry = arcpy.GetParameterAsText(3)

Wetland_Raster = arcpy.GetParameterAsText(4)
```

```
Impervious_Surface__Raster = arcpy.GetParameterAsText(5)

Trees_Raster = arcpy.GetParameterAsText(6)

Farmland_Grassland_Raster = arcpy.GetParameterAsText(7)

#*********************************************
# Local variables:
Watershed_boundaries_geodatabase =
"C:\\sysexec\\test\\Analysis_project\\Geodatabases\\Watershed_boundaries.gdb"
Watershed_or_Sub-watershed_Level__Element_ = Child_Data_Element__watershed_level
Selected_Watershed_or_Sub-watershed_for_Clipping_Raster_Data = Watershed_or_Sub-
watershed_Level__Element_
Extracted_Watershed_Level_from_Classidied_Raster = Selected_Watershed_or_Sub-
watershed_for_Clipping_Raster_Data
W__Output_table = Wetland_Raster
Classified_images_gdb =
"C:\\sysexec\\test\\Analysis_project\\Geodatabases\\Classified_images.gdb"
Classified_Raster__Data_Element = Child_Data_Element__2_
F_G__Output_table = Farmland_Grassland_Raster
IS__Output_table = Impervious_Surface__Raster
F_T__Output_table = Trees_Raster

# Process: Select Data: Classified Raster
arcpy.SelectData_management(Classified_images_gdb, Child_Data_Element__2_)

# Process: Select Data:  Watershed Level
arcpy.SelectData_management(Watershed_boundaries_geodatabase,
Child_Data_Element__watershed_level)

# Process: Select
arcpy.Select_analysis(Watershed_or_Sub-watershed_Level__Element_,
Selected_Watershed_or_Sub-watershed_for_Clipping_Raster_Data, \
                Watershed_or_sub-watershed_Name__Expression)

# Process: Clip
arcpy.Clip_management(Classified_Raster__Data_Element, "212899.5623 3832325.7094
860923.0456 4620816.5125", \
                Extracted_Watershed_Level_from_Classidied_Raster,
Selected_Watershed_or_Sub-watershed_for_Clipping_Raster_Data, \
                "", Use_Input_Features_for_Clipping_Geometry)

# Process: Extract by Attributes: Wetland
arcpy.gp.ExtractByAttributes_sa(Extracted_Watershed_Level_from_Classidied_Raster,
"\"Value\" = 1", Wetland_Raster)
```

```
# Process: Zonal Geometry as Table: W
arcpy.gp.ZonalGeometryAsTable_sa(Wetland_Raster, "VALUE", W__Output_table,
"20.0025868483065")

# Process: Extract by Attributes: IS
arcpy.gp.ExtractByAttributes_sa(Extracted_Watershed_Level_from_Classidied_Raster,
"\"Value\" = 3", Impervious_Surface__Raster)

# Process: Zonal Geometry as Table: IS
arcpy.gp.ZonalGeometryAsTable_sa(Impervious_Surface__Raster, "VALUE",
IS__Output_table, "20.0025868483065")

# Process: Extract by Attributes: Forestland/Trees
arcpy.gp.ExtractByAttributes_sa(Extracted_Watershed_Level_from_Classidied_Raster,
"\"Value\" = 4", Trees_Raster)

# Process: Zonal Geometry as Table: F/T
arcpy.gp.ZonalGeometryAsTable_sa(Trees_Raster, "VALUE", F_T__Output_table,
"20.0025868483065")

# Process: Extract by Attributes: Farmland/Grassland
arcpy.gp.ExtractByAttributes_sa(Extracted_Watershed_Level_from_Classidied_Raster,
"\"Value\" = 2", Farmland_Grassland_Raster)

