ABSTRACT

Title of dissertation: TREE COVER VARIABILITY IN THE DISTRICT OF COLUMBIA

Andrew K. Johnston, Doctor of Philosophy, 2013

Dissertation directed by: Professor Samuel N. Goward
Department of Geographical Sciences

Urban forests are increasingly a focus of interest as urbanized populations grow and urban areas expand. Urban forests change as trees are planted, grow, die, and are removed. These processes alter a city's tree cover over time, but this inherent dynamism is poorly understood. Better understanding of how tree cover is a variable land cover component will enhance knowledge of the urban environment and provide new perspectives for management of urban resources.

In this study, tree cover variability within a major urban center was observed over a 20 year period. Changes in tree cover proportion were measured in the District of Columbia between 1984-2004 utilizing highly calibrated satellite remote sensing data. Testing of alternate methodologies demonstrated that an approach utilizing support vector regression provided most consistent accuracy across land use types. Tree cover maps were validated using aerial photography imagery and data from field surveys.

Between 1984-2004, the city-wide tree cover remained between 22.1(+/-2.9)% and 28.8(+/-2.9)% of total land surface area. The District of Columbia did not experience an overall increase or decrease in total tree canopy area. Spatial patterns of tree cover variability were investigated to identify local scale changes in tree cover and connections with urban land use. Within the city, greatest variability was observed in low density

residential zones. Tree cover proportion in these zones declined 7.4(+/-5.4)% in the years between 1990-1996 and recovered after 1996.

Changes in tree cover were observed with high resolution aerial photography to determine relative contribution from fluctuation in the number of standing trees and changes in crown sizes. Land cover conversion removed dense tree cover from 50.2 hectares of the city's land surface between 1984-2004.

The results demonstrate that tree cover variability in the District of Columbia occurred primarily within low population density residential areas. Neighborhoods within these zones were analyzed to identify factors correlated with tree cover. Implications of the results include enhanced understanding of the possible impact of urban forest management, and how a focus on low density residential zones is appropriate in setting goals for expansion of urban tree cover.

TREE COVER VARIABILITY IN THE DISTRICT OF COLUMBIA

by

Andrew K. Johnston

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Advisory Committee:

Professor Samuel N. Goward, Chair
Professor Lisa M. Benton-Short
Professor Martha E. Geores
Professor Marla S. McIntosh
Professor Stephen D. Prince

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CHAPTER I

INTRODUCTION

Urban Forests

Urban forests consist of woody vegetation and associated plant life within densely populated human settlements. Despite the widespread presence of human-built structures and impervious surfaces in cities, urban areas contain a significant amount of vegetated land. Urban forests include tree cover in park lands and individual trees on streets and private property among a wide range of impervious surfaces within the urban environment (Rowntree 1984, 1986). Urban forests differ from traditionally defined forests due to the complex mixture of land cover types that define urbanized landscapes (Miller 1998). Within urban areas the prevalence of tree cover varies from lightly forested industrial zones to highly forested parks and residential areas. Tree cover occupies approximately 27% of the land area in US urban areas (Nowak and Crane 2001). By combining city-wide averages from municipal planning documents, the total size of urban forest cover in the United States has been estimated at approximately 70 million acres, including trees along streets, within parks, and on privately owned land (Clegg 1982).

Urban centers are home to more than half the Earth's people, and the urban population is growing more than twice as fast as the rural population (United Nations 1997, 2007). Urban areas cover about 3% of the total area of the conterminous United States (Defries et al. 1999; Imhoff et al. 2004), which is equivalent to about one third the surface area managed by the US. Forest Service. Within the United States urban development is accelerating faster than population growth (U.S. Department of Housing and Urban Development 2000), and 83% of the U.S. population resides within urban metropolitan areas (U.S. Census 2007). As the extent of urban land continues to grow, the importance of urban tree cover and its impact on ecosystem dynamics will increase in magnitude (Nowak et al. 2005).

Tree cover proportion within cities is a fundamental structural attribute of the urban environment (Nowak 2004). Tree cover proportion is a central factor in determining the ecologic function of the urban forest (Nowak and Dwyer 2007; Zipperer et al. 1997). Tree cover is a dynamic part of ecosystems that changes through time in response to anthropogenic and other factors.

Although urban vegetation has been widely examined in previous studies, there are limited numbers of reliable assessments of urban tree cover variability. The lack of knowledge on interannual changes in urban tree canopy is due in large part to the scale difference with city tree data and remote sensing data. The majority of past studies have observed tree cover as a static component of urban areas. While management authorities have many tools to evaluate amounts of tree cover and its ecosystem impact, interannual tree cover variability at the city or neighborhood scale is not well understood. It is currently a challenge to link street-level maintenance programs to wide-scale forest impact.

Spatially and temporally explicit mapping of urban tree cover variability would provide important new understanding of the urban environment. Tree cover observations can determine if static tree cover proportions are an appropriate assumption for urban ecosystem studies. Reliable maps of past urban tree cover variability would have implications for management. Better understanding of how urban tree cover changes through time would make it possible to better evaluate forest management decisions and their environmental impact.

District of Columbia Study Area

The District of Columbia is the capital of the United States, home to 617,000 residents (U.S. Census 2011), and the location of employment for approximately 740,000 people (Bureau of Labor Statistics 2012). The District of Columbia is an urban jurisdiction containing a full range of population densities and urban land use patterns. During the study period of 1984-2004, the city experienced significant population loss and demographic change.

The District of Columbia provides a unique opportunity to observe urban tree cover variability in a small area with diverse land tenure systems. As the national capital, Washington DC holds great interest for institutional and environmental stakeholders. As a result, a unique range of data is available on the city's forest resources. This includes survey and air photography not available for other large US cities.

Within the District of Columbia, federal and local government agencies and nongovernmental organizations have an extensive history in being engaged in maintaining trees and tree cover (Choukas-Bradley and Alexander 1987; D.C. Government 2012d), even as the city has experienced different oversight and planning strategies in its history. Washington DC is home to a strong non-profit urban forest advocacy community (Casey Trees 2003) with extensive resources and communications activity.

Study Overview

Objectives

The objectives of this study are to discover the extent to which tree canopy is a dynamic land cover component of the urban environment and how this dynamism is spatially variable in the context of urban land use patterns. This study also aims to improve observations of urban tree cover for understanding past variability. To achieve these objectives, the study includes a comparative assessment of remote sensing methods for observing tree cover, an analysis of urban tree cover temporal variability in the District of Columbia between 1984-2004, and an analysis of spatial variability of tree cover in the context of urban land use patterns.

Research Approach

The first phase of this research focuses on improving accuracy of urban tree cover measurements. Methods for observing proportional tree cover within a major urban center are explored for mapping proportional tree cover in 2000 for an entire city. This is accomplished through a comparative analysis of static urban tree cover in the District of Columbia. Two methods are applied to satellite remote sensing data to evaluate them for urban tree cover mapping. Validation of both techniques is performed with spatial tree cover from field surveys and public geospatial data on standing tree cover.

The second phase of the research study measures temporal dynamics of urban tree cover in the District of Columbia between 1984-2004. City-wide and local patterns of tree cover change are mapped with calibrated satellite observations every two years during the study period. Multitemporal validation and fine scale observations are made with image maps derived from aerial photography.

In the final phase of the research, the spatial variability of tree cover and land use patterns are examined. Spatial patterns of tree cover variability and urban land use are compared to understand local scale context for tree cover variability within low density residential zones, medium density zones, and high density zones. Residential property use and population data are compared to tree cover at the neighborhood scale. Possible implications for tree cover management are explored.

Spatial and Temporal Scale

The study area is the District of Columbia, a densely populated urban jurisdiction with tree canopy covering approximately 30% of its land surface area. Diverse types of data are available due to the city's status as the national capital. The District of Columbia is large enough to include diverse land use patterns including high density commercial uses, low density residential areas, and closed canopy forested park lands.

This study aims to observe tree cover 1984-2004. This temporal scale is appropriate to capture changes in tree cover occurring over multiple years. A 20-year study period is also appropriate to observe possible management and demographic changes. The years 1984-2004 were a period of immense human change when the city lost approximately 20% of its population.

Scope of This Research

To understand tree cover variability in an urban setting, alternate satellite remote sensing techniques were applied to observing past variability in proportional tree cover area within the District of Columbia. Links between tree cover variability, urban land use patterns, and zoning restrictions were investigated to determine possible links to tree cover variability.

Observations of tree cover changes were used in this study to illustrate the possible impact from land cover change on tree cover within the city. However, this research study was not aimed directly at understanding development strategies or specific projects that remove dense tree cover.

To better understand spatial variability, tree cover observations were analyzed in the context of urban land use and zoning restrictions. An analysis of selected demographic factors in urban neighborhoods provided insight for future work on the social processes that impact urban forests. The social factors involved in direct human uses of urban forests were beyond the scope of this study.

Weather and climate may play a role in urban tree cover variability but were beyond the scope of the current study. The possible impact of weather is interrelated with factors lacking sources of comprehensive data, such as management and species composition.

Contrast to Previous Work

The current study observed tree cover proportion as it varied within an urban setting. The majority of previous studies of urban forests have focused on observing static tree cover, spectral dynamics, or utilizing observations made in field survey plots. The studies that have measured change in urban tree cover (Nowak and Greenfield 2012; Walton 2008a; Poracsky and Lackner 2004) have compared tree cover on two or three dates. The current study measured tree cover every two years over a 20 year period to understand interannual variability.

Previous studies have utilized statistical estimates of uncertainty with air photography (Nowak and Greenfield 2012; Gillespie et al. 2012), field surveys (Nowak et al. 2006; Howard and Alonzo 2009), or satellite remote sensing (Walton, Nowak, and Greenfield 2008). These studies used statistical estimates of uncertainty without validation or comparisons to independent measurements to test the precision of tree cover estimates. In contrast, the current study measured uncertainty by utilizing multitemporal validation with high resolution aerial photography. These data were utilized to make consistent measurements of uncertainty based on independent observations, which were then applied to multitemporal tree cover observations.

CHAPTER II

BACKGROUND

Defining Urban Tree Cover

The method of quantifying forest cover can vary with the intended scale of observation. Physical measurements of canopy density and structure are appropriate at fine scales where observation of individual trees is needed. The total leaf or canopy surface area can be used to quantify tree cover in large areas. Generalized quantities such as proportional vegetation cover are useful when observing large areas at coarser scales, including the current research study.

Proportional tree canopy area is widely used in studies of the urban environment and resource management plans. This quantity is the proportion of land surface occupied by tree crown as viewed from above, which can vary from 0-100%. More specifically, tree canopy area is defined as the two-dimensional orthogonal projection of tree canopy onto the ground surface plane (Walton, Nowak, and Greenfield 2008). This is a useful way to quantify urban tree cover because it describes the spatial extent of forest in a given area, it is simple to compare between locations and time periods, it is a standard measure widely used by management authorities, and it is utilized in urban ecosystem studies as a fundamental metric of the urban environment (Zipperer et al. 1997).

Cover of shrubs can be included in the definition of urban tree cover. Some reports have assumed shrubs to be a part of urban forest cover (Walton, Nowak, and Greenfield 2008; O'Neil-Dunne 2009), while studies based on field surveys have mapped shrubs separately from tree cover (Nowak et al. 2006). Many studies have not explicitly addressed the question.

In the current study, shrubs smaller than two meters in diameter are considered to be separate from tree cover. This threshold was chosen based on the spatial resolution of the air photography used to produce the vector GIS tree data. Any shrubs smaller than the two meter threshold were not easily visible or separable from surface vegetation in these images.

Frameworks for Understanding Urban Land Cover

Conceptual models of urban spaces are useful for understanding the complex mixture of surface types in cities. All cities contain a mixture of trees, grass cover, bare soil, pavement, and buildings. Measuring the proportions of each land surface type is a fundamental method of describing the physical structure of a city. Past studies have utilized conceptual frameworks for understanding the physical makeup of urban landscapes.

A widely applied method for conceptualizing urban spaces for application with remote sensing is the V-I-S model (Ridd 1995). This model defines the urban landscape as the sum of three components: Vegetation, Impervious, and Soil. This ternary model was designed with remote sensing applications in mind and has been widely utilized to describe the spectral properties of urban spaces.

The V-I-S model has been used to study diverse urban spaces, from semiarid areas (Phinn et al. 2002) to temperate zones (Lu and Weng 2004). The initial application of the V-I-S model was in an urbanizing arid area (Ridd 1995). Although grass and trees occupy different functional parts of the urban ecosystem, the V-I-S model does not discriminate between the two. The problem of discriminating different types of vegetation is important especially in heterogeneous urban areas.

The V-I-S model has difficulty encompassing the wide range of reflectance values of impervious surfaces, which contain the widest range of reflectance values in urban areas (Herold et al. 2004). One method for extending the V-I-S approach to better define impervious spectral response is the incorporation of shaded and unshaded responses for impervious surfaces (Rashed, Weeks, and Gadalla 2001).

Defining alternative three-endmember generalizations for urban spectral response is another approach to solving the problem of reflectance variation. A three-endmember generalization for urban areas has been observed with the six reflective Landsat bands and with the four spectral bands available from IKONOS (Small 2001, 2003). In these studies, urban surfaces were assumed to consist of vegetation, high albedo, and low albedo surfaces. A positive correlation between a vegetation spectral response and proportional vegetation cover mapped using high resolution data was demonstrated, but with uncertainty ranging up to 10% vegetation cover, in large part due to confusion between tree and grass cover (Small and Lu 2006). A similar three-endmember approach can also be extended to discriminate urban grass and tree cover with moderate accuracy, utilizing estimates of tree shadow derived from airborne LIDAR data (Tooke et al. 2009).

The Substrate Vegetation Dark (SVD) model was introduced by (Small and Lu 2006) as an alternate to the V-I-S model. The SVD model describes spectral domain of urban areas as proportional values of bright, dark, and vegetated responses. While the SVD model neatly agrees with the spectral data found in satellite remote sensing data, it fails to describe the physical nature of an urban area. Studies that utilize a generalized three-endmember spectral model of urban spaces (Small 2001, 2003) do not provide estimates of physical land cover attributes that can be readily detected from a remote sensing perspective.

The Normalized Difference Vegetation Index (NDVI) can be used to estimate fractional vegetation cover with an assumed linear relationship (Arthur-Hartranft, Carlson, and Clarke 2003; Gillies et al. 2003). Comparisons between NDVI to fractional vegetation cover have shown that the relationship is not useful for estimating land cover at levels NDVI >0.4 (Small 2001).

Environmental Impact of Urban Forests

Carbon Dynamics

Urban forests play a role in global climate by sequestering atmospheric carbon. Urban forests contain 700 million tons of carbon and sequester 22.8 million tons annually in the 48 conterminous United States (Nowak and Crane 2001). Carbon storage in a single mid-size city can total about 150,000 tons (Myeong, Nowak, and Duggin 2006).

Urban forests are responsible for about 8% of the sequestration of atmospheric carbon by forests in the 48 conterminous United States (Pataki et al. 2003). This proportion will grow as urbanization expands. This is especially true for the heavily urbanized northeastern United States as the expansion of non-urban forest cover slows. Agricultural abandonment in the northeastern US allowed forests to expand by approximately 40% during the 20th century (Ramankutty, Heller, and Rhemtulla 2010). However, forest cover expansion slowed significantly by 1990 as few previously cleared agricultural spaces remained available for forest expansion (Ramankutty, Heller, and Rhemtulla 2010).

Urban growth replaces existing vegetation and agriculture, impacting net primary production (NPP), the increase of vegetation biomass over time. Urbanization has decreased NPP in the United States by about 1.6% compared to pre-urban times, which is roughly equivalent to the positive impact on NPP resulting from agriculture in non-urban areas (Imhoff et al. 2004). In the southeastern United States, urbanization during the 1990s decreased NPP by about 0.4% (Milesi et al. 2003). At the same time urban areas can exhibit extended growing seasons and higher photosynthetic production near the start and end of growing seasons, likely caused by higher temperatures, irrigation, and introduction of exotic species (Imhoff et al. 2000; Milesi, Potter, et al. 2005).

Air Quality

Forest cover plays a role in impacting urban air quality. Atmospheric particulates are intercepted by leaf surfaces, which can improve air quality by removing particulates smaller than 10 μm diameter linked to respiratory illness (McPherson 1992). Approximately 470 tons of particulates are removed by tree cover annually in New York City (Nowak, Crane, and Dwyer 2002). One study found that planting half a million trees in Tucson would remove 6,500 tons of particulates per year from the air (McPherson 1991). Urban forests also absorb ozone, sulfur dioxide, and nitric acid (Nowak, Crane, and Dwyer 2002); approximately 12g of these pollutants annually per square meter of canopy can be absorbed (Nowak and Crane 2000).

Many tree species are high emitters of Volatile Organic Compounds (VOCs) (Benjamin et al. 1997), which photochemically react with anthropogenic nitric oxide to produce ozone. VOCs emitted by trees are hydrocarbon compounds that include two classes of compounds known as isoprenes and monoterpenes (Rasmussen 1972). Between 0.5-8% of carbon fixed in photosynthesis is contained in isoprenes (Tingey et al. 1979; Monson and Fall 1991). Biogenic hydrocarbons are 2-3 times more reactive than those emitted during gas combustion (Carter 1994). These compounds are largely responsible for a visible haze of ozone over many partially wooded areas (Went 1960) and are a significant component of haze in fully wooded protected areas such as Great Smoky Mountains National Park (Shaver, Tonnessen, and Maniero 1994).

Emission rates vary by a factor of four between species (Benjamin et al. 1997). Only some plant families emit hydrocarbons. About 50 of the 400 existing plant families emit monoterpenes (Seiger 1981; Charlwood and Charlwood 1991). The reasons that trees produce hydrocarbons are poorly understood. VOCs appear to protect against photosynthetic damage and are toxic to some herbivores (Harborne 1988). Monoterpenes protect against some pathogens (Walter et al. 1989) and isoprenes may increase thermal tolerance (Sharkey and Singsaas 1991).

Emission of VOCs by urban forests can have significant air quality impact. Even without anthropogenic hydrocarbons, existing biogenic sources would make it difficult or impossible for Atlanta to meet federal air quality standards (Chameides et al. 1988). In the Houston area, biogenic sources accounted for more than 20 percent of total VOC emissions during the early 1990s (Texas Natural Resource Conservation Commission 1994). In the northeastern US, lower temperatures due to forest cover may reduce total VOC emissions, offsetting increases due to the presence of more trees (Nowak et al. 2000). High-emitting species common in Washington DC include red oak (*Quercus rubra*) and London plane tree (*Platanus x acreifolia*).

Local Climate and Hydrology

Forest cover impacts urban climate by reducing surface temperature and absorbing runoff precipitation. Trees lower surface temperature in urban areas by shading solar radiation and transpiring water vapor into the atmosphere (Scott, Simpson, and McPherson 1999). Urban tree cover has the potential for energy conservation by shielding buildings from wind in the winter and providing shade in the summer (Parker 1981). Methods of mapping these impacts have been incorporated into geospatial software tools marketed to forest management authorities (American Forests 2009).

Increased evapotranspiration by urban forests decreases temperature. The impact on the urban heat island effect has long been observed (Lowry 1967; Landsberg 1981). Nanjing, China claimed a decrease in temperature by 3ºC by planting 34 million trees in the late 1940s (EPA 1992).

Urban forests absorb and transpire water that would otherwise flow into storm drainage systems. Tree roots take up runoff and act as a reservoir for increased water flow into drainage systems. A modeling study in a Baltimore watershed showed that the proportion of rainfall intercepted by forest varied between 17-19% depending on the total canopy leaf area (Wang, Endreny, and Nowak 2008). An environmental advocacy group has estimated that each city-wide 5% increase in urban tree canopy reduces total storm runoff by 2% (American Forests 1999). However, these values have not been tested.

Ecosystem Services

Some biophysical functions of urban forests can be defined as "ecosystem services", such as absorbing storm runoff absorption and air pollution mitigation.

Advocacy by environmental groups has calculated these services as worth billions of dollars annually in large metropolitan areas (American Forests 1999). In these estimates, a single tree with a crown radius of 10 feet can annually provide about $94 worth of water runoff services and $1.25 for air pollution removal. The hypothetical replacement cost of urban trees can also be calculated. Cities with a population of just 100,000 can contain trees valued this way at $4.8 million (Nowak, Crane, and Dwyer 2002). Cities such as the District of Columbia cite environmental impacts in forest management plans (D.C. Government 2010a, 2012d).

<u>Social and Public Impact of Urban Forests</u>

Trees play a central role in determining the aesthetic nature of streetscapes and forming perceptions of desirability of urban neighborhoods. Neighborhoods with larger amounts of tree cover are viewed more positively by most residents (Ulrich 1986; Tyrväinen et al. 2005). Planning practices that incorporate significant amounts of urban tree cover are an important factor in the maintenance and increase of residential property values (Lullik 2000; Anderson and Cordell 1988). The visual appeal of tree cover is highly valued by urban residents, especially residential zones and areas with sidewalk-accessible retail spaces. Urban tree cover impacts perceptions of neighborhood safety and can play a role in reducing street crime (Prow 1999; Donovan and Prestemon 2010).

Property values and educational attainment of residents have been found to be correlated to health and mortality of street trees (Torres 2011). Street tree mortality has also been compared to demographic factors and subjective assessment of private property maintenance (Clapp 2010). Tree cover changes within urban residential neighborhoods have been analyzed to identify demographic and physical characteristics associated with high tree mortality (Lowry, Baker, and Ramsey 2012). Other studies have examined how social factors interconnect with the physical urban structure (Grove, Troy, et al. 2006) and crime statistics (Troy, Grove, and O'Neil-Dunne 2012).

Management of Urban Forest Resources

Government Management

Urban jurisdictions have responded to aesthetic desires of residents and environmental concerns by devoting resources to maintaining tree cover. Management goals for most of large US cities aim to maximize forest cover. Because of their visibility, public street trees are a primary focus of these efforts. The District of Columbia contains more than 130,000 street trees (Casey Trees 2003), which are the responsibility of the Urban Forestry Administration (UFA), a unit of the Department of Transportation (D.C. Government 2007b, 2010b).

On private lands, local governments create and enforce regulations limiting the removal of trees. The DC comprehensive plan includes environmental protection elements designed to protect the city's tree cover. The plan also called for city-wide forest canopy goals to be set (D.C. Government 2006). In 2009, the DC Department of Environment and Department of Transportation jointly adopted the goal of achieving 40% total tree canopy for the city by 2035 (D.C. Government 2010a).

Despite the demands in urban settings for healthy tree cover, resources devoted to tree maintenance significantly decreased in many large cities in the 1970s and 1980s (Tschantz and Sacamano 1994). In many cities during the 1990s renewed interest grew in maintaining urban forest resources (McPherson 1993; McPherson et al. 1997). Fiscal constraints on the District of Columbia government caused a decline in resources devoted to tree management in the 1990s (Johannsen 1998).

Management authorities have developed efforts to map standing trees. A national survey of municipal street tree programs estimated that the United States has 60 million street trees, with about the same number of empty street spaces available for additional trees (Keilbaso et al. 1988). The National Capital Planning Commission has contracted for the mapping of all trees in the District of Columbia using air photography in the same period (D.C. Government 2007a).

OASIS, an intergovernmental collaboration in New York City, has collected and distributes field data on tree cover across the city. The DC Green Infrastructure Collaborative, modeled on OASIS, aims to map trees and "green" roofs throughout the District of Columbia (DCGIC 2007). The DC Department of Environment and Department of Planning developed a planning initiative for environmental policy that includes setting goals for increases in tree planting on public and private land (D.C. Government 2012d).

Government management of trees on public lands can play a role in tree cover changes. Due to their high visibility and impact on local scale tree cover, shade trees on public land adjacent to streets and sidewalks are a significant focus of interest.

Non-Government Advocacy

Non-governmental organizations engage in advocacy to promote maintenance and expansion of urban forests. Casey Trees, a non-profit organization located in Washington DC, engages in advocacy and education efforts focusing on the city's tree cover. This organization comprehensively surveyed Washington DC street trees in 2000 (Casey Trees

2003).

Many urban jurisdictions, including the majority of the nation's large cities, have chosen to follow guidelines of the "Tree City USA" program sponsored by the National Arbor Day Foundation. Tree City USA certification requires jurisdictions to declare a responsible agency for maintaining tree cover, create legal structure for this body to implement policy, and provide an annual tree maintenance budget of at least $2 per capita (Arbor Day Foundation 2007). At the county or local level, every jurisdiction in the Washington metropolitan area including the District of Columbia is a "Tree City". The similar "Tree Campus USA" program was intended for universities (Arbor Day Foundation 2012). In the Washington metropolitan area, American University in northwest DC and the University of Maryland, College Park have joined the Tree Campus USA program.

Public awareness of urban forest dynamics in some cities was shaped by reports from the advocacy group American Forests showing significant declines in urban forests. Landsat-based observations of forest change in the District of Columbia showed a 40% decline in tree cover in the District of Columbia over a 30 year period (American Forests 2002b). A similar methodology was applied to several other US urban areas, indicating an average 30% decline of tree cover for urban areas in the eastern United States (American Forests 2001, 2003b). The subpixel classification module in Erdas remote sensing software was used to perform these analyses (Erdas Inc. 2010). The methodology included no data calibration, accuracy assessment, or validation.

Efforts to Set Goals for Urban Forest Cover

Urban jurisdictions set goals for the total amount of tree cover. Environmental advocacy organizations have promoted targets calling for 40% total tree cover in urban areas east of the Mississippi, with 50% in suburban residential areas, 25% in urban residential areas, and 10-15% in urban cores (American Forests 2002b, 2003a). Roanoke, Virginia (Urban Forestry Task Force 2003) and Montgomery Country, Maryland (Montgomery County 2000) selected these targets as future goals for urban forest cover.

Several other cities have declared specific forest canopy goals (Table 1). Boston set a goal of planting 100,000 trees (City of Boston 2007) and Salt Lake City 1 million trees (Salt Lake City 2007). Beijing embarked on an ambitious program of planting "greenbelts" to increase urban forest cover, with limited success (Yang and Jinxing 2007). Tucson, Arizona made plans for 500,000 new trees (McPherson and Haip 1989). Stuttgart, Germany developed a tree planting program with goals to increase forest cover in the 1970s (Akbari et al. 1992). Los Angeles planned 5 million new trees in the 1990s (Akbari et al. 1992), but announced a more limited goal of 1 million in the subsequent decade (McPherson et al. 2007, 2011).

The development of realistic and achievable targets for urban forest canopy requires analysis of the space available for future tree growth (Raciti et al. 2006). Geospatial data have been used to determine the space available for forest canopy expansion in Vancouver, Washington (Kaler and Ray 2005) and Portland, Oregon (Poracsky and Lackner 2004). Urban forest goals for Los Angeles were evaluated using remote sensing data to show that physical space exists for 1.3 million new trees (McPherson et al. 2007), which would increase forest canopy from 21 to 33%. Combinations of high resolution remote sensing and GIS data were used to evaluate space available for forest canopy in Baltimore (Galvin, Grove, and O'Neil-Dunne 2006b), Annapolis (Galvin, Grove, and O'Neil-Dunne 2006a), and New York City (Grove, O'Neil-Dunne, et al. 2006).

Table 1. Proposed Urban Tree Canopy Goals

Reference	City	Mapping Method	Goal (Current)
Galvin et al. 2006b	Baltimore	IKONOS, GIS	45% (20%)
Kaler and Ray 2005	Vancouver WA	LC stratification	28% (20%)
Poracky, Lackner 2004	Portland OR	LC stratification	45% (25%)
Grove et al. 2006	New York	FOS Toolbox	30% (23%)
McPherson et al. 2011	Los Angeles	GIS placement	28% (21%)
O'Neil-Dunne 2009	Washington DC	High res. class.	40% (30-35%)

The DC comprehensive plan includes environmental protection elements designed to protect the city's tree cover (D.C. Government 2006). This plan, intended to guide future zoning and land use in the city, called for mapping of tree canopy and setting proportional canopy targets. A goal of 40% total tree canopy cover was set in 2009 (D.C. Government 2010a), which is aligned with a neighboring jurisdiction (Montgomery County 2000) and recommendations from environmental advocacy groups (Casey Trees 2010).

Available space for new tree growth in the District of Columbia has been measured, showing the city can accommodate more than 20,000 additional street trees (Casey Trees 2003) and that space exists to theoretically double current tree cover to 67% land surface area (O'Neil-Dunne 2009, 2010). However, estimates of existing tree cover in these reports have not been validated or included accuracy assessments. The latter reports define tree cover as including shrubs, and therefore may overestimate tree cover compared to field surveys that exclude shrubs (Nowak et al. 2006).

Urban Tree Maintenance

The primary goals for urban forestry include maintaining trees for aesthetic reasons at the neighborhood scale. Maintaining trees in an urban setting requires attention to location of individual trees relative to surrounding impervious surfaces such as roads and sidewalks.

It is common for 10% of newly planted urban trees to die within a year of planting (Impens and Delcarte 1979). New urban trees are particularly vulnerable to drought stress (Gilbertson and Bradshaw 1990) and competition from weeds (Gilbertson and Bradshaw 1985). Soil compaction can limit root growth, and water logging can be caused by compacted subsoil and poorly designed planting pits (Hunt, Bradshaw, and Walmsley 1991). Salt runoff can cause significant problems for street trees in cities where it is used for de-icing (Dobson 1991).

Tree planting in urban environments can take place to support different types of urban forests for short-term or long-term rotation (Bradshaw, Hunt, and Walmsley 1995). Examples of short term rotation areas are industrial areas in need to rapidly growing tree cover with sufficient soil moisture and nutrients. Longer-term rotation would be more appropriate for publicly owned areas not likely to be developed. Tree species with slower growth rates would be appropriate for these areas (Bradshaw, Hunt, and Walmsley 1995). Species widely used for long term rotation in the District of Columbia include red maple (*Acer rubrum*), red oak (*Quercus rubra*) and London planetree (*Platanus x acerifolia*) (Bradshaw, Hunt, and Walmsley 1995).

The growing season for urban forests can be lengthened due to higher urban temperatures and maintenance. Compared to biomes not dominated by human activities, urban vegetation begins to green up earlier and enters dormancy later. Greening of urban forests can begin about 10 days earlier and end 20-25 days later than non-urban deciduous forests (Zhang et al. 2003).

Management for Disease and Insect Control

Limiting defoliation caused by insects and disease is a primary aim of urban forest management. The gypsy moth (*Lymantria dispar*) has played a role in defoliation in the northeastern United States since its accidental release in Massachusetts in 1869. The larval stage of the insect consumes significant leaf material during outbreaks. Typical gypsy moth defoliation events occur over 2-4 years. Light gypsy moth defoliation can remove 30% of the canopy leaf area in a way that may not be visually detectable from ground observers, while more significant events can remove more than 50% canopy leaf area (Hoover 2001). After defoliation, most deciduous trees produce new leaf buds and foliage in the following months. The refoliation events create stress for trees, which can be compounded in subsequent years of insect defoliation or climate impact. This can negatively impact canopy area for the years following peak defoliation (Hoover 2001).

Local and federal government agencies take steps to control other impacts of disease and insects, including in the Washington DC area. Dutch elm disease is a fungal infection spread by the elm bark beetle. In the early 20th century there may have been more than 40,000 *Ulmus* trees on DC streets (Choukas-Bradley and Alexander 1987). Dutch elm disease has killed at least 25,000 since 1950, and by 2008 only about 8,200 elm trees remained on the city's streets (U.S. Forest Service 2010a). Since that time the DC Urban Forestry Administration has developed plans to replace dead trees with disease-resistant elms (D.C. Government 2007b). A 2009 survey by the DC Urban Forestry Administration and USDA Forest Service found extensive bacterial leaf scorch in maple, oak, and elm species (D.C. Government 2010b). Although ash species make up only a small percentage of DC street trees, in 2011 the USDA added the District of Columbia to the quarantine area to control spread of the Emerald Ash Borer (*Agrilus planipennis*) (D.C. Government 2011a).

