TWIN CITIES URBANIZATION AND IMPLICATIONS FOR URBAN FOREST ECOSYSTEM SERVICES

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ABSTRACT

Urbanization affects ecological structure and function by impacting the provision of ecosystem services, or benefits we derive from the natural environment. It is broadly acknowledged that ecosystem services should be formally considered in land management decisions, but inadequate scientific understanding of urban ecological systems is a key obstacle to achieving this goal. In this dissertation, I address this shortcoming by assessing the relationships between urbanization and the urban forest, a key urban ecological component.

The three studies described here demonstrate spatial and temporal effects of urbanization on urban forest structure, function, and value in Minnesota's Twin Cities Metropolitan Area. In the first study, I used historical air photos to analyze past trends in tree canopy cover related to urbanization and other land cover changes. Urbanization events generally reduced tree canopy cover, but urban sites rapidly afforested following development. Older urban neighborhoods typically had higher tree canopy cover than newly developed areas. In the second study, I used factor analysis on a suite of urbanization indicator variables to derive an urbanization gradient that is more sophisticated than a simple urban-rural distance-based gradient. This synthetic gradient was strongly related to more types of urban forest structural variables than the distance-based gradient, highlighting the influence of secondary urbanization trends on urban forest structure. In the final study, I stratified the study area by property parcel land use, and compared estimated urban forest structure, function, and value across land use classes. Residential and undeveloped areas both had higher urban forest values than non-

residential developed areas, but were not statistically different from one another. This study showed which types of urban land uses promote good urban forest structure and function, and the results can be used to guide future urban forest study designs.

All three studies demonstrate the need to consider complexities associated with human-environmental systems. Two major themes were the importance of temporally lagged tree growth and nonlinear urban-ecological relationships. Specifically, urban forest structure was typically greatest at intermediate levels of urbanization where urban intensity was not too great, and where adequate time since urbanization had allowed ample tree growth to occur. By making these complexities more visible, this research will improve the design of future work, so that we can develop a more complete and nuanced understanding of the effects of urbanization on the urban forest.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ANOVA	=	Analysis of variance
DBH	=	Diameter at breast height
ES	=	Ecosystem services
FA	=	Factor analysis
GIS	=	Geographic information system
K-W	=	Kruskal-Wallis test
LC	=	Land cover
nonres	=	Non-residential developed study sites
PCA	=	Principal components analysis
res	=	Residential developed study sites
ROW	=	Right-of-way
TCC	=	Tree canopy cover
TCMA	=	Twin Cities Metropolitan Area
UF	=	Urban forest
undev	=	Undeveloped study sites

Chapter 1. Introduction—the state of urban forestry and motivations for this research

Overview. The world's urban population is growing rapidly and occupying more land than ever before. As we continue to learn about the impacts of urbanization on the natural world, it has become apparent that ecological interests must be considered explicitly in land management decisions to improve the sustainability of urban areas. However, inadequate scientific understanding of urbanization's past and present ecological impacts is delaying the implementation of sustainable practices. Compounding the problem, much of the existing urban ecological research has cast a narrow focus on central cities. While this improves our capacity to manage primary urban centers, it neglects large suburban areas where the most dynamic population growth and land cover changes are occurring. Moving forward, we need to pay increased attention to the relationships between land use, land cover, and ecological character to highlight land management styles that promote sustainable urban landscapes. This dissertation addresses these needs by documenting past and present urban ecological character associated with land use and land cover patterns along an urban-rural gradient. I focus on the structure, functions, and values associated with the urban forest, a primary component of most urban ecological landscapes.

LITERATURE REVIEW

Urbanization is a widespread and fundamental land change process. The world's population is over 50 percent urban for the first time in history, and 82 percent of Americans now live in urban areas (UN Population Fund 2011). Rapid urban growth will continue, as urban land in the United States is expected to increase by 79 percent between 1997 and 2025 (Alig et al. 2004). This rapid urban expansion has important consequences for the structure and function of ecological systems within metropolitan regions, and such implications need to be understood to maintain and enhance biodiversity, sustainability, and ecosystem services within urban areas (Alberti and Susskind 1996; McPherson 1998b; Williams et al. 2009).

Ecosystem services—the benefits humans derive from natural systems—play a foundational role in supporting human societies. The Millennium Ecosystem Assessment (2005) identified twenty-four key ecosystem services that perform provisioning, regulating, and cultural services. The annual value of these services outpaces global gross national product (Costanza et al. 1997). In urban areas, ecosystem services are especially important for mitigating the negative effects of urbanization, such as air pollution (Nowak et al. 2002, 2006), stormwater runoff (Sanders 1986), energy use (McPherson and Rowntree 1993), and urban heat island effects (Stone and Norman 2006). While our awareness of ecosystem services is continually increasing, inadequate scientific understanding of ecosystem service abundances and spatiotemporal dynamics are currently limiting the explicit implementation of ecosystem service perspectives in land management decisions (Daily et al. 2009).

The urban-rural gradient approach

Recognizing the importance of ecosystem services to urban quality of life (Bolund and Hunhammar 1999), urban ecologists have developed several conceptual approaches for documenting the effects of urbanization on ecological character. Modeled after a classic ecological approach, urban-rural gradient analysis is among the best established urban ecological frameworks (McDonnell and Hahs 2008). Urbanization's influence is generally strongest near the urban core and decreases toward the peri-urban fringe, so examining ecological character along this gradient can demonstrate the ecological impacts of varying urbanization intensity (McDonnell and Pickett 1990).

There are three common urbanization gradient designs—those based on linear distance, nominal land use categories, and urbanization indicator variables. Early urbanization gradient studies were based on simple linear transects extending from the urban core (e.g., Medley et al. 1995; McDonnell et al. 1997), but it was frequently concluded that such gradients inadequately captured urbanization patterns. An alternative approach was developed in which degree of urbanization was categorized from high to low according to nominal land use classes (Niemelä et al. 2002; Burton et al. 2005). For example, Porter et al. (2001) studied forest composition from highly urban (business, residential) to moderately urban (golf course, recreational areas) to rural (old growth forest) areas. More recently, researchers have defined urbanization gradients based on large sets of urbanization indicator variables (Hahs and McDonnell 2006; du Toit and Cilliers 2011). Under this approach, a suite of socioeconomic (e.g., population density, property value), physical (e.g., urban-rural distance), and landscape ecological variables (e.g., land cover diversity) are subject to a dimensionality reducing statistical technique to highlight primary underlying trends in urbanization that influence multiple indicator variables. This approach improves upon distance-based gradients because urbanization rarely declines regularly with distance from the urban core (Hahs and McDonnell 2006). It improves upon nominal land use categorizations by describing “urbanness” as a continuous variable, rather than assuming homogeneous urban character across broad land use classes. Continued advancements in urbanization gradient characterization will facilitate improved knowledge of the relationships between urbanization and ecological systems.

The importance of the urban forest

The urban forest has been well studied because it is a significant component of the urban ecological landscape (Dwyer et al. 1992). Urban forests have been defined narrowly as forested tracts of land within a larger urban area, or more broadly as all woody trees and shrubs in an urban area. The former regularly focuses on public lands and is more commonly applied in Europe than the United States (Van Elegem et al. 2002; Arnberger 2006; Georgi and Zafiriadis 2006; Gül et al. 2006; Nováková 2008). In the United States, narrowly defined urban forest studies have often assessed ecological structure (composition, size, abundance, and spatial distribution of biotic communities) of remnant forest patches, as opposed to ecological functions such as air pollution removal and carbon storage (Medley et al. 1995; Guntenspergen and Levenson 1997; Moffatt et al. 2004; Carreiro and Tripler 2005).

