ABSTRACT

BECK, SCOTT MICHAEL. Beyond Impervious: Urban Land-Cover Pattern Variation and Implications for Water Quality. (Under the direction of Melissa McHale and Gary Blank).

Impervious surfaces degrade urban water quality, but cannot explain persistent water quality variation among catchments with similar imperviousness levels. Land-cover patterns likely explain much of this variation in water quality, however, little is known about land-cover pattern variation among urban catchments with similar development levels. This study was conducted to determine whether land-cover patterns vary among small-scale (~1 -5km2) urban catchments featuring 20-30 percent impervious surface cover.

High-resolution (1m2) land-cover data were used to quantify 23 land-cover pattern and stormwater infrastructure metrics within 32 catchments across the Triangle Region of North Carolina. These metrics were used to quantify variability in land-cover patterns among the study catchments. We used hierarchical clustering to organize the catchments into four watershed-level groups, each with a distinct landscape pattern. Among these groups, the connectivity of combined land-cover patches accounted for 40%, and the size and shape of lawns and buildings accounted for 20%, of the overall variation in land-cover patterns among catchments. Stormwater infrastructure metrics accounted for 8% of the remaining variation.

Land-cover patterns did vary among urban catchments, which is supportive of previous research that also suggest patterns are important predictors of water quality variability. However, our study was inclusive of stormwater infrastructure and distinguishes between vegetation types. It demonstrates that trees and grass (lawns) are divergent cover types in urban systems – where grass cover actually increases with urbanization (pavement

and building cover)—and suggests that the alternative land-cover patterns feeding stormwater networks could further explain water quality variability.

Beyond Impervious: Urban Land-Cover Pattern Variation and Implications for Water Quality

by
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DEDICATION

This thesis is dedicated to my wife, Breana, who—despite all of my shortcomings—accepts and loves me with incalculable patience; to my mother and father, who have given me everything; and to my three older brothers, who have lead so that I could follow.

BIOGRAPHY

Scott Beck was born in Iowa City, IA and grew up in Chapel Hill, NC. In 2006, Scott graduated from Appalachian State University with a BS in Geography. After graduation, Scott worked for an advertising and marketing agency in Durham, NC. Realizing that marketing was not his calling, Scott decided to refocus on critical environmental and social issues. In the fall of 2010, Scott enrolled in North Carolina State University's Master of Science program in Natural Resources, focusing on geospatial science and environmental assessment and analysis. He earned a Graduate Certificate in Geographic Information Systems and Technology from the College of Natural Resources in 2011. Since enrollment, Scott has been an active Teaching and Research Assistant in the Department of Forestry and Environmental Resources, working on the Triangle ULTRA and IMAGINE South Africa projects under the direction of Drs. Melissa McHale and George Hess.

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1.1. Introduction:

Urban migration trends, and the recent recognition that cities are unique ecological landscapes, has thrust urban ecology to the forefront of cutting edge ecological science (Grimm et al, 2000; Grimm et al, 2008; Pickett et al, 2008; Pickett et al, 2011). Beyond scientific interest, cities must practically manage their regionally shared natural resources to ensure the safety and wellbeing of their inhabitants (Aplin, 2004). Therefore, cities are places where science and practical environmental management should intersect to achieve two common goals: responsible development to maintain positive environmental performance, and to equitably distribute beneficial ecosystem services. Whether this seemingly critical partnership is occurring, or is effective, is debatable; however, improving the tools used to aid managers and scientists in their efforts is a positive step toward bridging gaps between decision makers and scientists.

Remote sensing land use and land-cover classification is one such tool that has proven to be an essential, and often used, mechanism to study and manage urban environments (Miller & Small, 2003; Aplin, 2004; Weng & Quattrochi, 2007). Classifications allow users to identify ground cover changes over time and measure growth and landscape patterns over large spatial scales (Aplin, 2004; Alberti, 2005; Weng & Quattrochi, 2007); however, the human induced heterogeneity of urban areas has proven to be a significant classification issue (Welsh, 1982; Ridd, 1995; Cadenasso et al, 2007; Smith et al, 2010).

Problems ranging from classification accuracy and theme, to spatial and temporal scale and resolution, have all been identified as challenges to conducting accurate science using land-cover datasets (Kupfer, 2012). Furthermore, most existing regional classifications offer coarse spatial resolutions and are spatially and thematically irrelevant in cities (Welsh, 1982; Ridd, 1995; Pickett et al, 2001; Cadanasso et al, 2007; Smith et al, 2010). Compounding these problems is the lack of a single classification dataset that transcends regional boundaries and is useful along rural to urban gradients.

The improvement of regional resource management and advancement of urban ecological science will require a radical expansion of viable classification data. This paper offers a potential solution to urban classification issues by promoting a municipal-based approach to expand the current network of high-resolution, object oriented land-cover classifications. We achieve this objective by (1) examining trends in urban classification systems to identify the most appropriate approach for classifying urban environments; (2) using this approach to explore the feasibility of implementing an adaptable high-resolution classification protocol within a localized urban region (the North Carolina Triangle); and (3) highlighting examples of how these and other high-resolution land-cover data are used to manage and study cities.

1.1.2. Trends in Urban Classification

In 1976 the United States Geological Survey (now USGS) developed the first nationally oriented classification system, which was intended to standardize classification efforts across regions and allow for the temporal updating of datasets to compare and measure urban growth and land characteristics across the United States (Anderson et al., 1976). Formally known as The Anderson Classification System, it combines satellite and aerial photography to delineate patterns of land use across the United States (Anderson et al., 1976). The USGS and Department of the Interior sponsored Multi-Resolution Land Characteristics Consortium (MRLC) employed a modified Anderson classification approach to create the National Land Cover Dataset (now NLCD). NLCD has a 30m spatial resolution and is one of the most widely used regional classifications (Vogleman et al., 2001). NLCD and Anderson based classifications continue to be used in scientific analyses of both urban (e.g. Buyanthyeu et al, 2009; Shrestha et al, 2012; Song et al, 2013) and non-urban (e.g. Strayer et al, 2003; Maxwell et al, 2008; McElhone et al, 2011) areas.

Despite the continued promotion of NLCD since it was first released (Vogelman et al., 2001), the usefulness of land use data for biophysical analysis in urbanized areas has been called into question. Ecological processes in urban zones cannot be accurately assessed without the disaggregation of land use classes into true-ground land-cover features that directly influence urban biophysical properties (Ridd, 1995; Cadenasso et al., 2007). As a corollary, the Vegetation-Impervious Surface-Soil (now VIS) model was developed in an attempt to create a new standardized approach for exploring biophysical processes in cities

(Ridd, 1995). The VIS model recognizes the spatial and thematic shortcomings of Anderson derived classification systems for use in analytical studies and captures ground cover at its most basic levels (Ridd, 1995).

A recent and more refined approach to urban classification is the High Ecological Resolution Classification for Urban Environmental Systems (now HERCULES) model (Cadenasso et al, 2007). HERCULES classifies land-cover based on true-ground features, like buildings and pavement, which can be used as independent variables to test models linking spatial patterns to ecosystem functions (Cadenasso et al, 2007). It allows users to identify spatial patterns by capturing the stark heterogeneous land-cover transitions observed in urbanized areas (Cadenasso et al., 2007; Picket et al., 2008). HERCULES not only advances our ability to conduct ecological experiments in cities, but also allows users to explore the social factors that influence urban development. These factors ultimately drive the landscape patterns that influence ecological processes (Cadenasso et al., 2007; Pickett et al., 2008).

Clearly, the focus of urban remote sensing has shifted from nationally expansive, coarse resolution land use classification systems like NLCD (Anderson et al, 1976; Vogelman et al., 2001) to localized and ecologically sensitive, high-resolution land-cover classification systems like VIS (Ridd, 1995) and HERCULES (Cadenasso et al., 2007). The collateral damage of these advancements in urban classification is a minimization in the applicable uses of NLCD data for urban environmental management and analysis (Ridd, 1995; Smith et al, 2010). Simultaneously, opportunities to comparatively analyze cities—a necessary goal to advance urban ecological science (Pickett, 2008; Grimm, 2008)—are hindered without adequate high spatial resolution classification data coverage. A proliferation in the production of urban high-resolution classification datasets is desperately needed to advance urban science and ultimately improve the environmental management of cities.

Although we argue for classification expansion, it is important to remember that cities are not isolated or static (Grimm et al, 2000; Pickett et al, 2001). They rapidly expand into the surrounding countryside, consuming valuable resource and agricultural land, and often connect in sprawling, webbed patterns of modified impervious surfaces (Pickett et al, 2001; Hasse & Lanthrop, 2003). Therefore, the ongoing environmental characterization of cities requires creative and innovative solutions to urban land classification that can hold pace with the swiftly mutating nature of urban environments (Jantz et al, 2003). Also, environmental challenges are not uniform across ecosystem boundaries. Climatic shifts could produce within-region environmental extremes that vary from place to place. Hence, the ideal system of urban classification is one that is thematically adaptable to the current environmental needs of a given region.

1.1.3. A Municipal Approach to Urban High-Resolution Classification

In this section we highlight a protocol based on currently existing classification frameworks that promotes the expansion of adaptive high-resolution land-cover classifications and their symbiotic practical (management) and scientific (academic/research) uses (Aplin, 2004). This protocol allows municipalities and scientists to rapidly classify cities in localized-regions. The protocol relies on two critical components: (1) that municipal managers have collected and maintained CAD or shapefile planimetric data delineating impervious pavement and buildings, and (2) that high-resolution multi-spectral aerial photographic data that are scheduled for ongoing temporal updating can be collected for a given study area. We applied this protocol to the Triangle Region of North Carolina.

1.2. Methods

1.2.1. Study Site

The Triangle Region of North Carolina is positioned around one of the state's primary economic drivers, the Research Triangle Park. Biotechnology, medical, and research corporations are driven by an abundance of high-talent academic graduates from the area's three major research universities: The University of North Carolina at Chapel Hill, Duke University, and North Carolina State University (Rohe, 2011). The Triangle has an estimated population of nearly 2 million (Census, 2012), and Raleigh has been listed as the 6th fastest growing city in the country by Forbes magazine (Fischer, 2012). The ongoing growth of the region has put enormous pressure on the area's resources—especially its water resources. Many of the Triangle's recreational and drinking water sources are shared by several municipalities, and nearly all of them are affected by combined municipal growth and development. To cover much of the Triangle, we focused our classification efforts on the region's three foundational Cities: (1) Chapel Hill/Carrboro (Orange County), (2) Durham (Durham County), and (3) Raleigh (Wake County) (Figure 1.1).

1.2.2. Imagery Considerations

A significant obstacle impeding the creation of regional land-cover classifications is the dearth of freely available high-resolution multi-spectral imagery. Heterogeneous urban features cannot be identified through the use of course resolution satellite data (Welsh, 1982; Ridd, 1995; Jensen, 1999). A spatial resolution of 5m or better is required to recognize features accurately in most urban zones (Jensen, 1999), and higher resolution aerial photography of 1-m or better is preferred in order to distinguish between the densest of urban features (Welsh, 1982). Although satellite sensors have improved dramatically with the launch of the IKONOS, SPOT, and other imaging satellites—several of which boast better than 4x4m multi-spectral and 1x1m panchromatic spatial resolutions—they are not freely available and cannot produce the 1m multi-spectral imagery needed to classify urban infrastructure accurately (Jensen, 1999). Thus, urban classifications are often dependent on our ability to procure disjointed high-resolution aerial photography (Jensen, 1999).

There is currently no freely available, nationally complete high-resolution aerial photographic dataset. However, in 1994 the USDA Farm Service Agency (FSA) began a program to acquire national coverage of high spatial resolution (1m), multi-spectral (4-band color infrared in some areas) photographic imagery to track US farm resources during the growing season (Vanderbilt, 2008). While national coverage remains elusive, the National Agricultural Imagery Program (NAIP) runs annual aerial photo missions, increasing coverage each year since 2004 (Vanderbilt, 2008). The ongoing collection of NAIP data provides municipalities in most areas with consistent, high spatial and temporal resolution data to aid in localized-regional urban classification efforts.

1.2.3. High-Resolution Classification Protocol

Using Erdas IMAGINE, we performed three unsupervised classifications on mosaicked 2009 NAIP images of Orange, Durham, and Wake Counties. These high quality images are multi-spectral (4-band color IR), with a 1m spatial resolution. We employed a HERCULES (Cadenasso et al, 2007) inspired, object-oriented classification framework to define six unique, ecologically relevant land-cover classes that suit the canopy covered, water stressed nature of the Triangle Region: (1) coarse vegetation (trees and woody vegetation); (2) surface water; (3) pavement impervious surfaces (roads, sidewalks, driveways); (4) building impervious surfaces; (5) fine vegetation (grasses); and (6) bare earth (construction zones, dirt). Spectral class limits were set at 1,200 and defined based on an ideal number of 200 spectral clusters for each of our six land-cover classes. These 1,200 spectral classes were then checked individually until each cluster was spectrally identified as a particular ground feature and assigned to their appropriate land-cover class category. A seventh class category was reserved for those features obscured by shadows.

Further processing and shadow removal were completed in ArcGIS 10.1 (ESRI, Redding, CA), using a post-processing model developed specifically to improve high-resolution urban classification images (Bigsby et al, 2013). Most identifiable multi-pixel misclassifications (salt-and-pepper) were filtered out of the images through a majority filter process, which replaces small misclassified areas with the majority surrounding cover value. Shadows were then masked and replaced based on an eight-direction nearest-neighbor interpolation process (Bigsby et al, 2013). The classification images were then cleaned using shrink, majority filtering, and boundary cleaning processes that resulted in three county-wide base classification images. We used these images to produce the final, object oriented urban classifications of the primary Triangle municipalities using ArcGIS 10.1 (ESRI, Redding, CA).

1.2.4. Object Orientation using Ancillary Vector Data

Ancillary vector data outlining pavement, building, and water features were obtained via online geospatial portals or directly from the Chapel Hill/Carrboro, Durham, and Raleigh municipal GIS divisions (Table 1.1).The base classification images were extracted into the most recently updated Raleigh, Durham, and Chapel Hill/Carrboro municipal boundaries and run through an object-oriented processing model (Figure 1.2). This model removes the impervious and water features so that only the coarse vegetation, fine vegetation, and bare earth layers remain in the classification image. The missing impervious and water features are then replaced by the municipal planimetric pavement, building, and water vector layers.

In some instances, ‘heads-up’ digitizing was necessary to update pavement, building, and water features to match the NAIP photography. Once complete, these layers were converted from vector to raster format—designating a 1m cell size. We then mosaicked these layers into the ‘stripped down’ classification images. Once the impervious and water features were added, holes in the dataset were filled in using an eight-direction interpolation process. We then ran these object-based classification outputs through the aforementioned post-processing model (Bigsby et al, 2013).

1.3. Results

1.3.1. Accuracy Assessment

We validated these data in ArcMap 10.1 (ESRI, Redding, CA) by comparing the classifications to ultra-high-resolution (0.5ft) orthoimagery. This imagery was collected as part of the City of Durham's Emergency Communications Center 2010 statewide imagery acquisition program (Knowlton, 2011). Fifty random points were generated within each class category, creating a total of 300 random points per classified municipality (Congalton, 1991). We compared individual points to identifiable features in the ultra-high-resolution reference imagery (Congalton, 1991). Matrices were populated to assess the producers, users and overall classification accuracies, and khat statistics for each municipality (Congalton, 1991). Overall, we found the classification to be highly accurate: 89.33% in Chapel Hill/Carrboro (Table 1.2) (Figure 1.3), 90.67% in Durham (Table 1.3) (Figure 1.4), and 92.34% in Raleigh (Table 1.4) (Figure 1.5); however, producers and users accuracies for coarse (trees/shrubs) and fine (grass) vegetation features tend to have more errors than other class features. This is likely due to the spectral based classification approach, which could be improved by a more in-depth object-oriented vegetation classification method.

1.4. Discussion

The high spatial and thematic resolution of these classifications makes them ideal for discerning the heterogeneous subtleties of urban land-cover that influence urban ecological functions and the human influences that drive urban heterogeneity. Simultaneously, these data are highly adaptable to regional environmental needs. Cover types can be included or excluded, and emphasized or repressed depending on exceptional regional circumstances.

For instance, the HERCULES framework is not inclusive of water features and focuses on the terrestrial aspects of cities (Cadenasso et al, 2007); however, the stresses placed on the Triangle area's water resources due to drought (Manuel, 2008) and rapid growth (Fischer, 2012) made it pertinent to include water features in our modified classification approach. This simple adaptation has allowed us to personalize a high-resolution, high accuracy classification dataset that suits the current analytical needs of the Triangle, without compromising the integrity of ground features that are important to managers and scientists. In this section we further explore several examples of how high-resolution land-cover classification data are used to assess urban environments, and discuss their management implications.