# Process: Zonal Geometry as Table: F/G
arcpy.gp.ZonalGeometryAsTable_sa(Farmland_Grassland_Raster, "VALUE",
F_G__Output_table, "20.0025868483065")
```

APPENDIX C

PRECIPITATION RECEIVED 31 DAYS BEFORE SATELLITE IMAGING DATES

Precipitation received before the SPOT 2 1992 imaging date

Date before image acquisition	Day	Precipitation received (inches)
29-Dec-91	31	0
30-Dec-91	30	0
31-Dec-91	29	0.05
1-Jan-92	28	0.12
2-Jan-92	27	0.3
3-Jan-92	26	0
4-Jan-92	25	0
5-Jan-92	24	0
6-Jan-92	23	0.38
7-Jan-92	22	0
8-Jan-92	21	T
9-Jan-92	20	0
10-Jan-92	19	0
11-Jan-92	18	0
12-Jan-92	17	0.13
13-Jan-92	16	0.21
14-Jan-92	15	T
15-Jan-92	14	0
16-Jan-92	13	0
17-Jan-92	12	0
18-Jan-92	11	0
19-Jan-92	10	0
20-Jan-92	9	0
21-Jan-92	8	0
22-Jan-92	7	T
23-Jan-92	6	0.13
24-Jan-92	5	0
25-Jan-92	4	0
26-Jan-92	3	0
27-Jan-92	2	0
28-Jan-92	1	0
29-Jan-92	0	0

T = precipitation amount too small to be determined

Precipitation received before the SPOT 5 2008 imaging date

Date before image acquisition	**Day**	**Precipitation received (inches)**
7-Sep-08	31	0.2
8-Sep-08	30	0.23
9-Sep-08	29	1.2
10-Sep-08	28	0
11-Sep-08	27	0
12-Sep-08	26	0.95
13-Sep-08	25	2.85
14-Sep-08	24	0.4
15-Sep-08	23	0
16-Sep-08	22	0
17-Sep-08	21	0
18-Sep-08	20	0
19-Sep-08	19	0
20-Sep-08	18	0
21-Sep-08	17	0
22-Sep-08	16	0
23-Sep-08	15	0
24-Sep-08	14	0.6
25-Sep-08	13	0.1
26-Sep-08	12	0
27-Sep-08	11	0
28-Sep-08	10	0
29-Sep-08	9	0.09
30-Sep-08	8	0.03
1-Oct-08	7	0
2-Oct-08	6	0
3-Oct-08	5	0
4-Oct-08	4	0
5-Oct-08	3	0
6-Oct-08	2	0
7-Oct-08	1	0.42
8-Oct-08	0	0.08

Precipitation received before the SPOT 5 2009 imaging date

Date before image acquisition	Day	Precipitation received (inches)
23-Mar-09	31	0.07
24-Mar-09	30	1.53
25-Mar-09	29	0.37
26-Mar-09	28	0.12
27-Mar-09	27	0
28-Mar-09	26	0
29-Mar-09	25	0.1
30-Mar-09	24	0
31-Mar-09	23	0.15
1-Apr-09	22	0
2-Apr-09	21	0
3-Apr-09	20	0.36
4-Apr-09	19	0
5-Apr-09	18	0.15
6-Apr-09	17	0.25
7-Apr-09	16	0
8-Apr-09	15	0
9-Apr-09	14	0
10-Apr-09	13	0.52
11-Apr-09	12	0.02
12-Apr-09	11	0
13-Apr-09	10	0.46
14-Apr-09	9	0.12
15-Apr-09	8	0
16-Apr-09	7	0
17-Apr-09	6	0
18-Apr-09	5	0
19-Apr-09	4	0.25
20-Apr-09	3	0
21-Apr-09	2	0
22-Apr-09	1	0
23-Apr-09	0	0

Precipitation received before the SPOT 5 2010 imaging date

Date before image acquisition	Day	Precipitation received (inches)
11-Jul-10	31	0
12-Jul-10	30	0.04
13-Jul-10	29	0
14-Jul-10	28	0
15-Jul-10	27	0.76
16-Jul-10	26	0
17-Jul-10	25	0
18-Jul-10	24	0.03
19-Jul-10	23	0
20-Jul-10	22	0.47
21-Jul-10	21	0.13
22-Jul-10	20	0
23-Jul-10	19	0
24-Jul-10	18	0
25-Jul-10	17	0.02
26-Jul-10	16	0
27-Jul-10	15	0
28-Jul-10	14	0
29-Jul-10	13	0.05
30-Jul-10	12	0
31-Jul-10	11	1.38
1-Aug-10	10	0
2-Aug-10	9	0
3-Aug-10	8	0
4-Aug-10	7	0
5-Aug-10	6	0
6-Aug-10	5	0
7-Aug-10	4	0
8-Aug-10	3	0
9-Aug-10	2	0
10-Aug-10	1	0
11-Aug-10	0	0.04

APPENDIX D

SURFACE WATER COVER ANALYSIS AT KANSAS CITY METRO-POLITAN, WATERSHED AND SUB-WATERSHED SCALES

A. Kansas City Metropolitan Scale Data

Kansas City Metropolitan Area	**1992**	**2008**
Surface water =< 8ha	10110991	8511617
Surface water > 8ha	39531673	42042939
Combined surface water	49641664	50958300

B. Watershed Scale Data

Blue River	**1992**	**2008**
Surface water =< 8ha	2017276.3	1868818.4
Surface water > 8ha	475690.6	469609.2
Combined surface water	2492966.9	2338427.6

Little Blue River	**1992**	**2008**
Surface water =< 8ha	1713185.1	1579155.2
Surface water > 8ha	11555516.5	11684873.8