In addition to remnant forest patches, the broader definition of urban forests also considers trees located amongst homes, businesses, and institutions. Accordingly, research from this perspective has paid more attention to human-environment relationships than studies restricted to remnant forest patches. For example, researchers have documented the benefits and/or costs associated with municipally maintained street tree populations (Sanders 1981; Richards 1983; McPherson et al. 1999; Maco and McPherson 2003; Alvey 2006; Thaiutsa et al. 2008). Such efforts generally aim to take stock of the city's forest resources, with particular interest in demonstrating whether services provided outweigh public investment in the planting and maintenance of street trees.

Publicly maintained trees only comprise a small proportion of urban trees (Nowak 1994a, 1994b; McPherson 1998b), so it is also critical to understand urban forest structure and function on private property. The privately managed portion of the urban forest is challenging to understand because it responds to controls at multiple spatial scales. At the finest scale of land management, individual landowner choices influence property parcel-scale heterogeneity (Medley et al. 2003). While individual choices affect parcel-scale urban forest management, neighborhood-scale social identity also impacts parcel-scale patterns (Grove et al. 2006; Troy et al. 2007; Boone et al. 2010). Individuals are in turn subject to municipality-scale forestry management and policies (Conway and Urbani 2007). More broadly, trees evidence the effects of various biophysical constraints at the landscape scale (Whittaker 1967).

While gradient analysis is well suited to assessing structure and ecosystem services in the broadly defined urban forest, it has typically only been applied to understand variability among remnant urban forest patches (e.g., Medley et al. 1995; Guntenspergen and Levenson 1997; Kromroy et al. 2007). Instead, study of the broader urban forest has been conducted with respect to administrative boundaries (e.g., Nowak et al. 1996; McPherson 1998b; McPherson and Simpson 2002), presumably to enhance the usefulness of research findings to municipal urban forest managers and to allow for comparisons across cities. Gradient analysis across municipal boundaries can provide a better picture of regional metropolitan processes because land use patterns (Yuan et al. 2005) and attendant urban ecological factors are potentially different in central cities and suburbs (Nowak 1994b). Similarly, applying gradient analysis to the entire urban forest (i.e., all trees and shrubs on both public and private lands) can highlight differences attributable to landscape context and land management.

Existing research on the broadly defined urban forest has primarily followed two complementary strategies—ground-based assessment and analysis of remotely sensed imagery. Ground-based assessments involve collecting field data to describe urban forest structural characteristics including tree species composition, size, abundance, and health (McPherson et al. 1997; Nowak et al. 2008a). To improve the effectiveness of such assessments, several models have been developed to summarize both urban forest structure and associated ecosystem services (Walker 2000; McPherson et al. 2005; Brack 2006; Nowak et al. 2008a). For example, the i-Tree Eco (formerly UFORE) model incorporates sample measurements to estimate structure, function, and value of the urban forest (Nowak and Crane 2000; Nowak et al. 2008a). i-Tree Eco has been used extensively to estimate benefits such as air pollution removal and carbon sequestration in the United States (e.g., Nowak et al. 2006) and abroad (Yang et al. 2005; Escobedo et al. 2008). Another model, i-Tree Streets (formerly STRATUM), has similar functionality to i-Tree Eco, but is specialized to estimate services provided by municipal street trees (McPherson et al. 2005).

Models like i-Tree Eco are useful for making straightforward comparisons among urban areas because a standard set of input data is used to calculate urban forest structure, function, and value across diverse sites. However, since ecosystem services can be more or less valuable given the situational context (Chan et al. 2007), hidden model parameters and assumptions may present an obstacle to useful city-specific results. These models also address a limited set of ecosystem services, ignoring cultural, aesthetic, and provisioning benefits altogether. Finally, ground-based assessments have high time and labor costs, and large sample sizes are needed to reduce estimation errors (Nowak et al. 2008b). In light of these difficulties, ground-based assessments provide detailed urban forest structural estimates not readily gleaned from common remote sensing platforms.

Assessments based on remotely sensed imagery do not provide the rich structural information afforded by ground-based assessments, but they are useful for efficiently generating both regional-scale (Ward and Johnson 2007; Walton 2008) and long-term (Nowak 1993; Gillespie et al. 2012) perspectives on the urban forest. The ever-growing depth of data from multiple sensors makes this type of analysis applicable to a range of questions regarding the effects of urbanization on ecosystems. For instance, aerial photography has been used to estimate urban forest cover and associated benefits in cities across the United States (Nowak et al. 1996; McPherson and Simpson 2002, 2003), and to quantify ecologically important landscape metrics in China (Zhang et al. 2004). Compared to aerial photography, satellite imagery generally provides greater breadth of spectral reflectance information, making it more amenable to species- or genus-specific analysis. For example, Kromroy et al. (2007) classified Landsat imagery to assess the effects of urbanization on oak trees in the Twin Cities, MN. Although satellite data can provide more detailed spectral information, aerial photography permits a longer record of analysis in most areas (Gillespie et al. 2012). Recently, LiDAR technology has opened up new possibilities by permitting detailed urban forest structural analysis using remotely sensed imagery, but sparse LiDAR image availability is currently a limiting factor in most areas (Ward and Johnson 2007).

Research challenges in urban forest ecosystem service science

Although McKinney (2006) described the homogenizing effect of urbanization on biological diversity, local-scale studies of urban ecosystems are generally approached with the expectation of increased diversity relative to more natural settings. Nowak (2000) noted that urban forests are significantly more diverse than natural forests. Even where biological systems are simplified by human management, the significant role of human activity at multiple spatiotemporal scales complicates matters and prohibits straightforward assessment. While the urban forest is difficult to study, existing research has been successful in two important ways. First, urban foresters have contributed to

Millennium Ecosystem Assessment (2005) efforts by documenting multiple urban forest ecosystem services across a wide range of settings (Dwyer et al. 1992; Nowak et al. 2002; Yang et al. 2005; Alvey 2006; Chen and Jim 2008; Escobedo et al. 2008; McPherson et al. 2011). Second, by documenting current urban forest structure in major cities around the world, urban forest managers can better prepare for the future events such as destructive pest outbreaks (Raupp et al. 2006; Sydnor et al. 2007; Laćan and McBride 2008) and global climate change (Carreiro and Tripler 2005).

Even though urban forest research has exploded in the past decade, the field is emblematic of the larger discipline of ecosystem service science because urban forest perspectives are rarely considered explicitly in land management decisions. I argue that the field must advance in at least three key areas before urban forest ecosystem services will consistently influence urban land use decisions. Specifically, researchers should pay closer attention to urban forest dynamics beyond central cities, improve characterization of urban forest structure to understand how associated functions and values are distributed in space and time, and develop greater awareness of complex aspects of human-natural urban systems.

Existing urban forest structural assessments have often focused solely on central cities within metropolitan regions. For instance, i-Tree modeling studies have provided important urban forest information for major urban centers (Yang et al. 2005; Nowak et al. 2006; Soares et al. 2011), but have rarely considered broader metropolitan processes. The urban-rural gradient framework is promising because it provides an alternative approach that considers a more complete range of metropolitan settings. This is especially important where the central city's population density is higher, total population and land area is smaller, and land use is more static relative to the surrounding suburbs. Applying i-Tree Eco and similar models across metropolitan regions has the potential to substantially broaden perspectives on urban forest structure, function, and value.