1.4.1. Data Uses for the Study & Management of Urban Areas

At local management levels, land-cover classifications have been used to track urban growth into rural territory along wildfire boundaries (Cleve et al, 2008), measure imperviousness for regulation (Arnold & Gibbons, 1996), and assess current and future development impacts on regionally shared water resources (Wear et al, 1998; Shandas & Alberti, 2009; Somers et al, In Prep; Beck et al, in Prep)—for the general management of urban environments (Aplin, 2004). Alternatively, land cover classifications serve a dual purpose as tools to improve our scientific understanding of cities (Aplin, 2004; Weng & Quattrochi, 2007) and are an important mechanism to enhance and expand comparative analyses that measure human—environmental interactions.

High resolution land-cover classifications allow researchers to compartmentalize urban heterogeneity into alternating development patterns (Cadanasso et al, 2007; Zhou et al, 2011), which can be tied to varying levels of environmental performance (Alberti, 2005; Shandas & Alberti, 2009). They are also used to compare the neighborhood and parcel level effects of socio-economics, and cultural dynamics between cities (Grove et al, 2006; Boone et al, 2009; Bigsby et al, 2013). Currently, comparative studies utilizing high-resolution, object-based classification data to assess the physical and social elements of cities are few and far between. However, an expansion of existing networks of high-resolution land-cover data will further our ability to analyze several important, recent discoveries that have direct implications for the management of our urban areas.

1.4.2. Urbanization Patterns are Important Predictors of Environmental & Human Health

Urbanization patterns fluctuate between neighborhoods, blocks, and even adjacent parcels. The mechanisms driving this heterogeneity have only recently been thoroughly examined (Grove et al, 2006; Pickett et al, 2011; Bigsby et al, 2013). Heterogeneous alternative development patterns at parcel, neighborhood, and city-wide scales alter natural ecological functions (Grimm et al, 2000; Alberti, 2005; Cadenasso et al, 2007; Pickett et al, 2011), primarily through the spread and intermixing of impervious surfaces with vegetation (Alberti, 2005). These alterations can have critical effects on environmental cycles and biodiversity at local, regional, and global scales (Grimm et al, 2008; Pickett et al, 2011). Thus, landscape patterns are a critical determinant of localized and regional ecosystem services.

Aside from ecosystem functionality, urbanization patterns also influence the spatial dynamics of pollutant distribution. For example, lead (Pb) is a highly toxic heavy metal formerly used in paint and gasoline production and has collected and persisted in urban soils long after being banned as an additive by the federal government in1996 (Schwarz et al, 2012). High-resolution land-cover data have proven to be a useful tool to explore the spatial distribution of lead in residential soils because they allow users to examine landscape features and context at localized and city-wide scales (Schwarz et al, 2012). Predictive models intended to identify the spatial distribution of soil lead concentrations are already being developed (Schwarz et al, 2013), and parameterization could be improved by implementation in multiple cities across ecological gradients. In addition to the biophysical uses of high-resolution land-cover data, they are also highly valuable tools for assessing the social drivers of land-cover change in cities.

1.4.3. Social Characteristics Drive Urbanization Patterns

Recently, US Census and PRIZM market segmentation data (Claritas, 1999) have been linked to high-resolution land cover data at fine scale block and neighborhood levels, which creates a rich, spatially explicit socio-ecological dataset. These data are used to answer questions about the potential social drivers of urban vegetation patterns (Grove et al, 2006; Troy et al, 2007; Bigsby et al, 2013). In general, neighborhood or block level vegetation patterns (and the ecosystem service benefits they provide) can be predicted based on categorical variables like housing age, demographic groups, socioeconomics, and PRIZM lifestyle categories (Grove et al, 2006; Troy et al, 2007; Bigsby et al, 2013), in coordination with continuous measures of urban morphology and population density (Bigsby et al, 2013). For instance, Bigsby et al (2013) compared tree cover in Baltimore, Maryland and Raleigh, NC, and found that historical socioeconomic conditions in Baltimore are more predictive of tree cover patterns than current socioeconomic conditions. This implies that demographic changes don’t necessarily translate to parcel level vegetation changes over time, which could have implications for urban greening efforts in gentrifying areas and ecosystem service distribution.

1.4.4. Implications for Management

In order to improve urban livelihoods and facilitate the transition towards a sustainable urban design, we must fully understand the effects that development patterns have on ecosystem functions and acknowledge the role that humans play in urban morphological and vegetation variation. For example, best management practices intended to protect citizens from flooding channel pollutant laden stormwater runoff directly into streams, often bypassing best management practices that protect riparian vegetation zones to preserve stream water quality (Welsh et al., 2004, Hatt et al, 2004). If we learn how land-cover pattern variation influences water quality, we can devise more effective best management practices. Furthermore, the public health impacts of pollutant dispersal and potential human exposure to environmental toxins is a critical concern of municipal governments. Expanding the network of available high-resolution land-cover data will allow municipalities to work with scientists to study and manage the effects of land modification on ecosystem function, rapidly assess toxic exposure risks in urban areas, and ultimately devise new and effective management strategies.

1.5. Conclusions:

As we have demonstrated, high-resolution land-cover classifications are poised to play an increasingly important role in the management and study of cities. A radical expansion of high-resolution land-cover data will allow scientists to compare the bio-physical and social characteristics of cities, and provide municipalities with the fodder they need to better manage shared regional resources and engage the public. We propose a municipal based approach to urban classification, where city geospatial resources are used to aid in classifications and can be personalized depending on the environmental needs of the municipality or region. We have demonstrated this approach in the Triangle Region of North Carolina and present our regionally-appropriate high-resolution urban classification as a case study in municipal-centered urban land-cover classification and several, though not all, applicable uses.

These data have already been utilized in forthcoming analyses surrounding development patterns and their effects on the Triangle Regions' water resources. For example, Somers et al (In Prep) examines the effects of development configuration on thermal pollution in regional streams. In coordination with this writing, we present a companion paper in which we investigate land-cover pattern variation and present hypotheses that might explain water quality variation between 32 small-scale watersheds within the degraded (20-30%) range of impervious surface cover (Arnold & Gibbons, 1996) across the NC Triangle (Beck et al, In Prep). A future expansion of this analysis will link these data with water quality samples (not yet collected) in order to test our hypotheses for validity. It is our hope that through studies like these, municipalities will realize the value in expanding the high-resolution land-cover data network and begin to promote their development internally. Only though cooperation between environmental managers and scientists –whether it be through the sharing of data or ongoing partnerships— can this goal be achieved.

REFERENCES

1. Alberti, M. 2005. The Effects of Urban Patterns of Ecosystem Function. International Regional Science Review, 28: 168-192

2. Anderson, J.R., E. Hardy, J. Roach, and R. Witmer. 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data. USGS Professional Paper #964, Washington D.C., 28p.

3. Aplin, P. 2004. Remote Sensing: Land Cover. Progress in Physical Geography 28: 283

4. Arnold Jr., Chester L. & C. James Gibbons. 1996. Impervious Surface Coverage: The Emergence of a Key Environmental Indicator. Journal of the American Planning Association, 62 (2): 243-358

5. Beck, S.M., M.R. McHale, and G. Hess. In Prep. Beyond Impervious: Urban Land Cover Pattern Variation and Implications for Water Quality.

6. Bigsby, K., Melissa M.R., and G. Hess. 2013. Urban Morphology Drives the Homogenization of Tree Cover in Baltimore, MD and Raleigh, NC. Ecosystems, 1(16):

7. Boone, C. G., M. L. Cadenasso, J. M. Grove, K. Schwarz, and G. L. Buckley, 2009. Landscape, Vegetation Characteristics, and Group Identity in an Urban and Suburban Watershed: Why the 60's Matter. Urban Ecosystems, 13: 255-271

8. Buyantuyev, A., J. Wu, and C. Gries. 2010. Multiscale Analysis of the Urbanization Pattern of the Phoenix Metropolitan Landscape of USA: Time, Space and Thematic Resolution. Landscape and Urban Planning 94: 206-217

9. Cadenasso, M. L., S. T. A. Pickett, and K. Schwarz. 2007. Spatial Heterogeneity in Urban Ecosystems: Reconceptualizing Land Cover and a framework for Classification. Frontiers in Ecology and the Environment, 5(2): 80-88

10. Claritas Inc. 1999 PRIZM cluster snapshots. Claritas Inc., San Diego, CA

11. Cleve, C. M. Kelly, F.R. Kearns, and M. Moritz. 2008. Classification of the Wildland-Urban interface: A Comparison of Pixel- and Object-Based Classifications using High-Resolution Aerial Photography. Computers, Environment and Urban Systems, 32(4): 317-326

12. Congalton, R.G. 1991. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. Remote Sensing and the Environment, 37: 35-46

13. Fisher, D. “America’s Fastest-Growing Cities”. Forbes Business Online. Forbs.com, LLC. 4 Dec. 2012. Web. 29 Aug. 2013. http://www.forbes.com/sites/danielfisher/2012/04/18/americas-fastest-growing-cities/2/

14. Grimm, N. B., J. M. Grove, S. T. A. Pickett, and C. L. Redman, 2000. Integrated Approaches to Long-Term Studies of Urban Ecological Systems. BioScience, 50(7): 571-584

15. Grimm, N.B., S. H. Faeth, N. E. Golubiewski, C. L. Redman, J. Wu, X. Bai, J. M Briggs. 2008. Global Change and the Ecology of Cities. Science 319, 756.

16. Grove, J.M., A.R. Troy, J.P.M O’Neil-Dunne, W.R. Burch Jr., M.L. Cadenasso, S.T.A. Pickett. 2006. Characterization of Households and its Implications for the Vegetation of Urban Ecosystems. Ecosystems 9(4): 578-597

17. Hasse, J. E. and R. G. Lathrop. 2003. Land Resource Impact Indicators of Urban Sprawl. Applied Geography 23, 159-175

18. Hatt, B.E., T.D. Fletcher, and C.J. Walsh, 2004. The Influence of Urban Density and Drainage Infrastructure on the Concentrations and Loads of Pollutants in Small Streams. Environmental Management, 34(1): 112-124

19. Jantz, C. A., S. J. Goetz, and M. K. Shelly. 2003. Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropolitan area. Environment and Planning B: Planning and Design, 30, 251-271

20. Jensen, J.R. 1999. Remote sensing of urban and suburban infrastructure and socio-economic attributes. Photogrammetric Engineering and Remote Sensing 65(5): 611-622

21. Knowlton, J. "North Carolina Statewide Imagery 2010 Final Report". NC One Map. North Carolina Geographic Information Coordinating Council. Sep. 2011. Web. 29 Aug. 2013.

22. Kupfer, J. A. 2012. Landscape Ecology and Biogeography: Rethinking Landscape Metrics in a Post-FRAGSTATS Landscape. Progress in Physical Geography, 36 (3): 400-420

23. Manuel, J. 2008. Drought in the Southeast: Lessons for Environmental Management. Environmental Health Perspectives 116(4): 168-171

24. Maxwell, S.K., E.C. Wood, and A. Janus 2008. Comparison of the USGS 2001 NLCD to the 2002 USDA Census of Agriculture for the Upper Midwest United States. Agriculture, Ecosystems and Environment 127: 141-145

25. McElhone, P.M., P.B. Wood, and D.K. Dawson 2011. Effects of Stop-Level Habitat Change on Cerulean Warbler Detections Along Breeding Bird Survey Routes in the Central Appalachians. The Wilson Journal of Ornithology 123(4): 699-708

26. Miller, R.B. and C. Small. 2000. Cities from Space: Potential applications of remote sensing in urban environmental research and policy. Environmental Science & Policy 6: 129-137

27. Pickett, S. T. A., M. L. Cadenasso, J. M. Grove, C.H. Nilon, R.V. Pouyat, W.C. Zipperer, and R. Costanza. 2001. Urban Ecological Systems: Linking Terrestrial Ecological, Physical, and Socioeconomic Components of Metropolitan Areas. Annual Review of Ecological Systems, 32: 127-157

28. Pickett, S. T. A., M. L. Cadenasso, J. M. Grove, P. M. Groffman, L. E. Band, C. G. Boone, W. R. Burch Jr., C. S. B. Grimmond, J. Hom, J. C. Jenkins, N. L. Law, C. H. Nilon, R. V. Pouyat, K. Szlavecz, P. S. Warren, and M. A. Wilson. 2008. Beyond Urban Legends: An Emerging Framework of Urban Ecology, as Illustrated by the Baltimore Ecosystem Study. Bioscience, 58 (2): 139-150

29. Pickett, S.T.A., M.L. Cadenasso, J.M. Grove, Christopher G. Boone, Peter M. Groffman, Elena Irwin, Sujay S. Kaushal, Victoria Marshall, Brian P. McGrath, C.H. Nilon, R.V. Pouyat, Katalin Szlavecz, Austin Troy, Paige Warren. 2011. Urban Ecological Systems: Scientific Foundations and a Decade of Progress. Journal of Environmental Management, 92: 331-362.

30. Ridd, M.K. 1995. Exploring a VIS (Vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing; comparative anatomy for cities. International Journal of Remote Sensing 16(12): 2165-2185

31. Rohe, M.M. "The Research Triangle: From Tobacco Road to Global Prominence," Philadelphia, University of Philadelphia Press, 2011

32. Schwarz, K., S.T.A Pickett, R.G. Lanthrop, K.C. Weathers, R.V. Pouyat, and M.L. Cadenasso. 2012. The Effects of the Urban Build Environment on the Spatial Distribution of Lead in Residential Soils. Environmental Pollution 163: 32-39

33. Schwarz, K., K.C. Weathers, S.T.A. Pickett, R.G. Lathrop Jr., R.V. Pouyat, and M.L Cadenasso. 2013. A Comparison of Three Empirically Based, Spatially Explicit Predictive Models of Residential Soil Pb Concentrations in Baltimore, Maryland, USA:

Understanding the Variability within Cities. Environmental Geochemistry and Health: 1-16

34. Shandas, V. and M. Alberti. 2009. Exploring the Role of Vegetation Fragmentation on Aquatic Conditions: Linking upland Riparian Areas in Puget Sound Lowland Streams. Landscape and Urban Planning 90: 66-75
35. Shrestha, M.K., A.M York, C.G. Boone, and S. Zhang. 2012. Land Fragmentation due to Rapid Urbanization in the Phoenix Metropolitan Area: Analyzing the Spatiotemporal Patterns and Drivers. Applied Geography 32: 522-531
36. Smith, M. L., W. Zhou, M. Cadenasso, J. M. Grove, and L. E. Band. 2010. Evaluation of the National Land Cover Database for Hydrologic Applications in Urban and Suburban Baltimore, Maryland. Journal of the American Water Resources Association, 46 (2): 429-442
37. Somers, K., Bernhardt, E., Urban, D., Voss, K., McGlynn, B., Doyle, M., & Beck, S. (in prep.). All Pavement is not Created Equal: Examining the Effects of Development Characteristics on Thermal Pollution to Streams.
38. Song, Y., B. Popkin, and P. Gordon-Larsen 2013. A National-level Analysis of Neighborhood Form Metrics. Landscape and Urban Planning 116: 73-85
39. Strayer, D. L., R.E. Beighley, L.C. Thompson, S. Brooks, C. Nilsson, G. Pinay, and R.J. Naiman 2003. Effects of Land Cover on Stream Ecosystems: Roles of Empirical models and Scaling Issues. Ecosystems 6: 407-423
40. Troy, A.R., J. M. Grove, J.P.M. O'Neil-Dunne, S.T.A. Pickett, and M.L. Cadenasso. 2007. Predicting Opportunities for Greening and Patterns of Vegetation on Private Urban Lands. Environmental Management 40: 394-412

41. United States. Census Bureau. “Annual Estimates of the Population of Combined Statistical Areas: April 1, 2010 to July 1, 2012”. Population Estimates: Metropolitan and Micropolitan Statistical Areas. Washington: US Census Bureau, Feb 2012. Web. 28 Aug. 2013. http://www.census.gov/popest/data/metro/totals/2012/index.html

42. Vanderbilt, B. “Qualitative and Quantitative Synopsis on NAIP Usage from 2004-2008”. Support Documents. United States Department of Agriculture. 19th Mar. 2008. Web. 28th Aug. 2013. http://www.fsa.usda.gov/Internet/FSA_File/naip_usage.pdf

43. Vogelmann, J.E., S.M. Howard, L. Yang, C.R. Larson, B.K. Wylie, and J.N. Van Driel. 2001. Completion of the 1990’s National Land Cover Data Set for the Conterminous United States. Photogrammetric Engineering and Remote Sensing 67: 650-662

44. Wear, D.N., M.G. Turner, and R.J. Naiman. 2008. Land cover along and urban-rural gradient: implications for water quality. Ecological Applications 8(3): 619-630

45. Walsh, C.J., P.J. Papas, D. Crowther, P.T. Sim, and J. Yoon. 2004. Stormwater Drainage Pipes as a Threat to a Stream-Dwelling Amphipod of Conservation Significance, Austrogammarus Australis, in South-Eastern Australia. Biodiversity and Conservation, 13: 781-793