Mapping of Urban Tree Cover

Estimates From Field Plot Observations

The total amount of tree coverage in a city can be estimated by scaling up observations made at small survey plots. The most prominent examples are found in a series of modeling exercises performed by the U.S. Forest Service Northern Research Station that quantitatively estimated the proportional amount of tree cover in large North American cities (Nowak et al. 2000; Nowak, Crane, and Dwyer 2002; Nowak et al. 2006). Tree cover estimates ranged from a minimum of 7% (Calgary) to a maximum of 36% (Atlanta). New York was estimated to be 21% covered by tree canopy, while Baltimore and Washington DC were estimated to contain 25% and 29%, respectively. The model used in these analyses required randomly distributed 20x20 meter plots, stratified by land cover type (Nowak and Crane 2000). While broad characterizations of urban forest are possible using this approach, these methods do not produce the spatially explicit maps that could be used to investigate distribution of urban forest or how it changes through time.

For analyses using plot-based survey data, tree data are collected within small plots and then extrapolated to a wider area. The number and location of plots varies between studies. The CityGreen software used for many regional analyses (American Forests 2009) includes only general guidance for choosing site locations or their spatial distribution. The i-Tree software package (U.S. Forest Service 2010b), developed as an enhancement of the UFORE model (Nowak and Crane 2000), requires randomly distributed plots 1/10 acre in size. Plots locations can be stratified by land cover type.

Washington DC's urban forest has been characterized using this approach (Nowak et al. 2006). Survey data were collected in summer 2004 at 201 plots stratified by land use as defined by the DC zoning code. Tree cover proportion was mapped for each census tract by calculating zoning types within each tract. Tree cover proportion varied between 0%-65% in different census tracts.

It is also possible to identify urban vegetation units and then establish camera stations for monitoring change (Rogers and Rowntree 1988), but this method is not practical for city-wide observations due to cost and complexity.

Aerial photography is useful for mapping urban forests because the imagery scale allows individual trees to be visible (Walton, Nowak, and Greenfield 2008). Randomly distributed plots can be observed and scaled up to the entire study area (Walton 2008a; Nowak et al. 1996). Using this approach, trees are counted at points on airphotos, which can be scaled up to an entire jurisdiction, resulting in city-wide estimates of tree cover. This approach has been applied for estimating urban tree cover in upstate New York cities for validation of satellite remote sensing (Walton 2008a).

Spatially Explicit Observations

The use of remote sensing allows spatially explicit measurements to be made across the city and wider areas. By combining land cover proportions measured utilizing air photography and estimates of impervious surface area derived from observations of nighttime urban lights from the Defense Metrological Satellite Program, land surface within U.S. urban areas has been found to be evenly split between vegetation and impervious surfaces (Milesi, Running, et al. 2005).

Moderate resolution data can be used to map urban vegetation at a scale more useful for understanding the urban environment. Applications have included the use of spectral vegetation indices (Arthur-Hartranft, Carlson, and Clarke 2003; Gillies et al. 2003), per-pixel statistical clustering (Guindon, Zhang, and Dillabaugh 2004; Weber and Puissant 2003), decision tree classifiers (Goetz et al. 2004; Goetz et al. 2003), and subpixel mixture models (Weng, Lu, and Schubring 2004; Small 2003; Wu 2004).

Land cover classification of Landsat data estimated tree cover between 1-16% within different sections of Indianapolis (Weng, Lu, and Schubring 2004). A comparison of several methods for mapping of urban tree cover in Syracuse, New York showed that tree cover estimates were generally consistent when mapped with Landsat data and a subpixel technique, per-pixel classification of high resolution data, and with field survey plots (Walton, Nowak, and Greenfield 2008). However, estimates derived with continental-scale data at 1 kilometer resolution were unreliable (Walton, Nowak, and Greenfield 2008).

Image texture information makes use of the variation of pixel values in surrounding pixels to better characterize land cover, which has been utilized to better discriminate cover types in spectrally complex urban areas (Zhang 2001; Myeong, Hopkins, and Nowak 2001).

LIDAR scanning data can be incorporated into per-pixel classification. However, when this combination was applied with high resolution satellite data for mapping tree cover in Indianapolis, it did not improve classification accuracy above 80% (Baller 2008).

High Resolution Mapping

High spatial resolution data can be used to map urban land cover. In Montgomery County, Maryland high resolution multispectral data from the IKONOS satellite were used with a decision tree classifier to map tree cover, with 38% of this suburban landscape classified as tree canopy (Goetz et al. 2003). This map was used to train a regression tree classifier to map impervious surfaces and tree cover over the entire Chesapeake Bay watershed using Landsat data (Goetz et al. 2004).

Although the raw per-pixel accuracy of the Montgomery County classification was high, the total spatial extent of predicted tree cover (49,522 ha) was about 34% greater than tree cover mapped in the validation data (36,849 ha) (Goetz et al. 2003). This was likely due to the ability of the IKONOS data to detect very small groups of trees absent in the planimetric data used for validation, and spectral confusion between tree and grass cover. Urban and suburban tree cover was excluded from the training data, because the goal of the study was to identify fully forested areas instead of urban forests (Goetz et al. 2003). High spatial resolution can negatively impact accuracy of urban tree cover mapping because canopy density and structure can vary significantly between small pixels, while such variability is less evident in moderate resolution data such as Landsat (Goetz et al. 2003). The lack of high spatial resolution mid-infrared data in sources such as IKONOS limits their use for discriminating tree and grass cover.

Object-Oriented Techniques

Object-oriented classification of high resolution data is an approach that makes use of spatial information content of imagery. The shapes of objects such as trees can be used to identify them in remote sensing data. This type of approach has been applied for analysis of the urban forest of Baltimore (Galvin, Grove, and O'Neil-Dunne 2006b), New York City (Grove, O'Neil-Dunne, et al. 2006), and Dunedin, New Zealand (Mathieu, Freeman, and Aryal 2007). High resolution image data have been applied to urban forest mapping with eCognition software (Mathieu, Freeman, and Aryal 2007; Grove, O'Neil-Dunne, et al. 2006).

Object-oriented approaches have proven useful for forest stand delineation (Radoux and Defourny 2007) and mapping of heterogeneous forests (Van Coille, Verbeke, and De Wulf 2007). One study found that the incorporation of spatial data was needed to discriminate individual tree crowns, mostly due to similar tree and grass responses in the near infrared (Hirschmugl et al. 2007). While feature extraction is useful with high resolution data, testing with hyperspectral data and QuickBird data have shown that spectral resolution may be more important than spatial resolution for urban applications (Gamba and Dell'Acqua 2007). A study of urban land cover in the Phoenix area found that object-oriented techniques applied to four-channel high resolution satellite data produced accurate classifications, although 15% of reference tree pixels were misclassified as grass (Myint et al. 2011).

Other data sources can be combined with object-oriented approaches. Incorporation of Light Detection and Ranging (LIDAR) data allowed parcels to be classified in the Gwynns Falls watershed in Baltimore City and County, Maryland with 92% accuracy (Zhou and Troy 2008).

Using high spatial resolution data and feature extraction techniques based on application of eCognition software (Definiens 2007), the city of Baltimore was mapped as being 20% covered by tree canopy, with more than one third of the total within residential areas (Galvin, Grove, and O'Neil-Dunne 2006b). The tree canopy of New York City was mapped in a similar way (Grove, O'Neil-Dunne, et al. 2006). This analysis revealed the city to be 24% covered by tree canopy, more than half of which was found in public parks and along sidewalks.

Object-oriented methods were applied to high resolution data to map tree cover in the District of Columbia (O'Neil-Dunne 2009). The results show details of the city's tree cover, with individual trees visible in the data. However, no accuracy assessment or validation was performed. Tree cover mapped in this way totaled 35% for DC, contrasting with 28-29% proportion as mapped by plot-based measurements (Howard and Alonzo 2009; Nowak et al. 2006). The differences may be due to shrub cover mapped as tree cover in the object-oriented results. Shrub cover mapped using plot surveys (Howard and Alonzo 2009; Nowak et al. 2006) is approximately equal to the difference in tree cover proportion measured with high resolution data.

High spatial resolution observations by themselves have some shortcomings for detecting urban forest dynamics due to limited temporal coverage and the lack of middle infrared measurements. The temporal coverage available from high resolution satellite data products begins only in 1999, while moderate resolution Landsat data extend to 1984. While high resolution data and object-oriented techniques are useful for future urban forest monitoring, this research will focus on utilizing the Landsat data record to investigate how urban forests have changed through time in the past.

Urban Tree Cover Variability

Challenges to Understanding Urban Forest Dynamics

Interannual variability in urban tree cover is not well understood. Comparing urban forest maps at different scales can lead to inaccurate assessments of standing tree cover and canopy dynamics. After a city-sponsored program to plant 3,000 new trees, the city of Roanoke, Virginia claimed an increase in total tree cover proportion from 32% to 48% between 2002-2008 (City of Roanoke 2010). However the claimed increase is unlikely, as each new tree would need to account for an average 1.4 acres of canopy. The data used to compare tree cover in 2002 and 2008 differ in source data and scale. The 2002 assessment was a per-pixel classification of 4 meter resolution IKONOS satellite data (American Forests 2002a). The 2008 assessment was performed by the Virginia Department of Forestry, based on an object-oriented classification of 1 meter resolution air photography (Virginia Department of Forestry 2010).

Geospatial software products are used to assess the value and function of urban forests (i.e. (American Forests 2009). These tools incorporate spatial data on tree canopy in small sites, calculating the value of a group of trees for its shading, pollution removal, and reducing storm runoff. These results are then extrapolated to an entire city or metropolitan area (American Forests 2009). Despite being used by urban jurisdictions, the mapping portions of these tools have not been assessed in the scientific literature.

Fine Scale Observations

An analysis of 20 U.S. cities showed tree cover declines in 19 cities, but the observed declines were modest and exceeded the standard error of tree cover measurements in only two of the cities (Nowak and Greenfield 2012). This study utilized air photography surveys from two dates separated by 3-7 years. Baltimore was included in the study but Washington DC was not. For Baltimore, combined tree and shrub cover was observed to change from 30.4% to 28.5% between 2001-2005, a 1.9% change. This equates to annual tree cover loss for Baltimore of 0.48%. The mean annual decrease for all 20 cities was reported as 0.27%. However, the standard error for all measurements was approximately 1% (Nowak and Greenfield 2012). Uncertainty was statistically estimated but not derived from survey or remote sensing data.

Preliminary District of Columbia reports showed that city-wide tree cover changed by 2% between 2006-2011 (D.C. Government 2012a; O'Neil-Dunne 2012). Changes within different DC wards ranged from -8% in ward 3 to +7% in ward 4 (D.C. Government 2012a). These analyses were performed utilizing object-oriented classification (D.C. Government 2012a) and human image interpretation (O'Neil-Dunne 2012). However, error assessments and validation were not performed and a specific descriptions of the methodologies were not reported (D.C. Government 2012a; O'Neil-Dunne 2012).

An analysis of urban forest dynamics in Portland, Oregon showed that total tree cover changed from 25.1% to 26.3% between 1972-2002 (Poracsky and Lackner 2004). Unsupervised classification was applied to Landsat data on three dates (1972, 1991, 2002). Proportional tree cover in 15% increments was classified in different parts of the city. Classification accuracy was not high (69%) compared to visually inspected airphotos. Calibration was not performed for the satellite remote sensing data. Although major forest removal may have been observable using these methods, it was not possible to reliably confirm minor changes in urban forest canopy, because tree cover was classified in 15% increments and total canopy area was observed to change by less than 5% (Poracsky and Lackner 2004).

Airphotos were interpreted to measure possible changes in tree cover within cities and towns in western upstate New York (Walton 2008a). Tree cover in 36 cities was mapped using manually interpreted points on airphotos. This was used as validation data for application of satellite remote sensing data. The airphoto validation data showed that 6 of the populated places included in the analysis had slight increases in tree cover ranging between 5-10% from 1994-2002, The other 30 had no significant changes (Walton 2008a). The validation data were produced by interpretation of random points on airphotos. Therefore the results are estimates of total tree cover proportion instead of spatially explicit maps of changes in tree cover.

Field Surveys

Plot-based estimates can be repeated at different times to describe changes in a city's tree cover. Tree cover observed at plots in 2004 were used to estimate total tree cover at 28.6% land surface for DC (Nowak et al. 2006). This analysis was repeated in 2009 using the same 201 plots (Howard and Alonzo 2009), showing 28.1% total tree cover. Between 2004-2009 the number of trees was observed to increase from 1.93-2.88 million, with standard error of 223,000 and 288,000, respectively. Most of the increase occurred in smaller size trees. Changes including proportional tree cover were not observed to be statistically significant (Howard and Alonzo 2009). Only the increase in number of trees exceeded standard error. However, such a significant increase in tree numbers in only five years has not been validated with other observations.

Change in Number and Size of Trees

Both the number of standing trees and change in the size of tree crowns are aspects of tree cover dynamics. Knowledge of the relative importance of these two factors would provide important guidance for forest managers when allocating resources for tree planting and maintenance.

Numbers of trees in urban neighborhoods fluctuates as trees are planted, removed, and replaced. The mortality of street trees can be as high a 34% within two years of planting (Nowak, McBride, and Beatty 1990). Mortality of newly planted street trees in the District of Columbia averages approximately 10% annually (D.C. Government 2012c). Street trees planted by a non-governmental organization in the District of Columbia experienced 21% mortality within 3 years of planting (Torres 2011).

Tree cover change over 80 years observed with air photography indicated that the number of trees in arid Los Angeles grew by 250% between the 1920s and 2006 (Gillespie et al. 2012). However, the low spatial resolution of historical air photography limited precision of historical tree measurements (Gillespie et al. 2012).

The growth of tree crowns would impact overall tree cover. Urban street trees can grow in height at an annual rate of 0.2 meters (Lukaszkiewicz and Kosmala 2008), but there are few measurements of urban tree crown fluctuations at high precision. One study measured mean growth of crown radius for unshaded *Tilia* trees in an urban setting at 0.1 meter per year (Larsen and Kristoffersen 2002).

Uncertainty of Urban Tree Cover Observations

Studies of urban forest dynamics have typically utilized statistical estimates of uncertainty such as standard error to define precision of observations. In studies using field surveys (Nowak et al. 2006; Howard and Alonzo 2009), standard error was calculated as:

$$SE_{\bar{x}} = \frac{s}{\sqrt{n}} \qquad \text{Equation 1}$$

where *s* is the sample standard deviation and *n* is the number of samples.

Studies using only standard error to estimate uncertainty without supporting data have reported high precision observations, including a change in the number of District of Columbia trees by approximately 32% over five years (Howard and Alonzo 2009; Nowak et al. 2006). However, a study that performed repeated measurements of urban tree counts using historical air photography found errors between 14%-43% compared to field surveys (Gillespie et al. 2012).

Studies of air photography (Nowak and Greenfield 2012; Gillespie et al. 2012) and satellite remote sensing (Walton, Nowak, and Greenfield 2008) have utilized a modified calculation for standard error:

$$SE = \sqrt{p \times (1 - p)/n} \qquad \text{Equation 2}$$

where *p* is the proportion of land surface occupied by a land cover type and *n* is the number of samples. Standard error calculated this way for tree cover observations in Baltimore was 1.0%, which was used as a threshold to report changes in city-wide tree cover of 1.9% (Nowak and Greenfield 2012). Standard error for tree cover measurements in Syracuse ranged between 1.8%-2.5% (Walton, Nowak, and Greenfield 2008).

However, these studies did not include independent observations to demonstrate that urban tree cover could be observed with 1% precision.

Global and Continental Scale Observations

The use of global and continental scale remote sensing products has been explored for estimation of urban vegetation abundance. Tree cover proportion has been a widely used quantity for global scale studies. A global review showed that vegetation cover in urban areas varies from 76-82% from satellite observations taken 13 years apart (Zeng et al. 2003).

Data from the Advanced Very High Resolution Radiometer (AVHRR) sensor have been used to map global scale tree cover (Defries, Hansen, and Townshend 2000). At 8km resolution, it is possible to observe land cover variations exceeding 10%, but it cannot detect the minor changes likely caused by anthropogenic factors (Defries, Hansen, and Townshend 2000). Fractional forest cover has also been mapped for the conterminous US with 1km AVHRR data (Zhu and Evans 1994). Comparisons between both low resolution products show fractional forest cover ranging between 26-42% for the mid-Atlantic region of the US in 1991 (Zhu and Evans 1994; Defries, Hansen, and Townshend 2000).

Global scale AVHRR observations were used to estimate urban tree cover in the 48 conterminous US states (Dwyer et al. 2000). This report estimated urban tree cover averaging 27.1% for US cities. However, the results underestimated tree cover in many urban areas, especially in smaller urban centers (Dwyer et al. 2000).

The Landsat-based National Land Cover Database (NLCD) 2001 produced by the USGS indicates land cover proportions in that year for the United States (Homer et al.

2007). These data have been found to not produce reliable estimates of urban tree cover in cities in upstate New York (Walton 2008a). Both the NLCD and AVHRR products were found to underestimate urban tree cover and cannot be used to develop reliable estimates of urban tree cover dynamics (Greenfield, Nowak, and Walton 2009). Urban vegetation changes are most likely not observable using AVHRR or NLCD data, and any significant trends are not possible to observe (Walton 2008a).

Data from the MOderate Resolution Imaging Spectroradiometer (MODIS) sensor has been used to produce global maps of fractional vegetation cover (Hansen et al. 2003). To make an assessment of course scale tree cover variability in the District of Columbia, MODIS tree cover products were downloaded from the Global Land Cover Facility (Hansen et al. 2006). These data indicate that tree cover within the District of Columbia varied between 19-21% of land surface area from 2000-2005. This estimate fluctuates about 10% below values based on field surveys and finer scale remote sensing. This underestimation of urban tree cover is similar to that found in another study attempting to apply global scale data to mapping urban vegetation (Walton 2008a).

Tree cover maps derived from MODIS data were not intended for application at the scale needed to detect forest changes within an urban jurisdiction. Better-calibrated data at a more appropriate scale were needed to understand how and where tree cover changed within the District of Columbia.

Spectral Dynamics of Urban Vegetation

The spectral response of urban vegetation can be measured from satellite data to provide a measure of a city's "greenness". This can also provide broad measurements of changes over time. In New York City, the spectral signature of urban vegetation was correlated with total number of standing trees as mapped by municipal management agencies (Small and Lu 2006). Another study measured vegetation reflectance for New York City at three dates over a 20-year period (Small et al. 2010) and identified areas experiencing decreases and increases in vegetation spectral response. However, neither of the above studies included measurements of physical changes in tree cover. Although tree cover is one component of the spectral response of urban vegetation, turf grass present in cities would be expected to also play an important role.

Spatial Variability of Urban Tree Cover Dynamics

Changes in tree cover would be expected to vary between areas of the city with different types of land use and population density. Knowledge of the spatial variability of urban tree cover dynamics would provide important tools for understanding links between those changes and the nature of the human-built urban structure.

Reviews of the spatial variability of forests within cities are limited, as most studies have utilized methodologies that produce results for an entire jurisdiction or large sections of a city. Previous studies have compared tree cover in different political sub-units within the District of Columbia, but these did not investigate changes over time (Nowak et al. 2006; O'Neil-Dunne 2009). In Portland, Oregon some neighborhoods were observed to have slightly increased tree cover between 1991-2002 compared to other parts of the city (Poracsky and Lackner 2004). The study period roughly corresponded with a city tree planting program, but other fluctuations may have had larger impact as the majority of plantings took place in already well-forested neighborhoods (Poracsky and Lackner 2004).

Remote Sensing Background

Spectral Sensitivity

Advancing understanding of urban forests requires accurate mapping of urban tree cover. Remote sensing observations are well suited to perform analysis of urban land cover. The spectral response of trees in remote sensing data can be utilized to identify their presence and extent. Urban vegetation includes grass and trees, which contain different spectral responses due to shortwave infrared absorption and significant shade effects (Lu and Weng 2004). Tree cover has low reflectance in visible wavelengths and high reflectance in near infrared wavelengths, similar to the response seen with grass cover. Tree reflectance is lower than grass in shortwave infrared wavelengths, allowing a degree of discrimination between tree and grass in spectral data.

Table 2. Landsat spectral characteristics

Band	**Wavelength**	**Spectrum**	**Application**
Band 1	0.45-0.52 μm	Visible, Blue	Bathymetry, Ocean Color
Band 2	0.52-0.60 μm	Visible, Green	Cartography, Vegetation
Band 3	0.63-0.69 μm	Visible, Red	Cartography, Photosynthesis
Band 4	0.76-0.90 μm	Near Infrared	Vegetation Mapping
Band 5	1.55-1.75 μm	Shortwave IR	Soil Moisture, Tree/Grass Discrimination
Band 7	2.08-2.35 μm	Shortwave IR	Mineralogy, Tree/Grass Discrimination

Remote sensing data from the Thematic Mapper (TM) on the Landsat 5 satellite and the Enhanced Thematic Mapper plus (ETM+) on Landsat 7 are used in this study. Both sensors acquire observations of radiance in six channels ranging from 0.45-2.35 μm wavelengths (Table 2).

Several features of trees are spectrally detectable using satellite remote sensing data. In visible wavelengths between 0.4-0.7 μm, tree cover can be discriminated by absorption and shadowing effects. This wavelength range is referred to as Photosythetically Active Radiation (PAR). Radiation between 0.6-0.7 μm, seen as the color red in human vision, is strongly absorbed by chlorophyll pigment. In near infrared wavelengths longer than 0.7 μm, vegetation reflects strongly due to refractive effects of cell walls within plant leaves. In shortwave infrared wavelengths, tree cover reflects less strongly than grass due to absorption by leaf water (Woolley 1971), and shadowing of stems and branches (Ranson and Daughtry 1987).

High spatial resolution sensors on satellite platforms such as IKONOS provide observations using similar visible and near infrared channels that can be compared between sensors (Song 2004), although not including shortwave infrared. Significant differences in radiometric response have been demonstrated between Landsat and IKONOS data (Goward et al. 2003). Calibration sites should be selected near the classification area due to spectral variation within each satellite scene, preventing the use of calibration sites spatially far removed from mapping targets (Olthof and Fraser 2007).

Landsat data have been applied in past studies to map urban land cover change and tropical deforestation. Collections of Landsat data were utilized in systematic mapping of forest removal in the Amazon Basin (INPE 2000) and in Bolivia (Steininger et al. 2000). Landsat observations are scaled appropriately to detect tropical deforestation, and comprehensive Landsat coverage of large areas has been shown to be useful for accurate mapping of deforestation (Tucker and Townshend 2000).

Time series Landsat data have been used to investigate forest disturbance history (Cohen, Yang, and Kennedy 2010; Kennedy, Yang, and Cohen 2010) and understanding and predicting forest structure change (Pflugmacher, Cohen, and Kennedy 2012). Time series Landsat data have been developed and applied for understanding forest dynamics over large areas (Huang, Goward, Masek, Gao, et al. 2009; Goward et al. 2008).

Subpixel Land Cover Estimation

Spatial extent of tree canopy within pixels can be detected using remote sensing data. Although the spatial heterogeneity of urban areas presents challenges for mapping urban forests, remote sensing techniques can be used to estimate the prevalence of land cover types within pixels.

Transformations of remote sensing data have been used to convert reflectance values into estimates of vegetation proportions within urban spaces. Applications for urban areas have included combinations of multiple affine transformations to detect land cover types (Zha, Gao, and Ni 2003), specific transformations to investigate urban spectral properties (Goward and Wharton 1984), and principal components to indicate spectral dynamics (Small 2002). Spectral mixture analysis (SMA) techniques are mathematically similar and are used to determine the proportional amount of land cover types within single pixels (Settle and Drake 1993). This approach has a long history of use with remote sensing data (Horwitz et al. 1971). Each pixel in SMA is assumed to consist of a combination of different land cover types with distinct spectral responses, or "endmembers". Spectral data are transformed to estimate the prevalence of those land cover types within each pixel:

$$R_i = \sum_{k=1}^{n} f_k R_{ik} + \varepsilon_i$$

Equation 3

where i is the number of spectral channels; $k = 1,....,n$ is the number if endmembers, R_i is the spectral reflectance of band *i* in a pixel containing one or more endmembers; f_k is the proportion of endmember *k* within that pixel; R_{ik} is the spectral reflectance of endmember *k* within that pixel in band *i*; ε_i is a error term. Application of SMA requires that the number of endmembers be equal or less than the number of spectral channels.

Linear SMA can be applied to estimate the abundance of vegetation cover in dense urban areas (Wu 2004; Small 2001). Assuming a generalized three-endmember urban spectral signature, SMA techniques can be used to estimate vegetation and impervious fractions (Weng and Lu 2007).

When applied to Landsat and IKONOS data, the SMA approach can provide measures of subpixel urban vegetation, although tree and grass remain difficult to separate without data in shortwave IR wavelengths (Song 2007). Application of SMA is particularly difficult in urban areas due to their spatial and spectral heterogeneity. Multiple scattering within pixels can introduce significant nonlinearity for unmixing vegetation endmembers (Borel and Gerstl 1994).

Spectral Variability

A significant challenge facing application of SMA is the variation of spectral response of each land cover component (Somers et al. 2011). Because SMA is trained on spectral data assumed to be "pure" examples of the substance in question, the choice of training data can be an important source of uncertainty and error. This is especially true for impervious surfaces, which have a large range of reflectance values (Herold et al. 2004). Variation in spectral response can impact SMA results even when little has changed in the physical proportion of land cover types. This can lead to uncertainty between land cover dynamics or spectral variability of invariant land cover.

Spectral patterns can be successfully discriminated using principal components (Wu 2004) and other noise-reduction algorithms (Small 2001) applied to remote sensing data before application of SMA methods. In this way, urban landscape can be defined by proportion cover of vegetation, high albedo, and low albedo surfaces (Small 2002, 2001). For these applications, endmembers are described by spectral response so they do not correspond directly to physical components of the urban environment.

Nonlinear mixture models can be used with SMA to account for nonlinear responses from vegetation abundance (Somers, Cools, et al. 2009; Chen and Vierling 2006). However, the nature of spectral response from varying abundance of different vegetation cover is not well known, and the majority of studies utilizing SMA methods have applied linear mixture models (Somers et al. 2011).

Studies have also selected a stable subset of endmember spectral features, to identify only spectral regions less impacted by spectral variability (Asner and Lobell 2000). Utilizing only stable spectral responses in SMA can increase accuracy of subpixel vegetation cover in orchards (Somers et al. 2010).

Differential weighting of spectral bands can be applied to SMA to increase separability of land cover types (Chang and Ji 2006; Somers, Delalieux, et al. 2009). These methods make use of the fact that responses for many land cover types are more divergent in infrared wavelengths than visible wavelengths. Similar in concept are methods that perform SMA on transformations of the original spectral data. Urban spectral responses, when normalized to each channel's mean, can improve separability of land cover fractions (Wu 2004; Wu and Murray 2003). However this reduces the information content of the original data. It is also possible to use the calculated second derivative of spectral response as a way to better separate land cover fractions (Zhang, Rivard, and Sanchez-Azofeifa 2004). An iterative procedure can be applied to select optimal endmember spectra from a larger spectral library (Rogge et al. 2006). SMA can incorporate models of light transfer within tree canopy to better estimate forest cover proportion (Peddle and Smith 2005) and reduce soil moisture impact on unmixing results (Somers, Delalieux, et al. 2009). Multiple endmembers can be included in calculations for each component abundance, iteratively identifying the best fit model for each pixel (Roberts et al. 1998). This approach has been applied for subpixel mapping of urban land cover (Powell et al. 2007; Rashed et al. 2003).

Another way to address the problem of endmember variation is to incorporate probability into the SMA model. Bayesian techniques assess the state of knowledge instead of assessing knowledge of a natural system. Probabilities are assigned to the correctness of land cover fractions, making it possible to assess the reliability of SMA results (Song 2005). Testing this approach with simulated remote sensing data has shown promise for using probability density functions instead of constant spectral endmembers (Song 2007).

Support Vector Methods - Classification

Support Vector Machines (SVM) are a group of applications for classification developed from machine learning theory. When applied to remote sensing data, classification techniques aim to determine land cover type of each pixel. Data points near the margins of each class ("support vectors") are used to determine class boundaries (Vapnik 1995) with maximal distance in feature space between support vectors. SVM applied to remote sensing data are relatively insensitive to data dimensionality (Pal and Mather 2004), and require only small training sets (Foody and Mathur 2004; Foody et al.

2006; Huang, Davis, and Townshend 2002).

Because they do not assume a statistical distribution for training data, Support Vector Machines can be superior at identifying spectrally complex signatures compared to maximum likelihood or neural network classifiers (Pal and Mather 2005; Huang, Davis, and Townshend 2002). SVM has been demonstrated to provide higher accuracy than decision trees (Chan, Huang, and DeFries 2001) and can outperform a neural network classification (Foody and Mather 2004). SVM can be used to automate forest classification at high accuracy (Huang et al. 2008), and can be applied to nighttime light data to map extent of urban areas (Cao et al. 2009).

For urban areas, hyperspectral classifications can use a fuzzy possibilitic model (Chanussot, Benediktsson, and Fauvel 2006) or methods incorporating spatial information (Wang, Waske, and Benediktsson 2009) to develop multiple per-pixel solutions that are then compared for final results. An SVM classification was performed on airborne hyperspectral data for three urban areas including central Washington DC with moderate classification accuracy (Fauvel, Chanussot, and Benediktsson 2009a).

Classification with SVM can be used in situations with large amounts of hyperspectral remote sensing data but limited training data (Chi et al. 2009; Benediktsson et al. 2008). SVM can be used for classification of hyperspectral data to process the large amounts of data, and applied for its better tolerance to noise (Plaza et al. 2009). Accuracy of SVM per-pixel classification of hyperspectral data has been found to be higher than results from other methods for urban land surfaces (Waske et al. 2010). SVM can incorporate multispectral and radar data for per-pixel land cover classification (Waske and Benediktsson 2007).

Spatial data can also be incorporated with SVM for land cover classification

(Fauvel, Chanussot, and Benediktsson 2009b), which can improve per-pixel classification accuracy approximately 4% in urban areas (Fauvel et al. 2008). The SVM approach can be separated into a multi-stage process, with a classification followed by application of spatial data to refine results (Tarabalka, Chanussot, and Benediktsson 2009; Tarabalka, Benediktsson, and Chanussot 2009). This can increase SVM per-pixel classification accuracy from 81% to 91% (Tarabalka et al. 2010).

Support Vector Methods - Land Cover Proportion

Support vector machines can also be applied for estimating the subpixel proportion of land cover types. Margins in linear SVM are mathematically similar to linear SMA, and can produce identical results in most cases (Brown, Gunn, and Lewis 1999). A linear SMA classification has the property of defining the maximum margin between "pure" pixels, as with SVM. The alternative approach of Support Vector Regression (SVR) can be applied to data indicating the actual mixtures instead of "pure" pixels, providing a more flexible approach (Brown, Lewis, and Gunn 2000).

Support vector regression (SVR) is an application of support vector machines for linear and nonlinear regression, which is useful for estimating areas within pixels (Smola and Scholkopf 2004). SVR requires that spectral data be transformed into high-dimension feature space. As with support vector machine classification, SVR finds the optimal solution using data points ("support vectors") to define the class or land cover type. When applying SVR, data within a pre-determined zone are ignored when calculating the regression relationship. The norm is then minimized for a given margin width:

$$\min \Phi(\mathbf{w}, \xi) = \frac{1}{2} \|\mathbf{w}\|_2^2 + C \sum_{i=1}^{l} \xi_i$$ Equation 4

where $i = 1,....,l$ is the number of support vectors; ζ is the distance of support vectors from the "tube" margin and C is a cost parameter to determine closeness of fit.

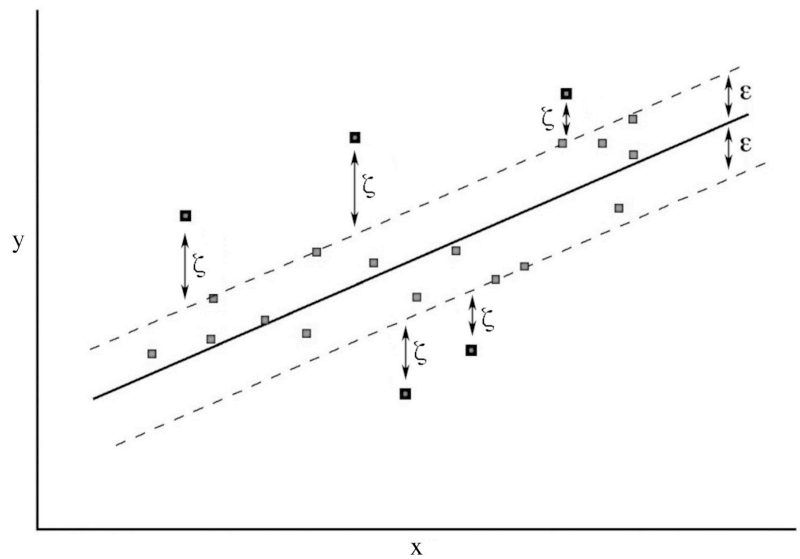

Figure 1. Support vector regression with hypothetical two-dimensional data. Solid line indicates the regression model and dashed lines show the margins of the insensitive zone.