Urban forest ecosystem services and value estimations are based on characterizations of urban forest structure (Nowak et al. 2008a), so more structural data is ultimately needed to robustly demonstrate urban forest benefits to land use managers. Specifically, there is a need to generate spatially and temporally rich data sets to demonstrate the relationships between land use and the urban forest across diverse settings and over time. For example, privately managed trees make up a large percentage of the urban forest (McPherson 1998b), but many studies have been restricted to municipally managed street trees (e.g., Maco and McPherson 2003; McPherson et al. 2005; Soares et al. 2011). Documenting urban forest structure on private lands is particularly important in suburban settings, where municipal street trees are less important than in the central city (Nowak 1994b). Assessing the urban forest at entire property parcels is needed to tie fine-scale parcel characteristics to urban forest structure and function. To achieve better historical context for current patterns, long-term studies using historical air photos can highlight the impacts of past land management on urban forest structure (Nowak 1993; Gillespie et al. 2012).

Urban forest researchers need to develop a more complete understanding of complex aspects that are typical in coupled human-natural environments (Liu et al. 2007). Human-natural systems routinely exhibit nonlinear relationships, which have been demonstrated where urban forest structure peaks at intermediate levels of urbanization (Grove et al. 2006). Scalar complexities are important in urban forestry because the forest is influenced at multiple levels. For instance, individual landowners determine parcel-scale urban forest structure, but they are subject to neighborhood- and municipality-scale policies (Conway and Urbani 2007) and group identity pressures (Grove et al. 2006; Troy et al. 2007; Boone et al. 2010). Physiographic, climatic, and infrastructural controls provide additional constraints on the urban forest at multiple scales. Human impacts on environmental phenomena such as pollution (Kozlowski 1985) and invasive species transport (Poland and McCollough 2006) impose another layer of human-natural complexity in the urban forest. Finally, temporal lags are an emerging topic in urban ecology (Ramalho and Hobbs 2012). Trees take decades to reach maturity, so present urban forest structure may reflect the preferences of previous landowners (Boone et al. 2010). Better accounting for these complexities will promote realistic perspectives to improve urban forest design and management.

SUMMARY OF CHAPTERS

In this dissertation, I study the relationship between urbanization and urban forest structure, function, and value. I build on existing urban forest literature by considering urbanization's effects on the urban forest along an urban-rural gradient and with respect to complex aspects such as nonlinearities, spatial scaling, and temporal lags. The research takes place within a transect located in Minnesota's Twin Cities Metropolitan Area (TCMA). The TCMA is an ideal place to study the impacts of urbanization on the urban forest because the region is growing rapidly (Yuan et al. 2005), and is characteristic of the United States' northern Midwest, where urban land is projected to expand by 80 percent between 1997 and 2025 (Alig et al. 2004). The following three research chapters are based in the same study area but use distinct sampling strategies and analytical approaches, so methodological details are provided separately within each chapter.

In Chapter 2, I use historical air photo analysis to understand how past land cover changes affected tree canopy cover, a key urban forest structural attribute. Compared to similar studies, this analysis offers an especially long record of change. This is important because tree canopy cover's response to land cover change may be lagged by decades. In this vein, I assess the relationship between urban development age and tree canopy cover.

Chapter 3 provides an examination of present day urban forest structure on residential properties along an urbanization gradient. Since linear distance-based gradients do not fully capture trends in urbanization (Hahs and McDonnell 2006), I use factor analysis to extract primary trends from a set of nineteen urbanization indicator variables. I then relate these major urbanization trends to urban forest structural variables, and compare the explanatory power of the factor analysis-derived gradient to that of a simpler linear distance-based gradient.

The final research study, Chapter 4, assesses select variables related to urban forest structure, function, and value across a variety of land uses. I begin by comparing urban forest characteristics on residential land, non-residential developed land, and undeveloped land. Then I use cluster analysis to divide these three broad land use classes into more detailed sub-classes. I assess whether this added level of detail is necessary for understanding urban forest characteristics by comparing land use clusters within versus among broad land use classes. I conclude Chapter 4 by comparing urban forest structure, function, and value in Minneapolis sites to suburban sites to assess the importance of studying the urban forest beyond the boundaries of the central city.

Chapter 5 concludes the dissertation by revisiting the primary research motivations in the context of Chapters 2-4. I reflect on the major findings, and describe several priorities for future research.

Chapter 2. Long-term urbanization effects on tree canopy cover along an urban-rural gradient

Overview. Urban forestry can benefit from improved knowledge of urbanization's effects on tree canopy cover (TCC), a prominent urban forest indicator. This study examined changes in TCC over a long time frame, with respect to land cover (LC) changes, and across municipal boundaries. Specifically, I used air photos at 14 dates from 1937-2009 to develop an exceptionally long record of TCC change in Minnesota's Twin Cities Metropolitan Area. During the study period overall TCC nearly doubled from 17% to 33% while the proportion urban land cover rose by 47%, highlighting the opportunity for substantial TCC gains following urbanization in previously agricultural landscapes, even in regions that were forested prior to European settlement. Results demonstrate that more intensely developed sites generally had lower TCC, and older urban sites had higher TCC. Modern TCC was not adequately characterized by linear distance along the urban-rural gradient, but instead peaked near the center of the gradient where mature residential neighborhoods are prevalent. Compared to other land cover changes, urbanization events caused the highest rate of immediate TCC loss (9.6% of events), yet urban areas had the second highest TCC (>35%) in 2009, indicating that urban land gained TCC relatively efficiently following development. The results of this study provide new historical context for urban forest management across an urban-rural gradient, and emphasize the need to consider ecological legacies and temporal lags

following land cover changes when considering TCC goals in urban settings. This material is published in *Urban Ecosystems* (Berland forthcoming).

INTRODUCTION

Urbanization, the transition of undeveloped land to built-up or paved areas, is one of the most important land cover (LC) change processes in the world today. The world's urban population grew from 220 million to 2.84 billion during the 20th century, and is projected to reach 5 billion by 2030 (UN Population Fund 2011). In the United States, around 80% of the population lives in urban areas, and developed area is expected to increase by 79% in the next two decades (Alig et al. 2004), positioning the urban-rural interface as one of the nation's most dynamic regions. While urbanization provides many positive opportunities including access to occupations, housing, and cultural amenities, it also impacts ecological systems (e.g., McDonnell et al. 1997; Luck and Wu 2002; Tratalos et al. 2007). Consequently, understanding urbanization's ecological effects is a foundational step in achieving sustainable cities (Alberti and Susskind 1996).

The urban forest—a collective term for all trees and woody shrubs in an urban area—is among the most important and well-studied urban ecological components (e.g., McPherson et al. 1997; Nowak et al. 2001). The urban forest provides significant ecosystem services such as stormwater interception (Dwyer et al. 1992), air pollution removal (Nowak et al. 2006), carbon benefits (Akbari 2002), urban heat island reduction (Hardin and Jensen 2007), and socioeconomic benefits (Dwyer et al. 1992; Tyrväinen and Miettinen 2000; Arnberger 2006). Urban forests are economically valuable (Nowak et al.

2002), and their benefits have been shown to outweigh management costs (McPherson and Simpson 2002; McPherson et al. 2005). Given the ecological, economic, and social importance of urban forests, it is critical that we understand how urbanization affects trees over time and across space. This study presents a particularly long record (>70 years) of interacting LC and forest change along an urban-rural gradient, and in doing so, expands on the spatiotemporal scope of similar projects.

Tree canopy cover (TCC) is a useful metric for characterizing the effects of urbanization and other LC changes on forest abundance (Walton et al. 2008). TCC is defined here as the proportion area occupied by tree or shrub canopies when viewed from above. TCC is simpler than metrics derived from field surveys or emerging technologies like LiDAR, as it does not consider tree species, leaf volume, health, or spatial distribution (Walton et al. 2008). So while TCC is of limited use in estimating detailed ecological benefits provided by urban forest, it holds several advantages that led to its selection as the primary variable in this study. Most importantly, TCC can be estimated using historical air photos, offering better temporal depth than LiDAR- or satellite-based metrics. In addition, TCC can be estimated efficiently using imagery that is often free and available online. It can be compared across regions, and is simple to communicate to the public (McPherson et al. 2011). American Forests (http://www.americanforests.org/) recommends that communities assess their TCC and set goals to expand TCC in order to promote the ecosystem services urban forests provide. In a recent survey of 135 American cities, 47% had stated goals to increase TCC (U.S. Mayors 2008), which suggests that TCC may be the most commonly monitored urban forest metric.