46. Welsh, R. 1982. Spatial Resolution Requirements for Urban Studies. International Journal of Remote Sensing, 3:2, 139-146

47. Weng, Q. and D. A. Quattrochi. 2007. Urban Remote Sensing. Taylor & Francis. 412pp., ISBN: 978-0-8493-9199-6

48. Zhou, W., G. Huang, and M. L. Cadenasso. 2011. Does Spatial Configuration matter? Understanding the Effects of Land Cover Pattern on Land Surface Temperature in Urban Landscapes. Landscape and Urban Planning, 102: 5

TABLES

Table 1.1: Ancillary vector data sources, types, municipalities, and class associations

Municipality	Data	Description	Type	Class
Chapel Hill http://gis.townofchapelhill.org/download_data/	Planimetrics	Roads, Sidewalks, Driveways	Shapefile,	Pavement Impervious (Class 3)
	Building Footprints	Building Footprints	Shapefile,	Building Impervious (Class 4)
	Water Body Polygons	Pond/Lake	Shapefile,	Water (Class2)
Carrboro http://ci.carrboro.nc.us/gis/towndownload.htm http://web.co.orange.nc.us/gisdownloads	Current Footprints	building footprints	Shapefile,	Building Impervious (Class 4)
	2003 Roads	Roads.	Shapefile,	Pavement Impervious (Class 3)
	2003 Driveways	driveways	Shapefile,	Pavement Impervious (Class 3)
	2003 Parking Lots	parking lots	Shapefile,	Pavement Impervious (Class 3)
	Hydrology (Orange County)	water	Shapefile,	Water (Class2)

Table 1.1 Continued:

Raleigh http://www.wakegov.com/gis/services/pages/data.aspx	Raleigh Buildings	Buildings	Shapefile,	Building Impervious (Class 4)
	Raleigh Parking	parking lots	Shapefile,	Pavement Impervious (Class 3)
	Raleigh MiscPolygons	driveway, sidewalk	Shapefile,	Pavement Impervious (Class 3)
	Raleigh Roads	Roads	Shapefile,	Pavement Impervious (Class 3)
	Raleigh Hydrology Areas	water features	Shapefile,	Water (Class2)
Durham Collected directly from City of Durham, via online ftp download -- worked with Triangle J Councel of Governments for data access	Building Planimetrics	Building footprint	Shapefile,	Building Impervious (Class 4)
	Durham Impervious Area	parking lot, driveway, and sidewalk	Shapefile,	Pavement Impervious (Class 3)
	Hydrology	Water resource polygons	Shapefile,	Water (Class2)
	Durham Parcels	Used to delineate roadways	Shapefile,	Pavement Impervious (Class 3)

Table1.2: Chapel Hill/Carrboro classification accuracy assessment results matrix. Shows errors of omission and commission vs correctly identified pixels.

Chapel Hill/ Carrboro	**CV**	**Water**	**Pavement**	**Building**	**FV**	**Bare**	**Total**
CV	41	3	1	2	1	0	48
Water	0	43	0	0	0	0	43
Pavement	2	1	44	0	2	1	50
Building	2	0	2	46	1	0	51
FV	5	2	3	1	46	1	58
Bare	0	1	0	1	0	48	50
Total	50	50	50	50	50	50	300

Producers Accuracy	**%**	**Users Accuracy**	**%**	**Overall Accuracy/KHAT**	**%**	
CV	82	CV	85.42	All Classes	89.33%	
Water	86	Water	100	**KHAT**		
Pavement	88	Pavement	88	N	300	
Building	92	Building	90.20	Part A	268	
FV	92	FV	79.31	Part B	15000	
Bare	96	Bare	96	Khat	0.872	87.20%

Table 1.3: Durham classification accuracy assessment results matrix. Shows errors of omission and commission vs correctly identified pixels.

Durham	**CV**	**Water**	**Pavement**	**Building**	**FV**	**Bare**	**Total**
CV	45	0	1	1	5	2	54
Water	1	49	0	0	0	0	50
Pavement	0	0	45	0	2	1	48
Building	1	0	0	45	0	0	46
FV	3	0	2	3	43	2	53
Bare	0	1	2	1	0	45	49
Total	50	50	50	50	50	50	300

Producers Accuracy	**%**	**Users Accuracy**	**%**	**Overall Accuracy/KHAT**	**%**
CV	90	CV	83.3333333	All Classes	90.67%
Water	98	Water	98	**KHAT**	
Pavement	90	Pavement	93.75	N	300

Table 1.3 Continued:

Building	90	Building	97.826087	Part A	272	
FV	86	FV	81.1320755	Part B	15000	
Bare	90	Bare	91.8367347	Khat	0.888	88.80%

Table 1.4: Raleigh classification accuracy assessment results matrix. Shows errors of omission and commission vs correctly identified pixels.

Raleigh	**CV**	**Water**	**Pavement**	**Building**	**FV**	**Bare**	**Total**
CV	45	0	0	0	2	0	47
Water	1	50	0	0	0	0	51
Pavement	1	0	46	2	0	4	53
Building	1	0	1	46	0	1	49
FV	2	0	3	2	46	1	54
Bare	0	0	0	0	2	44	46
Total	50	50	50	50	50	50	300

Producers Accuracy	**%**	**Users Accuracy**	**%**	**Overall Accuracy/KHAT**	**%**	
CV	90	CV	95.7446809	All Classes	92.33%	
Water	100	Water	98.0392157	**KHAT**		
Pavement	92	Pavement	86.7924528	N	300	
Building	92	Building	93.877551	Part A	277	
FV	92	FV	85.1851852	Part B	15000	
Bare	88	Bare	95.6521739	Khat	0.908	90.80%

FIGURES

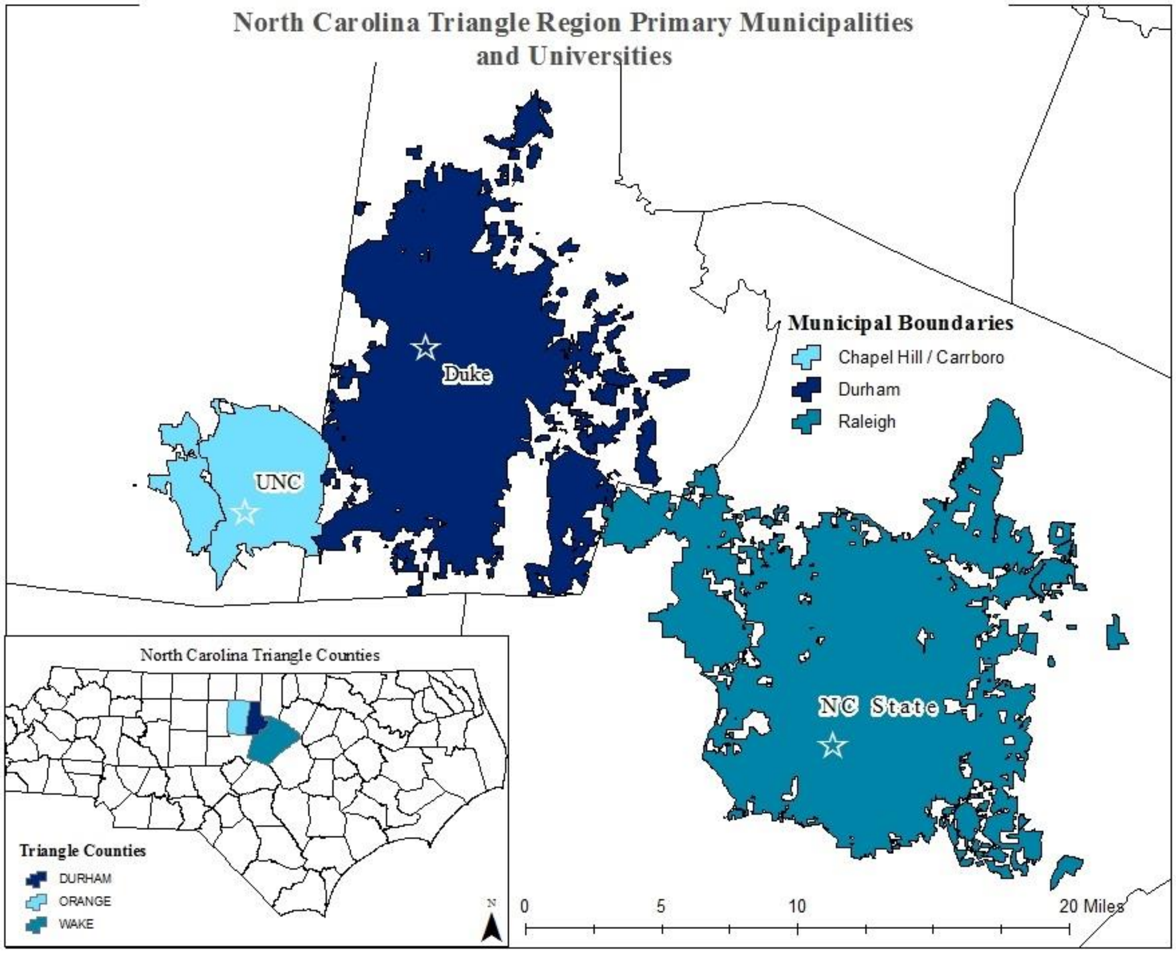

Figure 1.1: Map of North Carolina Triangle Region Municipalities included in the classification. These are the locations where ancillary vector data was collected directly from municipal governments and participating agencies.

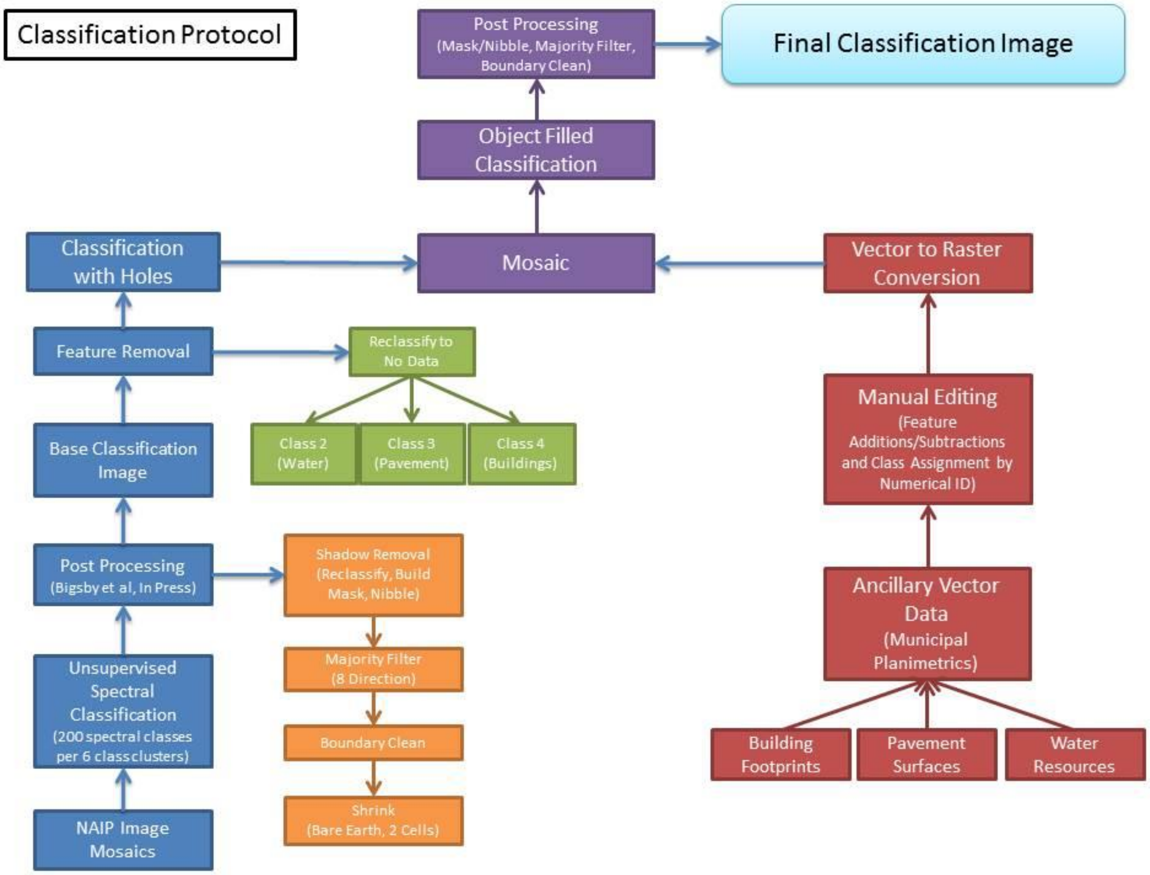

Figure 1.2: Classification Protocol Model: Erdas IMAGINE unsupervised classifications on 2009 NAIP images, using 200 spectral classes per 6 classification clusters, totaling 1,200 spectral classes. Post processing was completed in ArcGIS 10.0 using a methodology designed for high-resolution object-based urban classifications (Bigsby et al, In Press). Base Classifications are mosaicked with ancillary vector features. Vector features are updated manually in ArcGIS editor to reflect current image conditions and then converted into raster images before mosaicking. Post processing to fill data holes and clean the images occurs after mosaicking to produce the final classification image.

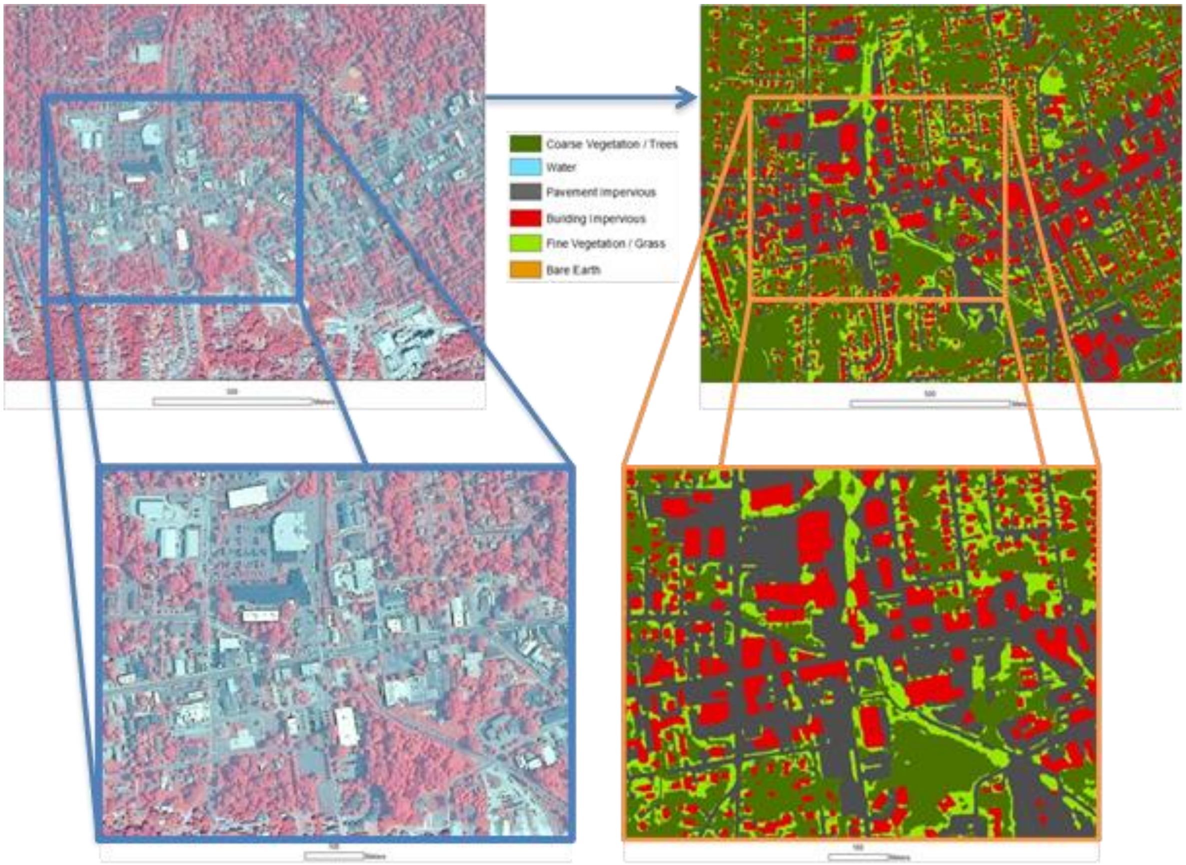

Figure 1.3: Classification Snapshot of Chapel Hill / Carrboro, NC. On the left is the zoomed color infrared image of downtown Chapel Hill (500m to 100m scale). The right is the final classification of this area, where trees are dark green, buildings are red, grass is light green, and roads are dark gray. A comparison of the aerial photograph and the classification image shows how well the classification protocol captures the heterogeneity of this urban core.