Support vector regression uses a subset of points to calculate the regression model (Figure 1). Only data points outside the insensitive zone (width indicated by ε) are used in calculating the regression model. The goal of SVR is to minimize ζ, the distance of each of these support vectors. The width of the insensitive zone ε can be adjusted to produce a close fit or to enable better generalization. As with support vector machine classification, the goal is to characterize a set of data based on its "shape" in multi-dimensional space, instead of using a statistical measure for the "center" of the training data.

Other machine learning algorithms have been developed for subpixel area estimation. The proprietary Cubist algorithm (Rulequest Research 2008) was used to produce the USGS National Land Cover Database (Homer et al. 2007). The Random Forests algorithm (Breiman 2001) is a model aggregating approach that has been applied to classification of agricultural crops in remotely sensed data (Pal 2005). SVR has been found to produce similar but more accurate estimates of urban tree cover when compared to Cubist and Random Forests (Walton 2008b).

Both SMA and SVR share the goal of estimating the fractional amount of a land cover type based on training data. However they have several important differences. Compared to SMA, SVR methods are less sensitive to noise and exhibit superior generalization properties. This is especially true for fractional land cover estimation. SMA uses training data only at "pure" sites 100% covered by the land cover type, and the spectral homogeneity of those sites is assumed. This places a significant limitation on SMA, because complete spectral purity is rarely to be found in satellite remote sensing data especially in urban settings. In SVR, training data can consist of the full range of the land cover type, from 0%-100%. This makes the algorithm sensitive to spectral changes in that full range, allowing SVR to potentially perform better at estimating fractional tree cover in spectrally complex urban settings.

<u>Support Vector Methods - Kernel and Parameters</u>

The target data must be transformed into feature space before application of support vector regression or classification. This transformation is usually nonlinear. Different kernel functions are available for this task. The Radial Basis Function (RBF), sigmoid, and polynomial kernels have been applied for support vector classification. The RBF kernel can provide higher and more stable SVM classification accuracy than the polynomial kernel, especially using a low order polynomial (Huang, Davis, and Townshend 2002). The application of SVM for classification has been experimented with custom designed kernels to produce classification maps that appear "cleaner", but an accuracy difference was not observed (Mercier and Lennon 2003). The RBF kernel was selected for application of SVR in a previous study of urban forest cover (Walton 2008b). The RBF kernel is:

$$k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \qquad \text{Equation 5}$$

where x_i, x_j are data points and γ is a defined parameter.

Two other parameters must be defined for SVR (Equation 4), the C (cost) parameter and ε, which defines the width of the insensitive zone. The cost parameter defines the trade-off between allowing errors and forcing closeness of fit. Higher values of C increase the cost of inaccurate predictions and forces a close fit that may not generalize well. Higher values of ε make it possible for the regression to include or exclude possible support vectors.

Parameter values can be selected directly from the training data (Cherkassy and Ma 2002) and optimization search algorithms can be used to determine optimal SVR parameters (Üstün et al. 2005). Comparison of multiple approaches for selecting parameters has shown that high accuracy can be achieved with minor differences in computational complexity (Villa et al. 2008).

For most applications of SVR, a cross-validation procedure should be used to find the optimal parameter values (Stone 1974). In implementing parameter cross-validation, values for each parameter are tested iteratively within a specified range. A random selection of the training data is used to test the regression with initially proposed parameter values. Parameter values are then tested in each direction from the first value. If the fit of the model improves, the new values are defined and the test is repeated. This procedure is run iteratively, with the parameter values altered after each run until the best accuracy is found.

While support vector classification is implemented as part of some remote sensing software packages, parameter cross-validation and support vector regression are not included in currently available commercial remote sensing software.

Summary

Tree cover in urban areas has important influence on the urban physical and social environment. Interest in urban forests has spurred governments and non-governmental organizations to devote resources to maintaining, examining, and expanding urban tree cover. Urban vegetation has been observed utilizing field surveys and remote sensing data. Many studies has analyzed the proportion of urban land surface covered by vegetation. Relatively few studies has focused on tree cover dynamics in urban areas. Remote sensing techniques have been applied for mapping urban tree cover, including spectral mixture analysis for subpixel land cover estimation. Support vector regression, based on machine learning classification techniques, shows promise for estimating land cover proportions but has not been tested specifically for measuring urban tree cover.

CHAPTER III

STUDY AREA: THE DISTRICT OF COLUMBIA

Urban Development

Laid out in the 1790s as the United States capital, Washington DC lies at the confluence of the Potomac and Anacostia Rivers (Figure 2). In the first half of the 20th century the world's largest urban concentration developed in the northeastern United States, with Washington DC as its southern node (Tunnard 1958; Gottmann 1961). Despite rapid urbanization this area still contained forests and agriculture that covered more than 80% of the region in the 1950s (Gottmann 1961). By the next decade forests still covered about 50% of the northeastern United States (Von Eckardt 1964). Even as late as 1970, the urbanized northeastern United States contained approximately 20% impervious surfaces, the remainder being split evenly between forest and agriculture (Browning 1974).

Regional spatial growth of the Washington metropolitan area continued through the late 20th century. Multitemporal comparisons showed a 61% increase in developed land in the Chesapeake Bay watershed between 1990-2000, with about one third of the growth occurring on forested land (Jantz, Goetz, and Jantz 2005).

The second half of the 20th century was a period of declining population in the District of Columbia itself. Economic and population growth diffused into the surrounding suburbs, a process experienced in most US metropolitan areas. From 1970 to 2005 the District of Columbia lost about 27% of its population, from 756,000 to 550,000 (U.S. Census 2007). The District of Columbia population increased in the following years, exceeding 601,000 by 2010 (U.S. Census 2011).

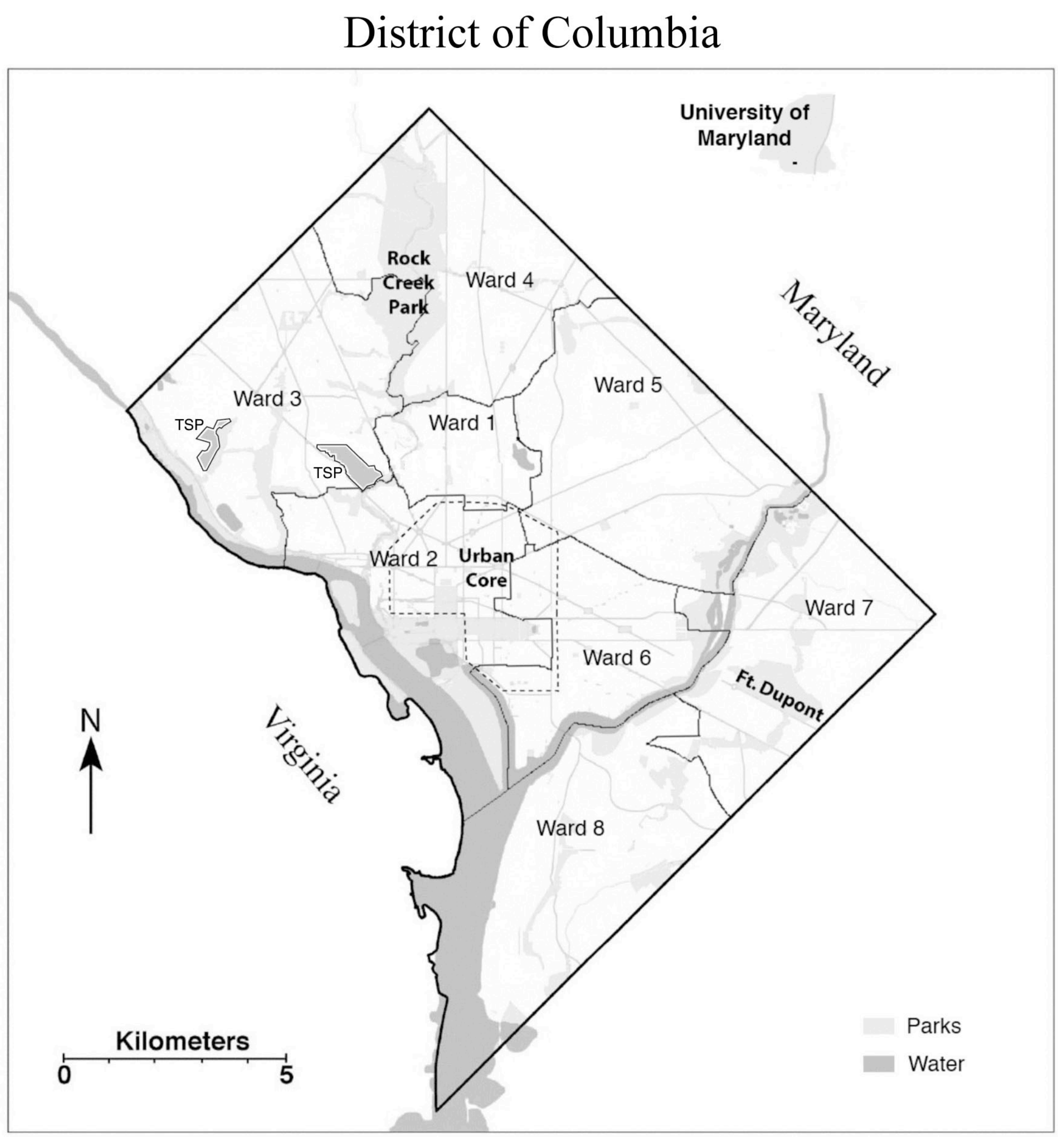

Figure 2. District of Columbia map.

<u>DC Wards</u>

The District of Columbia is divided into eight wards for purposes of political representation in the DC Council, Advisory Neighborhood Commissions (ANCs), and the elected public school board (Figure 3). Wards are used for allocating and recording municipal services such as parking restrictions, property records, real property taxation, and public schools. ANCs are elected neighborhood boards playing advisory roles in reviewing developments such as zoning adjustments, construction plans, and alcohol permits. Ward boundaries are redrawn after each US census to reflect population shifts, as each is required to have approximately equal population. The ward boundaries used in this research were in effect beginning in 2002. For consistency these boundaries were applied for all analysis in this research, although actual ward boundaries shifted after each census.

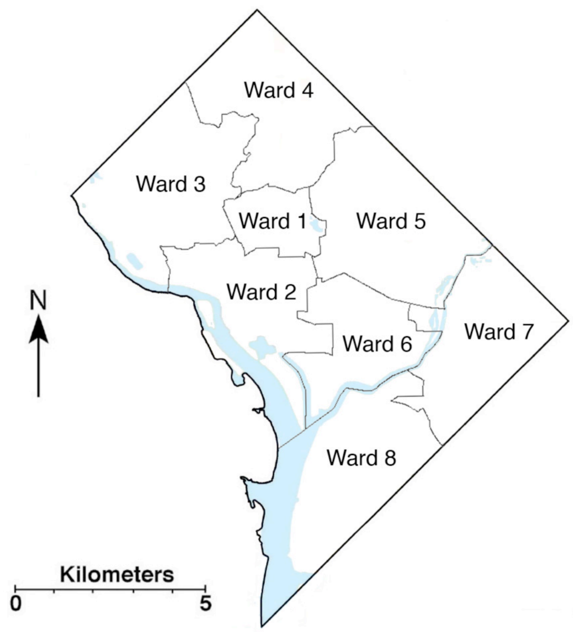

Figure 3. DC Wards

DC wards contain significant socioeconomic diversity (Table 3). Ward 3 has long had the highest income levels compared to other wards. Per capita income in ward 3 was more than twice that of any other ward during 1984-2004 (D.C. Government 2002a; U.S. Census 2011). Property values were highest in wards 3 and ward 2, which includes the downtown area. Median residential property values in ward 3 exceeded property values in wards 4 and 5 by 200%, and wards 7 and 8 by 400% (Tatian 2007). Owner occupation of residential property lots exceeds 80% in some neighborhood in wards 3 and 4, but averages below 30% in wards 7 and 8 (Tatian 2007).

Table 3. DC ward population and housing data from 2000 U.S. Census.

Ward	Population			Mean Income ($)	Median Home Value ($)	Housing Units		
	Total	per ha.	Change 1980-2000			Occupied by Owner	Detached	Vacant
1	73,364	113	+2.3 %	23,760	171,295	28.4 %	2.5 %	9.3 %
2	68,869	46	+8.4 %	42,660	451,419	32.2 %	3.0 %	8.1 %
3	73,718	30	+9.4 %	58,584	448,957	49.4 %	26.7 %	4.0 %
4	75,179	31	-10.2 %	27,075	163,800	61.7 %	29.4 %	6.4 %
5	71,440	31	-20.7 %	19,173	130,235	49.0 %	17.8 %	12.8 %
6	68,035	25	-12.3 %	28,636	169,802	41.0 %	3.4 %	10.0 %
7	70,527	44	-24.0 %	16,956	104,088	41.1 %	18.0 %	12.7 %
8	70,927	31	-26.0 %	12,630	97,837	21.4 %	6.2 %	15.9 %

A study of socioeconomic factors across eight wards in the District of Columbia found that rent costs and educational attainment of residents were the socioeconomic factors most highly correlated to street tree health and mortality (Torres 2011). This analysis was performed using census data that included mean income, unemployment rates, and percentage of youth population. It did not extend to other demographic factors possibly linked to the state of tree cover on private property, such as rates of owner occupation and property vacancy.

Land Ownership

The largest landowners in the District of Columbia are the federal and District governments, which collectively own 57% of the city's land surface (D.C. Government 2010b). The federal government alone owns 59% of all nonresidential land in the District of Columbia (Tatian 2007). The federal and DC governments collectively own 67% of nonresidential land in ward 8, the highest proportion among DC wards (Tatian 2007).

Several entities in the District of Columbia hold ownership of significant parts of the city's forests. The federal government holds 43% of total tree cover area and the DC government holds just 7%, with the remainder in private hands (O'Neil-Dunne 2010). The DC Parks Department oversees about 800 acres and maintains a small tree management budget (D.C. Government 2010a).

The National Park Service (NPS) oversees densely forested Rock Creek Park and Fort Dupont Park. These two park units alone account for 5% of the city's land surface area and about 18% of the city tree area (O'Neil-Dunne 2010). While there has been no systematic monitoring of canopy changes, NPS staff has collected data indicating number of trees lost and replaced. However only limited data for Rock Creek are available during 1984-2004. The management goal of the NPS is to limit tree losses to 3% annually (Defeo 2011). Tree mortality can be higher in stressed sites. On NPS land within the urban core, losses can be as high as 6% within 6 years (Defeo 2011).

Data collected by NPS indicates interannual variability of tree losses. For example, between 2009-2010 1.3% of elm trees were lost on NPS land. Between 2010-2011, 2.6% elms were lost (Defeo 2011). NPS-maintained cherry trees around the National Mall and tidal basin averaged 50-year life spans when they were planted. In recent years the average life span is approximately 35 years (Defeo 2011). While these data were not collected during the 1984-2004 period of the current study, they provide insight into possible canopy impact.

Forests of the District of Columbia

Forests in the District of Columbia contain more than 300 tree species (Choukas-

Bradley and Alexander 1987). Forests of the District of Columbia were analyzed in 2004 using field plots and city-wide maps of land cover types (Nowak et al. 2006). This analysis estimated the total number of trees at 1,928,000, covering 28.6% of DC's land area. Of the total number of the standing trees, 61% were in public parks. The remainder stood in heterogeneous land cover environments typical of an urban setting (Nowak et al. 2006). This forest cover removed approximately 540 tons of particulate pollution annually. Carbon storage totaled 523,000 tons, with 16,200 tons off gross carbon sequestration annually. The most common species were American beech (*Fagus grandifolia*) (14.1 %), red maple (*Acer rubrum*) (6.4 %), boxelder (*Acer negundo*) (5.5 %), tulip tree (*Liriodendron tulipifera*) (5.2 %), and flowering dogwood (*Cornus florida*) (3.7 %). 56% of all trees were 6 inches or less in diameter. Less than 3% of trees had a diameter greater than 30 inches (Nowak et al. 2006). This analysis was repeated in 2009 using the same methodology, showing minor changes in tree cover (Howard and Alonzo 2009).

Tree data for the District of Columbia are available from plot-based surveys (Nowak et al. 2006), the District government's GIS data online access system (D.C. Government 2007a), and street tree surveys (Casey Trees 2003). The plot-based surveys estimate total number of trees within park areas, the DC GIS data include counts of standing trees in private property outside parks, and the Casey Trees data count number of trees on public streets. Adding the three sources indicates the proportion of standing trees within park areas, private property, and public streets (Figure 4).

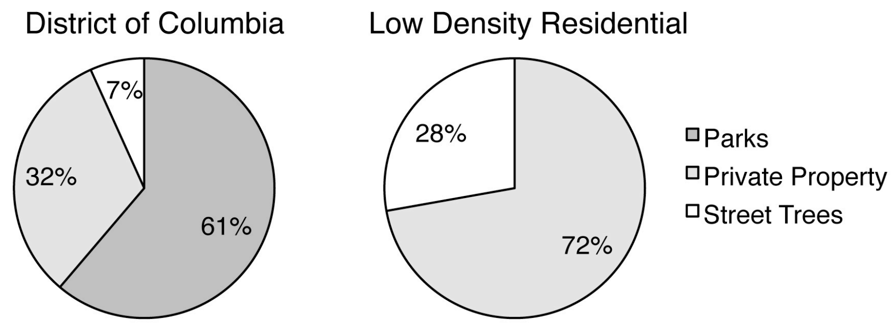

Figure 4. Proportion of trees in DC and low density residential zones.

The total number of trees in federal and DC park lands was estimated from plot-based measurements at 1.18 million, or 61% of the total. Most of the remaining trees in the DC GIS data (32% of the total) were standing within private property lots. Within low density residential zones as defined by the DC zoning code, 72% of standing trees in the DC GIS data were located within private property. The remaining trees were located within the right-of-way for public streets.

Broad observations of the species diversity of managed trees are possible by analyzing data collected on street trees. In the late 19th century street trees in the urbanized part of Washington DC were dominated by maples (*Acer* spp.), which comprised 39% of street trees at that time (Greene 1880). Poplar (*Populus grandidentata*) and linden (*Tilia americana*) each comprised about 10% of the city's street trees (Greene 1880).

In 2002, maple remained a dominant species of street tree along with oak (*Quercus* spp.), each of which comprised 35% of street trees (Casey Trees 2003). Another 14% were Elm (*Ulmus* spp.), while Ginkgo (*Ginkgo biloba*) and Zelkova (*Zelkova serrata*) each comprised about 4% of street trees (Casey Trees 2003) and sycamore/plane tree (*Platanus* spp.) comprised about 2%. The remaining 6% of the District's street trees included species of dogwood, ash, locust, cherry, pear, beech, cedar, spruce and pine. A few examples of redwood, cypress, and hemlock were found (Casey Trees 2003). By 2010, the proportion of maples and oak had changed to 38% and 31%, respectively (Corletta 2010). In recent years the District of Columbia Urban Forestry Administration has attempted to diversify street trees by reducing maple planting and increasing purchases of dozens of other species including ginkgo, dawn redwood, willow oak, and locust (D.C. Government 2012c).

Tree Cover Variability

Recent tree cover change in the District of Columbia has been measured utilizing field survey plots and high resolution satellite data. Reports suggest minor city-wide changes in tree cover but the accuracy of these estimates was not evaluated. Plot-based field surveys estimated that total District of Columbia tree cover varied 28.6-28.1% between 2004 and 2009 (Howard and Alonzo 2009). A District of Columbia government report from the Urban Forest Administration utilized high resolution remote sensing data and object-oriented classification to estimate that city-wide tree cover increased 2.1% between 2006-2011 (D.C. Government 2012a). Another analysis of the same remote sensing data, performed at an independent laboratory under contract by the non-governmental organization Casey Trees, utilized human image interpretation to estimate that tree cover decreased approximately 2% between the same two years (O'Neil-Dunne 2012). Error assessments, validation, and specific descriptions of the methodology were not included in either of these reports. The two reports are potentially of concern for District of Columbia management and policy authorities because they indicate opposite trends in tree cover and contain no error assessments.

District of Columbia Forest Planning and Management

Planning and Management History

The layout of Washington DC was based on plans developed by Peter L'Enfant, which called for a grid system of streets overlain by diagonal wide avenues. The Enfant plans included descriptions of the major avenues were to be lined with shade trees and wide enough to accommodate these trees. However, specific numbers or types of tree were not described (Choukas-Bradley and Alexander 1987; Berg 2008).

The earliest significant government effort at planting trees in the public spaces included in the L'Enfant plans took place during the Jefferson administration, when poplar trees were planted along on Pennsylvania Ave. between the Capitol and White House (Choukas-Bradley and Alexander 1987). In the 1870s the District government planted about 60,000 trees on streets and in parks.

In 1901 a U.S. Senate commission was formed to develop a vision for the monumental core of the city for the 20th century. The commission was chaired by Senator James McMillan and included landscape architect Frederick Law Olmsted, Jr., whose father had redesigned the U.S. Capitol grounds in 1873 (Gutheim and Lee 2006). The plan the commission developed, later known as the McMillan Plan, called for removing railways in the center of the city, extending the National Mall to the current locations of the Lincoln and Jefferson Memorials, and new landscaping in this central area. Without calling for specific numbers of trees, the Mall landscaping was to include tree cover along the length of the east-west axis of the Mall (Choukas-Bradley and Alexander 1987; Gutheim and Lee 2006). Notable tree planting programs in the 20th century include the donation of Japanese cherry trees in 1912 and plantings performed under the umbrella of the Committee for a More Beautiful Capital in the 1960s (Choukas-Bradley and Alexander 1987). The L'Enfant street network, the Olmsted capitol grounds design, and the McMillan Plan for the National Mall remain largely intact and still form the structure of central Washington DC.

Multiple agencies with the District of Columbia government have held tree maintenance responsibilities (Table 4). Since the 1950s an independent unit of the DC Department of Transportation has held responsibility for tree maintenance along the city's streets and roads. In 1972-1975 the Tree and Landscape Division of the DC Government's Highways and Traffic Department initiated a computerized management inventory system for street trees known as the Management Information System for TREes (MISTRE) (Johannsen 1975). Data were stored on paper cards and processed utilizing a computer operated for the Washington Area Law Enforcement System. The District of Columbia was the only major American city to develop such a system at the time (Johannsen 1998). The DC Department of Environment (DDOE) was created in 2006. In 2010 it took responsibility for managing storm water runoff and began to take responsibility for DC government policy related to urban forest management (D.C. Government 2010c, 2011b).

Table 4. DC Government agencies with tree responsibilities.

Agency	Dates	Responsibilities
Tree and Landscape Division	1950-1998	Street trees, highways, park landscaping
Urban Forestry Administration	1998 -	Street trees, private property inspections
Department of Environment	2006 -	Government-wide policy

Street Tree Maintenance

District of Columbia government agencies experienced changes in status and responsibility for street tree management. Until 1998 the Tree and Landscape Division (TLD) was responsible for street trees and utilized the MISTRE street tree inventory system. In the 1970s the TLD removed an average of approximately 3,000 dead or dying street trees annually, or between 2-3% of all street trees per year (Johannsen 1975). An average of approximately 3,000 trees continued to be planted and replaced annually by the TLD through the early 1980s (Johannsen 1998).

Management activity slowed significantly in the subsequent decade. The District of Columbia government experienced serious financial constraints during the 1990s and was placed under direct federal oversight beginning in 1995. TLD budgets for street tree maintenance decreased by approximately 80% between 1990-1993 (D.C. Government 2002b). In 1994 only one maintenance contract was funded for topping of minimal numbers of dead trees (D.C. Government 2002b). During the early 1990s, 3,000-4,000 street trees were lost annually to age or other causes and only approximately 500 were being replaced annually (Johannsen 1998). In the early 1990s the MISTRE inventory system was not actively updated and the data were not archived for later retrieval (Johannsen 1998). No street trees were planted 1994-1996 (D.C. Government 2002b), causing an annual net loss of approximately 3,000 street trees (Johannsen 1998). As the number of street trees being planted annually declined, the quality of planted trees also changed. The DC government tree nursery was closed by 1992. During the early 1990s almost all trees purchased for planting on streets were non-cultivar maple (D.C. Government 2002b). These were available at low cost but were not cultivated for optimal characteristics as an urban street tree, which would be expected to increase tree mortality.

In 1998 responsibility for street tree maintenance was transferred to the newly created Urban Forestry Administration (UFA). Besides street tree maintenance, UFA arborists began inspection of trees on private property to issue permits for removal. The UFA significantly increased planting of new trees. Between 1999-2005 the Urban Forestry Administration developed a new tree inventory system (Godfrey 2003) and began new planting programs that lead to an annual net increase of approximately 2,500 street trees (D.C. Government 2007b; Godfrey 2003). During those years the UFA contracted for the planting of about 14,000 new trees and removal of about 7,000 dead trees, with an annual budget of about 7 million dollars (D.C. Government 2007b). By 2009 the UFA had grown to a staff of about 50 people with a budget of approximately $8 million, a rate of per capita spending on urban trees exceeding other major eastern US cities (Arbor Day Foundation 2007). Between 2005-2012 annual tree plantings by the UFA totaled approximately 2,000, and exceeded 3,500 in some years (D.C. Government 2012b; Corletta 2010). In April 2012 the number of street trees was 126,602 and total number of spaces for trees was 148,347 (D.C. Government 2012c).

Insect Defoliation Management

Monitoring and controlling gypsy moth defoliation is a central concern for management authorities in the Washington DC area. The range of the gypsy moth reached Washington DC by about 1983. The fastest expansion of the gypsy moth's range ended by 1990 (Liebhold, Halverson, and Elmes 1992), and the most common forest impact has been found at elevations greater than 200m above sea level (Liebhold et al. 1994). A peak in defoliation occurred during 1989-1992 for the multi-state region including Washington DC (U.S. Department of Agriculture 2003). Peak years for gypsy moth defoliation in Maryland were 1993-1994 (Maryland Dept. of Agriculture 2008) and 1995 in Virginia (Roberts 2008). In the years leading up to 1994, most gypsy moth defoliation in Maryland was found north and west of DC. By 1994 this had subsided and most defoliation had moved to southern Maryland and the Eastern Shore (Maryland Dept. of Agriculture 2008).

Quantitative spatial data for insect defoliation within the District of Columbia between 1984-2004 were not maintained by the U.S. Forest Service or the District government (Whiteman 2010). However, gypsy moth defoliation in nearby Maryland and Virginia was reported by respective state agencies. The Virginia area adjacent to the District of Columbia includes Fairfax, Loudon, Prince William, and Arlington Counties (Virginia Department of Forestry 2012). Maryland gypsy moth defoliation is reported in four zones by the Maryland Department of Natural Resources (Maryland Dept. of Natural Resources 2012). The central and southern zones adjacent to the District of Columbia include Montgomery, Prince George's, Anne Arundel, Calvert, Charles, St. Mary's, Howard, Frederick, Baltimore, Hartford, and Cecil Counties. Significant defoliation in the combined Maryland/Virginia area surrounding the District of Columbia occurred 1989-1995 (Figure 5).

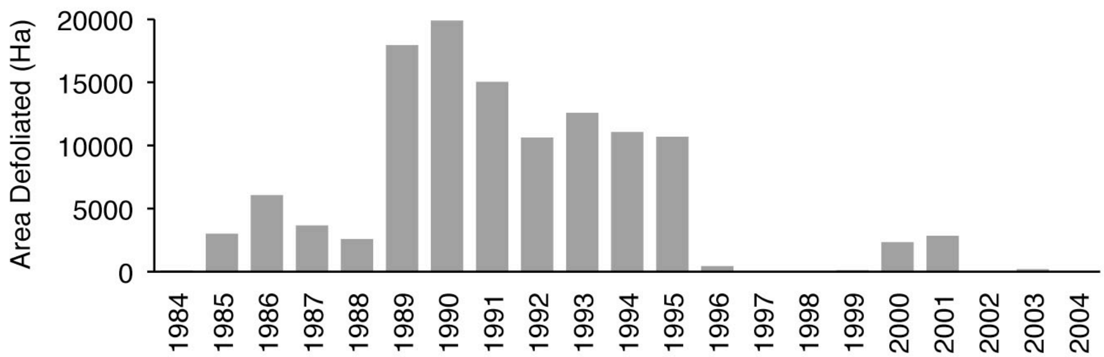

Figure 5. Total gypsy moth defoliated area for central and southern Maryland and Northern Virginia.

Within the District of Columbia, gypsy moth infestation in Rock Creek Park was high 1987-1988, although defoliation was limited (Favre, Sherald, and Schneeberger 1993). Chemical and natural predators were used to control defoliation in Rock Creek Park. No defoliation was observed in the park during 1988 air surveys (Favre, Sherald, and Schneeberger 1993). The largest and most intense area of gypsy moth infestation in DC occurred in subsequent years west of Rock Creek, in the area north and west of Nebraska Ave. NW in northern ward 3. The residential area south of Pinehurst Circle experienced severe defoliation in 1986 (Favre, Sherald, and Schneeberger 1993). In the same period a secondary area of defoliation existed between Pennsylvania Ave. SE and Fort Dupont Park in the southern part of ward 7 (Johannsen 1998). In 1989-1990 the U.S. Forest Service and the DC government contracted for helicopter spraying treatment in these two areas (Whiteman 2010).

Tree Protection and Open Space Requirements

Tree Protection Laws

Since January 2003 it has been illegal under DC law to remove, top, or destroy any tree with a circumference greater than 55 inches (D.C. Government 2007b). Removal of hazardous trees requires a permit issued by the UFA along with a payment and/or planting of new trees that equal or exceed the total circumference of the removed tree. If space is limited, new seedlings are required to be planted on other properties. Three species that are invasive or nuisance trees are issued removal permits without payment or replanting: tree of heaven (*Ailianthus altissima*), mulberry (*Morus* spp.), and Norway maple (*Acer platanoides*).

Zoning Restrictions

Zoning laws in the District determine available space for tree growth outside of streets and parks. The DC Office of Zoning has defined 29 categories of zoning districts that allow different land uses and varying densities (D.C. Government 2006). Limits on lot occupancy by buildings are the primary method by which zoning districts set aside open space. There are 12 categories of commercial districts that allow 60-100% lot occupancy and 10 categories of residential districts that allow 40-75% lot occupancy. Although zoning restrictions were not intended for environmental impact, they determine the amount of space available for tree growth.

In the current study, “Open Space” zones are defined based on lot occupancy zoning restrictions. For instance, “60% Open Space” indicates zones where 60% of each property lot must remain free of structures.

Tree and Slope Overlay Zones

Small areas of the District of Columbia have explicit tree protection restrictions. Within “tree and slope protection overlay" zones, buildings are limited to 30% lot occupancy and impervious surfaces limited to 50% of each property lot. Removal of trees with trunk circumference greater than 75 inches is prohibited unless it constitutes a safety hazard (D.C. Government 1992). The number of smaller trees that can be removed is restricted. Two overlay districts have covered the Wesley Heights and University Terrace neighborhoods in ward 3 since 1992 (labeled "TSP" in Figure 2). These districts were created within areas zoned "R-1-A", the most restrictive and lowest density residential zoning category. Lot occupancy may not exceed 40% and lots must be a minimum lot area of 7,500 square feet (D.C. Government 2007a, 2006).

Summary

The District of Columbia is a major US city, and has a wide range of stakeholders as the national capital. Approximately 30% of the land surface area of the District of Columbia is covered by tree canopy. Responsibilities of different management authorities have changed multiple times in the 20th century. The DC legal code has contained statutes limiting the removal of trees and limiting the proportion of property lots that can be occupied by structures. Although preliminary observations of recent tree cover change have been made, the accuracy of these estimates has not been tested. Reliable observations of historic tree cover variability would advance understanding the urban environment and the development of public policy in the District of Columbia.