Combined surface water	13268701.6	13264029.0

Shoal Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	1982319.4	1052021.5
Surface water > 8ha	10515015.1	11724541.5
Combined surface water	12497334.6	12776563.0

C. Sub-watershed Scale Data for each Major Watershed

BLUE RIVER WATERSHED

Blue River Outlet	**1992**	**2008**
Surface water =< 8ha	366072.7	189509.2
Surface water > 8ha	0.0	0.0
Combined surface water	366072.7	189509.2

Brush Creek Blue River	**1992**	**2008**
Surface water =< 8ha	162044.9	159435.0
Surface water > 8ha	0	0
Combined surface water	162044.9	159435.0

Camp Branch Blue River	**1992**	**2008**
Surface water =< 8ha	708109.5	744184.5
Surface water > 8ha	351280	336865.7
Combined surface water	1059389.5	1081050.2

Headwaters Blue River	**1992**	**2008**
Surface water =< 8ha	429037.8	525694.5
Surface water > 8ha	124410.6	132743.5
Combined surface water	553448.4	658438.0

Headwaters Indian Creek	**1992**	**2008**
Surface water =< 8ha	139270.2	108037.2
Surface water > 8ha	0	0
Combined surface water	**139270.2**	**108037.2**

Indian Creek	**1992**	**2008**
Surface water =< 8ha	211627.5	141906.2
Surface water > 8ha	0	0
Combined surface water	211627.5	141906.2

LITTLE BLUE RIVER WATERSHED

Burr Oak Creek Little Blue River	**1992**	**2008**
Surface water =< 8ha	115266.7	86687.0
Surface water > 8ha	0	0
Combined surface water	115266.7	86687.0

Cedar Creek Little Blue River	**1992**	**2008**

Surface water =< 8ha	205978.3	156829.7
Surface water > 8ha	1481822.1	1453831.7
Combined surface water	1687800.4	1610661.4

East Fork Little Blue River	**1992**	**2008**
Surface water =< 8ha	180222.2	310752.7
Surface water > 8ha	7064424.6	7076900.8
Combined surface water	7244646.8	7387653.5

Headwaters Little Blue River	**1992**	**2008**
Surface water =< 8ha	379231.6	249669.5
Surface water > 8ha	0	358669.1
Combined surface water	379231.6	608338.6

Headwaters Indian Creek	**1992**	**2008**
Surface water =< 8ha	139270.2	108037.2
Surface water > 8ha	0	0
Combined surface water	139270.2	108037.2

Little Blue River	**1992**	**2008**
Surface water =< 8ha	175423.2	141063.7
Surface water > 8ha	0	0
Combined surface water	175423.2	141063.7

Little Cedar Creek Little Blue River	**1992**	**2008**
Surface water =< 8ha	262587.6	307352.9
Surface water > 8ha	0	0
Combined surface water	262587.6	307352.9

May Brook Creek Little Blue River	**1992**	**2008**
Surface water =< 8ha	215842.3	204709.4
Surface water > 8ha	936993.7	882660.7
Combined surface water	1152836.0	1087370.1

Mouse Creek Little Blue River	**1992**	**2008**
Surface water =< 8ha	175696.4	121238.9
Surface water > 8ha	2072275.9	1912811.5
Combined surface water	2247972.3	2034050.4

SHOAL CREEK MISSOURI RIVER WATERSHED

Buckeye Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	477629.4	142343.8
Surface water > 8ha	3254848.6	3669701.1
Combined surface water	3732478.0	3812045.0

Dry Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	85251.3	51070.0
Surface water > 8ha	3133726.7	3605436.7
Combined surface water	3218978.0	3656506.7

Lower Shoal Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	102819.4	216258.5
Surface water > 8ha	389472.1	170492.5
Combined surface water	492291.5	386750.9

Middle Shoal Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	251148.4	274578.0
Surface water > 8ha	0	0
Combined surface water	251148.4	274578.0

Upper Shoal Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	96435.6	109249.1