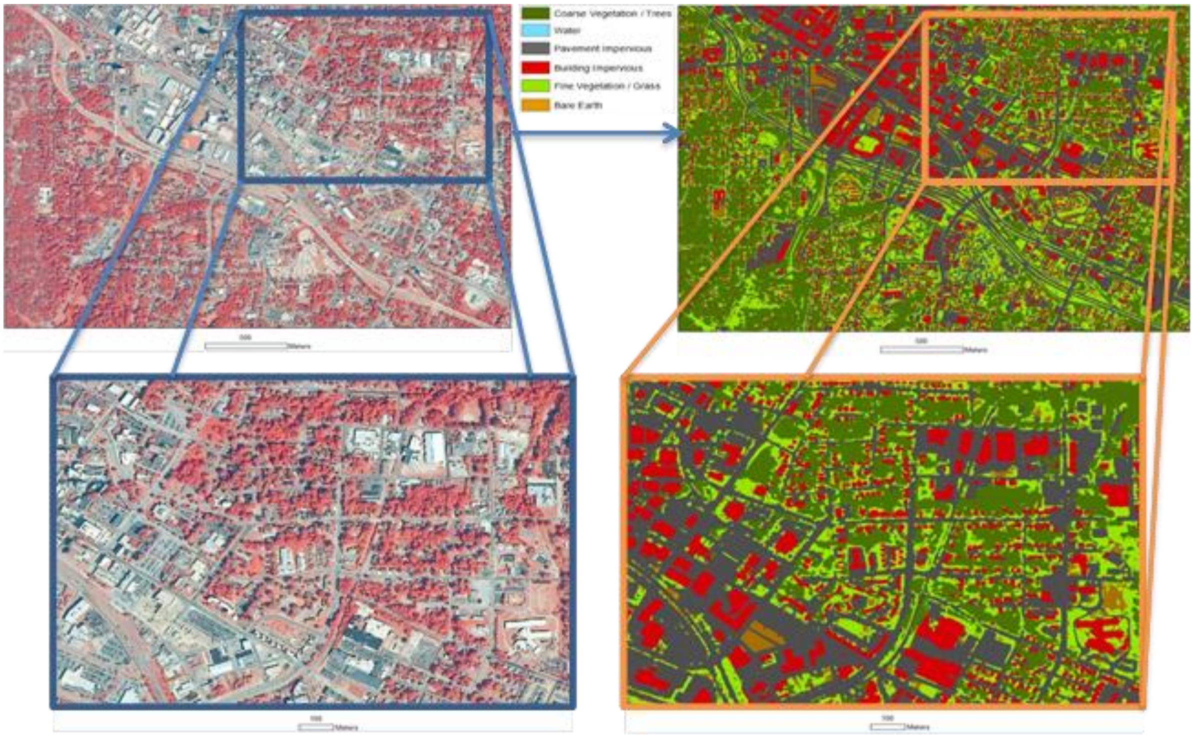

Figure 1.4: Classification Snapshot of Durham, NC. . On the left is the zoomed color infrared image of downtown Durham (500m to 100m scale). The right is the final classification of this area, where trees are dark green, buildings are red, grass is light green, and roads are dark gray. A comparison of the aerial photograph and the classification image shows how well the classification protocol captures the heterogeneity of this urban core.

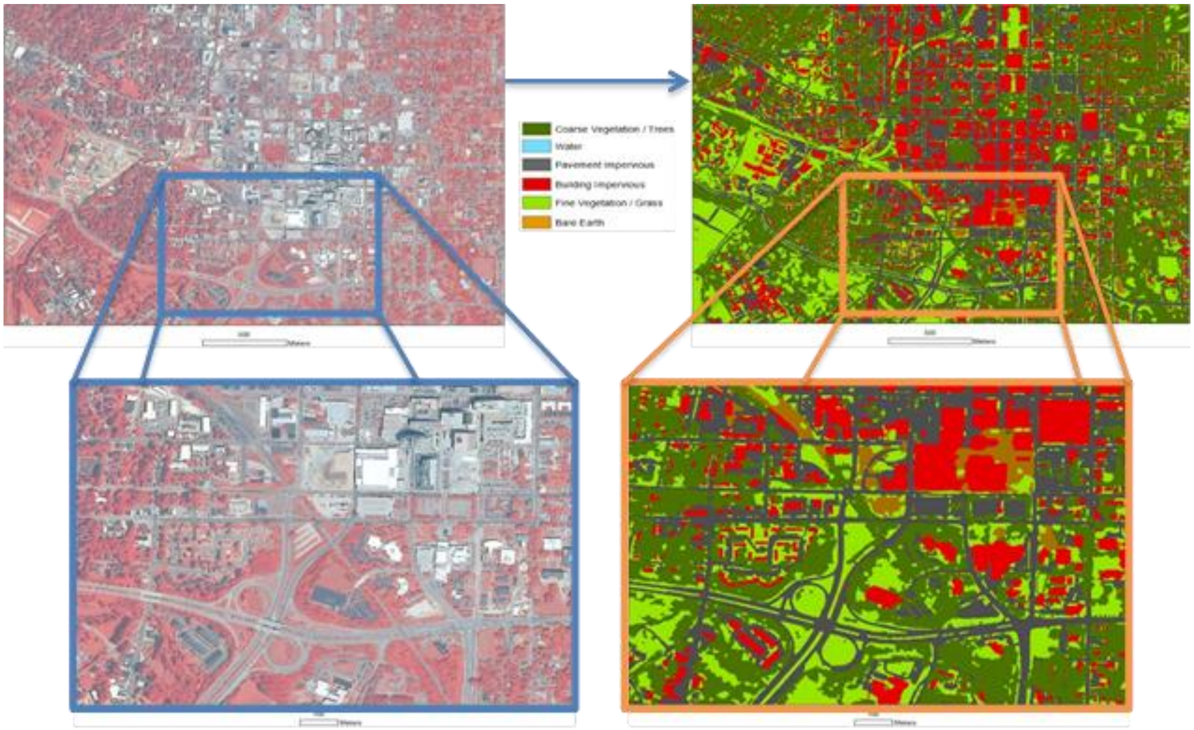

Figure 1.5: Classification Snapshot of Raleigh, NC. . On the left is the zoomed color infrared image of downtown Raleigh (500m to 100m scale). The right is the final classification of this area, where trees are dark green, buildings are red, grass is light green, and roads are dark gray. A comparison of the aerial photograph and the classification image shows how well the classification protocol captures the heterogeneity of this urban core.

II. Beyond Impervious: Urban Land-Cover Pattern Variation and Implications for Water Quality

2.1. Introduction

The link between surface water quality and urban land-cover has been well established through studies that have shown impervious surfaces are highly correlated with stream health and water quality (e.g., Arnold and Gibbons, 1996; Booth and Jackson, 1997; Brabec et al., 2002; Strayer et al., 2003; Nassauer et al., 2004). Increased imperviousness driven by urban growth amplifies storm water runoff that transports pollutants and nutrients from parking lots, roads, and buildings into urban streams, often directly through a network of channels and pipes (Arnold and Gibbons, 1996; Paul and Meyer, 2001; Walsh, 2004; Roy and Schuster, 2008). Generally, surface water quality begins to degrade as imperviousness approaches 10% within a watershed and becomes significantly degraded as it reaches 20-30% (Arnold and Gibbons, 1996; Booth and Jackson, 1997) (Figure 1.1). Impervious surfaces also replace and fragment areas of vegetative cover that could otherwise maintain or improve the quality of surface water (Bolund and Hunhammar, 2000; King et al., 2005; Paul and Meyer, 2001; Potter et al., 2004; Alberti et al., 2007; Shandas and Alberti, 2009; Nowak and Greenfield, 2012). Thus, management suggestions often emphasize limiting imperviousness and using alternative development patterns that maintain large, contiguous areas of vegetation, especially near streams (Arnold and Gibbons, 1996).

Although the general trends associated with water quality, impervious surfaces, and vegetative cover are well established, the interactions among these variables are not. Neither impervious surface nor vegetative cover alone fully explains water quality variability among catchments (Alberti et al., 2007; Shandas and Alberti, 2009). This makes it difficult to uncover the specific mechanisms by which urbanization affects water quality (Paul and Meyer, 2001). For example, a catchment with relatively low levels of impervious cover might have worse water quality than one with higher impervious levels. This could be a function of the spatial distribution of impervious surfaces, vegetation, and streams across the landscape. To reconcile such apparent contradictions, we must first seek to understand the dynamics of urban land-cover patterns fully before taking steps to link land-cover and water quality, or developing effective management strategies to mitigate potential damages.

Science utilizing quantified patterns of development, rather than simplified percentage measures of imperviousness, to explain ecological processes (e.g. hydrology, urban heat island, and nutrient cycling) in urban areas is plentiful (e.g. Alberti, 1999; Cifaldi et al, 2004; Alberti, 2005; Carle et al., 2005; Conway and Hackworth, 2007; Alberti et al., 2007; Shandas and Alberti, 2009; Lee et al., 2009; Zhou et al., 2011; Greve, 2012). Studies focusing specifically on urban patterns or infrastructure and water quality are less numerous but have achieved some success (e.g. Carle et al., 2005; Walsh et al., 2004; Alberti et al, 2007; Shandis and Alberti, 2009). Water quality variation has been partially explained by patterns of imperviousness and resulting forest fragmentation and vegetation distribution (Alberti et al., 2007; Shandas and Alberti, 2009); measures of urbanization density and type (Carle et al., 2005); and connectivity of effective impervious areas to streams via storm water infrastructure (Walsh et al., 2004; Carle et al., 2005). These studies suggest that land-cover patterns and infrastructure are determining factors of urban water quality.

Despite advances, unexplained water quality variation persists and differences in the experimental approach of these studies—though often innovative—spawn as many questions as answers. For instance, what are the mechanisms contributing to, and resulting from, upland and riparian forest fragmentation that influence in-stream biological conditions in urban systems (Alberti et al, 2007; Shandis and Alberti, 2009)? Is it solely fragmentation of forest vegetation that drives aquatic conditions, or are conditions more closely related to the connectivity of impervious areas to streams via stormwater infrastructure (Walsh et al., 2004; Carle et al., 2005)? Perhaps most importantly, urbanization patterns likely affect water quality differently across climate and ecosystem zones. Infrastructure, development and vegetation patterns in Phoenix, AZ, where rainfall events are sparse and large, will influence water quality differently than in Seattle, WA, where rain falls continuously throughout the year.

2.2. Objectives

Imperviousness and forest patterns are clearly very important water quality parameters, but we expect that water quality variation is best explained by the combined variation of storm water infrastructure, all land cover types, and the unique patterns they form among urban watersheds. Our overarching question was “How variable is the spatial configuration of land-cover and stormwater infrastructure within small-scale watersheds containing 20%-30% impervious surface cover?" We see this as an important first step in developing testable hypotheses about how these factors relate to variability in urban stream water quality, beyond those long attributed to simple measures of impervious cover. Specifically, we asked whether the configuration of land cover, and stormwater infrastructure, contributes to catchment level land-cover variability within potentially degraded watersheds? We also asked whether pattern metric correlations can identify 'sources' of watershed level land-cover variation? Answering these questions will allow us to develop testable hypotheses about the configuration of unique land-cover types as they relate to water quality variability in cities.

2.3. Methods

2.3.1. Study Area

Centrally located within the North Carolina Piedmont, the Triangle region encompasses portions of Wake, Durham, and Orange Counties. The three primary Triangle cities are Durham (Durham County), Chapel Hill/Carrboro (Orange County), and Raleigh (the state capital in Wake County). The Triangle is one of the fastest growing urban areas in the country largely due to the influx of high-tech workers to the Research Triangle Park industrial center, which is supported by the region's three top-tier research universities: NC State (Raleigh), Duke (Durham) and the University of North Carolina (Chapel Hill) (Rohe, 2011).

Raleigh ranked 6th on the 2012 Forbes fastest growing cities in the United States and has been cited as having the highest rate of projected population growth through 2016 (Fisher, 2012). Complementing its ‘fastest population growth’ status, Raleigh has also been placed in the top 15 of the most sprawling cities in the United States (Nasser and Overberg, 2001).

Situated in the US Forest Services’ Southern Mixed Forest Province, the region is characterized by woody vegetation, subtropical rainfall levels (between 40 – 60 inches/year), and numerous streams, pocosins, swamps, ponds, and lakes (Bailey, 1995). Triangle municipalities are dotted with moderate to dense tree cover, and an abundance of perennial and ephemeral streams. A recent study has shown that Raleigh boasts over 50% canopy cover, making it one of the most tree-covered cities in the country (Bigsby et al., 2013). These factors, coupled with the region’s high rate of growth, make it an ideal location to study complex urban land-cover patterns and their potential effects on stream water quality.

2.3.2. Watershed Selection

To select watersheds of similar size and imperviousness across the Triangle, Somers et al. (in prep) delineated all first-order streams for which stormwater infrastructure data were available within the municipal boundaries of Chapel Hill, Carrboro, Durham, and Raleigh. These streams were defined as first-order using available stream data, not including piped streams, and represent the best approximations of headwater, first-order streams in an urban environment. Of these delineated catchments, 32 fell within the significantly degraded (20-30%) range of imperviousness as measured by high-resolution land-cover data (Beck et al, In

Prep), and were selected for analysis; three in Chapel Hill/Carrboro, nine in Durham, 19 in Raleigh, and one that is split equally between Durham and Chapel Hill (Figure 1.2) (Table 1.1).

2.3.3. Land-Cover Classification

We used United States Department of Agriculture (USDA) 2009 color infrared National Agricultural Imagery Program (NAIP) aerial photo mosaics to create high-resolution (1m) land cover classifications for the Triangle cities of Raleigh, Durham, and Chapel Hill. We used Erdas IMAGINE's unsupervised classification protocol, setting 1200 individual spectral classes. We then used a custom post-processing model that relies on ancillary vector pavement and building footprint data to generate six unique 'true-ground' land cover class types, which are most useful for biophysical analyses in cities (Ridd 1995; Cadenasso et al, 2007): (1) coarse vegetation (trees); (2) water; (3) pavement impervious (roads, parking lots, driveways); (4) fine vegetation (grass, non-woody vegetation); and (5) bare earth (Figure 1.3). Accuracies were assessed using ultra-high-resolution (0.5ft) imagery with 50 random points assigned to each class in each municipality, checked against the classified land-cover (Congalton, 1991). Overall accuracies were 89.33% in Chapel Hill (KHAT = 87.2%), 90.67% in Durham (KHAT = 88.80%), and 92.33% in Raleigh (KHAT = 90.80%) (Beck et al, in prep).

2.3.4. Stormwater Infrastructure

We collected vector data delineating stormwater pipes, inlets, and outfalls directly from stormwater management and engineering departments within the study area. This is the most inclusive stormwater network coverage for the Triangle municipalities to date, though Raleigh, Durham, and Chapel Hill/Carrboro GIS personnel did not guarantee completeness due to ongoing projects and maintenance.

2.3.5. Metric Calculations

We isolated four land-cover types (trees, pavement, buildings, and grass) from our high-resolution (1m) land-cover classification into the 32 urban watershed boundaries using the spatial analyst extraction toolset in ArcGIS 10.1. The two remaining land-cover types, water and bare earth, are not sufficiently represented within these catchments, and did not warrant consideration in this analysis. Storm water inlets, outlets, and pipe networks were isolated to watershed boundaries to quantify density measurements.

Land cover configuration pattern metrics were derived using FRAGSTATS 4.0 (McGarigal et al., 2012). FRAGSTATS is a commonly used, fully automated spatial statistics tool originally developed for the USDA Forest Service to quantify spatial patterns for ecological assessments (McGarigal and Marks, 1995). Several studies suggest issues with its use (e.g. Luck and Wu, 2002; Huang et al., 2006; Shao and Wu, 2008; Greve, 2012; Kupfer, 2012); however, basic metrics that describe the shape, size, and complexity of land-cover patches are representative of heterogeneous urban structure (Alberti et al., 2005).

We calculated five class level metrics (patch density, edge density, mean patch area, mean contiguity, and land cover percentage) across the four land cover class types using our high-resolution (1m) classification dataset (Beck et al, In Prep) (Table 1.2). Stormwater inlets, outlets, and pipe densities were also calculated, creating a total of 23 analysis metrics for each of the 32 study catchments (Table 1.2). Patch and edge densities, mean patch area, and mean contiguity are relatively simplified metrics that describe the fragmentation, heterogeneity, and connectivity of urban catchments. While the percentage of land-cover types tells us little about landscape patterns, it does aid us in our interpretation of landscape variation by serving as a measure of land-cover composition.