CHAPTER IV

DATA AND METHODOLOGY

Introduction

To investigate urban tree cover variability and its linkages to other components of the urban landscape, this research proceeded in three phases: 1) A comparative analysis was performed of static tree cover utilizing satellite remote sensing data, 2) Temporal tree cover variability over a 20 year period was observed utilizing time series satellite data, validated with map products derived from aerial photography, 3) The spatial patterns of tree cover variability in the context of urban land use were identified.

In the first phase of this study, two methodologies were tested to derive accurate maps of urban tree cover from satellite remote sensing data. Results from Spectral Mixture Analysis (SMA), a widely applied technique for urban land cover mapping, are compared to results from Support Vector Regression (SVR). Tree cover results were compared to validation data compiled from field surveys and tree cover data derived from air photography. The spatial pattern of error for each technique was investigated by segmenting the study area into land use categories using government zoning data.

In the next phase of this study, the SVR technique was then applied to calibrated Landsat satellite data to map tree cover on 11 dates between 1984-2004. Multitemporal validation was performed using air photography to determine tree cover changes that can be measured with high confidence. Increases and decreases in tree cover were mapped every two years between 1984-2004. Fine scale changes in standing trees were observed with image products derived from aerial photography.

In the third phase of this study, the spatial variability of local scale tree cover changes was investigated. Connections between tree cover changes and spatial patterns of urban land use were identified. Differences in tree cover change between land use types as defined in zoning data were measured. Tree cover and variability was compared to selected demographic data in residential neighborhoods. Impact from land cover change was mapped, showing removal of dense tree cover between 1984-2004. Implications of tree cover observations for management and policy were explored.

District of Columbia Data Sets

Tree Cover Observations

Tree data from the District of Columbia were acquired from the District government's GIS data online access system (D.C. Government 2007a). They indicate the location of more than 380,000 trees throughout the city. This includes trees on public streets and on private property. The data were created by manually interpreting airphotos acquired in May 1999. The interpretation was performed by the geospatial technology company EarthData (now Fugro EarthData) under contract with the National Capital Planning Commission (D.C. Government 2007a). No tree attributes such as crown size were collected. The same source also includes a data layer indicating polygon coverage of closed-canopy forests. Only the polygon layer has been updated since initial production from 1999 imagery, which occurred in 2005 (D.C. Government 2007a). This was not utilized in the current study as it lies outside the study period.

These were supplemented with detailed data on District of Columbia street trees acquired by the nongovernmental organization Casey Trees. These data were collected in the field during summer 2000, and include the location and size of every street tree in

DC. Volunteers were issued GPS-enabled PDAs equipped with a District-wide GIS. Data on tree species, size, and health were recorded for all accessible street trees, totaling approximately 130,000 trees (Casey Trees 2003). In contrast to the DC GIS data, the Casey data include only street trees and not trees on private property. However the Casey data include attributes such as crown radius that are not included in the DC GIS data.

Satellite Remote Sensing Data

Calibrated Landsat data of the District of Columbia from 1984-2004 were used for this study. A time series of Landsat observations were compiled and processed to document land changes over the last 30 years within the North American Forest Dynamics (NAFD) project to evaluate the role of forest disturbance in North American carbon dynamics (Goward et al. 2008). The NAFD project has mapped forest removal and regrowth across large areas (Goward et al. 2012). The data were developed by applying an automated mapping approach for detecting forest disturbance (Huang, Goward, Masek, Thomas, et al. 2009). Disturbance maps have been validated using visual analysis and U.S. Department of Agriculture Forest Service Inventory and Analysis data, with 92% overall accuracy for identifying forest disturbance episodes (Thomas et al. 2011).

The NAFD Landsat data have been highly processed to address specific limitations of Landsat imagery when utilized in time series analyses, including atmospheric contamination and geographic registration errors. Atmospheric effects were addressed using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al. 2006). Top of atmosphere reflectance is been calculated by using published calibration coefficients (Landsat Project Science Office 2000; Markham and Barker 1986). Effects of atmospheric scattering were removed using a radiative transfer model (Vermote, Tanre, and Morcrette 1997) were atmospheric optical depth was measured by estimating visible reflectance from shortwave infrared reflectance. Geographic registration errors caused by topographic relief displacement were corrected by an orthorectification procedure (Gao, Masek, and Wolfe 2009). No corrections were applied for bi-directional reflectance (Masek et al. 2006).

Maps derived as part of the NAFD project show forest disturbance across North America, indicating the greatest rates of change in the southeastern United States (Masek et al. 2008). Analysis has been performed within experiment areas including the Great Lakes region (Huang, Goward, Schleeweis, et al. 2009) and Pacific Northwest (Huang et al. 2011). These observations applied across North America have demonstrated that approximately 1% of all forests experience anthropogenic disturbance each year (Masek et al. 2011). The spatial extent of the data allows forest stand age and disturbance history to be mapped across the North American continent (Pan et al. 2011). Analysis can reveal details of disturbance severity and history at regional scales and identify geographically specific carbon sinks within North America (Williams et al. 2012; Goetz et al. 2012).

As part of the NAFD project, sequences of Landsat scenes were compiled into Landsat Time Series Stacks (LTSS) covering mapping and validation sites across the United States (Huang, Goward, Masek, Gao, et al. 2009). Each LTSS consisted of Landsat scenes from every other year between 1982-2006 during the initial phase of the project. This temporal density was selected to allow for practical data processing and cost while capturing forest disturbance events (Huang, Goward, Masek, Gao, et al. 2009). However, some disturbance events would be expected to be missed with biennial sampling, so annual LTSS were developed for some of the experiment sites in the NAFD project (Goward et al. 2012).

Landsat scene selection in NAFD was restricted to leaf-on periods each year between June and September. The period was extended to May-October for the southern United States (Huang, Goward, Masek, Gao, et al. 2009). For some locations it was required to utilize scenes from additional years to acquire cloud-free imagery (Huang, Goward, Masek, Gao, et al. 2009).

The NAFD data covering the Washington DC region consists of Landsat TM and ETM+ scenes acquired 1982-2004. This research utilized 11 scenes acquired on even-numbered years 1984-2004 (Table 5). At two-year intervals, these data provide the necessary temporal resolution to discern urban tree cover dynamics. However, changes within individual growing seasons would not be observable with this approach.

The Washington DC LTSS scenes were acquired July-September, with two exceptions. The 1986 scene was acquired in May and the 1992 scene in October. Because late season acquisitions could lead to anomalous forest observations within an LTSS, the NAFD project replaced some scenes acquired late in the season with earlier images from the following or preceding year (Huang, Goward, Masek, Gao, et al. 2009). The LTSS covering Washington DC included a 1991 scene, but it was also acquired late in the season on 16 September (Goward et al. 2012). For the current study, biennial sampling was maintained to provide temporally consistent tree cover observations. Because this approach is limited by the available calibrated scenes, error may result from utilizing the scenes from different seasons. The possible impact of the difference in seasonality is discussed in the following chapter.

Table 5. Satellite remote sensing observations.

Date	Sensor	Cloud cover (total scene)	Cloud cover (DC only)	Scene ID
27 Aug 1984	L5 TM	0 %	0 %	LT50150331984240XXX10
29 May 1986	L5 TM	5 %	0.17 %	LT50150331986150XXX10
22 Aug 1988	L5 TM	0 %	0 %	LT50150331988235AAA03
12 Aug 1990	L5 TM	0 %	0 %	LT50150331990224XXX04
20 Oct 1992	L5 TM	0 %	0 %	LT50150331992294XXX02
23 Aug 1994	L5 TM	0 %	0.05 %	LT50150331994235AAA02
11 July 1996	L5 TM	0 %	0.5 %	LT50150331996193XXX02
2 Aug 1998	L5 TM	10 %	0.23 %	LT50150331998214XXX03
6 July 2000	L5 TM	0 %	0 %	LT50150332000188AAA02
6 Sept 2002	L7 ETM+	15 %	1.0 %	LE70150332002249EDC00
19 Sept 2004	L5 TM	5 %	0 %	LT50150332004263GNC01

It was not always possible to find cloud-free images in the eastern United States in the NAFD scene selection process (Huang, Goward, Masek, Gao, et al. 2009). Clouds covered at least 5% of total area for four of the Washington DC scenes (Table 5). For the current study focusing on the District of Columbia, clouds cover was much less abundant. In only one scene (2002) did cloud cover reach 1% of the study area. The 1994 and 1996 scenes contained minor amounts of cloud cover in the District of Columbia despite the full scenes being reported as cloud-free (Table 5). The following chapter includes as assessment of the impact of clouds on tree cover results.

The processed Landsat data utilized in this study provided advantages compared to other available data. The Landsat data record is the longest existing record of multispectral satellite remote sensing data. The temporal coverage of the Landsat data extends decades, unlike to shorter record available for high resolution satellite data such as IKONOS and other sensors. Neither high resolution satellite data nor aerial photography includes shortwave infrared channels that would permit reliable discrimination of tree and grass cover. Urban tree and grass cover exhibits different spectral responses due to absorption in the shortwave infrared (Lu and Weng 2004). Aerial photography has been available for greater periods of time, however these sources do not include multispectral data.

Mapping Products Derived From Aerial Photography

Satellite observations of urban tree cover require validation from independent sources. Multitemporal acquisitions of high resolution image products permit identification of fine scale tree cover changes and provide a data source for validating city-wide observations. In this study, cartographic imagery derived from aerial photography was utilized to validate satellite observations and provide detailed information on tree cover within sample survey plots.

Airphoto coverage was acquired from the District of Columbia public GIS data online access system (D.C. Government 2007a) for every year available corresponding with the study period (Table 6). The 1999 image was closest in time to the 2000 Landsat image. The 1995 image was closest in time to the 1994 Landsat image. These orthorectified air photographs were distributed as mosaics covering the entire District of Columbia. Digital Orthophoto Quadrangles (DOQs) were acquired from the U.S. Geological Survey (U.S. Geological Survey 2011) for 1988 and 1994 (Table 6).

Table 6. Image products derived from aerial photography.

Landsat Date	Air Photo Date	Data	Resolution
23 Aug 1988	5/5/88 - 5/23/89	DOQs (grayscale)	1 meter
22 Aug 1994	5/7/93 - 4/17/94 - 5/2/94	DOQs (color)	1 meter
22 Aug 1994	April 1995	DC Ortho	20 cm
6 July 2000	May 1999	DC Ortho	20 cm
6 Sept 2002	April 2002	DC Ortho	30 cm
19 Sept 2004	April 2005	DC Ortho	15 cm

Aerial photography and satellite observations were acquired at different times during the study period. Aerial photography utilized for validation was acquired in April-May of each year, while satellite data was acquired between July-September (Table 6). For two of the time steps in the study period (2000 and 2004), aerial photography was acquired in the previous or subsequent year as the satellite data.

Aerial photography was acquired during leaf-on periods each year, resulting in highly visible leaf canopy from above (Figure 6). It was not possible to avoid the difference in time between satellite and aerial image acquisition due to the limited available data. The implications of seasonal differences on tree cover results are discussed in the following chapter.

a. High density commercial, Ward 2

b. Medium density residential, Ward 6

c. Low density residential, Ward 3

d. Low density residential, Ward 8

Figure 6. Examples of 2005 air photography in validation plots.

Other sources of aerial photos were not useful for this study. National Agriculture Imagery Program (NAIP) data began only in 2003 (U.S. Department of Agriculture 2009). Imagery from the National Aerial Photography Program (NAPP) and National High Altitude Program (NHAP) dates to 1980, although the majority was acquired during leaf-off periods. NAPP data are available for the District of Columbia for 1988, 1994, and 1998 (U.S. Geological Survey 2011). These same photographs were scanned from the 1:40,000 scale films and orthorectified to produce the 1 meter resolution 1988 and 1994 DOQ images (U.S. Geological Survey 2011).

The focus of the current study is observing the proportion of land surface area covered by tree canopy, defined as the two dimensional projection of tree canopy area divided by land surface area. Measurements of canopy area and number of trees are made for validation of satellite observations. Other physical quantities such as total leaf area cannot be measured with the air photography used in this study. Although other quantities may be of interest for future studies of the urban environment, total canopy area remains the focus in current research and urban management strategies, and is the quantity used in this study.

District of Columbia Geospatial and Demographic Data

Geospatial data from the District of Columbia GIS data access system (D.C. Government 2007a) were utilized to delineate boundaries of DC wards, park lands, and land use restrictions as defined in the DC zoning code. These data were converted to projection information matching the Landsat observations using ArcGIS (ESRI 2011) and ENVI (Exelis 2012) programs.

Population and housing data were acquired from the U.S. Census (U.S. Census 2010, 2011) and reports compiled largely from Census data for the District of Columbia government (D.C. Government 2002a). These data quantify population characteristics within each DC ward and census tract. In this study, a preliminary comparison was made between tree cover variability and five factors related to urban land use and population: population density, population change, owner occupation of housing units, rates of housing unit vacancy, and percent of housing units that were detached dwellings.

Methodology

Introduction

To accomplish the research goals of advancing the understanding of temporal variability of urban tree cover, this study investigated methods of measuring urban tree cover, mapped temporal tree cover changes in the District of Columbia between 1984-2004, and identified spatial patterns of tree cover changes in the urban context.

The first phase of this research was a comparative assessment of methods for mapping of static urban tree cover. The second phase of the study focused on applying remote sensing methodology with calibrated Landsat data to observe tree cover changes in the District of Columbia. The results were validated with complimentary observations from cartographic products derived from high resolution multitemporal aerial photography. In the third phase of the study, connections between tree cover variability and spatial patterns of urban land use were identified.

Comparative Observations of Static Tree Cover

Compilation of Validation Data

To validate the Landsat-scale maps of static urban tree cover, a dataset of standing trees was compiled by combining data from field surveys of street trees and airphoto interpretation performed by the DC government. The dataset indicates the location of standing tree canopy corresponding to the 2000 Landsat image. The combined tree data covers the entire District of Columbia, allowing validation to be performed for the entire study area.

Three data sets were combined to produce a map of standing trees: 1) Casey street tree data, 2) DC GIS tree locations recorded as points, and 3) DC GIS closed canopy polygons.

Casey street tree data were used to create a data layer that indicated the location and crown size of each tree. Crown radius was recorded in 5 foot intervals. Of the approximately 380,000 trees in the DC GIS point data, approximately 130,000 were duplicated in the Casey street tree data and the remaining 250,000 were non-street trees. The median tree crown radius of duplicated street trees was 15 feet (4.6 meters), and 70% had a crown radius between 10-20 feet. Because the DC GIS data do not indicate tree size, the median crown radius from the trees duplicated in the two data sets was selected to represent all non-street trees. Both datasets were combined with the DC GIS polygon data indicating closed canopy forest to create a vector data layer of tree cover.

The vector data layers were combined into one binary raster with a cell size of one meter utilizing ENVI/IDL software. This raster layer was resampled to a Landsat-scale 30 meter cell size. A 30 meter raster layer was created in ENVI with map limits matching the one meter binary raster. The value for each 30 meter cell was calculated as the proportion of one meter tree pixels contained within that cell. The final city-wide raster layer indicates the proportion of each 30 meter pixel occupied by tree cover between 0-100% (Figure 7). The 30 meter cell size was selected to make it possible to compare to full resolution Landsat data.

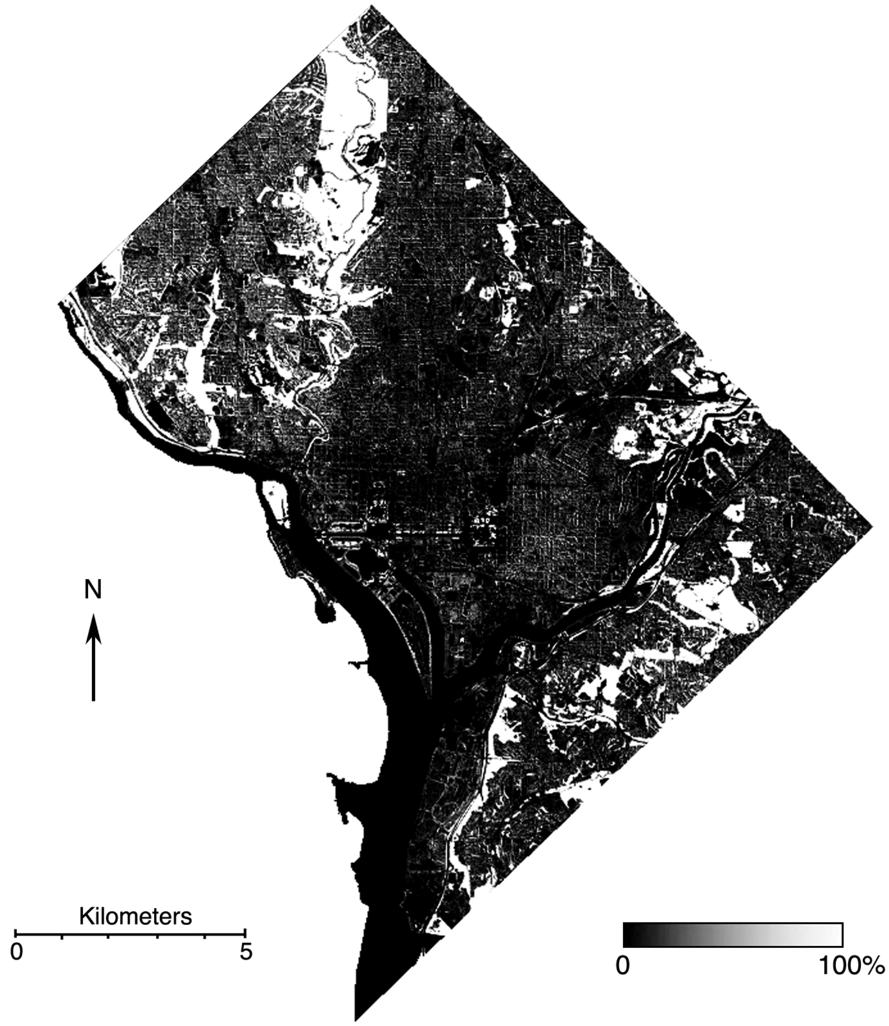

Figure 7. Tree cover validation data for 2000.

Urban Tree Cover Remote Sensing Observations

Subpixel proportion of urban tree cover was mapped using spectral mixture analysis (SMA) and support vector regression (SVR) to test these two techniques and identify methods for accurate urban tree cover mapping. These two techniques were selected to test the relative performance of a methodology applied in many previous studies and one that has not been widely utilized in studies of the urban environment.

The subpixel proportion of tree cover was estimated by applying a linear spectral mixture model to the 2000 Landsat scene. Training locations were selected at homogeneous sites of tree, grass, impervious cover high albedo, and low albedo water. Training samples were selected using visual analysis of air photography. SMA was applied as implemented in ENVI software (Exelis 2012), where SMA functions using linear unmixing algorithms (Gong et al. 1991). SMA calculations were constrained so that total land cover equaled 100%.

The LIBSVM program (Chang and Lin 2010) was used for support vector regression. Landsat reflectance data were scaled and converted for input into the LIBSVM package. Processing and data manipulation were performed using ENVI/IDL software (Exelis 2012). IDL routines were created to convert satellite data to proper format for LIBSVM.

Training sites for SVR were selected by generating random points utilizing procedures within the ESRI ArcGIS software package (ESRI 2010). An initial set of points were stratified by tree cover proportion in the 2000 validation data to identify locations with the full range of tree cover values. Tree cover was then manually interpreted using aerial photography for the plots, each sized to be equivalent to a 3x3 pixel Landsat window. Images were displayed and tree crowns were manually digitized using ENVI software (Exelis 2012). A set of 62 training data points resulted.

RBF kernel was selected and the LIBSVM cross-validation procedure was used to determine optimal parameters for support vector regression. After parameter validation was performed, the final SVR calculation was performed. LIBSVM was then used to calculate SVR estimates for each pixel in the 2000 Landsat data.

Tree cover error can be reported for each pixel because of the comprehensive validation data. Comparisons with validation data and scatter plots were produced using

3x3 pixel means, because per-pixel comparisons are not reliable due to geometric uncertainty inherent in Landsat-scale data. For the entire study area the root mean square error was calculated:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \qquad \text{Equation 6}$$

where y and $\hat{y}$ are the validation and estimated values for each observation, respectively, and n is the number of samples.

For both SMA and SVR the mean absolute error, RMSE, and coefficient of determination was calculated between the results and validation data. These measures are similar to that used in previous studies of urban forest change (Walton 2008a).

District of Columbia government zoning data (D.C. Government 2007a) were used to segment the city into land use categories. Mean error in park and non-park areas was measured. Spatial patterns of error with satellite measurements were identified by using zoning data to segment the city into zones of different density based on allowable lot occupancy: 60% open space requirement in low density residential areas, 40% open space required in medium density residential zones, and 25% or less in high density zones near the urban core and primary transportation routes.

Temporal Tree Cover Variability 1984-2004

Overview

Tree cover dynamics of the District of Columbia were mapped using the SVR approach applied to Landsat observations 1984-2004. Processing steps were performed using ENVI/IDL software (Exelis 2012) and the LIBSVM program (Chang and Lin

2010) was used for support vector regression. SVR was applied using the RBF kernel with same parameter values and training data derived for the 2000 Landsat data. High-confidence measurements of local scale tree cover change were mapped across the District of Columbia. Cartographic image products derived from aerial photography were used for multitemporal validation and fine scale observations of tree cover change.

Cloud Masking

The calibrated Landsat scenes were mostly cloud-free, but some clouds remained. Cloud and cloud shadow were masked in tree cover maps. Cloud cover is typically identified in Landsat data utilizing multiple filters incorporating thermal infrared data (Irish et al. 2006) and application of thresholds for visible and thermal infrared data (Hutchinson et al. 2005). Automated processes can perform highly accurate masking of clouds and cloud shadow with calibrated thermal infrared Landsat data (Huang et al. 2010).

For the current study, minimal cloud cover was present in the satellite data and the analysis included a limited number of scenes. Therefore, a more simple process was utilized. Multitemporal data in visible wavelength Landsat band 1 were utilized to identify cloud cover. The ratio of reflectance value to the mean value across all years was calculated for each pixel. Any pixels with a ratio greater than 2 were flagged as clouds. The accuracy of the cloud masks was assessed visually. Cloud shadows were manually digitized. Maximum cloud cover (1% total area of the District of Columbia) was observed in the 2002 Landsat scene. Cloud and shadow area exceeded 0.4% of the study area in only the 1996 and 2002 Landsat scenes. When comparing tree cover between different dates, cloud pixels were assumed to contain the mean tree cover of the previous and subsequent dates.

Compilation of Tree Cover Change Maps

Support vector regression was applied to calibrated Landsat data for all scenes 1984-2004. Data processing was performed with ENVI/IDL software (Exelis 2012). The SVR was applied with the LIBSVM program (Chang and Lin 2010).

Raster tree cover layers were overlaid to map tree cover dynamics over a 20 year time period. Change maps were produced using 3x3 raster cells spatially equivalent to 3x3 Landsat pixels to account for geometric uncertainty of Landsat data. The tree cover uncertainty of SVR estimates within each cell for each time step was evaluated by utilizing the error distribution measured for the 2000 tree cover observation. To assess the uncertainty of tree cover estimates, the standard deviation of the error was calculated as:

$$s = \sqrt{\frac{\sum_i (x_i - \mu)^2}{n}} \qquad \text{Equation 7}$$

where μ is the mean value for the error and *N* is the number of observations.

Because validation data were available for every remote sensing pixel, the entire error distribution was utilized to calculate the z statistic for each pixel in the 2000 SVR observation:

$$z = \frac{x - \mu}{s} \qquad \text{Equation 8}$$

where *x* is the error for a single pixel, μ is the mean error for all pixels, and s is the standard deviation of error for all pixels. This resulted in an error value in standard deviation units for each pixel. The z statistic was utilized to calculate confidence limits ($p<0.05$) for per-pixel tree cover observations:

$$\overline{X} \pm \mathbf{Z}_{\alpha/2} \qquad \text{Equation 9}$$

This was performed for each 5% increment to calculate confidence limits as a function of tree cover. Therefore confidence limits were sensitive to different levels of tree cover. Each pixel contained a tree cover value, the associated error threshold for that 5% tree cover range of estimated tree cover, and a value for tree cover change from the previous time step.

Change maps were produced by calculating which pixels contained tree cover change values exceeding confidence limits for each time step. For example, a pixel was be classified as tree cover increase if it changed from 20% to 35% and the confidence limits for that tree cover range was +/-14%. Tree cover gains or losses exceeding confidence limits were classified as tree change areas. These areas were mapped to show tree cover increases and decreases for each time step between 1984-2004. Cloud masks developed previously were used to remove cloud and cloud shadow from change maps.

The resulting maps were compiled to identify areas within the city that experienced tree cover change. Maps of tree cover change at this spatial resolution are at a scale appropriate for discrimination of trends between different neighborhoods, parks, and zones of high and low housing density.

Validation of Tree Cover Change Observations

Cartographic image products derived from aerial photography were utilized for validation of multitemporal satellite observations. The extensive vector data utilized to validate the 2000 static tree cover results was not available on other years. Therefore a procedure was developed to validate tree cover estimates at courser scale by comparing multitemporal satellite observations to aerial photography.

Validation of satellite observations was performed using aerial photography corresponding to satellite data acquisitions from four dates: 1988, 1994, 2000, and 2004. Images were displayed and tree crowns were manually digitized using ENVI software (Exelis 2012). Ellipses for each tree crown with visible leaf cover were digitized. Crowns with partial leaf cover were digitized, while trees with no leaf cover were not. Tree cover was then calculated as the proportion of each plot occupied by these ellipses.

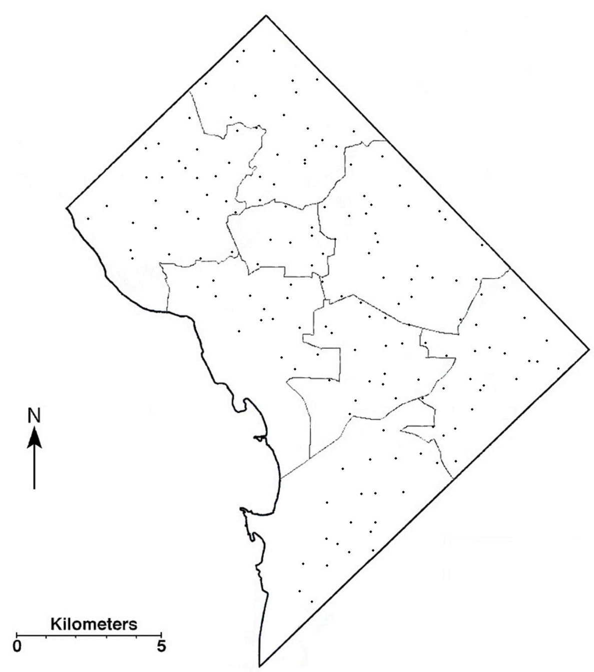

Figure 8. Location of validation plots.

Validation was performed in 160 plots, randomly located on land surface area stratified by ward boundaries (Figure 8). Plots were located by generating random coordinates utilizing procedures within the ESRI ArcGIS software package (ESRI 2010). Each DC ward was assigned a number of random points corresponding to its proportion of the city's total land surface area. The total number of plots was selected to provide at least 10 sample plots within low density residential zones in each DC ward. Each plot was 90x90 meters to match the size of 3x3 Landsat pixel windows.

Only DOQ imagery is available for validation of the 1988 time step, compared to higher resolution orthophotography for the other time steps. One way to address the difference in resolution between the two sources of aerial photography is to apply a correction to the low resolution validation. The difference measured between the two types of imagery could be applied to the 1988 time step, when only the low resolution product is available. However, because the DOQ and orthophotos were collected near each other in time only once (1994-1995) it was only possible to perform a single comparison to assess the difference. In addition, some change in tree cover between acquisition of the DOQ and orthophotos would be expected. For these reasons, no correction was applied to the 1994 DOQ imagery. The possible implications of validating tree cover using the lower resolution aerial data are discussed in the following chapter.

This number of plots is similar to that used in previous field studies. For a previous study of Washington DC forests, 201 plots were used for a field survey (Nowak et al. 2006). An analysis of the number of survey plots for urban forest studies indicated that uncertainty decreased with increasing numbers of plots up to approximately 200 plots (Nowak et al. 2008). This analysis also suggested a plot size of 0.04 hectare to allow rapid field surveys.

Multitemporal Uncertainty Assessment

The difference between SVR tree cover and air photography validation was calculated for 1988, 1994, 2000, and 2004. This resulted in four measurements of the difference between SVR estimates and high resolution air photography. From these measurements the *t* statistic distribution was utilized to determine confidence limits for error of tree cover estimates. Confidence limits were defined as:

$$\overline{X} \pm t_{\alpha,\, n\text{-}1} \frac{S_n}{\sqrt{n}}$$

Equation 10

where $\overline{X}$ is the mean error measured with validation data, S_n is the standard deviation of the error measurements, and n is the sample size (4). Confidence limits for tree cover measurement were calculated to show high confidence observation of tree cover change ($p<0.05$). This resulted in an estimated mean and 95% confidence limits for the error in tree cover measurement. The same confidence limits were applied to all tree cover measurements in the multitemporal analysis. The confidence limits were recalculated for each area being analyzed, such as the entire DC land area, low density residential zones, or other land use category. In contrast to previous studies, this measure of uncertainty was based on multiple observations using independent validation data.

Observations with Fine Scale Image Data

Observations of tree cover based on high resolution aerial photography were made to identify fine scale changes in tree cover. Besides providing validation of satellite observations, the aerial photography measurements were used to produce independent observations of tree cover change. Tree cover proportion was measured within all the air photography plots used for validation (Figure 8). The spatial distribution of the plots made it possible report tree cover city-wide and within land use types. Tree cover values for the four air photography dates (1988, 1994, 2000, and 2004) were recorded for the entire city and within land use categories in each DC ward. Tree cover was calculated as the mean value among randomly distributed plots within each area.

Fluctuation in Size and Number of Trees

To better understand fine scale changes in urban tree cover, the change in number of standing trees and crown sizes were evaluated to determine how each contributes to tree cover variability. Standing trees were counted and crown sizes mapped using high resolution aerial photography collected on two dates separated by 10 years. This was performed using vector digitizing tools in ENVI software (Exelis 2012) within the 90x90 meter plots used to validate SVR tree cover within low density residential zones. The analysis was performed using the 55 plots in low density residential zones, which contain the majority of the land surface area and tree cover within the District of Columbia. The number of trees and the crown radius of each tree were digitized on aerial photography from 1995 and 2005. These two dates were selected because high resolution photography was available, because they are separated by a decade, and because they represent a low and high amount of tree cover observed with satellite data.

Spatial Patterns of Tree Cover and Urban Land Use

Overview

The temporal variability of tree cover was observed in the previous section of this study. The current phase of this research focuses on spatial variation of tree cover and its connections with urban structure. Tree cover change observations were compared to spatial patterns of urban land use and population to better understand how variability of urban tree cover is interconnected with urban settlement and environment. The connections between tree cover variability and resource management and oversight were examined by comparing tree cover in zones with different management regulations. The analysis included a comparison of tree cover change with neighborhood-scale demographic data.

Land Use Zones

Tree cover variability and land use patterns were evaluated. DCGIS data were used to stratify the study area into land use categories defined by the District of Columbia zoning code sets a maximum allowable "lot occupancy", or proportion of each property lot that may contain structures. District of Columbia zoning laws set a maximum lot occupancy for private property ranges between 60-100% for commercial land uses and 40-75% for residential uses. The remaining open space in each lots can include trees, grass, and impervious surfaces.

Zoning data also describe types of land ownership, including categories of government land ownership and park lands. Within each of these categories the lot occupancy is defined based on desired density. This is not true with park areas, which do not have lot occupancy requirements because individual property lots do not exist there.

Tree cover variability was compared between land use types by segmenting the study area into lot occupancy categories. Mean, maximum, and minimum tree cover were compiled for zones requiring 60%, 40%, and 0-25% open space in property lots. Separate results were also reported for each DC ward.

Residential Zones

Tree cover variability was analyzed in detail within low and medium density residential zones that occupy most of the District of Columbia. Medium density zones with 40% open space requirements exist mostly in DC wards 1 and 6, while the 60% open space zones are spread across five wards surrounding the urban core (Figure 9).