Knowledge of past urban forest dynamics can guide future management efforts, for instance, by providing a baseline for measuring the success of management goals. However, to have a more meaningful impact on land management efforts, historical TCC analysis should be conducted with several considerations in mind. First, explicit recognition of LC dynamics is important, as LC influences TCC potential (Rowntree 1984a). For example, the densely developed urban core likely has less space to increase TCC than a sparsely developed suburb. Second, temporal lags in TCC due to tree growth should also be considered, because canopy goals cannot be achieved immediately by planting immature trees. Third, the spatial extent of analysis is important, and analyses can benefit from considering metropolitan scopes beyond the central city. Focusing on a central city is important for addressing research needs for that municipality's urban forest resources. However, expanding research into the greater metropolitan area is also needed if regions are to adopt landscape-scale approaches to resource management (Wu 2008). Furthermore, understanding ecological changes in the more dynamic suburban and peri-urban areas may offer more insight into the effects of urbanization than focusing exclusively on the central city, where LC is typically more stable (Medley et al. 1995). The urban-rural gradient approach (McDonnell and Pickett 1990) is applicable for documenting these regional impacts of urbanization because it accounts for multiple urban densities from the urban core to the sparsely developed peri-urban fringe. However, more recent studies have noted that it may be more useful to consider the urban-rural gradient in terms of urban intensity at a series of sites, rather than as a strictly distance-based measure from the urban core outward (Alberti 2005; Tratalos et al. 2007).

In this study, I implemented these key design considerations to examine changing TCC in the context of LC change, over time, and across an urban-rural gradient in Minnesota's Twin Cities Metropolitan Area (TCMA). Specifically, I used historical air photos to understand how TCC has changed over time and space as the urban region grew from 1937-2009. Focusing on a general urban-rural gradient, I examined four questions regarding the effects of urbanization on TCC. First, how does LC change affect TCC? Second, how does TCC vary along an urban-rural transect from the urban core to the peri-urban fringe? Third, how does TCC relate to the intensity of urban development? Finally, does TCC vary with the age of urban development? Results are intended to provide long-term historical context for current discussions of urban forest management, especially in situations involving TCC goal monitoring and LC change across heterogeneous metropolitan regions. The analysis of an urban-rural gradient with unique temporal coverage (i.e., 14 dates over >70 years) provides a richness of spatiotemporal information not seen in other TCC analyses.

METHODS

Study area

The study area is a transect (40 km long by 3 km wide) extending from the urban core in downtown Minneapolis, Minnesota, USA, through the suburbs to the peri-urban fringe (Figure 1). Today the transect represents a general urban-rural gradient running from north to south within the TCMA, a 7,705 km^2 region that is home to 2.85 million people and is expected to add nearly 1 million people by 2030. The northernmost center of the study transect was placed at the heart of downtown Minneapolis, where urbanization should theoretically be highest. In addition to Minneapolis, the transect encompasses portions of Richfield, Bloomington, Burnsville, Apple Valley, Lakeville, and Eureka Township. The study area is roughly bisected by the southwest-northeast oriented Minnesota River, which is buffered by the Minnesota Valley National Wildlife Refuge. This natural area forms a border between Bloomington and Burnsville.

In recent decades the study region has experienced extensive LC change, especially from agriculture to urban land uses. The widespread legacy of agricultural land use in this region may lead to different findings than in places where urban growth largely replaced forested lands (e.g., Hutyra et al. 2011). Within the study area, the most recent urbanization is concentrated toward the urban-rural interface at the southern end of the transect, and urban expansion is expected to continue. Study area municipalities have varying TCC policies. For example, Burnsville has a stated goal to increase TCC, Minneapolis strives for no net loss of TCC, and Bloomington does not have an explicit TCC policy.

A transect approach was chosen to broadly capture the history of urban development from the innermost to outermost suburbs. By running the transect south from Minneapolis I was able to contain the study area within two counties, which led to better historical air photo availability. This transect placement captures a fairly consistent urban-rural impervious surface gradient, whereas alternative placements may have been complicated by the neighboring urban center of St. Paul via less regular distance decay of impervious surfaces, or by large lakes via a lower proportion land surface for analysis.

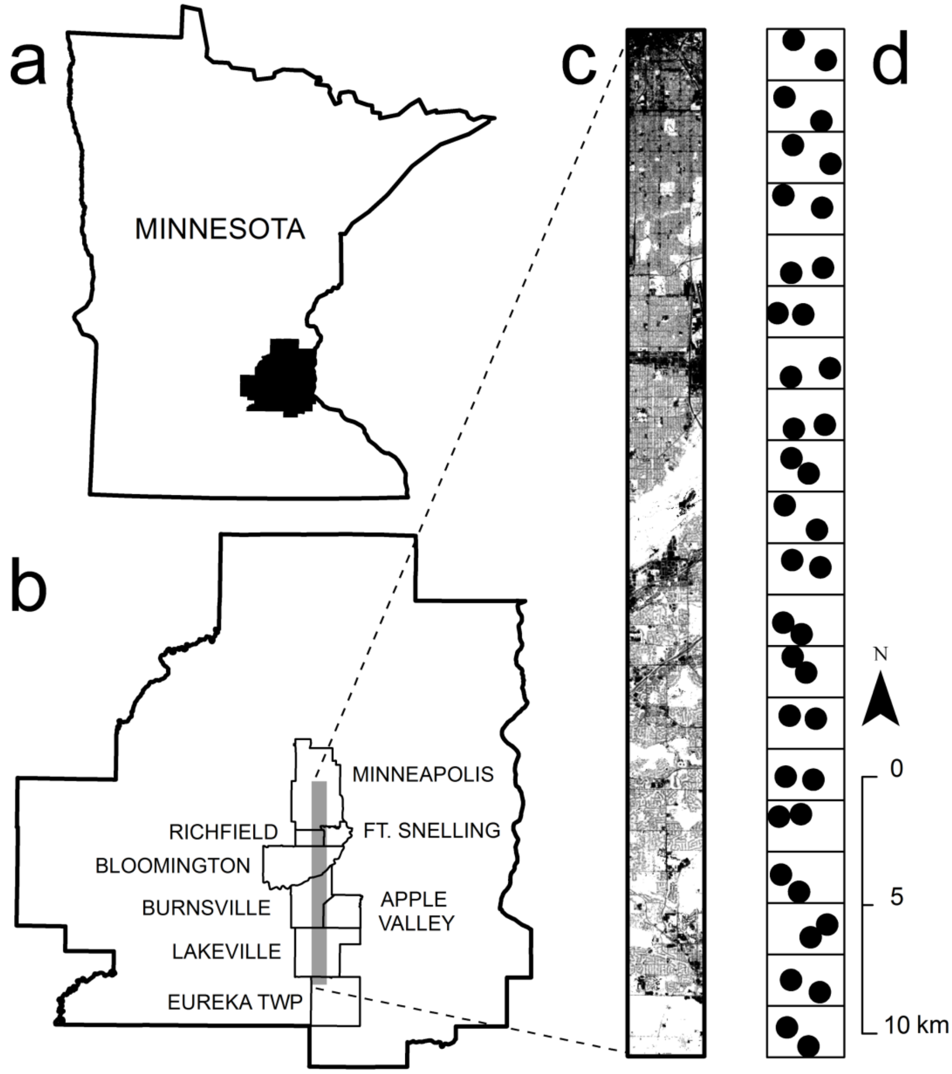

Figure 1. Study area. (a) Location of the TCMA within Minnesota. (b) Position of the study transect within the TCMA and municipalities. (c) Impervious surface classification from 0% (white) to 100% (black). (d) Distribution of circular analysis zones within the study transect.