2. 3.6. Statistical Analysis

To test for the presence of structural variations in land-cover among urban catchments, all 23 metrics (5 pattern metrics across 4 land cover types, and 3 stormwater infrastructure density variables) were subjected to three multivariate statistical analyses: (1) multivariate scatterplots/correlations (JMP 10.0; SAS); (2) a hierarchical cluster analysis with heat-map (JMP 10.0); and (3) a Principal Components Analysis (SAS). These three tests constitute a comprehensive, though interpretive, method for uncovering structural variations in land-cover configuration, allowing us to make inferences about potential causes of water quality variation among urban catchments.

2.4. Results

2.4.1. Watershed Clustering

Four distinct watershed clusters emerged from the cluster analysis, which suggested to us that land-cover patterns do vary among potentially degraded catchments (Figure 1.4). We examined the land-cover patterns in each cluster and describe the four categories below.

Cluster 1: Semi-City Living (9 catchments)

These catchments are comprised of large, well connected forest patches, and relatively moderate levels of pavement. Buildings are large and fairly close together, and grass patches are sparse and fragmented by other cover types. These catchments boast moderately dense developments, many of which are likely commercial (large buildings), mixed with clustered residential developments that are obscured by tree canopy as indicated by low grass metric values (Figure 1.5).

Cluster 2: Suburban Lawn Mowers (11 catchments)

Group 2 catchments are developed with dense residential parcels that have ample grass cover, or lawns. Buildings are small, numerous, and close together. Tree patches are large and contiguous, though there are fewer trees than in the semi-city living catchments. Pavement is spread out across the landscape, and not obscured by tree canopy due to the dense residential nature of development in these catchments (Figure 1.6).

Cluster 3: Shaded Urban Homesteads (10 catchments)

These catchments are fairly fragmented by the complex interaction of land-cover types. Tree canopy obscures roads in some areas, while roads cut tree patches where they are not obscured by canopy. Buildings are cordoned off and partially obscured by canopy, which gives the impression that residential zones in these catchments consist of larger parcels, and less treeless development. This implies that the majority of development in these catchments is dispersed residential, though there are likely some commercial areas with parking lots as indicated by moderate pavement levels (Figure 1.7).

Cluster 4: Well-Drained (2 catchments)

The two catchments that comprise group 4 are somewhat similar in structure to group 3. Significantly higher stormwater infrastructure metric values are what separate these catchments from the other groups. While inlet and outlet densities for nearly all other catchments are very low, they are much higher in these two catchments. Both are more urbanized, with large parking lots and buildings mixed into clusters of residential neighborhoods. This density of urbanization requires significantly more stormwater management than the other groups (Figure 1.8).

2.4.2. Observed Cluster Variation

The cluster groupings indicate variation occurs in landscape structure among the analysis catchments. However, metric variation also occurs within cluster groups. Interestingly, the density and shape of grass patches across all clusters are highly inconsistent. Within groups that have the highest grass patch and edge density variability, the shape and density of tree patches are also variable. We found high correlations among the size, shape, and density of grass and forest patches. Essentially, catchments with smaller, more fragmented tree patches have larger, more complexly shaped grass patches (r=0.91). This interaction suggests that grass affects forests in a similar manner as buildings and roads and could ultimately serve as a measure of urbanization alongside imperviousness. The Principal Components Analysis further explains inter-cluster land-cover variation.

2.4.3. Principal Component Analysis

To identify the metrics potentially responsible for land cover variation within catchments, we applied a principal components analysis. Each principal component constitutes a unique landscape measurement. The first four principal components accounted for 82.20% of total variance in the land-cover metric dataset (Table 1.3) and allowed us to identify those measurements that are responsible for a majority of this variation. These PCA results allow us to distinguish which aspects of land-cover might be important factors in future urban water quality assessments.

Using eigenvector scores (Table1.4) to aggregate metrics into principal component measurements, we determined that the first principal component (PC1) is measuring the patch connectivity of all land-cover types, and is responsible for 39.55% of the variance in land-cover among catchments (Table 1.5). Levels of connectivity are highly influenced by the extent of development, as indicated by the inclusion of mean patch area metrics for pavement and building surfaces. In catchments with high values for these metrics, development is more concentrated and denser in some areas, and vegetation patches are larger and more connected.

Metrics describing amount, number, and shape of building and grass patches show that the second principal component (PC2) is measuring the type of development in catchments (single-family residential vs. multi-family or commercial), which accounts for 19.81% of overall variation in watershed land-cover (Table 1.5). More buildings mean more grass, and the size and density of building patches influences the size and shape of grass cover.

The amounts of trees, and size of tree patches, constitute the third principal component (PC3), which accounts for 14.37% of overall variation in watershed land-cover (Table 1.5). However, at least three metrics must be assigned to a component to interpret a measurement (SAS).

Storm water infrastructure metrics were assigned to principal component four (PC4), which accounts for 8.11% of total variation in watershed land-cover (Table 1.5). Pipe densities are highly variable, although inlet and outlet variation is very low. Inlet and outlet variability was inflated due to extremely high numbers in two catchments. Despite their lack of variability, stormwater inlets and outlets could still contribute to water quality variability.

2.5. Discussion

We have successfully described how land-cover patterns vary across the landscape and identified important metrics that explain this variation. Although we did not link our finding to water quality parameters, they are supportive of prior studies that have identified impervious and forest cover patterns as important predictors of water quality (e.g. Carle et al, 2005; Alberti, 2007; Shandas & Alberti, 2009). Simultaneously, our analysis has identified grass and building cover as critical components of landscape variation that have been largely ignored. Additional variation in water quality could potentially be explained by analyzing grass and building patterns in coordination with forest and pavement cover, rather than relying on forest or pavement cover as the sole predictors. In this section, we further explore the potential linkages between these sources of land-cover pattern variation and urban water quality to form hypotheses for future testing.

2.5.1. Lawns are a Measurement of Urbanization

In most studies assessing the effects of urbanization on stream ecosystems, “urbanization” usually refers to some quantified measurement of impervious surface (e.g. Carle et al, 2005), or a combination of development and human population density (e.g. Jones and Clark, 1987). However, our cluster groups demonstrate that ‘urbanization’ should ultimately refer to a more complex interaction among land-cover variables. For example, in our “Lawn Mowers” catchments (Figure 1.6), high grass cover is associated with increased building cover, well connected pavement, and less forest cover that is more fragmented. Conversely, “Semi-City

Living” catchments (Figure 1.5) feature less grass and building cover, well connected pavement, and more tree canopy. The typical indicator of urbanization (pavement) remains unchanged, but is accompanied by stark and varied change to the vegetative landscape that appears to be influenced by the size, shape, and amount of buildings. While buildings are clearly a major component of the built environment, grass is not typically thought of as a contributing factor of urbanization. We argue that it is not only a factor of urbanization, but it may contribute more to forest fragmentation and loss than does pavement.

The complex relationship between grass and forest cover in urban systems becomes more apparent when comparing the simple percentages of each land-cover type to the percentage of total impervious area across catchments (Figure 1.9). While total vegetation declines as the amount of imperviousness increases, the disaggregated measurements of forest and grass cover follow diverging patterns. Forest cover declines at a rate similar to total vegetation cover; however, grass cover increases with pavement and building cover. Grass and forest cover are both highly variable, while pavement and buildings are far less variable. This implies that the human induced seeding of grass in urban and suburban areas contributes to a significant proportion of the variation seen in forest cover within the study catchments. Essentially, adding pavement, buildings, and grass to the naturally forested landscape of the Triangle replaces and shapes forest cover, but it’s the varying levels of grass cover that have the strongest influence on forest cover among catchments. This realization has important implications for analyzing urban water quality variation.

2.5.2. Vegetative Patterns and Implications for Water Quality

Forests absorb and process runoff and associated pollutants with far greater efficiency than grass or prairie patches (Brabec et al., 2002). Furthermore, grass in urban and suburban areas tends to be treated with fertilizers and other chemicals. Agricultural fields are similarly managed and have been linked to decreased diversity of macro-invertebrate assemblages in less forested watersheds in the North Carolina Piedmont (Potter et al., 2004). In suburban residential zones, grass cover has been shown to increase pollution concentrations in surface water runoff (Bannerman et al., 1993). Due to the close proximity of suburban lawns to pavement, this pollutant laden runoff could easily find its way into streams. We have shown that the introduction of grass cover does more to influence forest cover patterns than pavement and buildings in catchments within a 20 to 30 percent gradient of imperviousness in the Triangle, and we expect that urban catchments with more complex grass patterns (e.g. “Suburban Lawn Mowers” cluster) will have worse water quality than those with high forest cover in the region (e.g. “Semi-City Living” & “Shaded Urban Homesteads” Clusters). However, this effect could be compounded by existing stormwater infrastructure networks.

2.5.3. Land-cover Patterns Feed Stormwater Networks

Studies that analyze stormwater infrastructure focus primarily on direct connections of impervious areas to streams via pipe networks (e.g. Walsh et al, 2004; Hatt et al., 2004; Carle et al, 2005), which makes sense given that pavement carries the highest stormwater runoff pollutant loads in urban areas (Bannerman et al., 1993). However, grass and building cover have also been identified as important sources of urban runoff pollution (Bannerman, 1993), and a recent study has shown that the percentage of pipe connectivity in a catchment is often a better predictor of some water quality parameters than the percentages of total and directly connected impervious areas (Hatt et al., 2004). Given these inadequacies, we suggest that much of the unexplained variability in water quality can be explained by assessing patterns of all land-cover types that directly feed pipe networks, rather than focusing on total and effective (directly connected) impervious areas.

An unexpected result of our analysis shows that there is essentially no variation in stormwater inlet and outlet levels among our study catchments (outside of the two "Well-Drained" cluster catchments), but the land-cover patterns that feed these networks are highly variable. It is plausible that variations in vegetation and building patterns, especially those that share edge boundaries with roads, could influence pollutant loads that reach streams via pipe networks. For example, "Lawn Mowers" catchments could see increased amounts of chemical-laden runoff flowing into stormwater networks as opposed to catchments featuring canopy covered developments like the "Shaded Urban Homestead" and "Semi-City Living" clusters. Cutting direct connections to streams could help mitigate any damaging effects (Hatt et al., 2004), but in order to develop a truly effective prescription we must first acknowledge the drivers of land-cover pattern variation.

2.5.4. Socio-Ecological Drivers of Land-Cover Change

Forest, pavement, and quantified urbanization patterns explain a proportion of water quality variability (Carle et al., 2005, Alberti et al, 2007; Shandas and Alberti, 2009), and grass and building patterns are likely explainers of additional variation; however, our analysis doesn't tell us what drives variation in land-cover patterns. Recent research in Raleigh, NC, has shown that management of residential parcels is based on a variety of neighborhood level social characteristics ranging from lifestyles and preferences to historical legacies (Bigsby et al., 2013). Factors like lifestyle play an important role in shaping the vegetative patterns of neighborhoods (Grove et al, 2006; Boone et al, 1009; Bigsby et al, 2013). Socio-economic status (now SES) is also a determining factor of land-cover (Grove et al., 2006). Low SES, minority neighborhoods typically feature an over-abundance of imperviousness and very few trees (Pickett et al, 2008). In these areas, grass cover provides dual benefits as a pervious surface to slow runoff, and fosters neighborhood pride (Pickett et al., 2008). This suggests that the potential disservices of grass cover within the degraded range of imperviousness for watersheds only extends so far along the impervious gradient – some pervious cover is better than no pervious cover. Regardless, the socio-ecological characteristics of cities are primary drivers of landscape change through the management of parcels (Boone et al, 2009), and should be considered when developing management strategies to mitigate water quality degradation.

2.6. Conclusions and Future Testing

We have looked beyond the percentage effects of impervious surface cover on water quality and gained an understanding of how land-cover patterns and stormwater infrastructure may vary across the landscape. Four distinct clusters of catchments emerged from our analysis, each with a distinct land-cover pattern signature. Furthermore, complex interactions between vegetative patterns in potentially degraded catchments contribute to variation in land-cover. Studies that lump different vegetation types into aggregate measures of vegetation cover, or exclude grass cover from analyses, are overlooking potentially critical water quality factors. For instance, the dispersal of roadways does contribute to forest fragmentation and explains some variation in water quality (Alberti et al., 2007); however, we have shown that variation in grass cover is the primary indicator of forest cover. While previous research has primarily focused on imperviousness and stormwater connectivity as explainers of water quality, we recognize that grass cover likely explains additional variation and should be viewed as a measure of urbanization in future analyses. These relationships lead us to develop a few testable hypotheses about the associations between urban land-cover patterns and water quality variation.

1.*Combining pavement, building, forest and grass cover patterns into catchment cluster groups will better explain water quality variability than imperviousness or forest patterns alone.*

Within potentially degraded urban catchments (20%-30% impervious surfaces) alternative residential development patterns will influence water quality differently. Developments that encourage canopy growth and limit the extent and connectedness of grass patches (e.g. "Shaded Urban Homesteads) will experience better water quality than those that limit canopy cover and emphasize grass cover (e.g. "Lawn Mowers"). To test this hypothesis, high-resolution land-cover data can be used to calculate patch, edge, and contiguity metrics for potentially degraded catchments. Water quality metrics, such as macro-invertebrate indices and pollutant loads, should be collected at catchment pour-points. Watershed hierarchal clustering will separate catchments into clustered land-cover pattern groups. Metrics for each catchment cluster group are then collapsed into multiple linear regression models, and tested against water quality data to determine how much variability in water quality is explained by these alternative development patterns.

2. *As a measure of urbanization, grass cover patterns are a critical determinant of degraded water quality even among catchments that fall within the same cluster groups.*

While different vegetation patterns help to distinguish between land-cover cluster groups, water quality variation can be expected within these groups as well –despite similar development structures. A Principal Components Analysis has highlighted several grass and building metrics that account for roughly 20% of the total variation in land-cover throughout the study catchments. Using the “Lawn Mowers” cluster as an example, grass and building cover metrics are more similar in catchments within this cluster than those in other clusters, but they are still inconsistent. While the land-cover patterns in each cluster will likely explain some proportion of water quality variability, it is most likely the subtle variation in grass patterns that will be responsible for any observed variation in water quality *within* cluster groups.

REFERENCES

1. Alberti, M., 1999. *Urban Patterns and Environmental Performance: What Do We Know?* Journal of Planning Education and Research, 19: 151-163

2. Alberti, M., 2005. *The Effects of Urban Patterns of Ecosystem Function.* International Regional Science Review, 28: 168-192

3. Alberti, M., D. Booth, K. Hill, B. Coburn, C. Avolio, S. Coe, and D. Spirandelli. 2007. *TheImpact of Urban Patterns on Aquatic Ecosystems: An Empirical Analysis in Puget Lowland Sub-basins.* Landscape and Urban Planning, 80: 345-361

4. Arnold Jr., C. L. & C. J. Gibbons, 1996. *Impervious Surface Coverage: The Emergence of a Key Environmental Indicator*. Journal of the American Planning Association, 62 (2): 243-358

5. Bailey, R. G., 1995, 231 Southern Mixed Forest Province, *UDSA Forest Service Descriptions of the Ecoregions of the United States*, http://www.fs.fed.us/colormap/ecoreg1_provinces.conf?662,326 (December 4th, 2012)

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

7. Basnyat, P., L.D. Teeter, B.G. Lockaby, and K.M. Flynn, 1999. *The Use of Remote Sensing and GIS in Watershed Level Analyses of Non-Point Source Pollution Problems.* Forest Ecology and Management, 128: 65-73

8. Bigsby, K., M.R. McHale, and G. Hess. In Press. *Urban Morphology Drives Urban Tree Cover in Baltimore, MD and Raleigh, NC.* Submitted to Ecosystems, January 2013.