Figure 9. DC Wards with residential zones. Low density residential zones (left) and medium density residential zones (right) in gray.

Mean tree cover within each land use zone was calculated from SVR results between 1984-2004. Uncertainty of tree cover estimates was evaluated using the same methodology applied to the entire study area, but incorporating observations from validation plots with each land use category.

Tree cover variability within tree and slope overlay zones was compared to changes outside those zones to identify possible differences. These zones were investigated because they are the only explicit legal restrictions for tree removal in the DC legal code tied to a specific spatial extent (D.C. Government 1992). Mean tree cover and variability were calculated for tree and slope zones and areas outside the overlay zones of the same residential zoning density. These areas were zoned "R-1-A" in the DC code, the lowest density zoning for residential areas. Tree cover values were extracted from DC zoning polygons using ENVI/IDL software.

Land Cover Change

Tree cover maps were overlaid to identify areas where dense tree cover receded or expanded. Raster layers showing the extent of dense tree cover were overlaid to produce maps showing areas of at least 90x90 meters that experienced a change between >75% tree cover and <25% tree cover. Cells with >75% and < 25% stable tree cover in both 1984-1986 were compared to the same areas in 2002-2004. Change in both directions was mapped. Cells identified as tree cover losses were compared to geographically corresponding cells in all satellite observations between 1984-2004. The first date each cell changed from tree to non-tree was recorded to determine the year of status change for that cell. Change areas were overlain and mapped using ENVI/IDL software (Exelis 2012).

Polygons experiencing change were stratified by DC ward using DC government geospatial data (D.C. Government 2007a) using ENVI vector processing tools (Exelis 2012). The area of land cover change and dates for changes within each ward were compiled. The surface area experiencing change was reported for each ward, along with the year of the changes in each ward.

Residential Property Use and Population

To extend the ward-based analysis of urban tree cover to finer scale, tree cover proportion was compared to demographic data from the U.S. Census from 2000 (U.S. Census 2010) compiled by the District of Columbia government (D.C. Government 2002a).

Five factors were selected for comparison to mean tree cover: Population density, population change between 1980-2000, proportion of housing units occupied by owners, proportion of units vacant, and proportion of housing units that were detached houses. These variables were selected because they have possible links to tree cover and because their relationships with urban vegetation have not been tested in previous research. Linear regression was performed for each factor to test the relationship between tree cover and demographic data.

Tree values for census tracts were taken from tree raster data in cells spatially matching the polygon extent of census tracts. Data were processed using vector tools in ENVI software (Exelis 2012) and ArcGIS (ESRI 2011) software. The analysis was performed in the five DC wards (3, 4, 5, 7, and 8) where low density residential was the dominant land use type (Figure 9). Census tracts were grouped into DC wards. Tree cover and demographic differences within low density residential zones were identified between wards.

Summary

Calibrated satellite remote sensing data and cartographic image products derived from aerial photography were utilized to observe tree cover in the District of Columbia. The first phase of the methodology tested Spectral Mixture Analysis (SMA) and Support Vector Regression (SVR) methodologies for observing urban tree cover from satellite remote sensing data. The second phase applied the SVR technique to map temporal changes in tree cover between 1984-2004. High resolution aerial photography was utilized for multitemporal validation. The third phase of this study analyzed the spatial variability of tree cover changes and spatial patterns of urban land use. Public geospatial data were utilized to segment the study area to compare tree cover changes in zones of different densities and land use types.

CHAPTER V

RESULTS AND DISCUSSION

Introduction

Results are presented in three phases: 1) A comparative analysis of static urban tree cover, which includes comparative testing and analysis of remote sensing of static urban tree cover. The relative accuracy of two alternate approaches is discussed. 2) Observations of temporal change in District of Columbia tree cover between 1984-2004 as observed with satellite remote sensing and aerial photography. 3) Analysis of tree cover within the context of the spatial patterns of urban land use. Connections between tree cover variability and spatial patterns of urban land use and resource management are identified.

Static Tree Cover Mapping

Spectral Mixture Analysis

Application of Spectral Mixture Analysis (SMA) resulted in a tree cover estimate for each satellite pixel between 0-100%. The resulting map of proportional tree cover shows spatially variable tree cover across the District of Columbia (Figure 10).

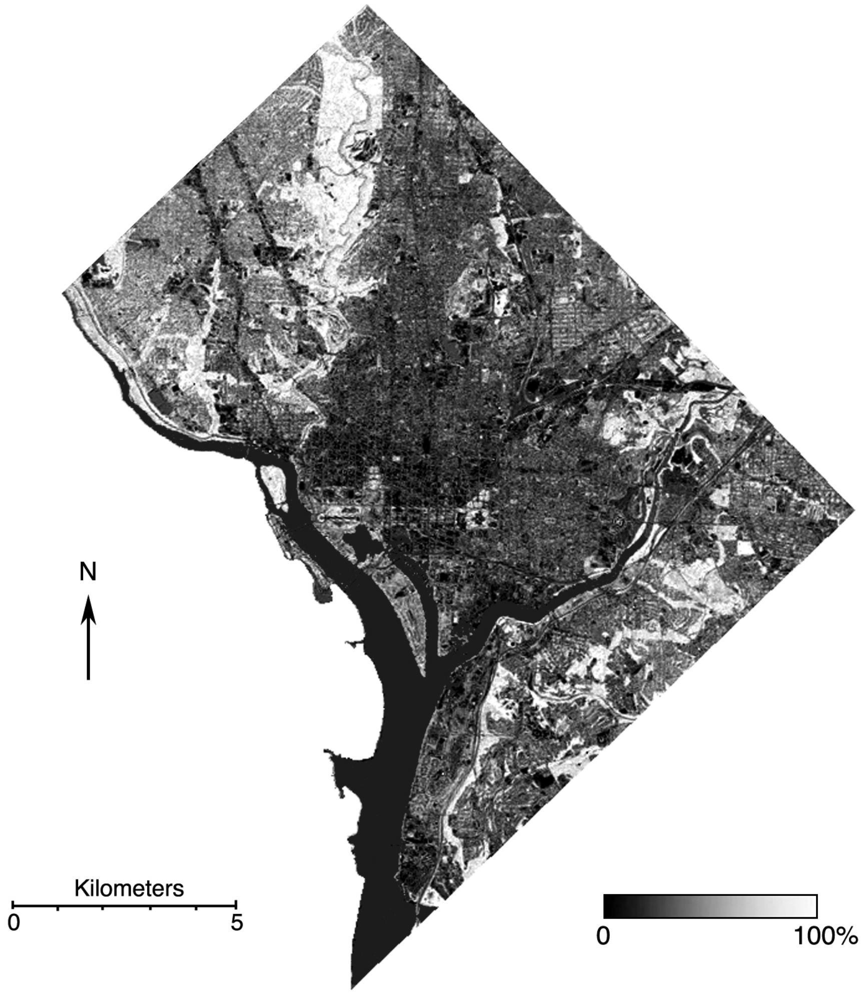

Figure 10. SMA Tree cover proportion

In the SMA map, densely forested parks areas such as Rock Creek Park lie in the northern part of the city (Figure 10). Moderate amounts of tree cover are visible in residential zones of the city. The urban core and some corridors in outer sections of the city have the lowest tree cover proportions.

The total tree cover proportion estimate for the District of Columbia was 32.9% land surface area, and RMS error of the SMA estimates was 21.0% land surface area. The SMA results and validation data for all 3x3 pixel windows (n=21851) are positively correlated (R^2=0.75) but nonlinear (Figure 11).

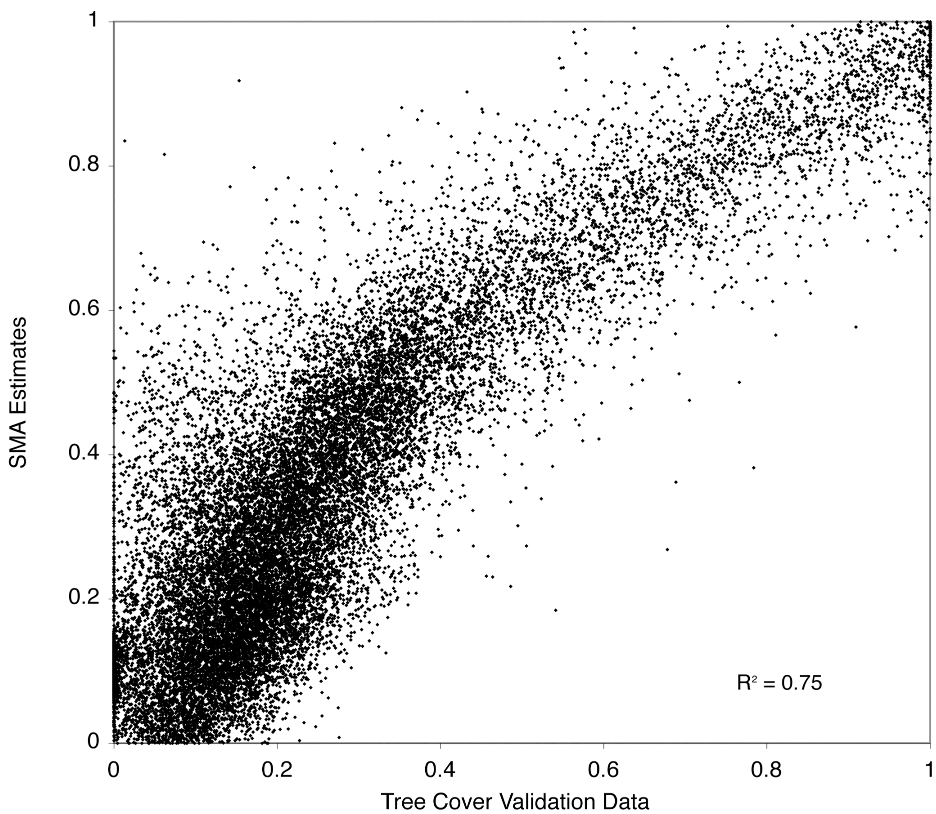

Figure 11. SMA tree cover estimates vs. validation data.

Comparisons between SMA and the validation data show that SMA overestimates tree cover, especially at intermediate tree cover values (Figure 12). A least-squares polynomial fit ($y=-0.439x^2 + 1.416x + 0.023$) demonstrates the nonlinearity of the SMA results. SMA error is greatest when tree cover proportion is approximately 30%-40%. That tree cover range is typical for the low density residential areas of the District of Columbia.

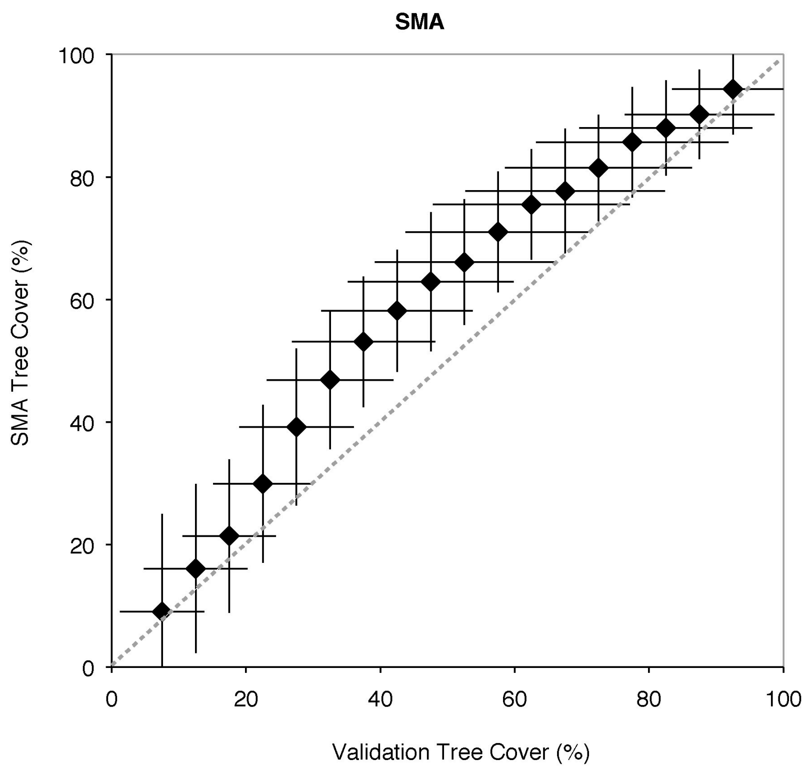

Figure 12. SMA tree cover and validation data. Mean values and one standard deviation shown in each 5% bin.

Error for SMA observations was determined for each 5% bin of estimated tree cover (Figure 13). SMA error across all tree cover values at the per-pixel scale was highly variable. Lower variability at high values for tree cover estimates is likely due to spectrally similar responses of closed canopy tree cover with training data.

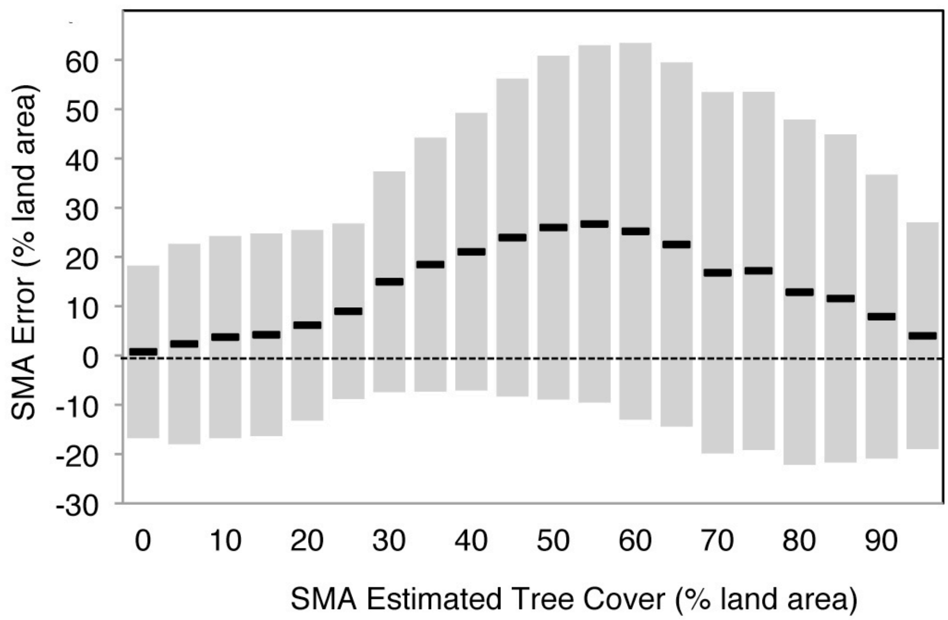

Figure 13. Error distribution of SMA tree cover estimates. Mean error and confidence limits for each 5% tree cover bin.

Support Vector Regression

The application of Support Vector Regression (SVR) resulted in a map of proportional tree cover for the District of Columbia (Figure 14). Fine-scale differences in tree cover are more visible in the SVR results in densely developed zones of the city.

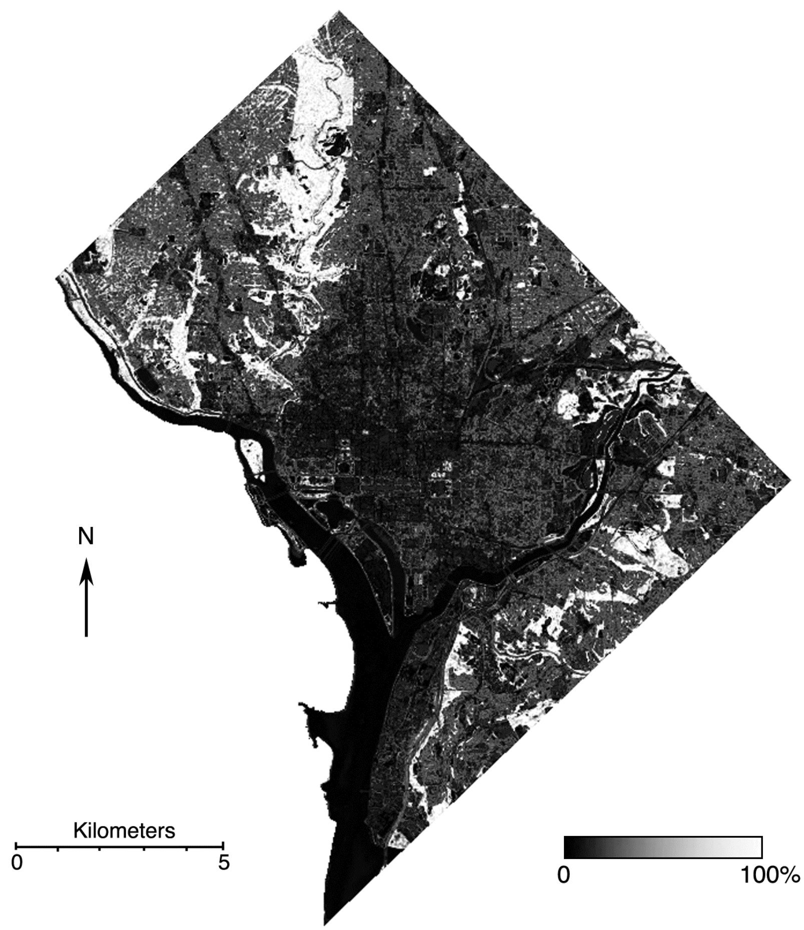

Figure 14. SVR Tree cover proportion

The total tree cover estimate for the District of Columbia was 26.8% land surface area, compared to 27.0% for the validation data. Root mean square error of the SVR estimates compared to validation data is 7.7% land surface area. The relationship between SVR results and validation data for all 3x3 pixel windows is more linear than SMA results (Figure 15).

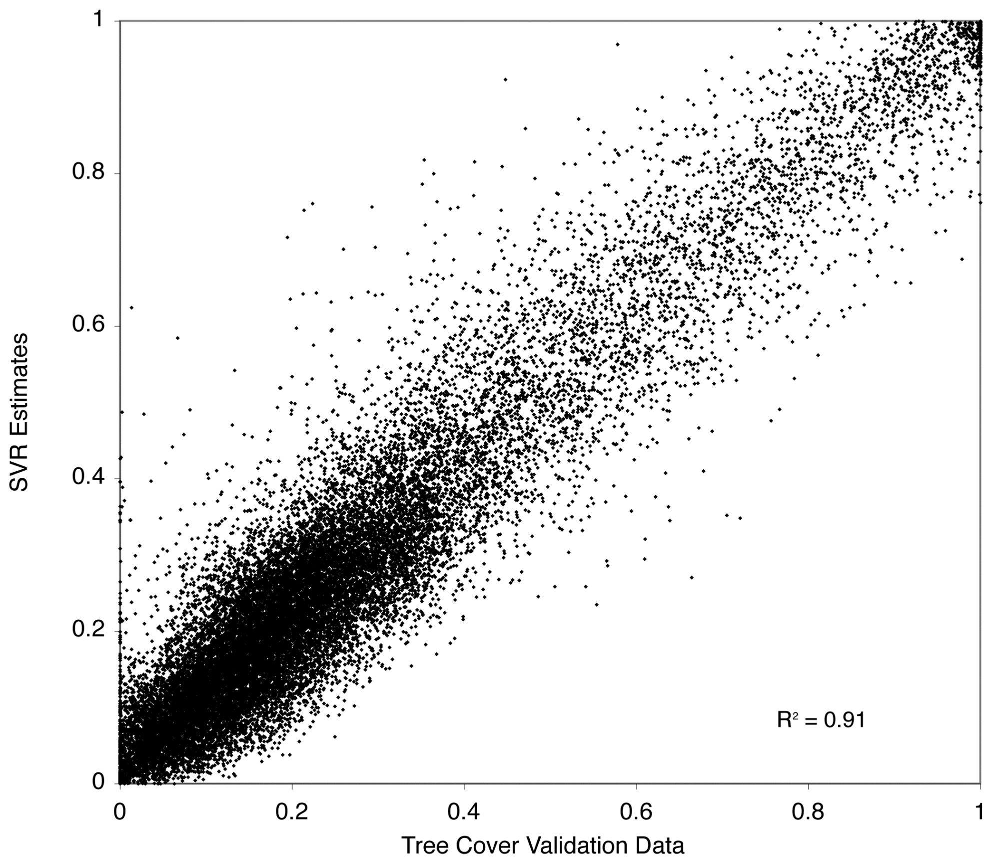

Figure 15. SVR tree cover vs. validation data.

SVR produces more linear and consistent estimates of tree cover compared to SMA. The SVR tree cover results better match the validation data, but with a wide distribution of error still evident (Figure 16). RMS error was about one third as high for SVR compared to SMA (7.7% land area, compared to 21%). Fit to validation data was closer with results from SVR (R^2=0.91) than SMA (R^2=0.75).

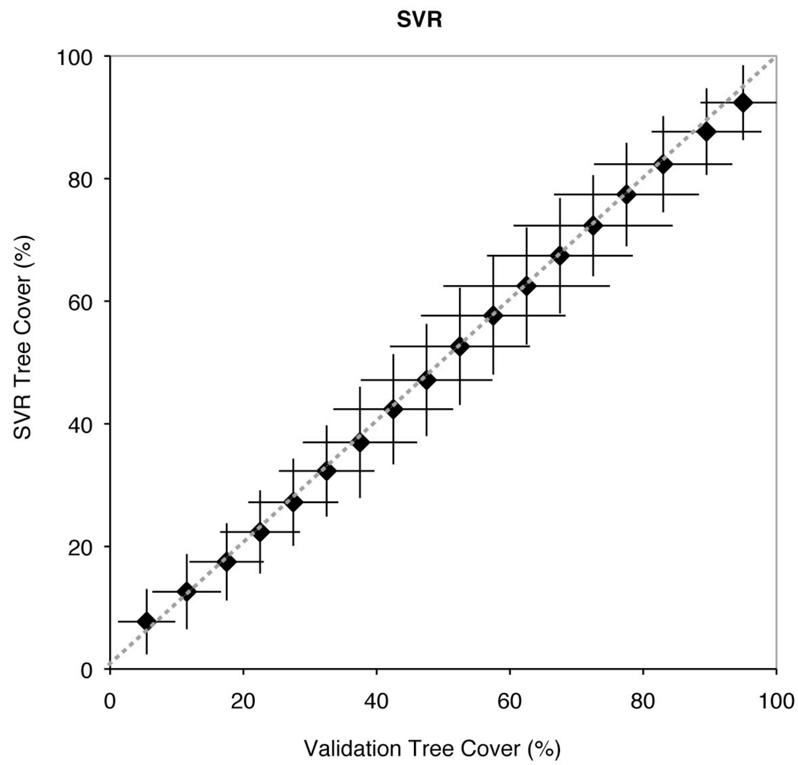

Figure 16. SVR tree cover and validation data. Mean values and one standard deviation shown in each 5% bin.

Within a range of values 40-60% tree cover, error distribution is wider (Figure 16). Variability is lower at tree cover extremes that are spectrally simple to discriminate. Error for SVR observations was determined for each 5% bin of estimated tree cover

(Figure 17). Error was greatest at tree cover values between 45-80% land surface area.

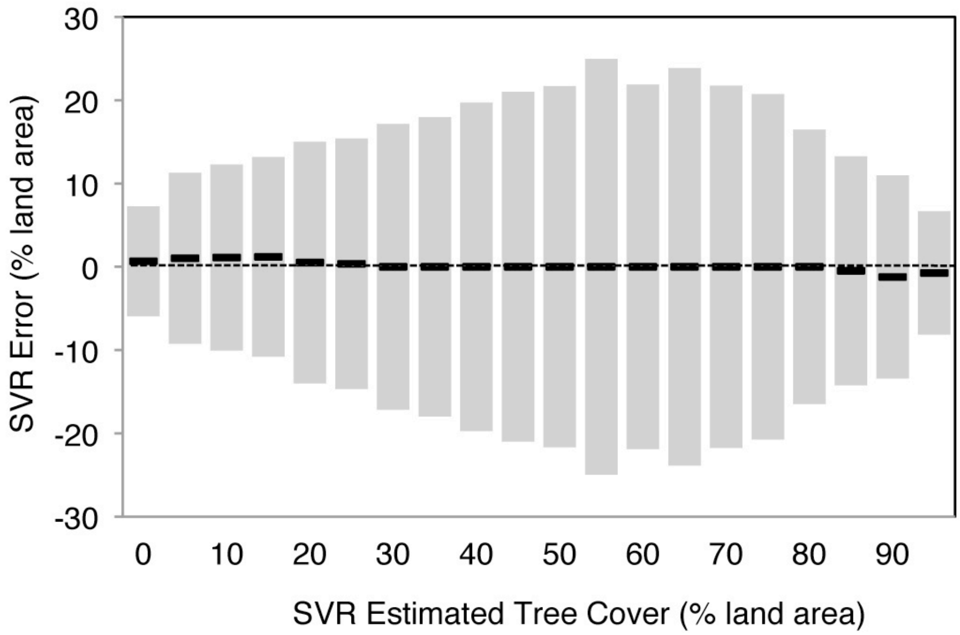

Figure 17. Error distribution of SVR tree cover estimates. Mean error and confidence limits for each 5% tree cover bin.

Spatial Variability of Error

The use of comprehensive validation data makes it possible to evaluate the spatial distribution of error using the SMA and SVR techniques. The spatial patterns of errors were compared to the physical layout of the urban study area to determine if the techniques provided consistent error across land use types.

Validation data for the District of Columbia was compared to SMA results to produce a map of spatial variability of tree cover error (Figure 18). SMA error is variable and related to land use type. With the SMA approach, tree cover is overestimated in areas with extensive forest and grass, while tree cover is underestimated in more higher density areas. Densely forested Rock Creek Park exhibits low error, which is likely a result of the model being trained on homogeneous tree cover.

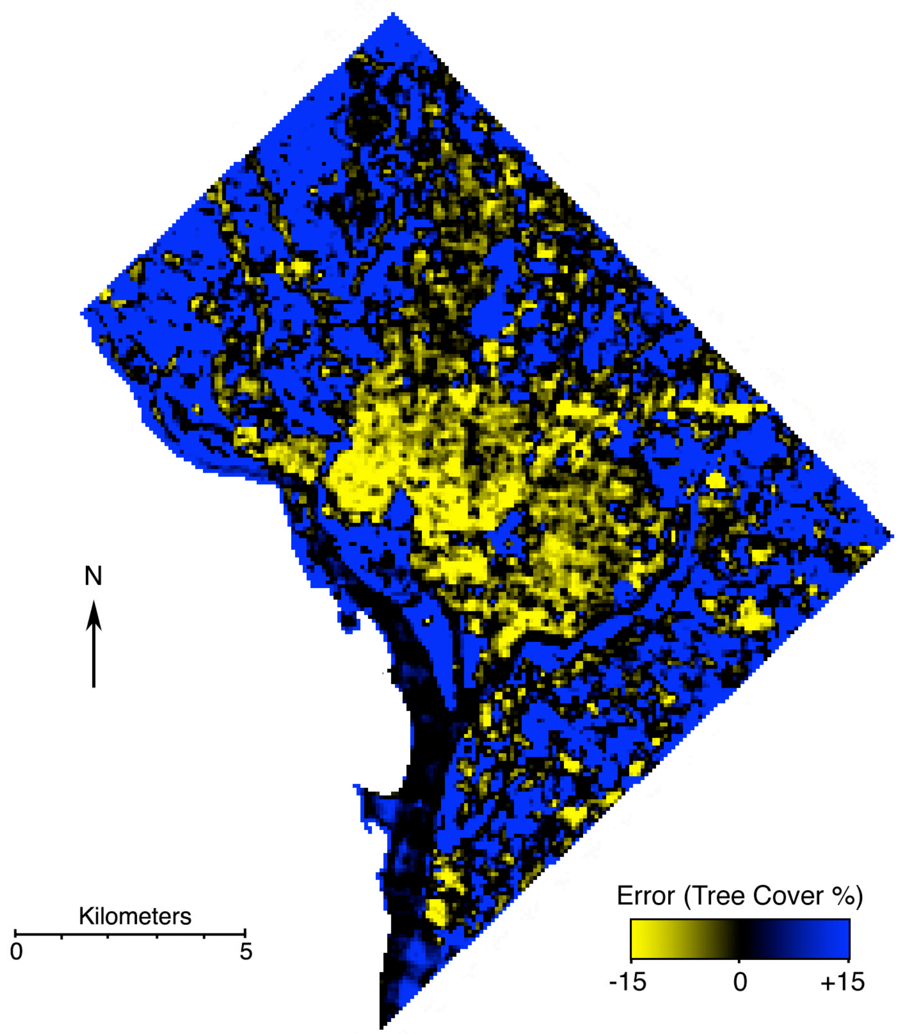

Figure 18. SMA Error Map

In contrast the SMA results, SVR error is lower and more consistent across different land use types (Figure 19). Tree cover is underestimated in much of the urban core and some large park units. Tree cover estimates exceeded validation data in many outer sections of the city and in smaller park units near the urban core.

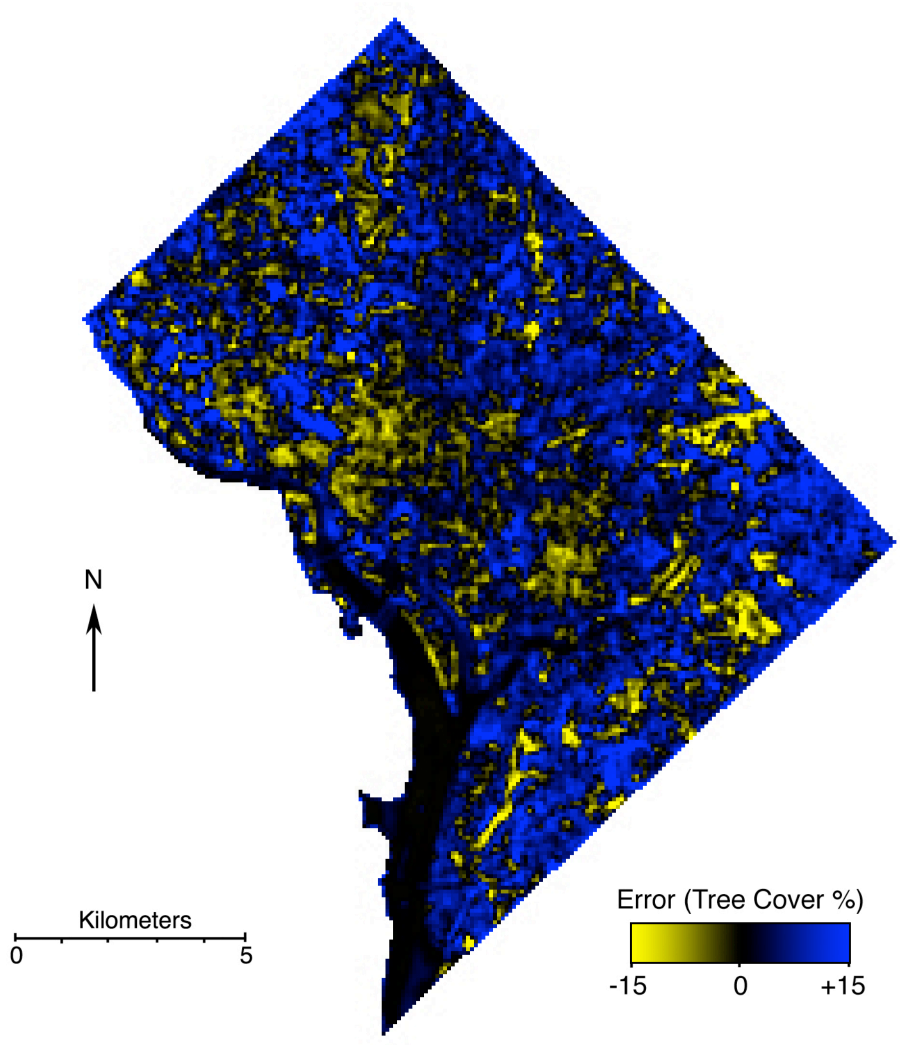

Figure 19. SVR Error Map

Error from SVR and SMA was stratified into land use categories using DC government zones data (Figure 20). The data shown include the entire population of data points in the study area. SVR results more closely match validation data while error from SMA results is more widely distributed.