Compared to the entire seven-county TCMA, the present day study transect has proportionally more urban land (+19.0% compared to entire TCMA), less water (-4.0%) and wetlands (-15.0%), and roughly the same amounts of agriculture (-1.7%), forest (+0.2%), and grassland/shrubland (+1.5%).

Data preparation

Historical air photos were available at 14 dates between 1937 and 2009 (Table 1). I obtained orthorectified air photos from 1991-2009 from the Minnesota Geospatial Information Office (http://www.mngeo.state.mn.us). Air photos prior to 1991 were collected from the John R. Borchert Map Library at the University of Minnesota. Photos were compiled by scanning hard copies in the library, and by downloading images from the library's online interface (http://map.lib.umn.edu/mhapo/index.html). I georeferenced pre-1991 photos to <10 m root mean square error. All photos were stored and analyzed within a GIS (geographic information system). Although photo coverage was incomplete for four dates (1947, 1953, 1957, 1960), these dates were included because photos were available for ≥50% of the analysis zones (see below).

I analyzed LC and TCC in 40 circular analysis zones distributed along the transect. To create the analysis zones, I first divided the transect into 20 regularly-spaced 2-km segments along the (north-south) general gradient of urbanization (Figure 1d). Each segment measures 3 km (east-west) by 2 km (north-south). Within each segment, I randomly distributed two 0.5-km^2 circular analysis zones to serve as the unit of analysis. Analysis zones extending beyond the edges of the segment, comprised of more than 20%

Table 1. Historical air photo sets

Year	Agency	Scale/ Resolution	Accuracy	Color	Leaf status	Coverage (out of 40)
1937	ASCS	1:20,000	Georeferenced	B&W	On	40
1947	USGS	1:17,000	Georeferenced	B&W	On	23
1953	ASCS	1:20,000	Georeferenced	B&W	Partial	32
1957	ASCS	1:20,000	Georeferenced	B&W	On	39
1960	Mark Hurd	1:9,600	Georeferenced	B&W	On	20
1962	MnDOT	1:9,600	Georeferenced	B&W	On	40
1970-71	ASCS/ Mark Hurd	1:9,600/ 1:40,000	Georeferenced	B&W	On	40
1991	USGS	1-meter	Orthorectified	B&W	Partial	40
1997	Met Council	0.6-meter	Orthorectified	B&W	Partial	40
2000	Met Council	0.6-meter	Orthorectified	B&W	Partial	40
2003	FSA/NAIP	1-meter	Orthorectified	Nat	On	40
2006	USGS	0.3-meter	Orthorectified	Nat	Off	40
2008	FSA/NAIP	1-meter	Orthorectified	Nat+IR	On	40
2009	FSA/NAIP	1-meter	Orthorectified	Nat	On	40

Agency abbreviations: ASCS: Agricultural Stabilization and Conservation Service; USGS: United States Geological Survey; Mark Hurd: Mark Hurd aerial mapping contractor; MnDOT: Minnesota Department of Transportation; Met Council: Twin Cities Metropolitan Council; FSA: Farm Service Agency; NAIP: National Agriculture Imagery Program. Color abbreviations: B&W: black and white; Nat: 3-band natural color; IR: near infrared. Coverage represents number of analysis zones with photo coverage.

open water, or overlapping other analysis zones were discarded and reselected. I used circular analysis zones to avoid artifacts of regularly gridded landscape features such as city blocks and agricultural fields.

In each analysis zone, I digitized LC polygons greater than 750 m^2 for each photo date. LC was categorized into the following nine categories: agriculture, forest, golf course, herbaceous grassland/shrubland, park, transportation, urban, water, and wetland. The transportation category included railroad right-of-ways and major highway right-of-ways, as defined by the Metropolitan Council. To avoid small mismatches in polygon size/shape from year to year, I based each year's LC delineation on a copy of the previous year's delineation. This strategy made certain that documented changes in LC were attributable to actual LC change and not delineation inconsistencies.

I documented TCC by randomly distributing 100 points in each analysis zone. Random point distributions helped to avoid artifacts of regularly gridded landscape features such as roads. At each point, for each photo date, I determined whether tree or shrub canopy was present or absent. I used the same point locations for each photo date. To determine percent TCC for each analysis zone, I divided canopy presence counts by 100 total dots (following Rowntree 1984b; Nowak et al. 1996). I chose this dot analysis approach because canopy presence/absence could be determined accurately, but lacking air photo quality in some years prohibited precise on-screen delineation of canopy extents.

The reliability of the 100 point dot method was tested in two ways using 2008 imagery. First, I estimated percent TCC using an additional 100 random points (200 total points). 100 point estimates were on average 0.8% lower than 200 point estimates (st. dev. = 1.6%). Second, I generated percent TCC estimates by delineating tree canopy polygons for each entire analysis zone and dividing by the total analysis zone area. Delineating tree canopy polygons was aided by the availability of color infrared photos for 2008. 100 point estimates were on average 1.5% higher than polygon estimates (st. dev. = 3.3%). These tests indicated that 100 point TCC estimates were adequate, and that error introduced by sampling strategy was relatively small compared to long-term TCC change associated with LC change. After TCC estimation was completed, four random analysis zone estimates per photo date were repeated to ensure interpretation consistency. All LC delineation and TCC interpretation was performed by one person, thus avoiding problems associated with multi-interpreter inconsistency (Congalton and Mead 1983). Errors may have been introduced from year to year by varying air photo perspectives relative to tree canopies, shadows, georeferencing error, and interpreter error.

Data analysis

I conducted several analyses to explore the effects of urbanization on TCC. Specifically, I investigated how TCC relates to LC change and urban history, distance from the urban core, and intensity of urban development.

Conversion to urban land cover

To assess whether LC changes and, particularly, urbanization have an immediate impact on TCC, I compiled observations of LC and TCC at all photo dates. I compared both LC and TCC from one date to the next at each analysis point and recorded changes in one, both, or neither. This information was summarized to show the frequency with which a given LC change (or lack of change) resulted in a TCC change (or lack of change). No observation was made when photo coverage was missing. Ranked comparisons between urban LC and other LCs were made to understand the TCC effects, relative to other LC types, of changing *to* urban LC, changing *from* urban LC, and *remaining* urban from one date to the next.

Distance from the urban core

I used regression analysis to determine whether analysis zone TCC may be adequately characterized by linear distance from the urban core (i.e., by a linear urban-rural gradient). The independent variable, distance from the urban core, was calculated as the difference between the analysis zone centroid and the northern edge of the study transect. TCC, the dependent variable, was summarized by analysis zone for each photo year. I fit linear through quartic (i.e., first- through fourth-order) polynomial regressions separately for each photo year, and used analysis of variance (ANOVA) testing to determine regression significance. F-tests were used to compare the four regressions for each photo year in terms of explanatory power and parsimony. For example, the addition of a quadratic term is assumed to produce a higher r^2 value than a linear regression, but if the increase in r^2 was not statistically significant the linear regression was selected to characterize the relationship parsimoniously.