9. Boone, C. G., M. L. Cadenasso, J. M. Grove, K. Schwarz, and G. L. Buckley, 2009. *Landscape, Vegetation Characteristics, and Group Identity in an Urban and Suburban Watershed: Why the 60's Matter.* Urban Ecosystems, 13: 255-271

10. Booth, D. B & C. R. Jackson, 1997. *Urbanization of Aquatic systems: Degradation Thresholds, Stormwater Detection, and the Limits of Mitigation*. Journal of the American Water Resources Association, 33(5): 107-1090

11. Bolund, P. and S. Hunhammear. 2000. *Ecosystem Services in Urban Areas.* Ecological Economics, 29: 293-301

12. Brabec, E., S. Schulte and P. L. Richards, 2002. *Impervious Surface and Water Quality: A review of Current Literature and its Implications for Watershed Planning*. Journal of Planning Literature, 16: 499-514

13. Carle, M. V., P.N. Halpin, and C. A. Stow, 2005. *Patterns of Watershed Urbanization and Impacts on Water Quality*. Journal of the American Water Resources Association, June: 693-708

14. Cadenasso, M. L., S. T. A. Pickett, and K. Schwarz, 2007. *Spatial Heterogeneity in Urban Ecosystems: Reconceptualizing Land Cover and a framework for Classification.* Frontiers in Ecology and the Environment, 5(2): 80-88

15. Cifaldi, R. L., J. D. Allan, J.D. Duh, and D. G. Brown, 2004. *Spatial Patterns in land Cover of Exurbanizing Watersheds in Southeastern Michigan.* Landscape and Urban Planning, 66: 107-123

16. Conway, T. and J. Hackworth, 2007. *Urban Pattern and land Cover Variation in the Greater Toronto Area.* The Canadian Geographer, 51(1): 43-57

17. Fisher, D., 2012, America's Fastest-Growing Cities, *Forbes Business Online*, http://www.forbes.com/sites/danielfisher/2012/04/18/americas-fastest-growing-cities/2/ (December 4th, 2012)

18. Greve, A. I., 2012. *Linking Urban Form, Land Cover Pattern, and Hydrologic Flow Regime in the Puget Sound Lowland.* Urban Ecosystems, 15:437-450

19. Grimm, N. B., J. M. Grove, S. T. A. Pickett, and C. L. Redman, 2000. *Integrated Approaches to Long-Term Studies of Urban Ecological Systems.* BioScience, 50(7): 571-584

20. Grove, J.M., and W. Burch Jr., 1997. *A Social Ecology Approachand Applications of Urban Ecosystem and Landscape Analysis: A Case Study of Baltimore, Maryland.* Urban Ecosystems, 1: 259-275

21. Grove, J.M., M.L. Cadenasso, W.R. Burch Jr., S.T.A. Pickett, and K. Schwarz, 2006. *Data and Methods Comparing Social Structure and Vegetation Structure of Urban Neighborhoods in Baltimore, Maryland.* Society and Natural Resources, 19: 117-136

22. Grove, N. E., R. T. Edwards, and L. L. Conquest, 2001. *Effects of Scale on Land Use and Water Quality Relationships: A Longitudinal Basin-Wide Perspective.* Journal of the American Water Resources Association, 37(6): 1721-1734

23. Hatt, B.E., T.D. Fletcher, and C.J. Walsh, 2004. *The Influence of Urban Density and Drainage Infrastructure on the Concentrations and Loads of Pollutants in Small Streams.* Environmental Management, 34(1): 112-124

24. Huang, C., E.L. Geiger, and J.A. Kupfer. 2006. *Sensitivity of Landscape Metrics to Classification Scheme.* International Journal of Remote Sensing, 27 (14): 2927-2948

25. Jones, C.R., and C.C. Christopher, 1987. I*mpacts of Watershed Urbanization on Stream Insect Communities.* Journal of the American Water Resources Association, 23(6): 1047-1055

26. King, R. S., M. E. Baker, D. F. Whigham, D. E. Weller, T. E. Jordan, P. F. Kazyak, and M. K. Hurd. 2005. *Spatial Considerations for Linking Watershed Land Cover to Ecological Indicators in Streams.* Ecological Applications, 15 (1): 137-153

27. Kupfer, J. A. 2012. *Landscape Ecology and Biogeography: Rethinking Landscape Metrics in a Post-FRAGSTATS Landscape.* Progress in Physical Geography, 36 (3): 400-420

28. Lee, S-W, Soon-Jin H., S-B Lee, H-S Hwang, and H-C Sung. 2009. *Landscape Ecological Approach to the Relationships of Land Use Patterns in Watersheds to Water Quality Characteristics.* Landscape and Urban Planning, 92: 80-89

29. Luck, M. and J. Wu. 2002. *A Gradient Analysis of Urban Landscape Pattern: A Case Study from the Phoenix Metropolitan Region, Arizona, USA.* Landscape Ecology, 17(4): 327-339

30. Martin, C. A., P. S. Warren, and A. P. King, 2004. *Neighborhood Socio-Economic Status is a Useful Predictor of Perennial Landscape Vegetation in Residential Neighborhoods and Embedded Small Parks in Phoenix, AZ.* Landscape and Urban Planning, 69: 355-368

31. McGarigal, K., and B. J. Marks, 1995, *Fragstats: Spatial Pattern Analysis Program for Quantifying Landscape Structure*, USDA General Technical Report PNW-GTR-351

32. McGarigal, K., S.A. Cushman, and E Ene. 2012. *FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps.* University of Massachusetts, Amherst. Available at: http://umass.edu/landeco/research/fragstats/fragstats.html

33. Nassauer, J.I., J. D. Allan, T. Johengen, S. E. Kosek, D. Infante, 2004. *Exurban Residential Subdivision Development: Effects on Water Quality and Public Perception*. Urban Ecosystems, 7: 267-281

34. Nasser, H. E., and P. Overberg, 2001, A Comprehensive Look at Sprawl in America, *The USA Today Sprawl Index*, http://usatoday30.usatoday.com/news/sprawl/main.htm (December 4th, 2012)

35. Nowak, D. J. and E. J. Greenfield. 2012. *Tree and Impervious cover change in U.S. Cities.* Urban Forestry & Urban Greening, 11: 21-30

36. Paul, J. M. and J. L. Meyer, 2001. *Streams in the Urban Landscape*. Annual Review of Ecology and Systematics, 32: 333-365

37. Potter, K. M., F. W. Cubbage, and G. B. Blank, 2004. *A Watershed Scale Model for Predicting Non-Point Pollution Risk in North Carolina.* Environmental Management, 34(1): 62-74

38. Roy, A. H. and W. D. Shuster, 2009. *Assessing Impervious Surface Connectivity and Applications for Watershed Management.* Journal of the American Water Resources Association, 45:1, 198-209

39. Roy, A. H., A. L. Dybas, K. M. Fritz, and H.R. Lubbers. 2009. *Urbanization Affects the Extent and Hydrologic Permanence of Headwater Streams in a Midwestern US Metropolitan Area.* Journal of the North American Benthological Society, 28(4): 911-928

40. Picket, S.T.A., M. L. Cadenasso, J. M. Grove, C.H. Nilon, R.V. Pouyat, W.C. Zipperer, and R. Costanza. 2001. *Urban Ecological Systems: Linking Terrestrial Ecological, Physical, and Socioeconomic Components of Metropolitan Areas.* Annual Review of Ecological Systems, 32: 127-157

41. Pickett, S. T.A., M. L. Cadenasso, J. M.Grove, P. M. Groffman, L.E. Band, C. G. Boone, W. R. Burch Jr., C. S. B. Grimmond, J. Hom, J. C. Jenkins, N. L. Law, C. H. Nilon, R.V. Pouyat, K. Szlavecz, P. S. Warren, and M. A. Wilson. 2008. *Beyond Urban Legends: An Emerging Framework of Urban Ecology, as Illustrated by the Baltimore Ecosystem Study*. Bioscience, 58 (2): 139-150

42. Rohe, M.M. "The Research Triangle: From Tobacco Road to Global Prominence," Philadelphia, University of Philadelphia Press, 2011.

43. SAS, Principal Component Analysis, http://support.sas.com/publishing/pubcat/chaps/55129.pdf (December 4th, 2012)

44. Shandas, V. and M. Alberti, 2009. *Exploring the Role of Vegetation Fragmentation on Aquatic Conditions: Linking upland Riparian Areas in Puget Sound Lowland Streams*. Landscape and Urban Planning, 90: 66-75

45. Shao, G. and J. Wu. 2008. *On the Accuracy of Landscape Pattern Analysis Using Remote Sensing Data.* Landscape Ecology, 23(5): 505-511

46. Smith, M. L., W. Zhou, M. Cadenasso, M. Grove, and L. E. Band. 2010. *Evaluation of the National Land Cover Database for Hydrologic Applications in Urban and Suburban Baltimore, Maryland.* Journal of the American Water Resources Association, 46 (2): 429-442

47. Somers, K.A., S.M. Beck, E.S. Bernhardt, B.L. McGlynn, D.L. Urban, and K.A. Voss. In prep. *All Pavement is Not Created Equal: Examining the Effects of Development Configuration and Connectivity on Thermal Pollution to Streams*.

48. Strayer, D. L., R. E. Beighley, L. C. Thompson, S. Brooks, C. Nilsson, G. Pinay, and R. J. Naiman. 2003. *Effects of Land Cover on Stream Ecosystems: Roles of Empirical models and Scaling Issues*. Ecosystems, 6: 407-423

49. Turner, W. R., T. Nakamura, and M. Dinetti, 2004. *Global Urbanization and the Separation of Humans from Nature.* Bioscience, 54(6): 585-590

50. Walsh, C. J. 2004. *Protection of In-Stream Biota from Urban Impacts: Minimize Catchment Imperviousness or Improve Drainage Design?* Marine and Freshwater Research, 55: 317-326

51. Walsh, C.J., P.J. Papas, D. Crowther, P.T. Sim, and J. Yoon. 2004. *Stormwater Drainage Pipes as a Threat to a Stream-Dwelling Amphipod of Conservation Significance, Austrogammarus Australis, in South-Eastern Australia.* Biodiversity and Conservation, 13: 781-793

52. Weng, Q.. 2001. *Modeling Urban Growth Effects on Surface Runoff with the Integration of Remote Sensing and GIS.* Environmental Management, 28(6): 737-748

53. Z., Robert A., N. A. Procopio, R. G. Lanthrop, and C. L. Dow, 2007. *Relationship of Land-Use/Land Cover Patterns and Surface-Water Quality in the Mullica River Basin.* Journal of the American Water Resources Association, 43(3): 594-604

54. Zhou, W., G. Huang, and M.L. Cadenasso, 2011. *Does Spatial Configuration matter? Understanding the Effects of Land Cover Pattern on Land Surface Temperature in Urban Landscapes.* Landscape and Urban Planning, 102: 54-63

TABLES

Table 2.1: Watershed Summary Statistics

Watershed Area (km2)	
N	32
Mean Size (km2)	1.5976
Median Size (km2)	1.3608
Standard Deviation	0.918
Min Size (km2)	0.5948
Max Size (km2)	4.2021

Table 2.2: Analysis Metric List / Measurements. Variables are used to determine landscape patterns within catchments.

METRIC	METRIC CODE	COVER TYPE	Cover Type Code	CALCULATION METHOD	DESCRIPTIVE MEASUREMENT
Percent Cover/ Percentage of Landscape	%, percent	Coarse Vegetation Transportation Impervious Building impervious Fine Vegetation	CV, Trees TIMP, Pavement BIMP, Buildings FV, Grass	FRAGSTATS 4.0 (McGarigal & Marks, 2005)	Measures the total percentage of a specific land-cover type existing within a watershed boundary. High percent cover values mean there is an excess of the measured land-cover type in the watershed.
Patch Density	PD	Coarse Vegetation Transportation Impervious Building impervious Fine Vegetation	CV, Trees, TIMP, Pavement BIMP, Buildings FV, Grass	FRAGSTATS 4.0 (McGarigal & Marks, 2005)	Measures the number of unique land-cover type patches based on the area of the watershed. High patch densities mean there are a large number of patches within a watershed. High patch density values could mean that a specific land-cover type is very fragmented and dotting the landscape
Edge Density	ED	Coarse Vegetation Transportation Impervious Building impervious Fine Vegetation	CV, Trees TIMP, Pavement BIMP, Buildings FV, Grass	FRAGSTATS 4.0 (McGarigal & Marks, 2005)	Measures the total boundary length of land-cover types based on the area of catchments. High edge density values mean that patches of unique land-cover types are complexly shaped and high in volume.

Table 2.2 Continued:

Mean Patch Area	AREA_MN, MPA	Coarse Vegetation Transportation Impervious Building impervious Fine Vegetation	CV, Trees TIMP, Pavement BIMP, Buildings FV, Grass	FRAGSTATS 4.0 (McGarigal & Marks, 2005)	Measures the average patch size of land-cover types within catchments. High mean patch area values mean that specific land-cover types are present in large patches, which means that they are likely not fragmented. This metric is used with percent cover and patch density to make judgments as to the makeup of land-cover with in a catchment boundary.
Mean Contiguity	CONTIG_MN	Coarse Vegetation Transportation Impervious Building impervious Fine Vegetation	CV, Trees TIMP, Pavement BIMP, Buildings FV, Grass	FRAGSTATS 4.0 (McGarigal & Marks, 2005)	Measures the internal connectivity of patches. Patches might be large and connected, but have alternative land-cover types present within them. High mean contiguity values suggest that patches are very well internally connected, and not split by alternative land-cover types. Low contiguity values suggest that patches consist of very few pixels, are not large in size, or generally well connected.
Density	none	Inlets Outlets Pipe Length	none	ESRI ArcMap # / watershed area	Measures the density of inlets, outlets, and pipe length existing with catchments.

Table 2.3: PCA Eigenvalues for first 4 Principal Components show the increasing cumulative percentages of variance explained by each principal component (SAS).

PC	Eigenvalue	Difference	Proportion of Variance	Cumulative Variance
1	9.10	4.54	0.40	0.40
2	4.60	1.17	0.20	0.59
3	3.39	1.52	0.15	0.74
4	1.87	0.58	0.08	0.82

Table 2.4: PCA Eigenvector scores for first 4 Principal Components. High metric values (~ 25) load metrics to principal components, which are used to determine measurements

All Configuration and Storm Water Analysis Variables		**PC1** **20-30** n=32	**PC2** **20-30** n=32	**PC3** **20-30** n=32	**PC4** **20-30** n=32
Storm Water Metrics	Inlet Density	-0.052	-0.181	-0.088	0.625
	Outlet Density	-0.087	-0.180	-0.053	0.605
	Pipe Density	0.207	-0.047	0.114	0.354
Coarse Vegetation Metrics	% Coarse Vegetation	-0.129	-0.247	0.380	-0.072
	Patch Density Coarse Vegetation	-0.232	0.105	-0.306	-0.046
	Edge Density Coarse Vegetation	-0.221	0.212	0.202	0.025
	Mean Patch Area Coarse Vegetation	0.170	-0.236	0.323	-0.076
	Mean Contiguity Coarse Vegetation	0.277	0.152	0.059	0.094
Transportation Impervious Metrics	% Transportation Impervious	-0.036	-0.222	-0.309	0.037
	Patch Density Transportation Impervious	-0.303	-0.065	-0.036	-0.070
	Edge Density Transportation Impervious	-0.305	0.044	-0.119	0.062
	Mean Patch Area Transportation Impervious	0.276	0.017	-0.145	-0.061
	Mean Contiguity Transportation Impervious	0.294	0.083	0.178	0.012
Building Impervious Metrics	% Building Impervious	0.124	0.283	0.154	0.194
	Patch Density Building Impervious	-0.157	0.308	0.209	0.058
	Edge Density Building Impervious	-0.040	0.398	0.183	0.157
	Mean Patch Area Building Impervious	0.243	-0.143	-0.127	0.005
	Mean Contiguity Building Impervious	0.263	0.171	0.104	0.061
Fine Vegetation Metrics	% Fine Vegetation	0.109	0.299	-0.337	0.033
	Patch Density Fine Vegetation	-0.227	0.191	0.190	0.065
	Edge Density Fine Vegetation	-0.153	0.362	-0.171	0.070
	Mean Patch Area Fine Vegetation	0.202	0.103	-0.344	-0.040
	Mean Contiguity Fine Vegetation	0.276	0.156	-0.016	0.001
	% Variance Explained	39.55	19.81	14.73	8.11

Table 2.5: Land Cover Configuration PCA for 20-30% Impervious Watersheds (n=32**).** PCA Eigenvector loading metrics for each principal component. Interpreted principal component measurements are determined based on the metrics representing each principal component. The overall percentage of variance in the dataset explained by each principal component is in the far right column. Mean contiguities and patch areas of trees, grass, pavement, and buildings describe the connectivity and area of land-cover types.