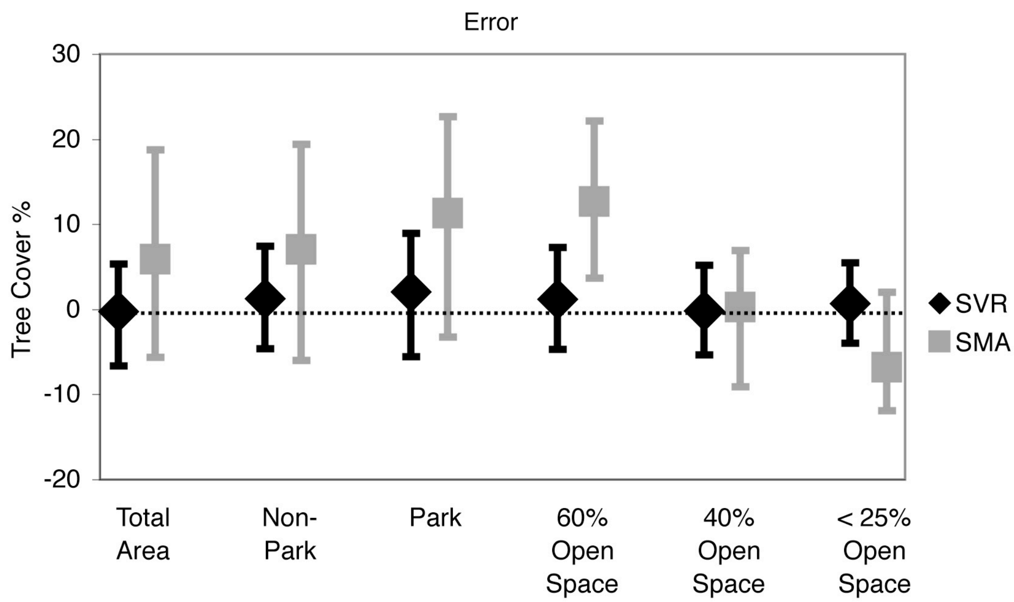

Figure 20. Tree cover error mean and standard deviation in land use categories defined by DC zoning code.

Tree cover estimates from SVR were stratified into DC wards. Mean tree cover and standard deviation of error were calculated for each DC ward in park and non-park areas (Figure 21). Tree cover proportion was greatest in wards 3 and 4 in the northern part of the District of Columbia. Lowest tree cover proportions were in wards 2 and 6 in the central part of the city.

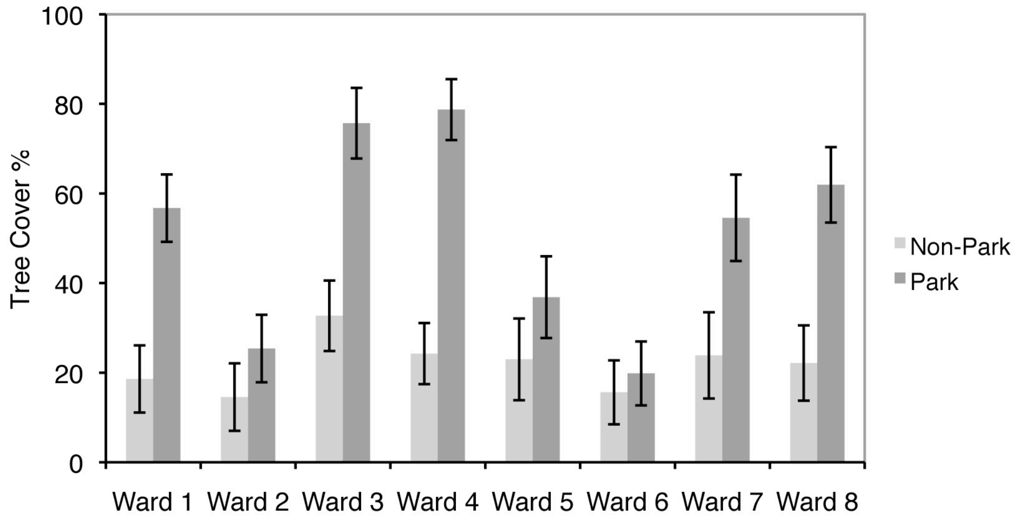

Figure 21. SVR tree cover in DC wards.
Mean tree cover and error standard deviation shown.

Assessment of SMA and SVR Approaches

Tree cover estimates from SVR had higher overall accuracy than SMA. The consistent error with the SVR results allows this technique to be used to discern tree cover differences between sections of the city.

The SMA technique overestimates tree cover in the middle range of values, possibly due to confusion between tree and grass cover. Enhancements of SMA are available to provide higher accuracy for estimating land cover proportions. For instance, it may be possible to better discriminate tree and grass using nonlinear SMA techniques. However, the scatter of results near the 40-60% tree cover would still have been present (Figure 16). SMA techniques may not be able to address tree/grass spectral confusion because they are trained on homogeneous tree cover. The SVR methodology addresses the problem of tree/grass confusion by incorporating spectral information from a range of tree cover proportions.

SVR Parameters

Parameters for SVR were calculated using a cross validation procedure. The parameter values were: C=0.268, γ=0.649, e =0.064. The values for C and ε are below the default LIBSVM values, while γ is higher. The low value for ε indicates that the SVR used a relatively large number of support vectors in the model. Although one of the strengths of support vector techniques is the ability to describe complex data with small numbers of samples (support vectors), this did not occur in this research. The low value for the ε parameter indicates a narrow insensitive range. The number of support vectors used in the 2000 data (44) exceeded 70% the number of original training samples (62). The C parameter defines the trade-off between closeness of fit and good generalization. The low value indicates the most accurate solution was one that placed more importance in generalization than closeness of fit.

An earlier study that applied SVR to estimate urban tree cover proportion (Walton 2008b) utilized the "e1071" library of the R statistical software package (Dimitriadou et al. 2006), which was developed from the same LIBSVM tool used in this research. A systematic parameter cross-validation procedure was not applied in that earlier study, but parameters were chosen after experimenting with a subset of the data (Walton 2008b).

Comparative Assessment of Urban Tree Cover

Tree cover proportion in the District of Columbia was estimated using several methods in previous studies (Table 7). Comparisons including results from the current study indicate broad agreement across different types of methodologies and data types.

Table 7. District of Columbia tree cover results.

Previous Studies	
Plot-Based Estimate (Nowak et al. 2006)	28.6% cover, 1.9 million trees (2004)
Plot-Based Estimate (Howard, Alonzo 2009)	28.1% cover, 2.6 million trees (2009)
High Resolution Object-Oriented Technique (O'Neil-Dunne 2009)	34.8% (2006) (includes shrub cover)
Current Research	
Remote Sensing (SVR results)	26.2% cover (2000)
Remote Sensing (SMA results)	32.9% (2000)
Field Survey, Airphoto Mapping (Validation data)	27.0% cover (2000)

Results from field surveys (Nowak et al. 2006; Howard and Alonzo 2009) and the moderate resolution SVR observations used in the current study both estimate total tree cover proportion for DC at just under 30% (Table 7). The estimate from object-oriented classification was 34.8% land surface area (O'Neil-Dunne 2009). The original data were provided for examination for this study at its original 0.6 meter spatial resolution by staff at Casey Trees.

Three factors influence the higher total tree cover measured using high resolution data. First, tree cover variability occurred between the dates of the two observations but its magnitude is unknown. Second, the definition of forest is different: At least some amount of shrub cover is included in the object-oriented classification and not the other results. The results from field surveys estimate trees and shrubs covering 28.6% and 7.8% of the DC land surface, respectively (Nowak et al. 2006). This totals 34.6%, closely matching the object-oriented results (34.8%). Third, the spatial scale of observations may impact the results. Issues of scale require more study to better understand how to compare different measures of urban forest cover.

Temporal Tree Cover Variability 1984-2004

Local Patterns of Tree Cover Change

The SVR methodology was applied to the processed Landsat data. Confidence limits ($p<0.05$) for detecting per-pixel tree cover change between satellite observations were calculated from the error distribution of SVR results (Figure 17). The confidence limits vary by tree cover estimate (Table 8). The precision of mapped tree cover changes was therefore variable across the study area. Changes exceeding confidence limits for each 3x3 Landsat pixel window were classified as tree cover change.

Table 8. Confidence limits for SVR tree cover.

Tree Cover	Conf. Limits	Tree Cover	Conf. Limits
0%-5%	+/- 6.6	50%-55%	+/- 21.6
5%-10%	+/- 10.2	55%-60%	+/- 25.0
10%-15%	+/- 11.2	60%-65%	+/- 21.8
15%-20%	+/- 11.8	65%-70%	+/- 23.8
20%-25%	+/- 14.4	70%-75%	+/- 21.8
25%-30%	+/- 15.0	75%-80%	+/- 20.6
30%-35%	+/- 17.2	80%-85%	+/- 16.4
35%-40%	+/- 18.0	85%-90%	+/- 13.6
40%-45%	+/- 19.8	90%-95%	+/- 12.2
45%-50%	+/- 21.0	95%-100%	+/- 7.4

Combining SVR results produced maps of tree cover change for the District of Columbia 1984-2004. The maps show areas where a high confidence observation of tree cover change took place between each time step in the District of Columbia (Figure 22).

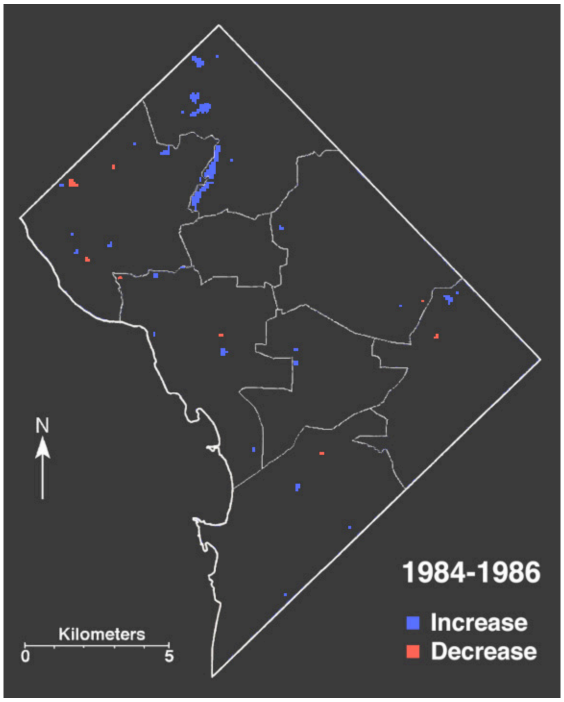

Figure 22a

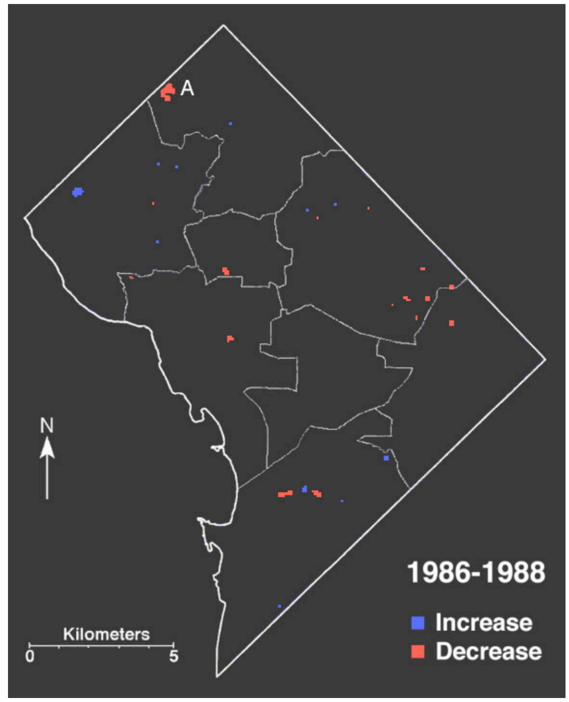

Figure 22b

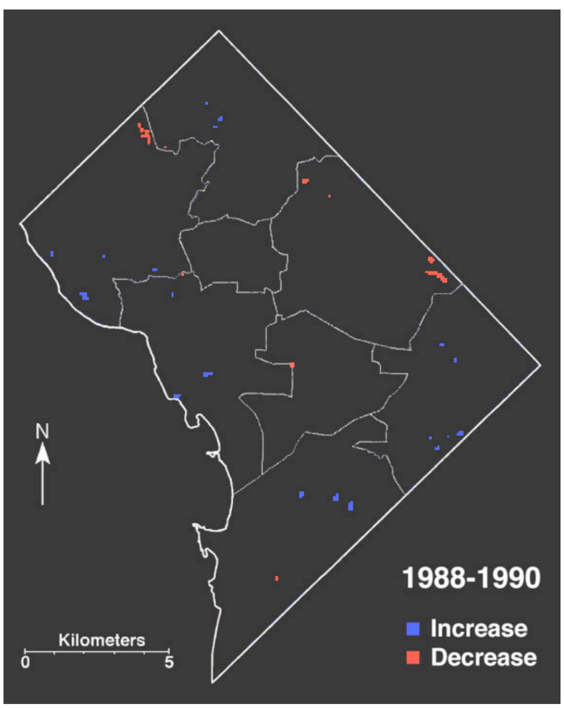

Figure 22c

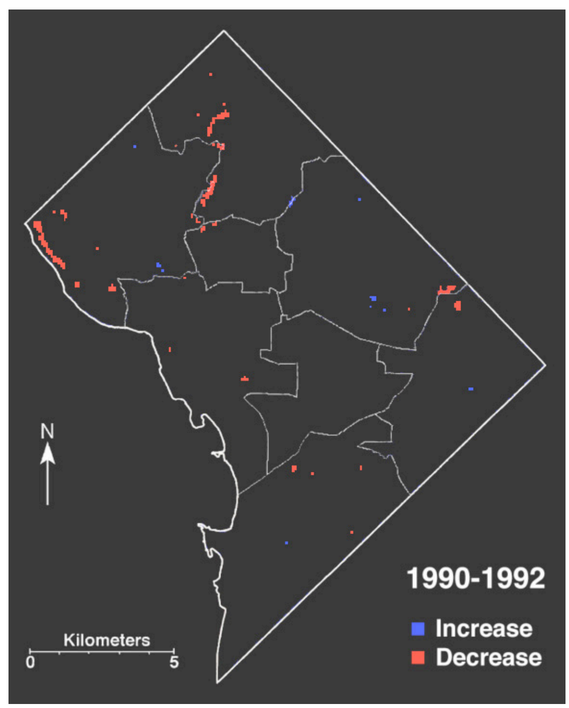

Figure 22d

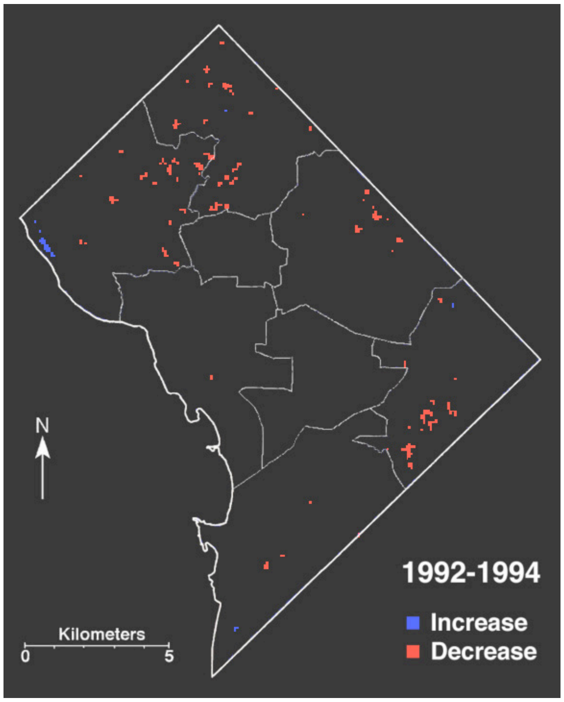

Figure 22e

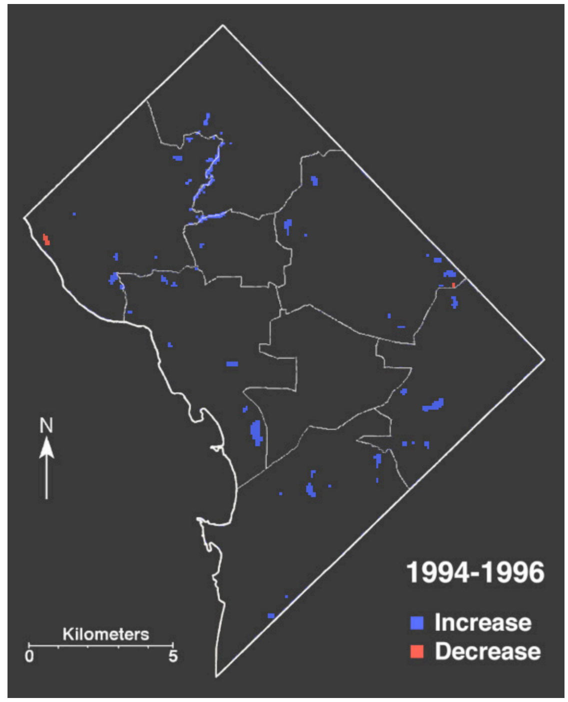

Figure 22f

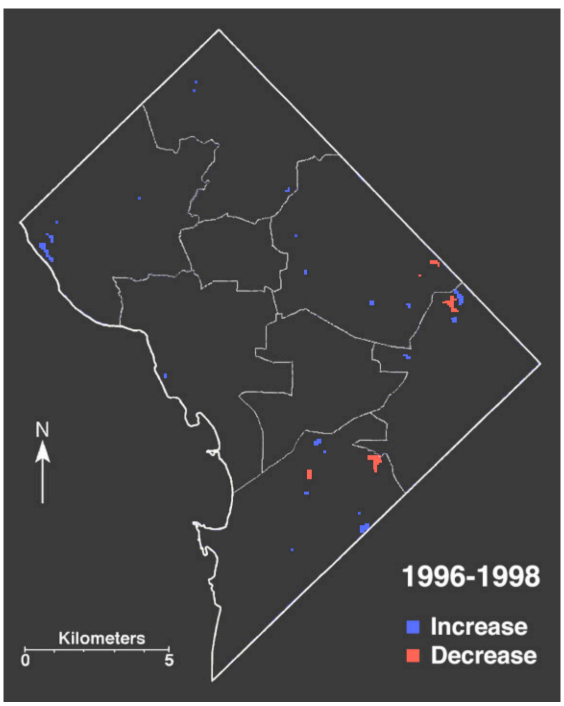

Figure 22g

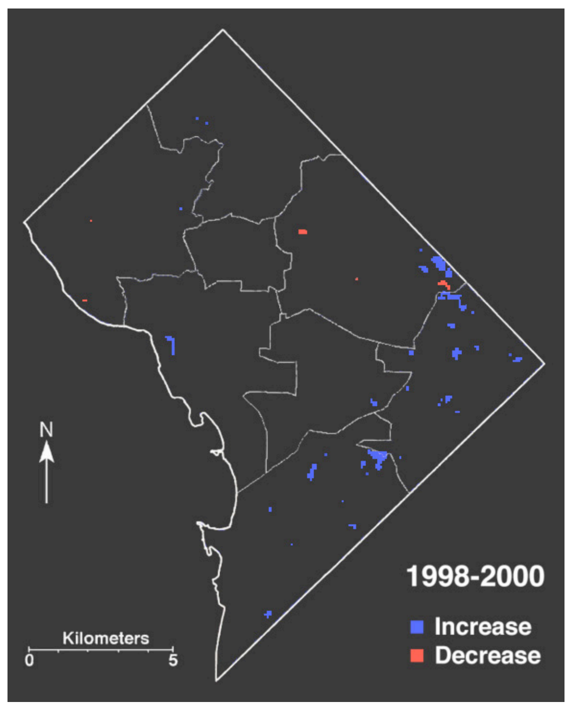

Figure 22h

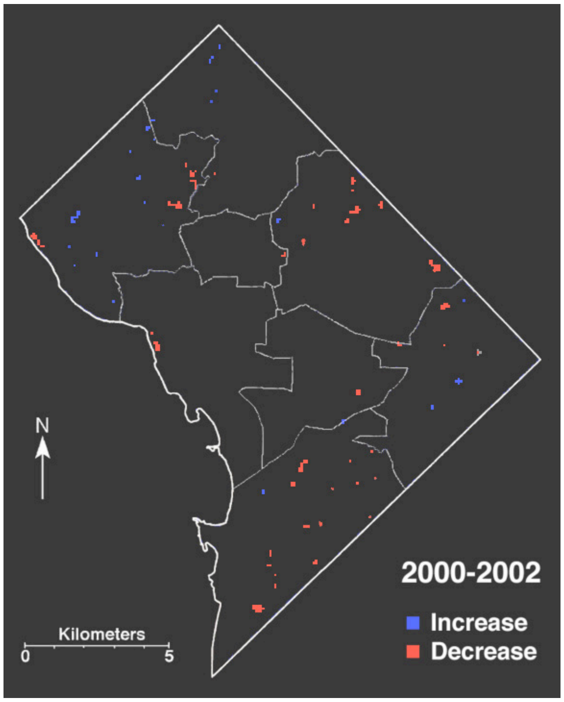

Figure 22i

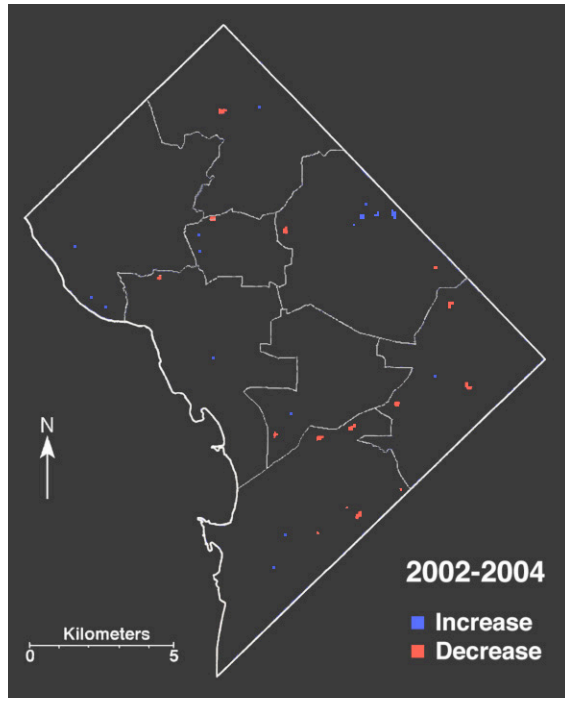

Figure 22j

Figure 22. Maps of District of Columbia tree cover change.
Red indicates tree cover decrease. Blue indicates increase.

<u>*Tree Cover Observations with Fine Scale Image Data*</u>

Tree cover was digitized from aerial photography in sample plots to measure overall tree cover proportion in the District of Columbia. Measurements were made on four dates corresponding to satellite observations (1988, 1994, 2000, and 2004). The mean value for randomly distributed plots shows that tree cover varied by 3.6% total land surface area for the entire District of Columbia (Figure 23). Tree cover variability was greatest in low density residential areas required to maintain 60% open space within property lots. Tree cover varied by 6.8% land surface area in these zones between the four measurement years (Figure 23).

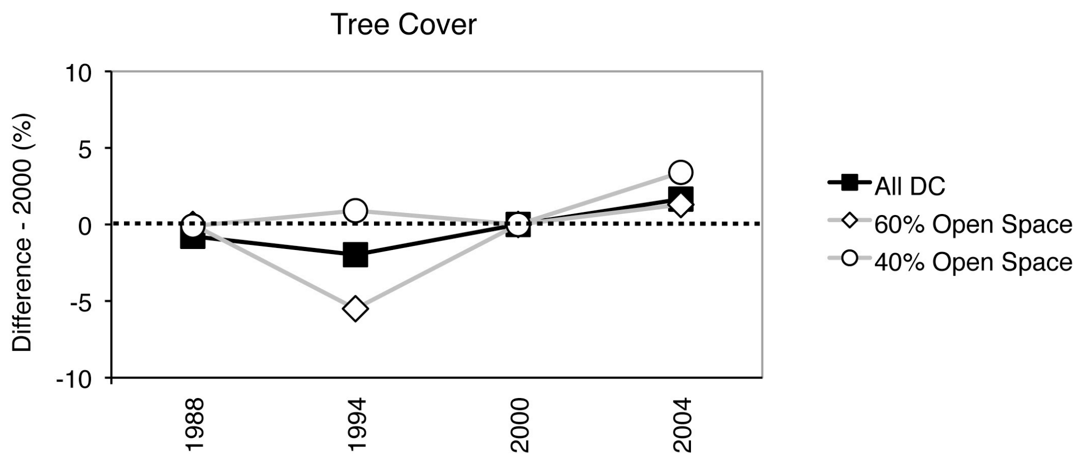

Figure 23. Tree cover variability from observations derived from air photography.

Tree Cover Uncertainty

Error for multitemporal tree cover mapping was determined for four dates corresponding to acquisition of satellite data and aerial photography: 1988, 1994, 2000, and 2004. The mean and 95% confidence limits for the difference between the two observations were calculated for the entire study area and for different land use zones (Figure 24).

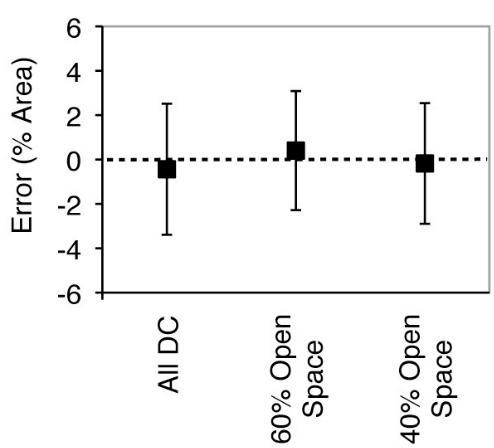

Figure 24. Tree cover error mean and confidence limits.

The mean error and confidence limits were calculated for the entire District of Columbia (-0.4+/-2.9%), low density residential zones (0.4+/-2.7%), medium density residential zones (-0.2+/-2.7%), park areas (-1.3+/-3.6%), and non-park areas (-0.04+/-2.9%). These confidence limits were used as a measure of the accuracy of the SVR technique. Confidence limits were applied to all tree cover measurements within each zone.

The current study utilizes an approach including validation with independent observations to develop reliable estimates of uncertainty in tree cover measurements. Previous studies not utilizing validation with independent observations may have overestimated the precision of tree cover measurements. Uncertainty in previous studies has often been estimated utilizing statistical measures such as standard error. Previous studies have claimed tree cover change in Baltimore of 1.9% (Nowak and Greenfield 2012) and change in tree numbers in the District of Columbia of 950,000 trees (Howard and Alonzo 2009; Nowak et al. 2006). Although these changes exceeded the standard error, neither study incorporated multitemporal validation.

Due to large sample sizes, utilizing standard error with remote sensing data may result in estimates of error that exceed the precision of the techniques being used. The satellite scenes utilized in the current study covering the District of Columbia exceed 20,000 pixels each. Calculated in the same way as previous studies of urban tree cover utilizing aerial photography in sample plots (Nowak and Greenfield 2012), the standard error for application of SVR to the 2000 Landsat data in the current study would be 0.3% land surface area.

City-Wide Tree Cover Variability

Total tree cover within the entire District of Columbia varied by 6.7(+/-5.8)% total land surface area (Figure 25), equivalent to 1065(+/-922) hectares of tree canopy. Between 1984-2004 the District of Columbia did not experience trends of increase or decrease in overall tree cover. The average change between time steps was 1.7% land surface area, or 270 hectares of tree canopy area.

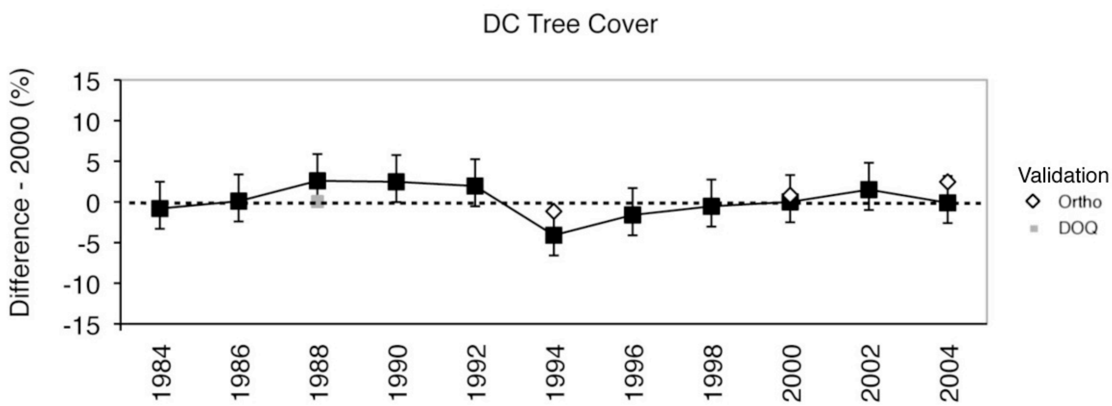

Figure 25. DC tree cover variability from SVR satellite observations. Difference and confidence limits shown.

Fluctuation in Size and Number of Trees

To better understand fine scale changes in urban tree cover, standing trees and crown sizes of trees were mapped using high resolution cartographic products derived from aerial photography collected on two dates separated by 10 years. This was performed in sample plots within the low density residential zones that experienced tree cover changes exceeding city-wide variability (Figure 23).

The number of trees in low density residential zones increased 4.3 trees per hectare between 1995-2005 (Figure 26). Of the total number of standing trees, 84% were identified in air photography acquired on both dates.

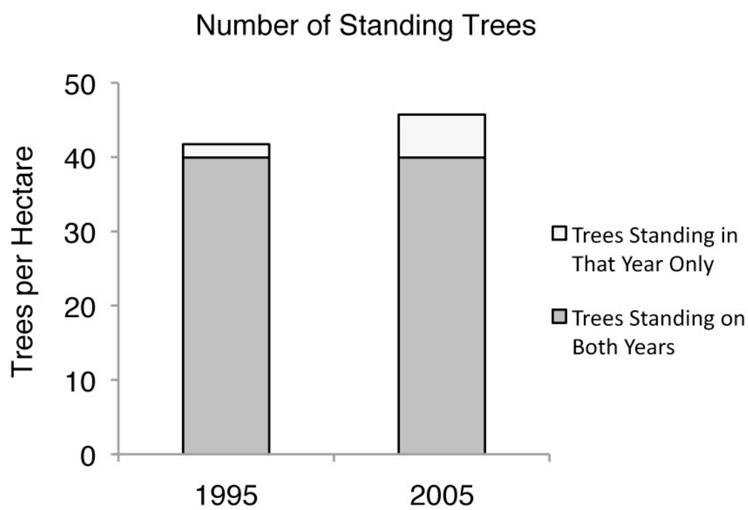

Figure 26. Change in number of standing trees.

The mean crown radius increased by 0.3 meters between 1995 and 2005 (Figure 27). Trees that were lost or gained had smaller mean crown radius (2.2 meters) than persistent standing trees (4.8 meters). The mean crown radius of new trees visible only in 2005 was 0.9 meters smaller than trees appearing only in the 1995 photography. However, the precision of individual crown size measurement was limited by the spatial resolution of the aerial photography. Edges of tree crowns could be identified within approximately two pixels, or +/-40 cm.

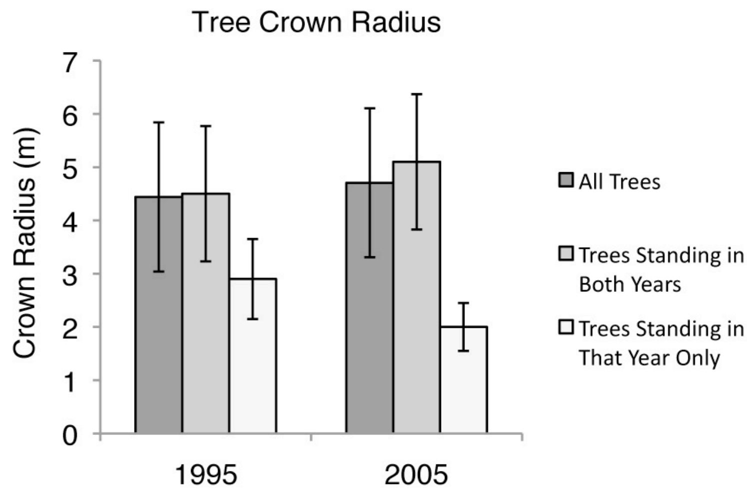

Figure 27. Mean and standard deviation of tree crown radius.