Surface water > 8ha	0	0
Combined surface water	96435.6	109249.1

Rock Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	397812.9	58059.5
Surface water > 8ha	2348011.1	2419825.4
Combined surface water	2745824.0	2477884.9

Rush Creek Missouri River	**1992**	**2008**
Surface water =< 8ha	283531.5	200029.7
Surface water > 8ha	1671726.4	1858278.7
Combined surface water	1955257.9	2058308.4

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VITA

Dzingirai Murambadoro was born on May 1970 in Masvingo province, Zimbabwe. He was educated at local schools and appraised as one of the best students. In 1992 he entered University of Zimbabwe, located in Harare, the capital city of Zimbabwe. He majored in Soil Sciences and in 1994 he received his Bachelor of Agriculture (Honors) degree. He joined Soils Incorporated Inc., Harare, Zimbabwe as an assistant consultant from 1994 to 1997. He received an M.S. degree in Land and Geographic Information Systems (GIS) in 1999 also from the University of Zimbabwe. He continued his professional experiences when he joined the International Crops Research Institute for Semi-Arid Tropics (ICRISAT) where he was a GIS Scientific Officer from 1999 to 2002. From 2002 to 2005, he was with the Scientific and Industrial Research and Development Centre (SIRDC) – a national research institute – in Harare, Zimbabwe, as a research scientist in the Environment and Remote Sensing Institute (ERSI). He began work toward his Interdisciplinary PhD at the University of Missouri-Kansas City, in the Fall of 2005, where he combined Geosciences and Computer Science. He was awarded the William and Catherine Repp. Memorial scholarship in 2008 and was a Chancellor Scholar during the 2009-2011 academic years. In September 2011, he joined Tradewinds Energy as a GIS Consultant (Analyst/Developer). Mr. Murambadoro is a member of the American Society of Photogrammetry and Remote Sensing (ASPRS) and the Association of American Geographers (AAG). His research interests include GIS, remote sensing and wetland research.

Major Publications:

1. D. Murambadoro and W. Ji. 2011. Multi-scale analysis of urban wetland changes using satellite remote sensing techniques. (In Press).

2. Ji, W. and D. Murambadoro. Digital Earth: Quantifying Urban Landscape Changes for Impact Analysis. In Proceeding of Digital Earth Summit, Nessebar, Bulgaria, 12-14 June 2010. 9 pages.

3. Ji, W. and D. Murambadoro, Urban Wetland Dynamics: An Indicator of Human-Environment Coupling Impacts. Presented at the Second International Conference on Earth Observation for Global Changes (EOGC2009), Chengdu, China, 25-29 May 2009. 6 pages.

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1. D. Murambadoro and W. Ji. 2011. Multi-scale analysis of urban wetland changes using satellite remote sensing techniques. (Presented at the Association of American Geographers (AAG) annual meeting in Seattle, April 2011.)

2. The national chairperson's presentation of the annual progress report on the activities of the Metadata Working Group at Cresta Jameson Hotel, Harare, Zimbabwe. 2004. A Global Spatial Data Infrastructure (GSDI) sponsored workshop.

3. "D. Murambadoro & Gilford T Hapanyengwi. A Knowledge Based GIS for Crop Production. Symposium on Science and Technology for the Research Council of Zimbabwe, August 1999."