Principal Component	**Eigenvector Loading Variables**	**Measurement**	**Percentage of Total Variance Explained**
Principal Component 1	Contiguity Coarse Veg Mean Patch Area Transportation Imp Contiguity Transportation Imp Mean Patch Area Building Impervious Contiguity Building Impervious Contiguity Fine Veg	Patch Connectivity and Development Level	**39.55%**
Principal Component 2	Percent Building Imp Patch Density Building Imp Edge Density Building Imp Percent Fine Veg Edge Density Fine Veg	Development Type (residential vs. commercial)	**19.81%**
Principal Component 3	Percent Coarse Veg Mean Patch Area Coarse Vegetation	Unknown Measurement	**14.73%**
Principal Component 4	Inlet Density Outlet Density Pipe Density	Storm Water Infrastructure	**8.11%**
		Total Variance Explained	**82.20%**

FIGURES

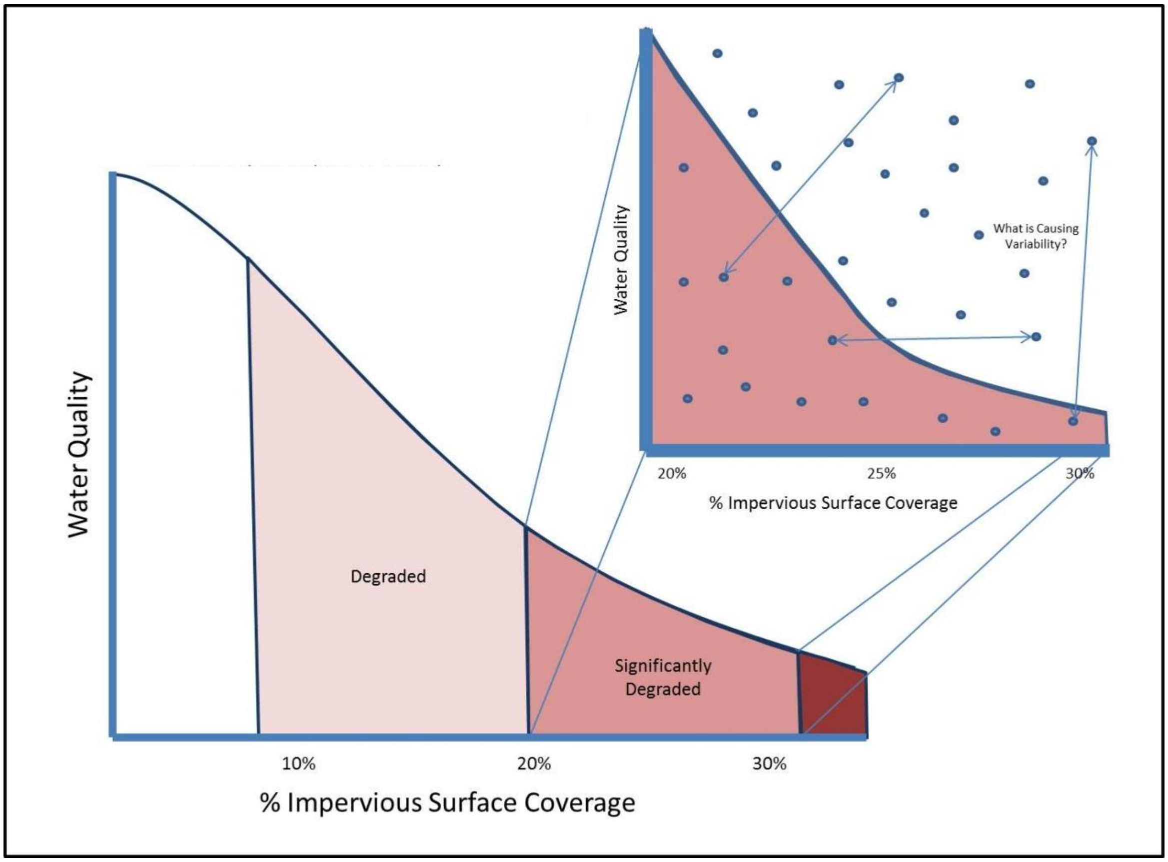

Figure 2.1: Impervious and water quality conceptual diagram demonstrates the thresholds at which water quality begins to decline, and subsequently becomes degraded or impaired (Arnold and Gibbons, 1996). The relationship between water quality and impervious surface cover is well established (Arnold and Gibbons, 1996; Brebec et al., 2002); however, water quality variability between catchments within the same range of imperviousness has not been sufficiently explained (Alberti et al., 2007).

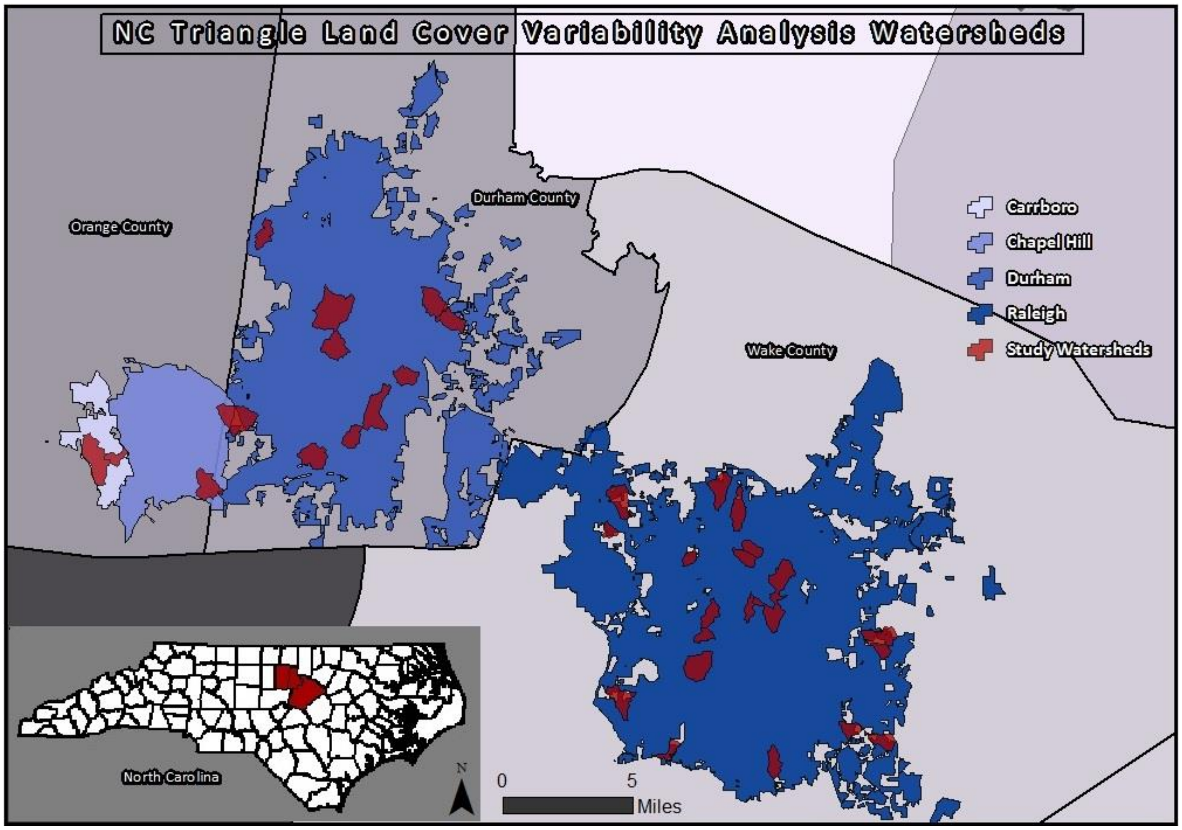

Figure 2.2: Study Area Watershed Map shows locations of small-scale catchments within Raleigh, Durham, and Chapel Hill/Carrboro. There are three in Carrboro/Chapel Hill, 9 in Durham, and 19 in Raleigh. One is split between Chapel Hill and Durham.

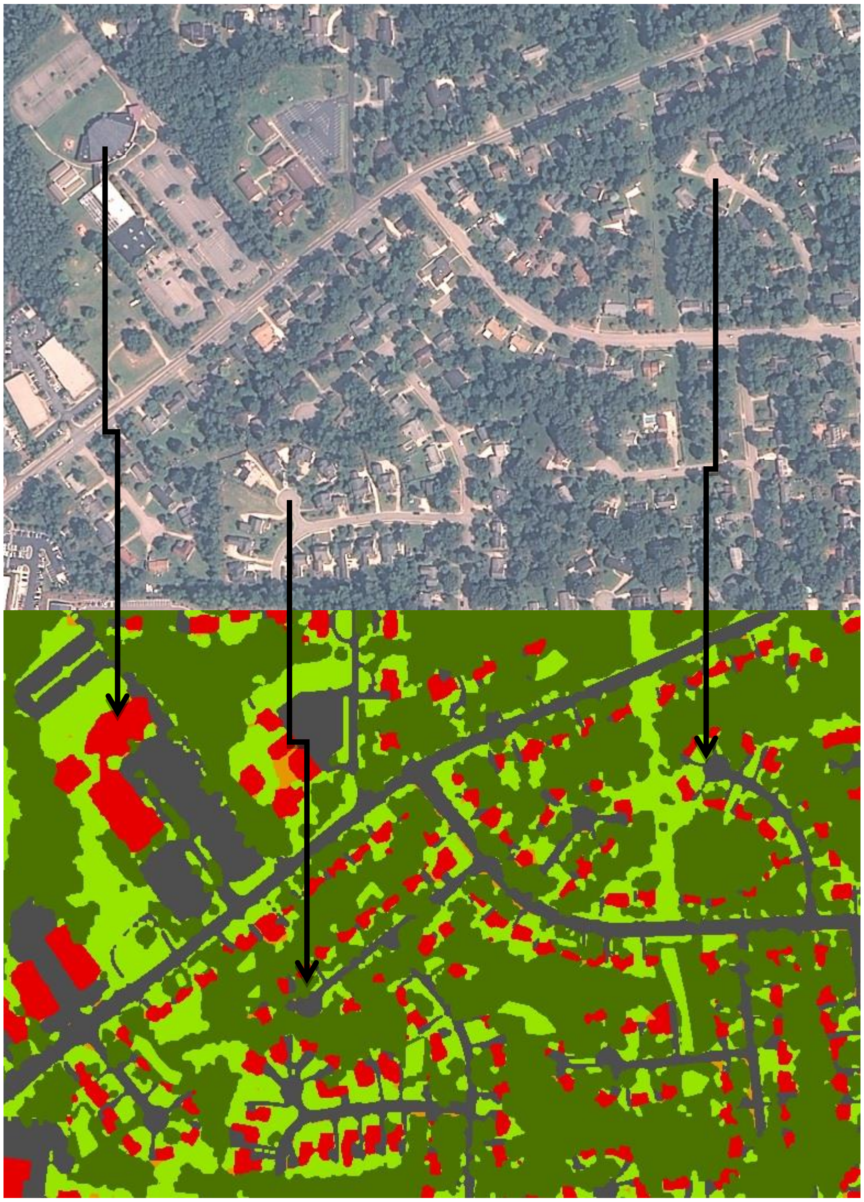

Figure 2.3: High-Resolution Land-Cover Snapshot: shows fine detail of 1m land-cover classification. With this, we are able to accurately measure urban land cover patterns within our study catchments. Coarse vegetation is represented in dark green, pavement impervious surfaces are grey, building impervious surfaces are red, open water is blue, fine vegetation is light green, and bare earth is tan/brown.

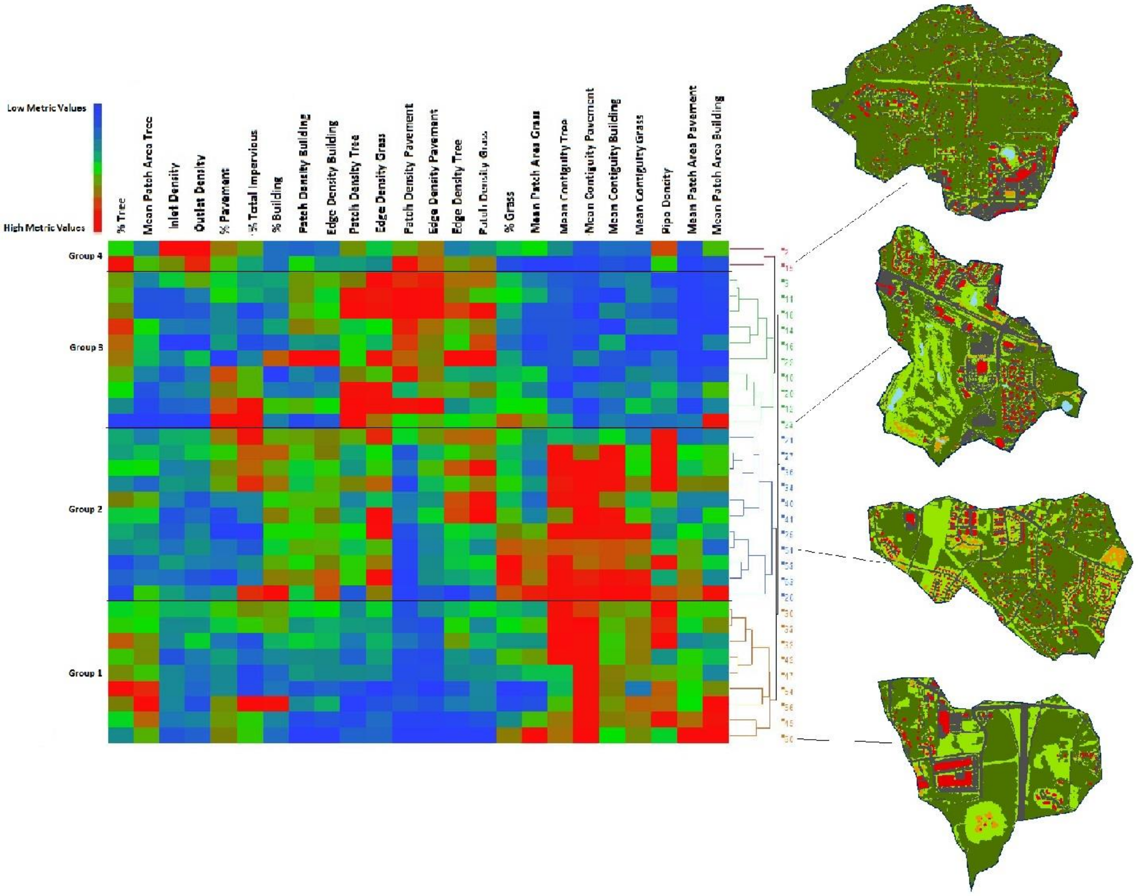

Figure 2.4: Watershed Clustering: shows 4 distinct watershed groupings (JMP). Land-cover from single watersheds selected from cluster groups 1- 4 (Group 1 on bottom, group 4 on top) are shown to the right of the dendrogram. Analysis metrics are shown in columns, numerical watershed identifiers are shown on the right as rows. High metric values are depicted as red, low metrics values are blue, and middle range values are green to orange. Clusters of values can be easily viewed in the heatmap, and the general landscape structure of each cluster group can be interpreted based on these metric values

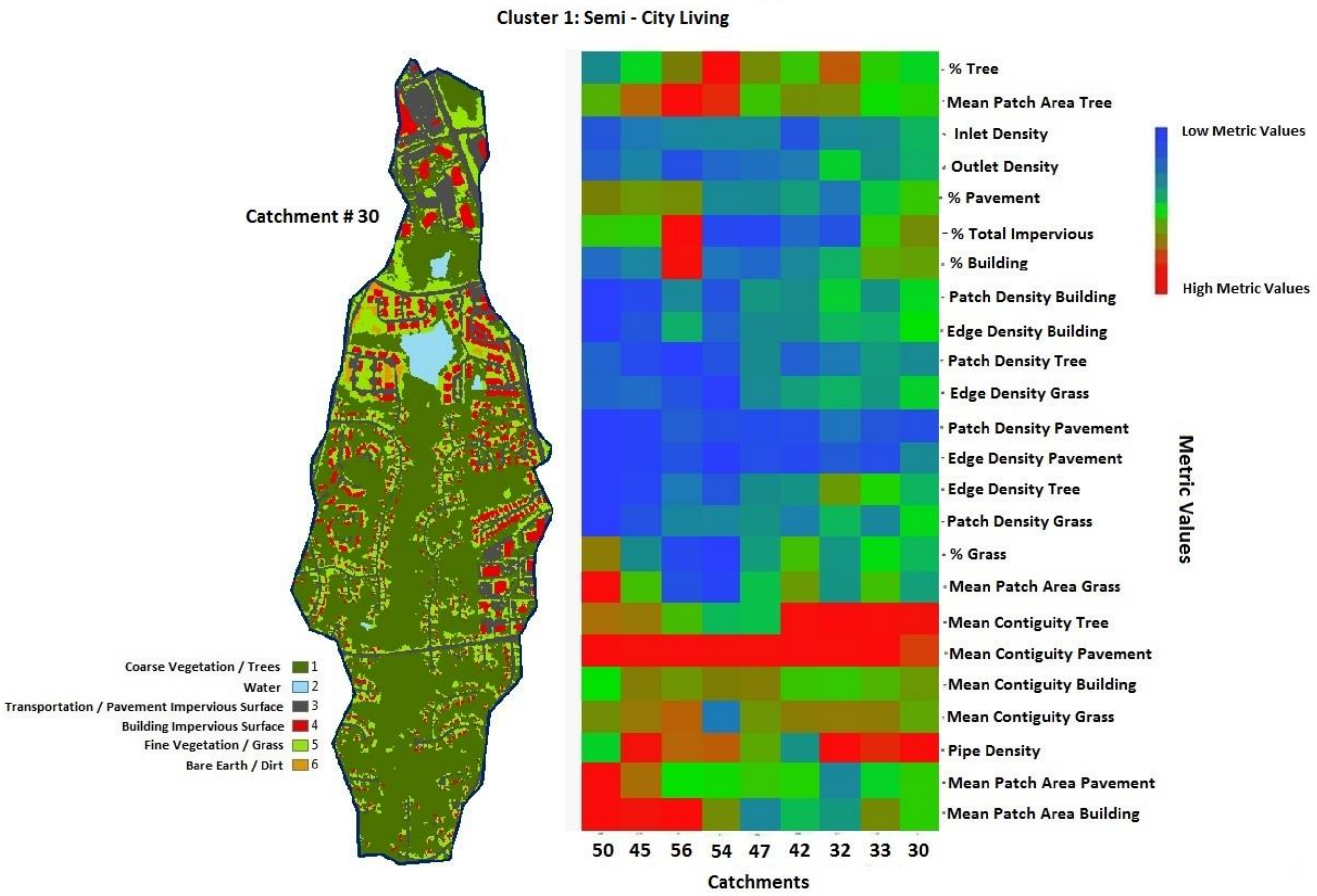

Figure 2.5: Cluster Group 1 Catchments are comprised of large, well connected forest patches, and relatively moderate levels of pavement surfaces. Buildings are large and fairly close together, and grass patches are sparse and fragmented by other cover types. These catchments boast moderately dense developments, which are likely commercial due to building size, mixed with clustered residential developments that are obscured by tree canopy as indicated by low grass metric values.