Urban intensity

To assess the relationship between TCC and urban development intensity, I compared summarized analysis zone TCC observations to a 2007 LC/impervious surface classification (Figure 1c; available from http://land.umn.edu). Since no air photo coverage is available for 2007, I averaged 2006 and 2008 TCC estimates for each analysis zone. The mean and median differences between 2006 and 2008 estimates were 0.25% and 0%, respectively, so averaging for a 2007 estimate had only a minor effect on input data. The LC classification is based on stacked Landsat Thematic Mapper images of the TCMA from spring and summer 2007, georeferenced to <7.5 m root mean square error. The classification is divided into five level-1 classes (agriculture, forest, urban, water, and wetland/shrubland/grassland) with assessed overall accuracy >93%. The classification contains an impervious surfaces classification for the urban class. Impervious area was mapped as a continuous variable from 0-100% for each 30 m pixel, based on an inverse relationship between impervious surfaces and the "greenness" component of a tasseled cap transformation (Bauer et al. 2004). Impervious calibration data was generated by delineating impervious surfaces on high resolution (0.3 m) air photos for 120 Landsat pixels of varying impervious intensities. Impervious calibration data was delineated "through" tree canopies so that roads and other impervious surfaces below tree canopies were incorporated into the calibration, even though they may have been obscured in the Landsat imagery. Impervious classification accuracy, as measured by r^2 and standard error values, was 0.94 and 10.3%, respectively.

I found the mean impervious surface intensity for each analysis zone, and used Spearman's rank correlation to elucidate the relationship between impervious surface intensity and TCC. Permutation testing with 1,000 replicates was used to assess significance. Although the impervious classification relied on an inverse relationship between impervious surfaces and greenness, circularity was not a problem due to the impervious classification methodology (i.e., delineating impervious calibration data "through" tree canopies). So while the impervious classification was influenced by all types of vegetation, this analysis explicitly relates impervious surfaces to TCC. The distinction between TCC and other green vegetation is important because TCC has different ecological properties than other vegetated LCs such as turf grass or herbaceous wetlands.

I also compared urban intensity to TCC at 4,000 individual canopy analysis points. Pixel-based impervious surface intensity estimates were summarized according to binary canopy presence/absence observations separately for 2006 and 2008. A Mann-Whitney *U*-Test was used to evaluate the hypothesis that impervious surface intensity is significantly higher at sites without TCC. Since air photo coverage was not available to pair with 2007 impervious surface estimates, I compared impervious estimates separately to 2006 and 2008 TCC observations. Obtaining consistent results for 2006 and 2008 would alleviate concerns about the 1-year mismatch between canopy observations and impervious surface estimates.

Age of urban development

I hypothesized that older urban sites would generally have higher TCC compared to more recently developed urban sites, and assessed this by relating TCC to LC information at canopy analysis points. For all canopy analysis points in urban or transportation LC (i.e., developed urban categories), I determined the range of years during which the site was developed. I then calculated the urban development's age at each photo date. For example, consider a site that changed from agriculture to urban from 2000-2003, and then remained urban through 2009. Since the actual year of development is unknown, the urban development was between 6–9 years old in 2009, 5-8 years old in 2008, and so on. Sites that were already developed in the first photo year (1937) were grouped into an open-ended category (e.g., ≥72 years in 2009, ≥71 years in 2008). A small number of sites (n = 23) reverted from developed urban land to undeveloped land, so these were only considered in this analysis until urbanization was reversed. After calculating urban development ages I determined, for each photo date, percent TCC for each urban age range. I summarized this data into age categories based on the median of each urban age range, and assessed 2009 TCC relative to urban development age using Spearman's rank correlation coefficient, which accommodated skewness in both inputs.

RESULTS

I documented LC and TCC across an urbanization gradient over 14 air photo dates from 1937-2009. Specific analyses were used to investigate how TCC varied along an urban-rural transect, and how modern TCC relates to the intensity of urban development. I also assessed the impact of LC change on TCC, and determined how the age of urban development related to TCC.

Land cover

LC delineation in the analysis zones at 14 dates from 1937-2009 revealed two key trends in LC change. First, urban LC was the most dynamic category, rising from 19.15%

of the total land in 1937 to 66.58% in 2009 (+0.66%/year; Table 2). Other LC categories with increasing abundance included park (+0.09%/year), transportation (+0.06%/year), golf course (+0.01%/year), water (+0.01%/year), and wetland (+0.004%). Growth in these categories came at the expense of agriculture (-0.65%/year), grassland/shrubland (-0.10%/year), and forest (-0.09%/year). Second, LC change occurred unevenly across the study transect, especially in regards to developed land (i.e., urban and transportation classes). From 1937-2009, the analysis zones 0-4 km from the urban core lost an average of 2.29% developed land, analysis zones 4-8 km from the urban core gained 10.04%, analysis zones 8-38 km from the urban core gained 67.29%, and analysis zones 38-40 km from the urban core gained 5.01%. On average, analysis zones in Minneapolis gained 10.41% developed land compared to 63.42% in analysis zones in the greater metropolitan area. The largest overall gain in proportion developed land was 97.44% (zone 7A in suburban Bloomington), while the largest overall loss of developed land was near the Minneapolis urban core (zone 2B, -4.94%).

Tree canopy cover

Overall transect TCC increased from 17.3% to 33.6% from 1937-2009 (Figure 2), representing a 0.25% TCC gain/year. From 1937-2009, 35 analysis zones gained TCC, 1 remained stable, and 4 lost TCC (Figure 3). The largest overall canopy loss in an analysis zone was 18%, while the largest gain was 54%. Mean and median TCC change for the period 1937-2009 for all 40 analysis zones was +16.3% and +14%, respectively. The photo interval exhibiting the greatest transect-wide yearly rate of change was 2008-2009

Table 2. Land cover and tree canopy cover, 1937 and 2009. Land cover based on 40 analysis zones. Tree canopy cover based on 4,000 analysis points (100 per analysis zone) per year.

	% of Study Area		% Canopy Cover	
Land Cover	1937	2009	1937	2009
Agriculture	51.05	4.40	1.73	1.63
Forest	12.77	6.62	93.13	96.30
Golf course	0.00	1.01	N/A	26.53
Grass/shrub	11.57	4.03	19.43	9.09
Park	1.31	7.85	30.95	34.23
Transportation	0.62	4.68	12.50	7.95
Urban	19.15	66.58	20.65	35.01
Water	1.05	2.08	5.56	4.26
Wetland	2.48	2.75	12.37	18.35
		Mean	17.30	33.60