The total change in number of trees was divided by number of years between aerial photography observations to evaluate the magnitude of the change in numbers of trees. The annual change per hectare between 1995-2005 was 0.4 trees, or a mean gain of one tree per hectare every 2.5 years. In low density residential zones of DC, one hectare is the size of approximately 1-2 city blocks.

The change in number of standing trees and changes in tree crown size contribute to tree cover variability. Tree cover measured by air photography increased by 6.8% land surface area between 1995-2005. Assuming invariant crown sizes, the change in tree numbers would have increased tree cover by 2.5% land surface area between 1995-2005, or 37% of the observed increase. Changes in tree sizes were responsible for the remainder of the tree cover change, although precise measurements of changes in crown size were limited by air photography resolution. Small crown sizes of newly planted trees are likely to be less visible in the aerial photography because of the limited spatial resolution of the imagery.

More precise field measurements are needed to detect changes in crown size that would impact urban tree cover. Past urban tree field surveys in the District of Columbia (Nowak et al. 2006; Howard and Alonzo 2009) measured crown radius in 5 foot increments. Repeated surveys at high precision may be more able to detect small changes in tree crown size than using aerial image data.

Remote Sensing of Urban Tree Cover

Spectral Variability in Satellite Observations

Error in tree cover estimates is partially the result of spectral confusion in areas with complex land cover heterogeneity. Spectral variability was explored by plotting initial training data against estimated tree cover fraction (Figure 28). The reflectance in all six reflective Landsat bands is well defined at 100% tree cover. Reflectance values at 0% tree cover are extremely variable due to the wide range of land cover types present in the absence of trees. A wider range of reflectance values exists at intermediate amounts of tree cover.

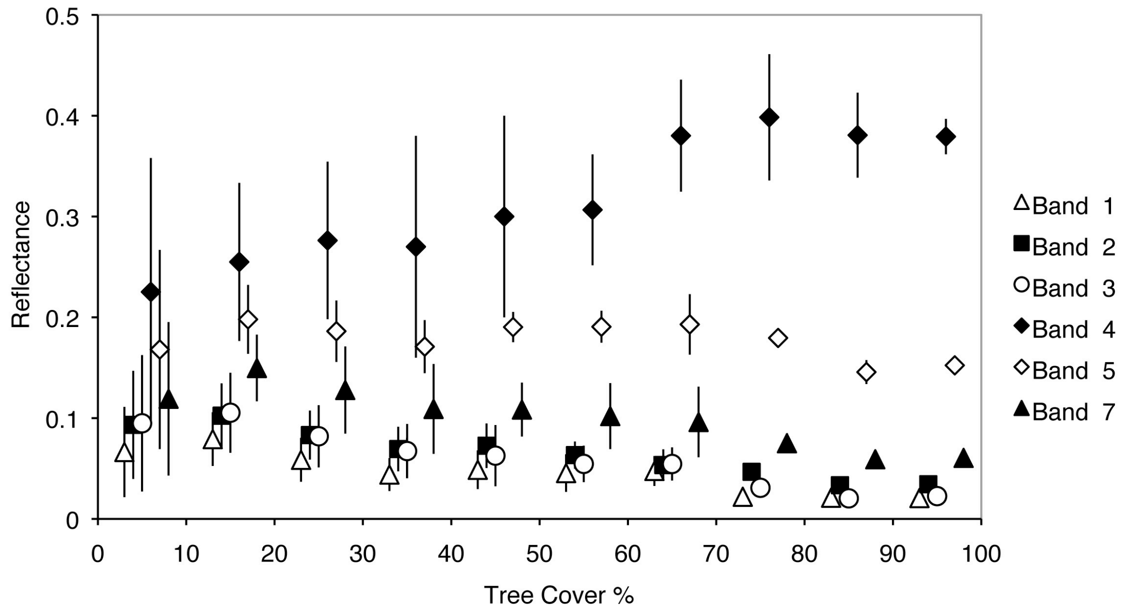

Figure 28. Mean reflectance and standard deviation of SVR training data and tree cover.

The wide range of reflectance around 40-60% tree cover makes variation of error more likely for tree cover estimates using remote sensing methods. The SMA results generally overestimate tree cover in this range, while the SVR results perform better at generalizing complex spectral data.

The choice of spectral training data is an important source of error in remote sensing applications. Selecting variable spectral signatures may result in uncertainty when estimating the proportion of that land cover type. Observations may be just as sensitive to spectral changes within training data as actual changes in fractional land cover. Because SVR performs generalization of complex spectra, it may be better suited for incorporating variable spectral patterns than SMA methods.

The satellite observations used in this study were calibrated to surface reflectance using an approach developed for identifying forest disturbance (Masek et al. 2006). Although this processing was designed to remove impact of atmospheric scattering, some variation in reflectance would be expected to remain due to solar geometry and other factors (Masek et al. 2006). Significant variation would introduce uncertainty in urban tree cover estimates in different years.

In the absence of land cover change, well-calibrated data should have little variation in reflectance across multiple dates. To assess reflectance variation of the calibrated Landsat data, the mean standard deviation of reflectance values across all dates was calculated for pixels in multitemporal sample plots (Figure 29). Variation is low in visible wavelength channels and higher in the infrared.

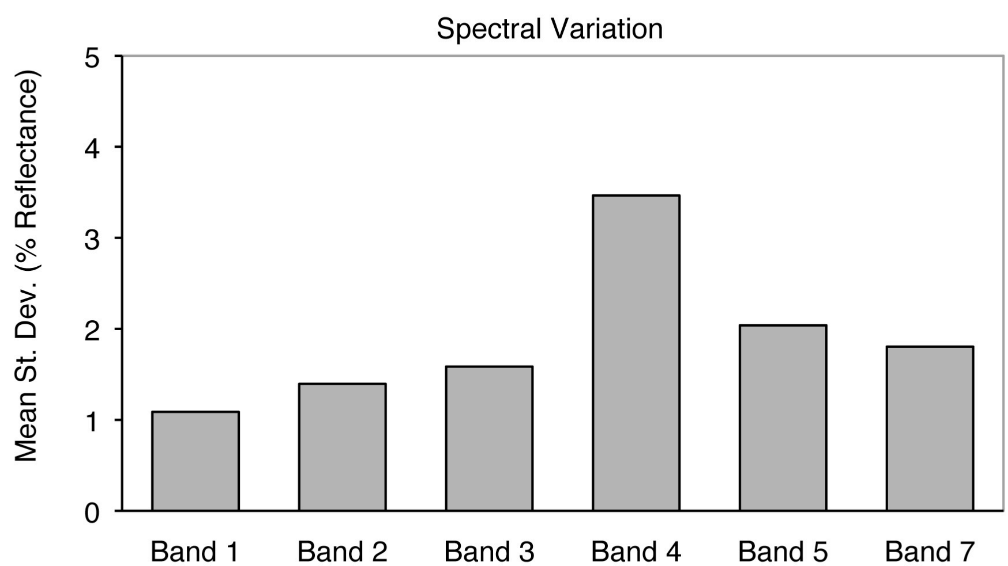

Figure 29. Reflectance variation in calibrated Landsat data.

An earlier analysis of a time series stack consisting of 13 LEDAPS-processed Landsat scenes showed similar spectral variation in band 4 but lower variation in other channels (Huang, Goward, Masek, Gao, et al. 2009). In that analysis, the standard deviation in visible bands 1, 2, and 3 for coniferous forest targets did not exceed 0.5%

reflectance (Huang, Goward, Masek, Gao, et al. 2009). The greater variability in the training data analyzed in the current study is likely due to the fact that the training pixels represent a wide range of urban land cover types, unlike the coniferous forest stands used in the earlier analysis.

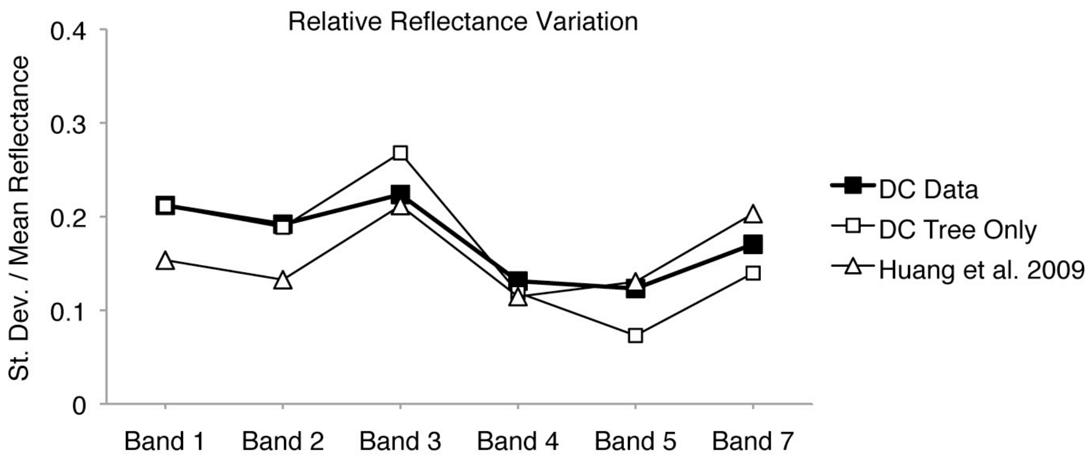

Figure 30. Ratio of reflectance standard deviation to mean reflectance for all DC training data, DC data for 100% tree cover, and data from an earlier study.

Expressed as the ratio of standard deviation to mean reflectance, the relative variability of the calibrated Landsat data is similar in the earlier study (Huang, Goward, Masek, Gao, et al. 2009) and the current analysis of DC tree cover (Figure 30). Similar reflectance variation was also observed for the subset of the DC data containing only fully forested pixels. The relative variation in reflectance was highest in band 3 for all three groups of data. Higher variation in bands 1 and 2 is likely due to land cover patterns typical in an urban setting.

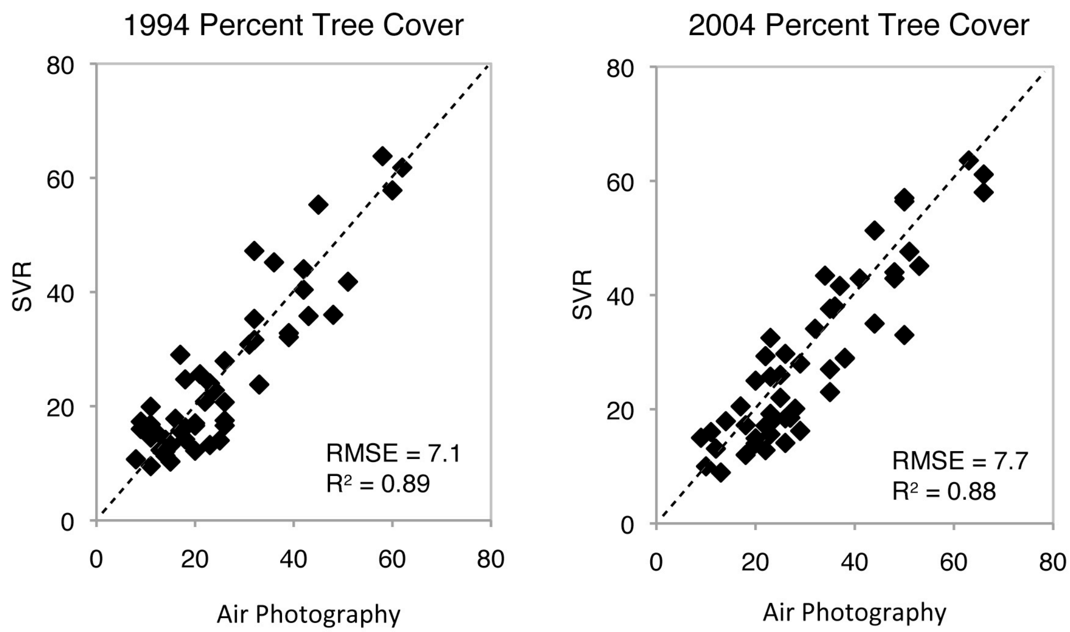

Figure 31. Tree cover observations in low density residential zones.

To evaluate the possible impact of spectral variability, SVR tree cover estimates in the sample plots were compared to air photography measurements from different years (Figure 31). Among dates with high resolution air photography, the minimum tree cover in low density residential zones was observed in 1994 and the maximum in 2004. The relationships between SVR tree cover and air photography validation in the two years were similar to each other (Figure 31) and the city-wide relationship with 2000 validation data (R^2=0.91, RMSE=7.7, see Figure 15).

Impact of Cloud Cover

Cloud cover can prevent remote sensing methods from detecting tree cover because it obscures the land surface. Although the Landsat data were processed to remove atmospheric effects, some visible cloud cover remained. To correct for this impact, masks were developed for cloud and cloud shadow as described in the previous chapter. Maximum cloud cover was in the 2002 image, in which cloud cover occupied 1.0% of the DC land surface. Limited cloud and cloud shadow were found in four other scenes. The remaining Landsat scenes contained no visible cloud cover (Figure 32). No relationship was found between cloud cover and estimated tree cover (R^2=0.0002), suggesting that the presence of cloud cover in each scene did not significantly impact tree cover estimates outside visible cloud cover.

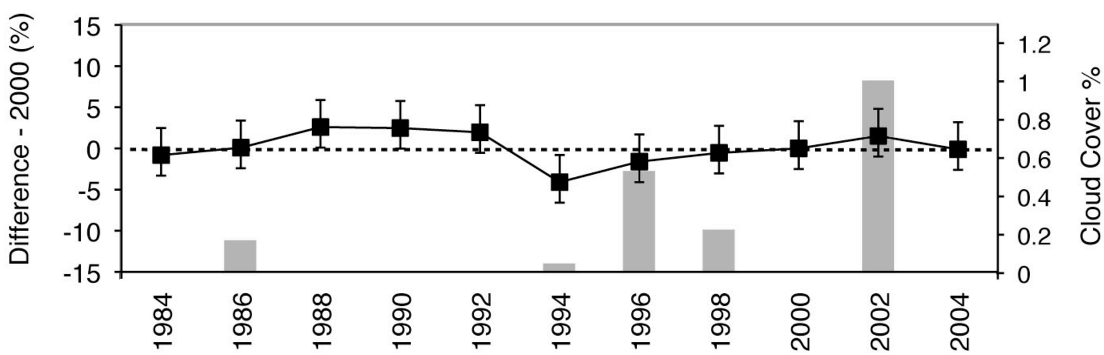

Figure 32. Tree cover variability and cloud cover.

Satellite Observation Geometric Issues

The Landsat data utilized in this study contained some geometric distortions. Image pixels did not precisely correspond between some dates. This became visible only by overlapping scenes. The 1988 image contained a swath of approximately 15 pixels that was shifted 3-5 pixels to the east. This impacted the 1988 data cutting across the central portion of ward 8 in southern DC. The 1994 image contained missing pixels in a 2 pixel swath stretching from central ward 3 to the western boundary of DC.

Geometric variation between Landsat scenes prevented quantitative per-pixel comparisons. Although full resolution data are appropriate for visual analysis of individual scenes, per-pixel comparisons were not reliable for studying changes between image dates. Uncertainty in image geometry prevents reliable per-pixel comparisons in land cover classification (Townshend et al. 2000). Some studies of urban vegetation dynamics have used mean values of 40x40 Landsat pixels for validation (Song 2005, 2007). However, averaging reflectance over too large an area would limit the spatial information content of the results. Visual inspection of the calibrated Landsat data used in this study revealed no geometric distortions causing an offset greater than 1 pixel in any direction. All comparisons with validation data were performed using 3x3 pixel means.

Impact of Seasons

Landsat images were collected during leaf-on season, but on different dates than aerial photography. Aerial photography used for validation was acquired early in each growing season. On three dates (2000, 2002, 2004) air photography was collected one year removed from the timing of satellite acquisitions (Table 2 and Table 5). Tree canopy changes may have occurred between the time of air photo and satellite image acquisition, a possible source of uncertainty for tree cover estimates. More frequent highly calibrated Landsat data and high resolution air photography would allow comparisons to be made closer in time.

Changes in seasonality and sun illumination may be a source of error in tree cover estimates. Lower sun angle would be expected to increase shadows within tree canopy. This spectral impact may cause anomalous values for urban tree cover as shadows cover turf grasses and other land cover types.

Of the 11 Landsat scenes utilized in this study, nine were acquired between ordinal dates 188-249. The two remaining scenes were collected on May 29 (1986) and October 20 (1992).

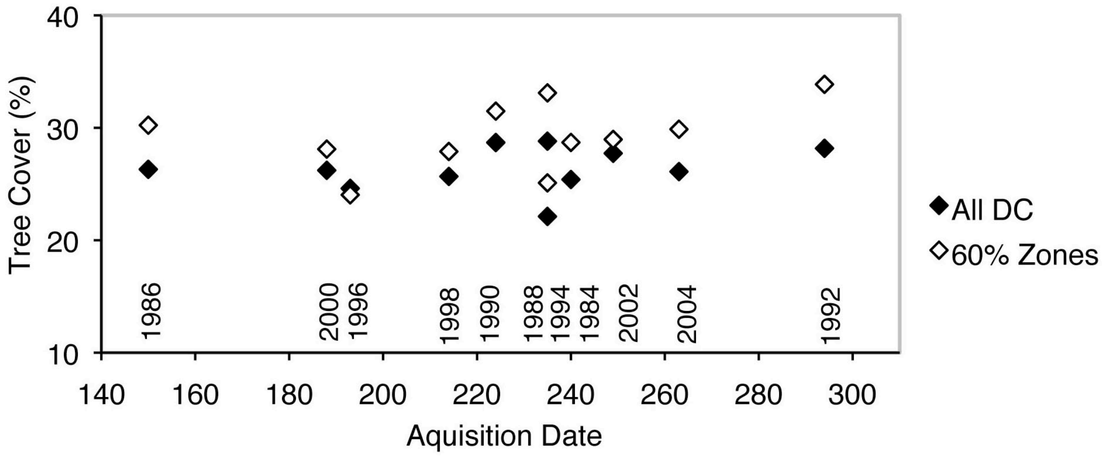

Figure 33. Satellite acquisition date and observed tree cover for entire District of Columbia and 60% open space zones.

The relationship between satellite acquisition date and tree cover was tested by comparing the ordinal date of scene acquisition with tree cover estimate for each Landsat scene (Figure 33). Despite the spread of acquisition dates, no strong correlation exists between satellite-based tree cover estimates and the timing of image acquisitions during each growing season ($R^2 = 0.05$). The early 1986 tree cover observation falls in the middle of the tree cover estimates. Although overall tree cover was similar across dates, the tree cover estimate for the 1992 image in low density residential zones was high compared to other dates.

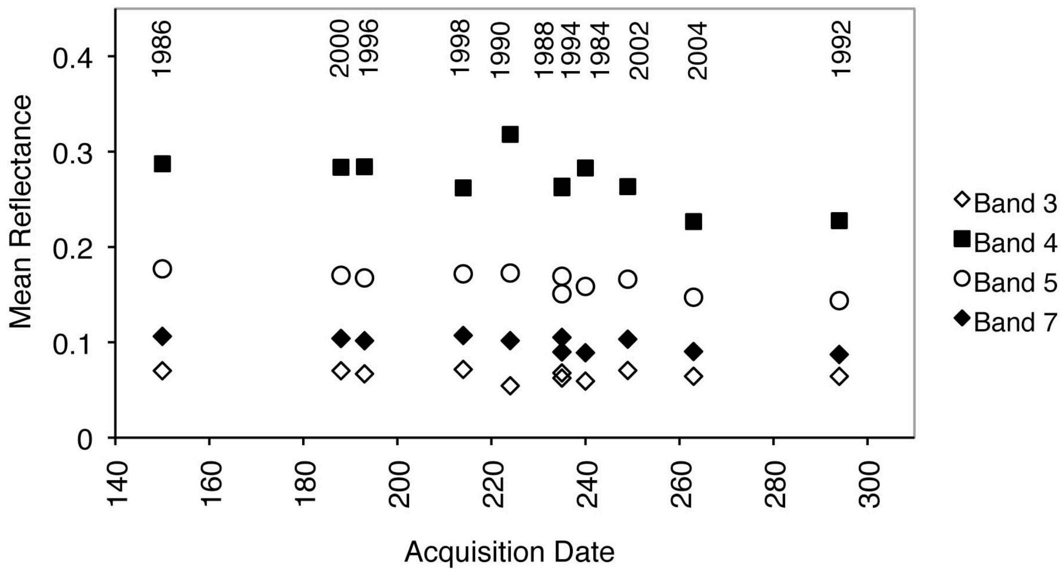

Figure 34. Satellite acquisition date and mean reflectance for the entire District of Columbia in four Landsat bands.

Individual Landsat channels were investigated to determine relationships to satellite acquisition dates. No strong relationship was observable in visible wavelength band 3 or mid-infrared band 7 (Figure 34). Scenes acquired later in the year contained lower reflectance in mid-infrared band 5 and near-infrared band 4. The impact of acquisition date is most prominent in band 4. A similar relationship between reflectance and date of scene acquisition was measured as part of a previous analysis of LEDAPS-processed Landsat data (Huang, Goward, Masek, Gao, et al. 2009).

Scene comparisons suggest that the date of satellite acquisition was not the determining factor in SVR tree cover estimates. The 1992 and 2004 scenes were the latest acquisitions and contained lowest band 4 reflectance. These two scenes had comparable mean reflectance values (Figure 34) while the 1992 tree cover estimate was higher (Figure 33). The 1994 and 1988 scenes were acquired on the same date and have similar mean reflectance values, but the 1994 tree cover estimate was lower. Both the 1988 and

1990 tree cover estimates are similar to the 1992 estimate (Figure 25) despite the fact that they were acquired in August. Validation with air photography indicates less extensive tree cover in 1994-1995 compared to 2000.

The October date of the 1992 Landsat scene corresponds to a high tree cover estimate (Figure 25), which may play a role in the mapped 1992-1994 tree cover change (Figure 22e). Tree cover may be overestimated in the 1992 observation due to tree shadowing effects. Decline in tree cover during the early 1990s in low density residential zones was validated with aerial photography, but at a courser temporal resolution. If tree cover is overestimated with the 1992 scene, this would cause the estimates of tree cover decline to be incorrectly concentrated in the 1992-1994 change map (Figure 22e) instead of spread over 1990-1994. This uncertainty means that tree cover decline in outer sections of the city during the early 1990s may have been more gradual and taken place over 1990-1996.

Aerial Photography Temporal and Spatial Scale

Seasonal differences are a potential source of uncertainty for applications of aerial photography. Aerial photography in this study was acquired in April and May, while satellite data were acquired between July-September (Table 6). It was not possible avoid this difference due to limited available data. Comparing tree cover measured with aerial photography and satellite data (Figure 31) shows no systematic error for different time steps.

Aerial photography utilized in this study was acquired for planning purposes and to map details for the built environment, and not all imagery was acquired at optimal times in the season to show maximal extent of tree cover. Acquisition in April or May could miss greening of many tree species, which could be source of error in mapping tree crowns with aerial photography.

Validation image products were derived from aerial photography at two spatial resolutions. Orthophotography corresponding to satellite acquisitions in 1994, 2000, and 2004 was archived at 15-20cm resolution, while the 1988 DOQ photography had 1 meter resolution (Table 6). Although it proved possible to identify tree crowns in the DOQ imagery, the lower spatial resolution impacted the visual appearance and clarity of individual trees. To assess the impact of the lower resolution aerial photography, the DOQ imagery from 1994 was compared to the orthorectified imagery from 1995. Tree crowns were manually interpreted and digitized in the imagery in 90x90 meter sample plots. The interpretation was performed with the same methodology and sample plots utilized in the multitemporal validation phase in this study. Tree crowns and forest canopy were digitized in ENVI software (Exelis 2012). Each type of aerial imagery was evaluated several weeks apart at the same workstation and display.

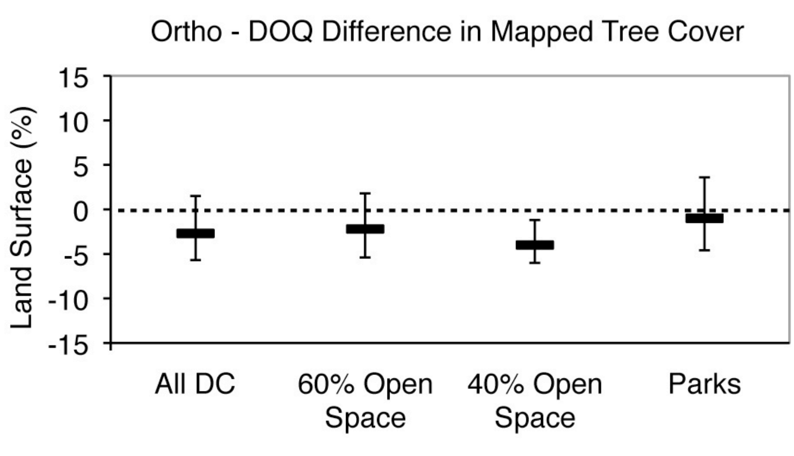

Figure 35. Mean and 2 standard deviations of difference between tree cover mapped from DOQ and orthophoto imagery.

The comparison between DOQ and orthophoto tree cover demonstrated that the low resolution of the DOQ imagery had a modest but negative impact on the ability of a human interpreter to identify urban tree cover (Figure 35). Some tree cover is missed in the lower resolution data. The city-wide difference between the two image sources was 2.7% land surface area. For medium density residential 40% open space zones, the mean difference was 4.0%, while for park areas the mean difference was 1.2% land surface area (Figure 35). Tree cover in open park areas is possibly easier to interpret compared with residential sections of the city occupied by trees and attached buildings.

In this study no correction was applied to account for the resolution difference between the two sources of aerial photography, because it was not possible to repeat the comparison for more than one time step (1994-1995) to assess the uncertainty of the measured difference. DOQ photography was the only validation imagery available corresponding to the 1988 satellite acquisition. The total DC tree cover measured by satellite observation exceeded measurement by DOQ aerial photography by 2.5% land surface area (Figure 25). If higher resolution validation data were available for 1988, and assuming tree cover were mapped with the same degree of difference measured in 1994, the 1988 satellite observation of mean tree cover would instead have been 0.2% greater than validation. However these amounts are well within the uncertainty as determined by multitemporal validation (Figure 25).

Spatial Patterns of Tree Cover Variability and Urban Land Use

Introduction

This phase of the research examines how tree cover dynamics vary spatially across the city and how they are linked to the spatial patterns of urban land use within a major city. As with the city-wide analysis, tree cover was mapped using fine scale cartographic image products derived from aerial photography on four dates during the study period. The large number of survey plots allowed for validation to be performed within selected land use categories. The analysis focuses on the low density residential zones that occupy the majority of the land surface in the District of Columbia and contain greater tree cover variability than higher density land use types.

Spatial Variability of Urban Tree Cover

Tree cover observations were segmented by land use category as defined in the DC zoning code. The results indicate tree cover variability within different allowable lot occupancy levels, from open space parks to property lots where structures can occupy 100% of available space.

Within the District of Columbia, total tree cover proportion was greater in park areas but variability was similar between park and non-park areas (Figure 36). Tree cover totaled approximately half of land surface area within parks. Tree cover varied within park areas between 46.4(+/-3.6)% to 54.2(+/-3.6)%. Tree cover outside park areas ranged between 17.9(+/-2.9)% to 24.2%(+/-2.9)%.

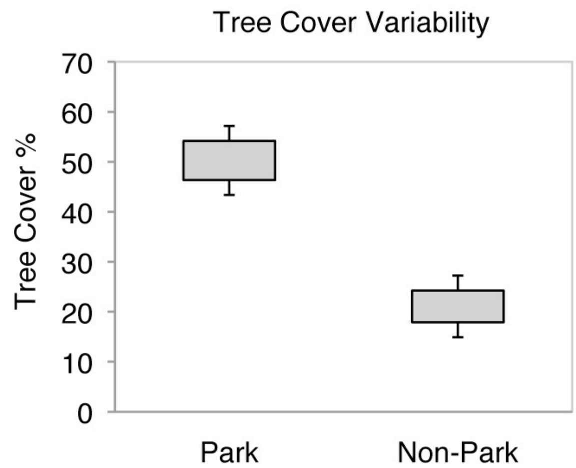

Figure 36. Minimum and maximum tree cover in park and non-park areas. Error bars indicate SVR uncertainty.

The difference between maximum and minimum tree cover was calculated for all non-park areas in different land use zones and DC wards. Comparing maximum and minimum tree cover showed that tree cover was more variable in zones required to maintain a greater proportion of open space within each property lot (Figure 37). The 60% open space zones, the lowest density residential zoning in the District of Columbia, contained greatest tree variability while zones with 25%, 20%, and 0% open space requirements contained the least. Within the 60% open space zones, wards 3 and 4 in northern DC contained greatest tree cover variability (Figure 37).

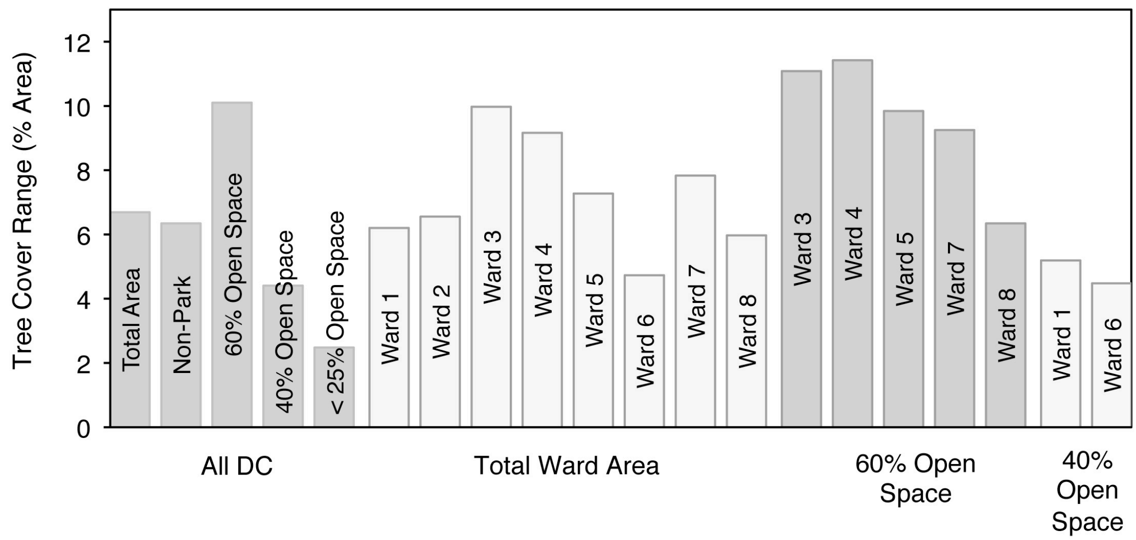

Figure 37. Tree Cover Variability in Wards and Land Use Zones 1984-2004.

<u>*Low and Medium Density Residential Zones*</u>

Residential zones were investigated to analyze the sections of the city containing the highest magnitude changes in tree cover. Low density residential zones with the greatest tree cover variability (Figure 37) also had higher proportions of tree cover. In both the 60% and 40% zones, tree cover occupies approximately half the remaining open space (Figure 38). This observation corresponds to coarse scale observations that urban open spaces are evenly split between tree and grass cover (Milesi, Running, et al. 2005). Greater tree cover variability was found in low density residential zones requiring 60% open space (Figure 38) within each property lot that can be occupied by tree, grass, or impervious surfaces.

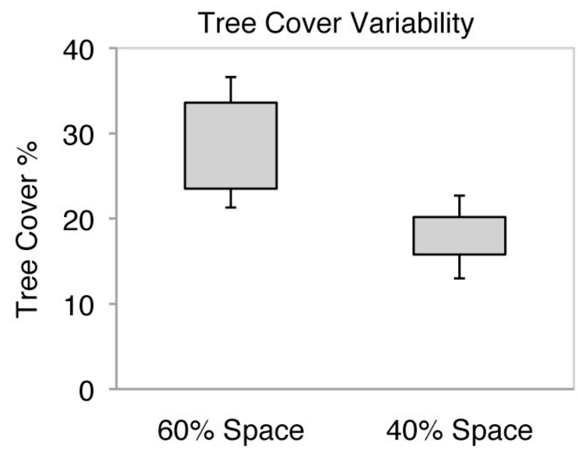

Figure 38. Minimum and maximum tree cover in low density 60% open space zones and medium density 40% open space zones. Error bars indicate SVR uncertainty.