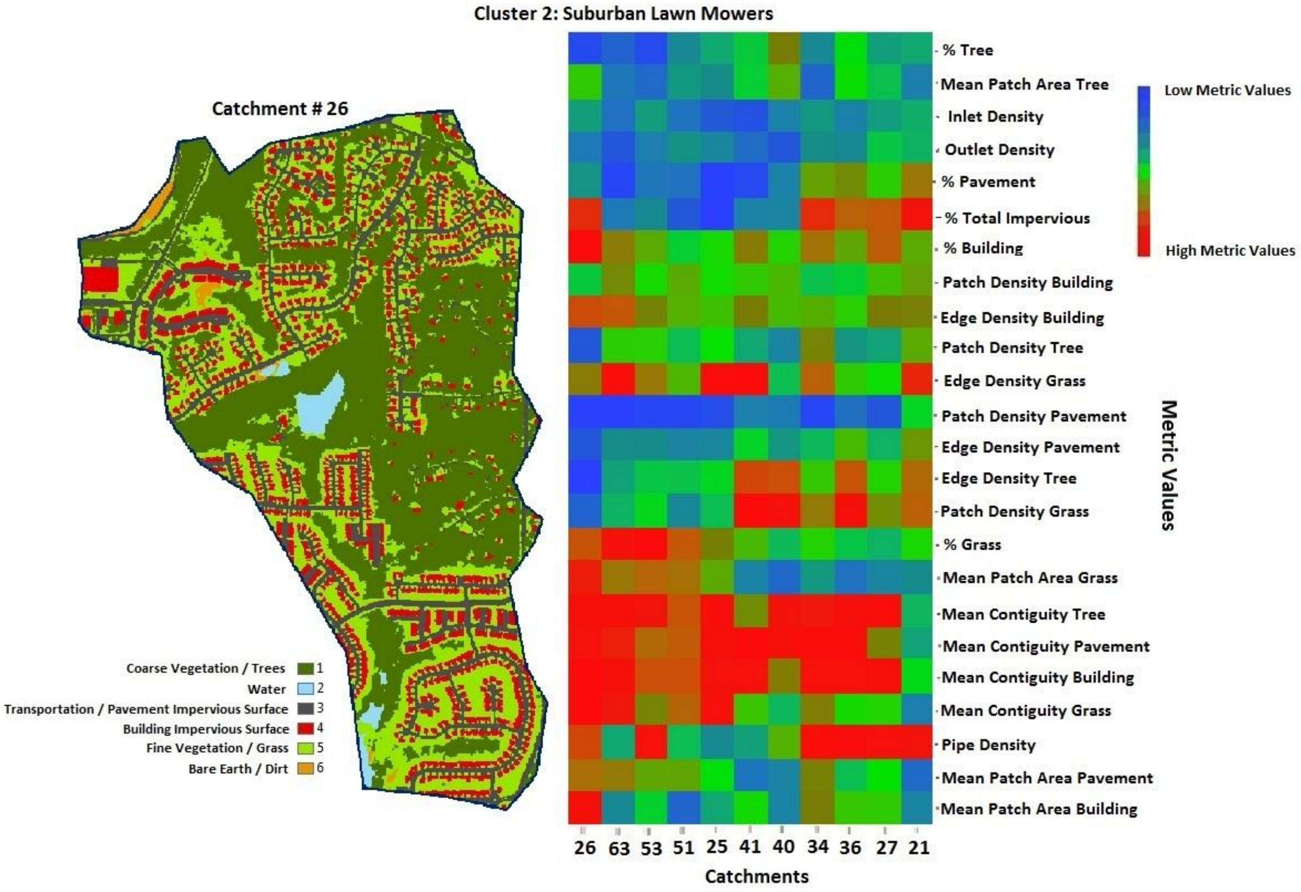

Figure 2.6: Cluster Group 2 Catchments: are developed with dense residential parcels that have ample grass cover, or lawns. Buildings are small, numerous, and close together. Tree patches are large and contiguous, despite lower tree cover levels. Pavement is spread out across the landscape, and not obscured by tree canopy due to the dense residential nature of development in these catchments.

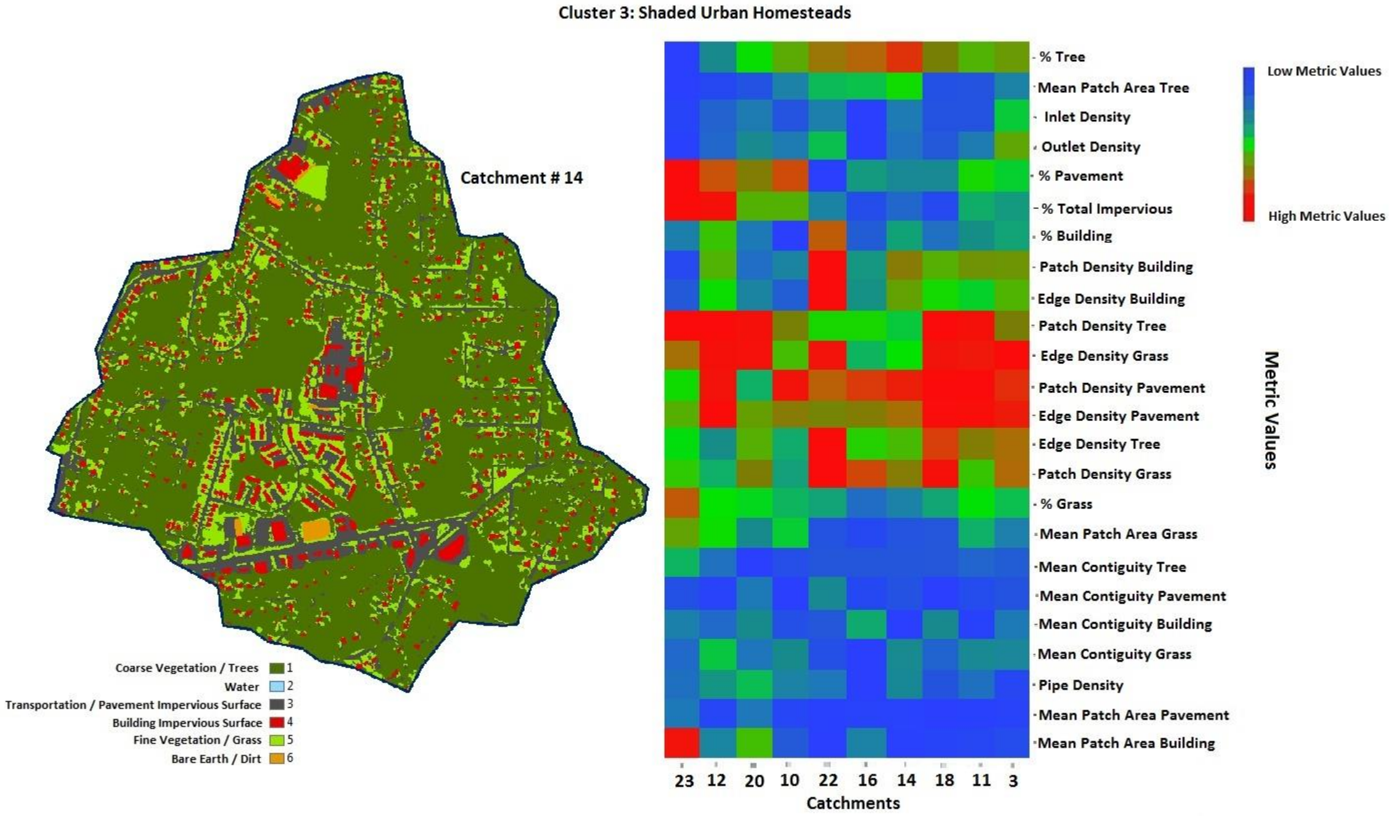

Figure 2.7: Cluster Group 3 Catchments: are fairly fragmented by the complex interaction of land-cover types. Tree canopy obscures roads at certain points, while roads cut tree patches where they are not obscured by canopy. Buildings are cordoned off and partially obscured by canopy, which gives the impression that residential zones in these catchments consist of larger parcels, and less clear-cut development. The majority of development in these catchments is dispersed residential, though there are likely small areas of commercially zoned development as indicated by moderate percent pavement levels.

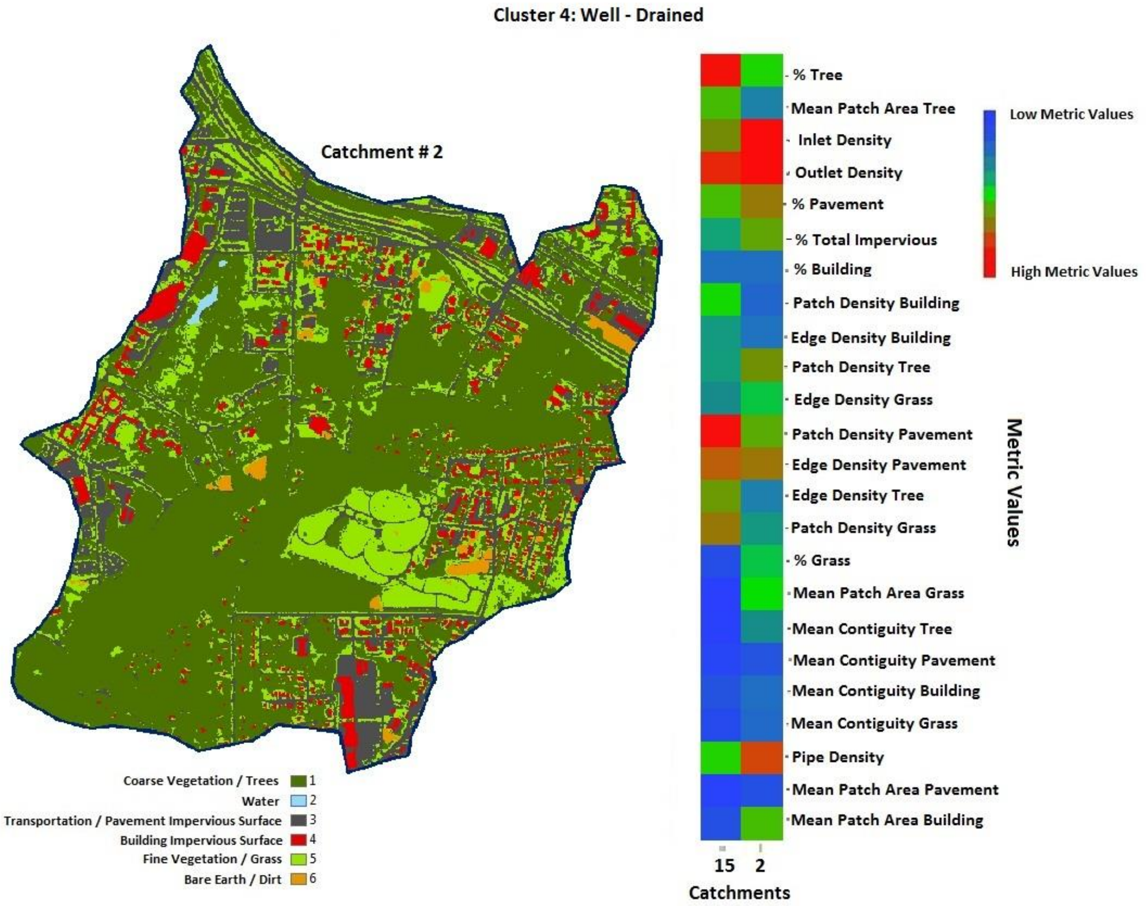

Figure 2.8: Cluster Group 4 Catchments: are very similar in structure to catchments in cluster group 3. The difference is that these two catchments have very high stormwater infrastructure metric values, where all other catchments have low values for inlet and outlet densities. Both of these catchments are located in more highly developed urban areas, where the majority of development is dense and non-residential.

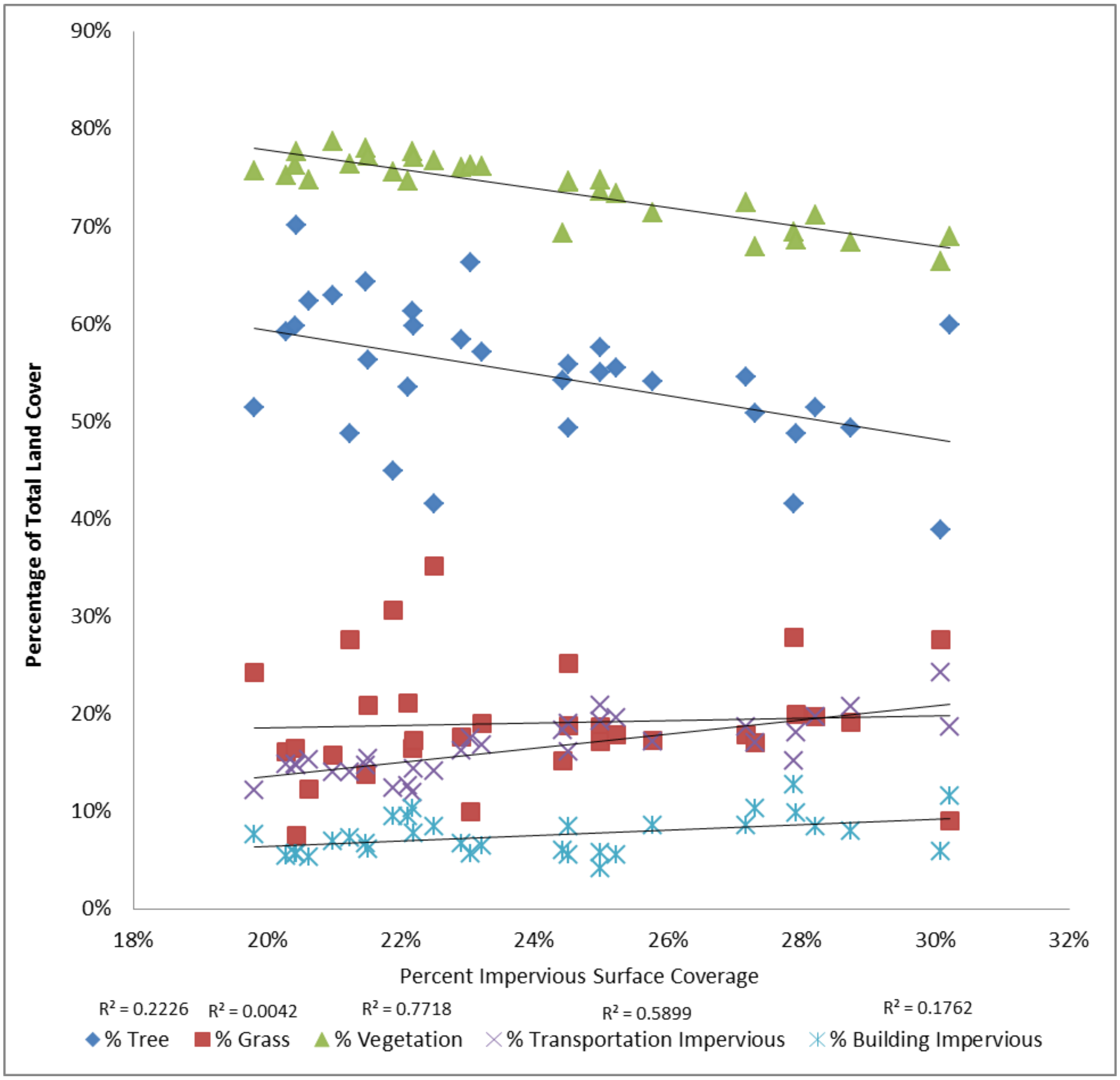

Figure 2.9: Percent Land-Cover Types vs. Percent Total Impervious Surface: Tree cover drives the relationship between total vegetation and impervious surface. High grass values and low tree values still equate to high vegetation values, even though water quality control potential is minimized as forest patches shrink. Grass contributes to variation in tree cover, similarly to buildings and roads, although the effects of grass seem to compound tree loss in urbanized watershed.