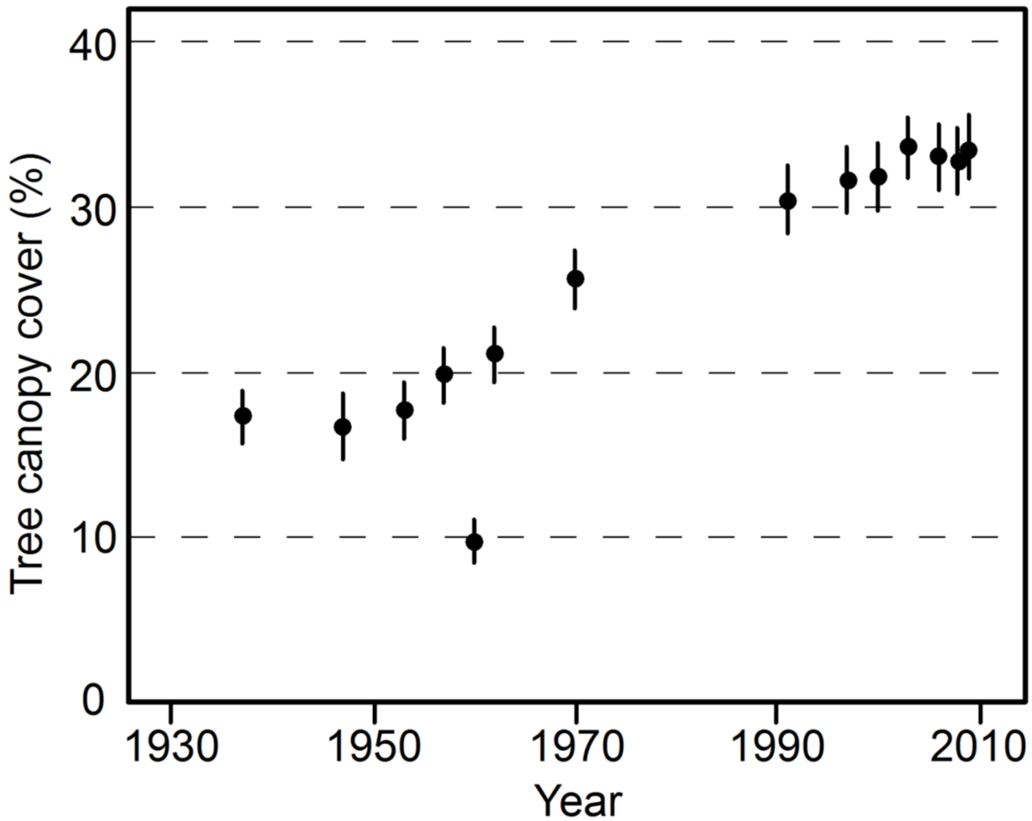

Figure 2. Study area TCC (1937-2009) with 99% confidence intervals. Note that study area photo coverage was incomplete for 1947, 1953, 1957, and 1960.

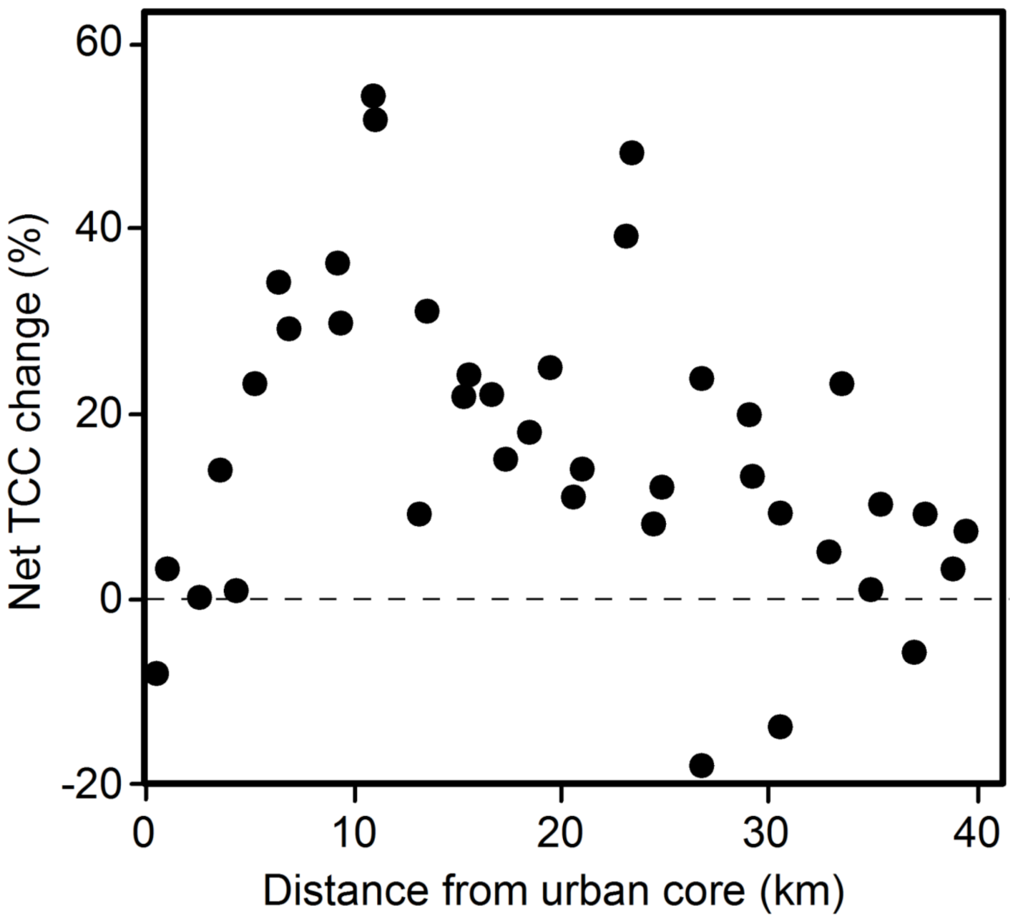

Figure 3. Net percent TCC change by analysis zone (1937-2009), from the urban core (0 km) to the peri-urban fringe (40 km).

(+0.78%/year), followed by 2000-2003 (+0.58%/year) and 1962-1970 (+0.57%/year). Two photo intervals showed overall TCC loss: 2003-2006 (-0.19%/year) and 2006-2008 (-0.13%/year).

Canopy responses to land cover change

Most changes in TCC from one photo date to the next were not directly associated with changing LC (Table 3). Of 3,061 canopy gain events over all dates for all analysis points, 5.23% concurred with a LC change event. Of 2,451 canopy loss events, 9.30% coincided with a LC change event. Urban land was most likely to experience TCC changes without coincident LC changes, while analysis points in agricultural lands were least likely to experience TCC changes without coincident LC changes. Forest sites had the highest net rate of canopy gain without coincident LC changes (3.11%), followed by urban (2.19%).

The largest TCC gains were seen when LC changed to forest (34.57% of events; Table 3), while the largest losses occurred when LC converted to transportation (13.13% of events). Out of nine LC categories, changing to urban LC resulted in the second-lowest net TCC change (-4.28%), and changing to transportation LC netted the lowest rate of TCC change (-11.88%). When LC changed from urban to another class (n = 108) there was net TCC loss of 8.33%. By comparison, the highest rate of gains occurred when LC changed from water to another category (28.57% of events), while changing from forest to another category coincided with TCC losses 35.03% of the time.

Table 3. Tree canopy cover change with respect to land cover dynamics. Values represent proportion of events from one date to the next in which (A) land cover did not change, (B) land cover changed *to* a given class, and (C) land cover changed *from* a given class. LC: land cover.

Land Cover	Canopy Gain (% of total)	Canopy Loss (% of total)	No Change (% of total)	Observations
(A) No LC change				
Agriculture	1.12	0.98	97.90	6,095
Forest	7.37	4.26	88.37	3,473
Golf course	2.04	1.63	96.33	245
Grassland/Shrubland	6.44	5.38	88.18	2,343
Park	6.91	5.18	87.90	2,315
Transportation	2.45	1.78	95.77	1,346
Urban	9.78	7.59	82.63	21,862
Water	2.67	2.88	94.44	936
Wetland	4.74	4.23	91.03	1,371
Mean (no LC change)	4.84	3.77	91.39	39,986
(B) LC change TO				
Agriculture	5.26	0.00	94.74	19
Forest	34.57	3.70	61.73	81
Golf course	4.08	8.16	87.76	49
Grassland/Shrubland	3.26	3.43	93.31	583
Park	4.12	3.00	92.88	267
Transportation	1.25	13.13	85.63	160
Urban	4.98	9.26	85.76	1,847
Water	3.03	0.00	96.97	33
Wetland	5.33	1.33	93.33	75
(C) LC change FROM				
Agriculture	3.20	1.27	95.53	1,654
Forest	6.42	35.03	58.56	374
Golf course	n/a	n/a	n/a	0
Grassland/Shrubland	7.45	5.34	86.21	899
Park	11.11	5.56	83.33	18
Transportation	n/a	n/a	n/a	0
Urban	6.48	14.81	78.70	108
Water	28.57	0.00	71.43	7
Wetland	9.26	3.70	87.04	54
Mean (with LC change)	5.14	7.32	87.54	3,114
TOTAL	4.86	4.03	91.09	43,100

Distance from the urban core

Quadratic regressions produced the best fits for the years 1991-2009, and for 1960, which had incomplete air photo coverage (Figure 4). Linear regressions produced the best fits for the years 1937-57 and 1962-70. Regressions were statistically significant at the $P < 0.01$ level for 2003-09, at the $P < 0.05$ level for 1991-2000, and no earlier regressions were significant (except 1960, which was highly significant but showed an inconsistent pattern due to many missing observations).