Tree cover varied 10.8(+/-5.4)% in zones required to maintain 60% open space (Figure 39). The lowest tree cover observed 1994-1996. For 60% open space zones the 1984-2004 mean tree cover was 29.2% with mean variation between time steps of 2.5% land cover.

The greatest tree cover proportion was observed in 1992, corresponding to a late satellite acquisition data. This may be a source of uncertainty as noted previously for the city-wide results. Excluding the 1992 observation, the magnitude of the overall change 1984-2004 is reduced by 0.7%, well within the uncertainty (+/-2.6%) measured with aerial photography.

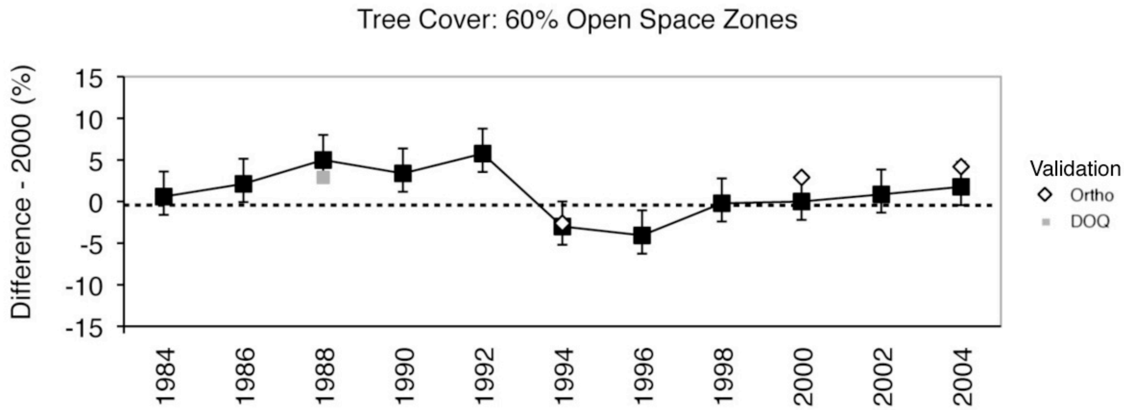

Figure 39. Tree cover variability in low density residential zones from SVR satellite observations. Difference and confidence limits shown.

Tree cover variability in 40% open space zones was also observed (Figure 40). Within 40% open space zones the 1984-2004 the mean change between sequential observations was 1.3% land surface area. Total tree cover variability in these zones did not exceed 9.7% land cover between 1984-2004.

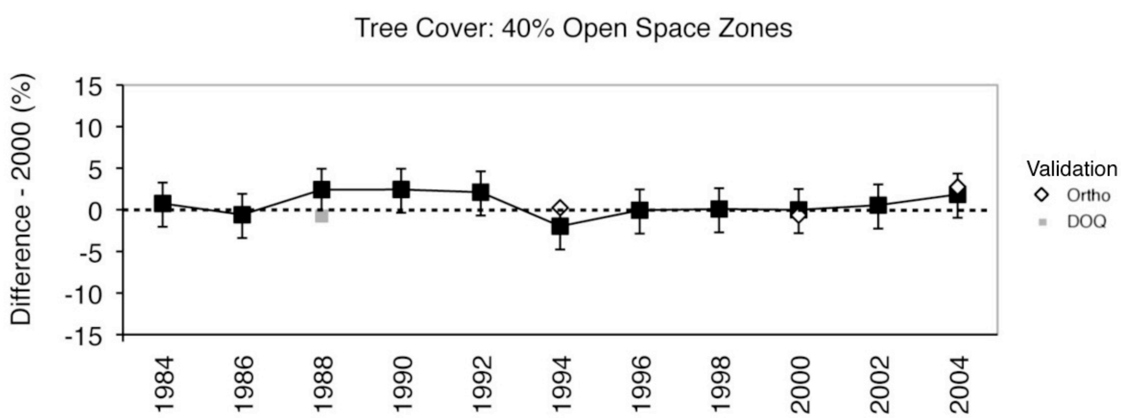

Figure 40. Tree cover in medium density residential zones from SVR satellite observations. Difference and confidence limits shown.

Tree cover in residential areas varied between DC wards. Within low density residential zones, ward 3 contained the most tree cover. Tree cover variability was greatest in wards 3 and 4 (Figure 41).

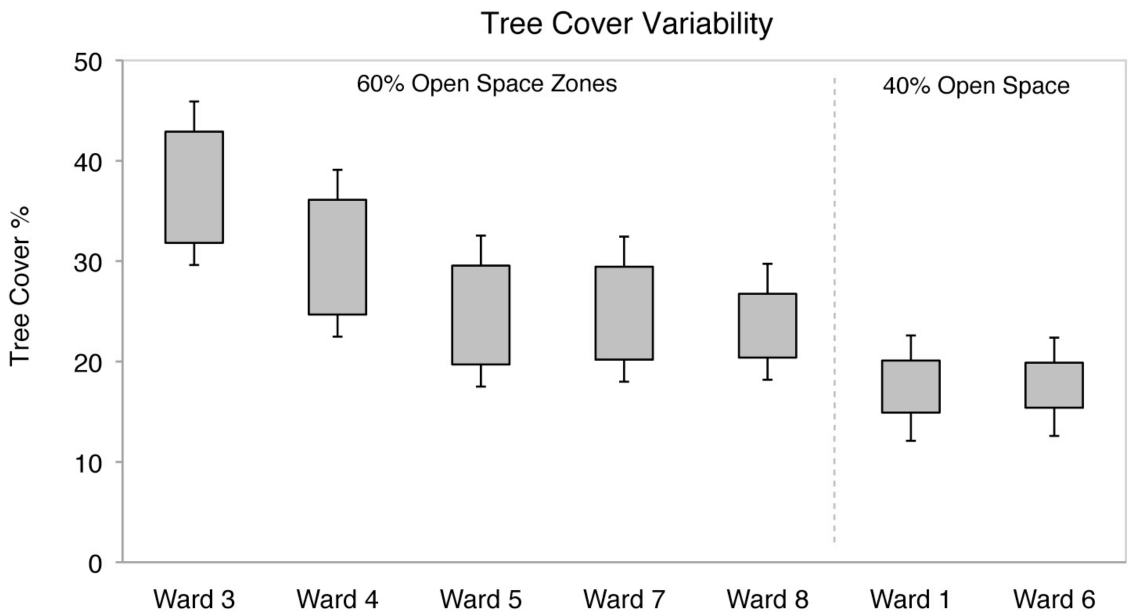

Figure 41. Minimum and maximum tree cover in residential zones in DC wards. Error bars indicate SVR uncertainty.

Tree cover variability and average tree cover was least extensive in ward 8. In the medium residential zones required to maintain 40% open space, no significant differences in tree cover variability were observed between wards 1 and 6.

The rate of change in number of standing trees in low density residential zones was previously observed with aerial photography in this research as 0.4 trees per hectare annually between 1995-2005. The rate of change in tree cover observed in satellite data was higher previous to 1995 (Figure 39), which are years lacking high resolution air photography. Assuming invariant tree crown sizes, an annual rate of change of 0.7 trees per hectare would account for the minimum tree cover change observed in low density residential zones with satellite data between 1990-1996.

Tree and Slope Zones

Tree cover variability within tree and slope zones was analyzed to identify possible impact of these zones. Tree and Slope overlay zones are the city's only spatially defined legal restrictions for tree removal, and provide a test of this type of resource management.

Tree and slope protection overlay zones were compared to areas of the same zoning density and residential land use outside the overlay districts (Figure 42). A difference in overall tree cover was found, with tree cover within the overlay zones containing an average 5.9% more land surface area than outside the zones. However, no significant difference was observed before and after 1992, when the two overlay zones were created. This suggests that the higher tree cover within the two overlay zones is likely the result of pre-existing conditions.

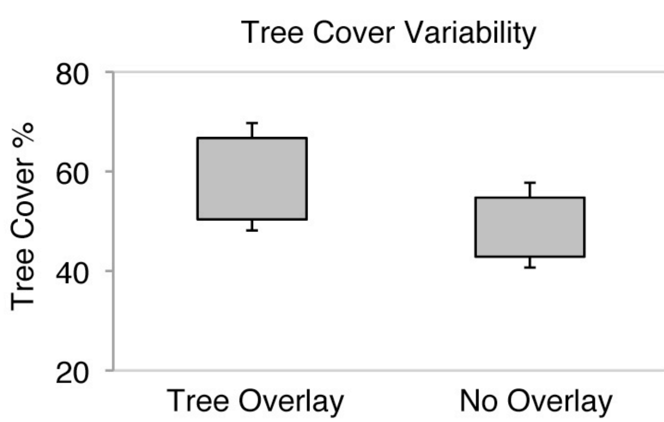

Figure 42. Minimum and maximum tree cover in tree and slope protection overlay zones. Error bars indicate SVR uncertainty.

Land Cover Change

Areas transitioning between >75% to <25% were identified by overlaying tree cover maps from the beginning and end of the study period. Increases of dense tree cover occurred in several locations (Figure 43). These show the spatial extent of areas changing from less than 25% to greater than 75% tree cover. Increases in the dense tree cover between 1984-2004 occurred in a total of 16.7 hectares.

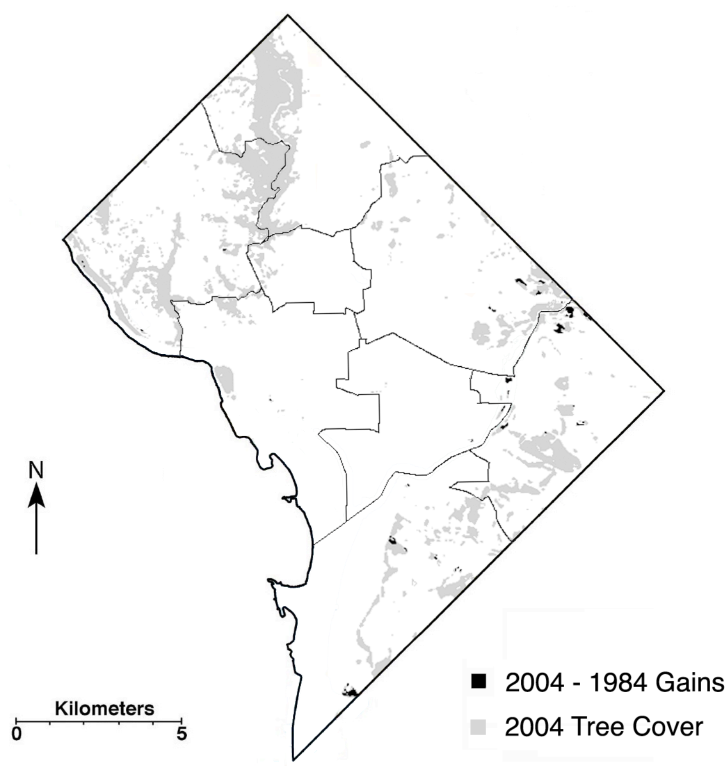

Figure 43. Gains in dense tree cover 1984-2004.

Several areas covered by dense tree canopy experienced land cover change and tree cover loss 1984-2004 (Figure 44). Between 1984-2004 the District of Columbia lost dense forests in 50.2 hectares of land surface area.

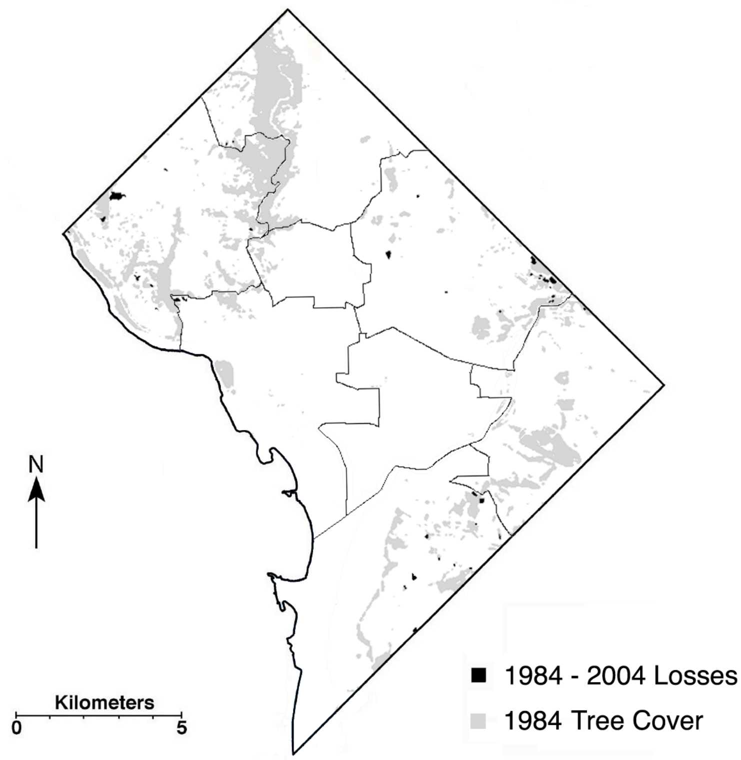

Figure 44. Losses in dense tree cover 1984-2004.

The areas undergoing removal of dense tree cover were concentrated within wards 3, 5, and 8. The locations changed during the study period. In the early periods of this study, most projects were located in the northern parts of the city in wards 3 and 5. Land cover change shifted partially to ward 8 in southeast DC during later years (Table 9).

Table 9. Land cover change area in hectares within DC wards.

Years	Change Total	Ward 2	Ward 3	Ward 4	Ward 5	Ward 7	Ward 8
1984-1988	9.6	2.4	4.1		3.2		
1988-1992	18.7	0.8	6.5	1.6	4.1		5.7
1992-1996	1.6		1.6				
1996-2000	3.2				3.2		
2000-2004	17.0		1.6		7.3	0.8	7.3
All Years	50.2	3.2	13.8	1.6	17.8	0.8	13.0

These examples of land cover change suggest that land cover change has remained an agent of change for urban forests, despite the fact that the District of Columbia has long been a densely populated city.

Residential Property Use and Population

To investigate possible connections between neighborhood characteristics and spatial patterns of urban tree cover within DC wards, selected variables from U.S. Census data were compared to tree cover proportions and variability. Housing unit vacancy and 20-year population change were the demographic factors most related to the 1984-2004 mean tree cover (Table 10). Owner occupation was correlated to tree cover but not with high significance. Population density and proportion of detached homes were correlated to each other but were not significantly related to tree cover.

Table 10. Demographic variables and tree cover.

Demographic Variable	Tree Cover relationship (R^2)	Significant ($p<0.05$)
Population Change	0.99	yes
Vacancy	0.92	yes
Owner Occupation	0.57	no
Detached Homes	0.53	no
Population Density	0.03	no

Tree cover and demographic factors in wards 3 and 4 were divergent from values in wards 5,7, and 8. Wards 3 and 4 included low density residential census tracts in northern and western DC, while wards 5, 7, and 8 cover the eastern and southern sections of the city (Figure 9). Wards 3 and 4 contained greater tree cover and higher tree cover variability than wards 5, 7, and 8. Wards 3 and 4 contained fewer vacant properties, higher proportions of owner-occupied housing units, and greater tree cover. Population change was more negative in wards 5, 7, and 8. Housing unit vacancy was the demographic variable related to tree cover that had a significant difference ($t=4.1$, $p<0.01$) between the two groups of DC wards.

These preliminary results suggest connections between demographic factors such as population loss and rates of property vacancy and tree cover variability in residential areas. However, the human factors involved in interactions between urban residents and tree cover are beyond the scope of this research. Future research is required to understand the specific connections between neighborhood scale demographics and urban tree cover.

<u>Discussion of Management and Tree Cover Variability</u>

Analysis of Tree Cover Management

Because quantitative data records of government management were not available, it was not possible to measure the impact on tree cover dynamics from management. However, it is possible to broadly assess the potential implications of tree cover observations for two aspects of management: insect defoliation management and maintenance of tree resources on public spaces. This discussion is a preliminary step towards bridging the gap between spatial analysis and public policy and resource management. Future research and more extensive data will be required to identify causal factors.

Insect Defoliation Management

Years of decreased tree cover in DC low density residential zones corresponded with some, but not all, years of peak gypsy moth defoliation reported by management authorities in surrounding states. Although spatial data for insect defoliation do not exist for the District of Columbia between 1984-2004, such data do exist for the surrounding area of central Maryland and northern Virginia. The total defoliation in a multi-county area surrounding the District of Columbia peaked in 1990 but remained high 1989-1995 (Figure 5). Tree cover in low density residential areas in the District of Columbia declined during this period (1990-1996) and recovered in subsequent years. However, a strong statistical relationship was not found between observed DC tree cover change in low density residential zones and single season defoliation area (R^2=0.19) or two-year mean defoliation area (R^2=0.23) for all years 1984-2004. Identification of a stronger relationship may require defoliation data collected within the study area.

At the local scale, one specific zone of gypsy moth defoliation within the District of Columbia was identified in this study. The Pinehurst Parkway area south of Pinehurst Circle and west of Rock Creek Park experienced severe gypsy moth defoliation between 1986-1988 (Favre, Sherald, and Schneeberger 1993). The reported spatial extent of the defoliation corresponds to an area of tree cover decline in the 1986-1988 tree cover map (marked "A" in Figure 22b).

Defoliation in other parts of the city may be responsible for tree cover change observations in this study. However, no spatial data exist to confirm where non-park areas would have experienced defoliation. Because much of the urban tree cover in the District of Columbia is managed, defoliation may be limited even during infestation events. The temporal resolution of the Landsat data may also not be optimal to observe impact from short-term insect defoliation. Some amount of defoliation would not be observed with satellite data in this study because images were acquired every two years.

The October acquisition date for the 1992 may introduce error and elevate that estimate of tree cover proportion due to increased shadowing. A decrease in tree cover was observed in low density residential areas between 1992-1996 (Figure 39). However, due to the limited temporal resolution of the Landsat data and the seasonality issue with the 1992 scene, it is difficult to determine the timing of the tree cover decrease with greater precision using archival satellite data. The actual timing of that tree cover decline in low density residential zones may have taken place between 1990-1996 instead of being confined to 1992-1996. This uncertainty lowers the precision with which it is possible to determine links to insect defoliation.

Street Tree Maintenance

The middle of the study (1992-1996) was the period of greatest tree cover declines in low density residential zones. This period corresponds to years of decreased budgets for street tree maintenance and replacement. While it is not possible evaluate a causal impact because of the lack of quantitative data and incomplete records, the potential proportion of tree cover variability caused by changing numbers of street trees can be estimated. Budget records indicate no street tree replacement 1993-1996. This would lead to an annual net decline of approximately 3,000 street trees, totaling 9% of all street trees over those years. Assuming the same proportion of street trees as a total of all trees observed in 2000 (Figure 4), the lost street trees would therefore reduce the number of trees by 2.5% within low density residential zones. Tree cover observed using SVR satellite measurements in those zones was 7.4(+/-5.4)% lower in 1996 compared to 1990.

Interpretation of the role of street tree maintenance in canopy variability is limited by the low spatial resolution of the archival satellite data. The 90 meter pixel size of these observations does not permit discrimination of street and non-street tree cover in the maps of tree cover change between each observation. Because management records are incomplete and street trees are responsible for a limited portion of overall tree cover variability, future research is needed to determine links between this type of government management and urban tree cover variability.

Summary

A Support Vector Regression (SVR) methodology estimated tree cover with lower and more consistent error across land use types compared to Spectral Mixture

Analysis (SMA). Consistency of error across land use types is of high importance for understanding vegetation within an urban setting. Between 1984-2004 the city-wide tree cover varied between 22.1(+/-2.9)% and 28.8(+/-2.9)% of the total land surface area. The impact of cloud cover, spectral variability, and seasonal effects were analyzed. Seasonal effects were observed in one satellite scene acquired late in the year. Within the District of Columbia, spatial variability of tree cover dynamics was observed in different land use types. Greatest variability occurred in low density residential zones. Tree cover proportion in these zones declined 7.4(+/-5.4)% in the years between 1990-1996. The fluctuation in the number of standing trees and changes in crown sizes were both responsible for portions of tree cover change in low density residential zones. Between 1984-2004, land cover conversion removed dense tree cover from 50.2 hectares of the city's land surface. Selected demographic variables and aspects of management history were compared to tree cover dynamics to illustrate connections between these factors in the urban environment.

CHAPTER VI

SUMMARY AND CONCLUSIONS

Urban Tree Cover Temporal Variability

Interannual tree cover variability 1984-2004 was observed for the District of Columbia using moderate resolution satellite data. City-wide tree cover varied between 22.1(+/-2.9)% and 28.8(+/-2.9)% of the total land surface area. This variability is equivalent to 1065(+/-922) hectares of tree canopy area. For the entire city, total tree canopy area did not increase or decrease between 1984-2004. Variability did not exceed 12.5% land surface area. Average variation between consecutive observations was 1.7% land surface area, or a 6.9% change in the tree cover proportion. Tree cover measured by high resolution aerial photography varied by only 3.6% total land surface area for the District of Columbia.

During the study period 1984-20004, tree cover in the District of Columbia varied but did not experience an overall increase or decrease. In contrast to past reports of District of Columbia tree cover at city-wide scale (American Forests 2002b) and preliminary fine-scale measurements (D.C. Government 2012a; O'Neil-Dunne 2012), the results of this study are validated with independent observations to assess precision of tree cover values across time steps.

Spatial Variability of Tree Cover Dynamics

Within the District of Columbia, spatially explicit mapping of tree cover variability indicated local scale areas experiencing gains or losses in tree cover.

Observations were stratified into land use categories to identify areas of high variability. Within park areas maintained by federal and DC government agencies, tree cover totaled approximately half of land surface area and varied between 46.4(+/-3.6)% and 54.2(+/-3.6)%. Outside park areas, tree cover varied between 17.9(+/-2.9)% and 24.2%(+/-2.9)%.

Urban tree cover variability in the District of Columbia 1984-2004 occurred largely within the city's low density residential areas. Tree cover was more variable in zones required to maintain a greater proportion of open space within each property lot. Greatest tree cover variability occurred within low density residential zones required to maintain 60% open space. Zones with 0-25% open space requirements contained the least tree cover and tree cover variability.

Tree cover in low density residential zones decreased by 7.4(+/-5.4)% land surface area between 1990-1996 and increased after 1996. Within these zones, wards 3 and 4 in northern DC contained greatest tree cover variability. Tree cover variability and average tree cover was least extensive in ward 8 in the southeastern part of the city. In the medium residential zones required to maintain 40% open space, no significant differences in tree cover variability were observed between different DC wards. No significant differences were observed in the city's tree and slope zones designed to protect dense tree cover in residential zones.

Urban Tree Cover Variability Factors

Land cover conversion was an agent of tree cover change in the District of Columbia between 1984-2004. Between 1984-2004, 50.2 hectares of dense tree cover was removed within the District of Columbia. During the same period 16.7 hectares experienced expansion of dense tree cover, for a net decrease of 33.5 hectares.

Within low density residential zones, changes in numbers of standing trees occurred primarily among smaller trees. The number of trees and crown sizes were measured with cartographic imagery derived from aerial photography. Observations separated by 10 years indicate a net increase in the number of standing trees by 4.3 trees per hectare during the second half of the study period. Trees that were lost or gained during this period had smaller mean crown radius than persistent standing trees.

Connections between demographic factors in low density residential zones and spatial patterns of urban tree cover were investigated. Sections of the District of Columbia with trends of population loss and high rates of property vacancy contained lower proportional tree cover during a 20 year period. While these preliminary results show correlation and not causation, they suggest paths for future research into other factors. Housing unit vacancy and population change may impact tree cover over long periods by playing a role in the maintenance of trees on private property.

Management and Policy Implications

Urban Tree Cover Management

The results of this research provide data useful for formulating effective strategies for maintaining and expanding urban forest cover. Comparing changes in the number of standing trees and crown sizes indicates that both tree growth and replacement can have observable impact on overall tree cover. This suggests the importance of both planting new trees and growth of current trees for maintaining overall tree cover.

The results of this research included maps of local scale fluctuations in tree cover. These maps are of potential use to authorities for formulating management plans by enhancing understanding of tree cover impact from development and land use changes.

Although land cover change removed dense tree cover in only 50.2 hectares of the city's land area, this impact is surprising given that Washington DC has contained fully "developed" land for a century. Although heavily developed and densely populated, the District of Columbia potentially continues to be altered by land cover change. Land cover conversion takes part as part of construction and development projects, potentially removing tree cover. Understanding how large construction projects remove dense urban forests could enhance management and protection of a city's tree cover. Jurisdictions seeking to maintain forest cover may need to weigh economic development goals against tree protection when formulating or approving large development projects.

Tree Canopy Goals

The District of Columbia government has set a goal of achieving 40% total tree cover (D.C. Government 2010a, 2012d). This target was earlier developed by environmental advocacy organizations, which promoted a target of 40% total tree cover in cities and 25% in urban residential areas (American Forests 2002b, 2003a). Tree cover in the District already exceeds 25% for many low density residential areas. Reaching 40% total tree cover proportion would require more than 216,000 new trees to be planted (Casey Trees 2010). Reliable estimates of tree cover and how it changes are required for setting specific tree cover goals.

A focus on tree cover goals in low density residential zones would potentially be more useful than city-wide goals. Tree cover and variability is greatest in ward 3 in the northwestern section of the District of Columbia. Although similar in total population and topography, wards 7 and 8 east of the Anacostia River contain approximately 40% less tree cover than ward 3 (Figure 41). By calculating the total surface area and tree cover area of each ward, the possible city-wide gains in tree cover can be determined. Increasing tree cover in low density residential zones within wards 4, 5, 7, and 8 to the levels of ward 3 would increase total District of Columbia tree cover by approximately 4% total land area.

Evaluating Ecosystem Impact

Urban jurisdictions including the District of Columbia cite the ecosystem impact of tree cover in their management plans (City of Boston 2007; City of Alexandria 2012; D.C. Government 2012d) and have utilized software packages such as i-Tree to estimate that impact (U.S. Forest Service 2010b). The i-Tree package incorporates measurements at field survey plots to estimate biophysical impact city-wide. Tree cover variability impacts values for some ecosystem functions such as interception of aerosol pollution. Other impacts such as carbon sequestration are less directly linked to tree cover area.

The i-Tree package utilizes the 2001 National Land Cover Database (NLCD) to map tree cover proportion, which provides unreliable results in urban areas (Greenfield, Nowak, and Walton 2009; Walton 2008a). Documentation for i-Tree encourages users to observe differences between NLCD and tree cover field measurements to correctly interpret results (U.S. Forest Service 2010b). Using more accurate tree cover maps would improve accuracy for estimating biophysical impact of urban forests.

Currently the i-Tree package does not incorporate variable measures of tree cover. Tree cover variability observed for District of Columbia would have only a minor impact on city-wide estimates of values such as interception of aerosol pollution and carbon sequestration. Tree cover variability would have larger impact when using a package such as i-Tree to map ecosystem impact in smaller areas. In particular it would alter estimates of surface temperature impact from shaded tree cover area. The magnitude of the impact depends on the mix of tree species and other factors. This issue may require attention as management authorities make use of programs such as i-Tree.

Application of Remote Sensing Methods

Tree cover of the District of Columbia was mapped using two methods applied to calibrated satellite remote sensing data. Support Vector Regression (SVR) produced results with lower and more spatially consistent error than Spectral Mixture Analysis (SMA) for observing urban tree cover. Results from SMA overestimated tree cover in low population density areas. In contrast, accuracy across land use types was more consistent with SVR. The consistent reliability across land use types provides an important advantage, which allows SVR results to be used for identifying tree cover changes between different regions within a city.

Possible sources of uncertainty in tree cover estimates were investigated. Relative spectral variability of the calibrated Landsat data in visible and infrared channels was found to be similar to a previous study (Huang, Goward, Masek, Gao, et al. 2009). Despite spectral variation, tree cover estimates were consistently related to aerial photography validation in different time steps.

The results from this study suggest the importance of using calibrated data for multitemporal analysis. The satellite remote sensing data used in this study (Goward et al. 2008) were calibrated to minimize the impact of atmospheric scattering (Masek et al. 2006). This type of calibration was not performed in a previous report that suggested significant changes in District of Columbia tree cover (American Forests 2002b). This previous study compared Landsat satellite images acquired by the Multispectral Scanner

(MSS) in 1973 and the Thematic Mapper (TM) sensor in 1997 (American Forests 2002b). MSS data lack shortwave infrared channels, which could lead to overestimation of tree cover due to spectral similarity with turf grasses common in urban landscapes. The presence of atmospheric haze is another possible source of error, which would tend to decrease detected tree cover. Visual inspection of the 1997 Landsat TM scene downloaded from the U.S. Geological Survey (U.S. Geological Survey 2011) indicates observable amounts of atmospheric haze. The American Forests report (American Forests 2002b) may therefore overestimate 1973 tree cover due to spectral confusion and underestimate 1997 tree cover due to atmospheric scattering effects. Avoiding these errors requires consistent spectral data calibrated to surface reflectance.

Reflectance in visible channels was not related to scene acquisition date, but scenes acquired later in the year contained lower reflectance in shortwave infrared and near-infrared channels. This was most prominent for the 1992 satellite observation. This introduces uncertainty for observing the timing of tree cover declines in the early 1990s, although tree cover change was validated with independent observations.

Directions for Future Research

Measures of tree cover variability could be used to enhance understanding of the urban environment in future studies. The results of this study provide new understanding of urban areas by making measurements of interannual tree cover variability over decadal periods within a major urban center. Reporting static values for tree cover proportion may ignore important dynamism occurring within the urban environment.

The relationship between tree cover variability and land use in other cities could be investigated in future work. This study found that greatest tree cover variability was found within low density residential zones. Finding the same relationship in other cities would suggest that urban tree cover variability can be found mostly within low density residential areas, while other land use types contain more consistent tree cover.

High resolution data show spatial details not available in the Landsat-scale observations utilized in this study. However, the lack of shortwave infrared channel in these data sources is a significant limitation for discriminating tree and grass cover. Addition of high resolution data in the shortwave infrared would be a significant advance for understanding urban vegetation cover. This capability will be included in the WorldView-3 satellite, planned for launch in 2014 (DigitalGlobe 2012).

A possible direction for future research would be to investigate tree cover changes within growing seasons by utilizing multiple acquisitions of high resolution satellite data. Unlike the current study of past tree cover variability, future monitoring of urban tree cover could rely on available high resolution satellite data for fine scale validation.

Future research could include analysis of finer scale data based on the aerial survey sketch maps used for monitoring of insect defoliation. Spatial data derived from those surveys (Liebhold et al. 1996) could also be utilized for comparison to satellite remote sensing observations. Because defoliation was indicated in aerial surveys only if defoliation reaches 30%, it is possible that more modest impact was spatially extensive.

Application of object-oriented classification with high resolution data, shortwave infrared response, and LIDAR may hold promise for future monitoring of urban tree cover, providing a complement to the results of this research. Data from LIDAR sensors could be utilized to evaluate the spatial variation of measures of canopy structure such as LAI in urban forests.

In this study SVR was trained on fractional canopy coverage, a quantity widely utilized in research studies of the urban environment. Training SVR using physical canopy measurements such as leaf area index (LAI) is worth exploring in future research with data sources sensitive to canopy structure such as LIDAR.

This study compared SVR with linear SMA to determine if improvements were possible in remote sensing of urban tree cover. A more comprehensive analysis in the future could include comparative assessments with other methodologies, including nonlinear spectral mixture analysis and object-oriented classification with moderate spatial resolution data.

Available software tools place limits on the practical application of the SVR methods for large areas. The LIBSVM program used for this study lacks a simple user interface and was not intended for large volumes of remote sensing data. At least one remote sensing software package, ENVI (Exelis 2012), includes support vector capabilities. However, this package implements only support vector classification, not support vector regression or parameter validation procedures. Implementation of SVR methods in commercial software packages would be a significant advance.

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