Intensity of urbanization

A significant inverse relationship between analysis zone impervious surface intensity and TCC was demonstrated by Spearman's rank correlation ($r_s = -0.405$; $P = 0.012$) for developed sites (Figure 5). A Mann-Whitney *U*-Test comparing impervious surface intensity at each of the 4,000 canopy analysis points revealed significant differences between sites with and without TCC in both 2006 ($P < 0.001$) and 2008 ($P < 0.001$). For 2006, mean impervious intensity was 24.0% at sites with TCC, and 38.7% at sites without TCC. Similarly, in 2008, mean impervious intensity was 23.7% at sites with TCC, compared to 38.8% at sites without TCC.

Age of urban development

Urban development age was correlated to mean TCC using Spearman's rank correlation coefficient (r_s). In 2009, $r_s = 0.7132$ ($P = 0.001$), indicating that TCC

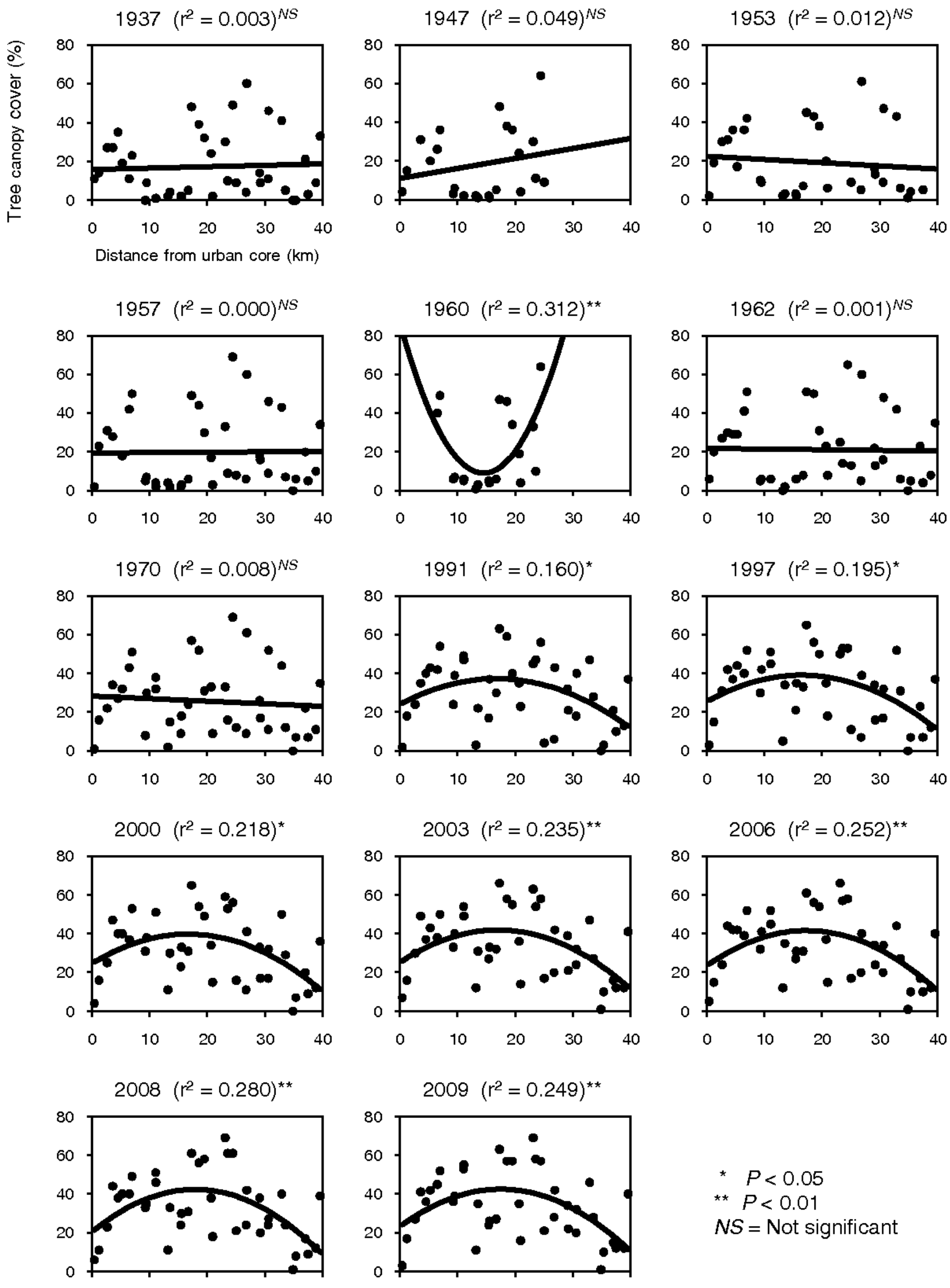

Figure 4. Analysis zone TCC (%) by distance from the Minneapolis urban core for 14 photo dates. Regression line represents the best-fit line (linear or quadratic), as determined by *F*-tests. Significance values were determined by ANOVA.

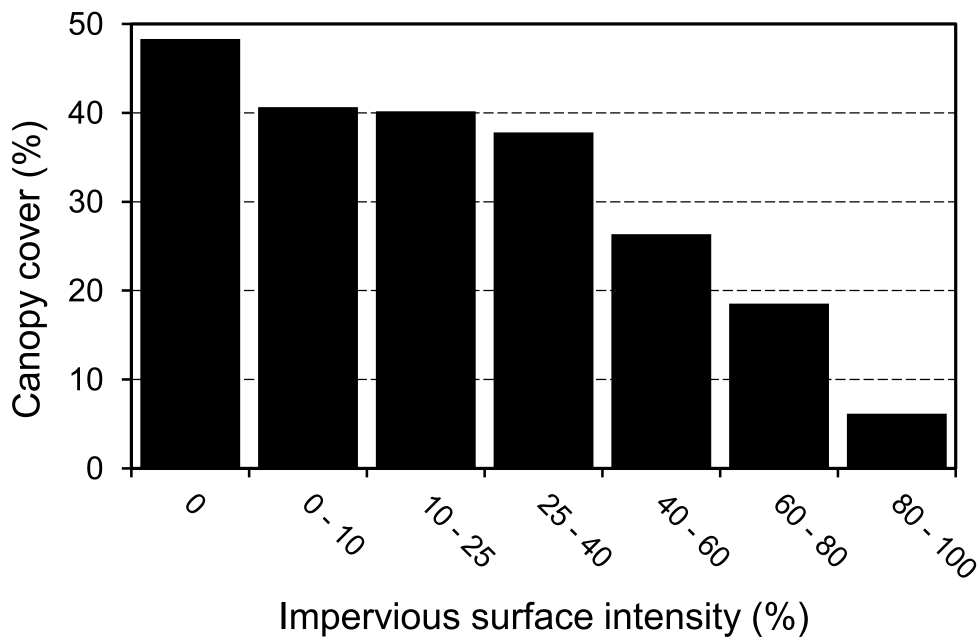

Figure 5. TCC by impervious surface intensity. Comparison of 2008 TCC at analysis points (n = 4,000) and corresponding 2007 impervious surface estimates.

increases with age of urban development (Figure 6). This statistic was calculated at each photo date back to 1957, beyond which the number of observations dropped below six. The test indicated positive relationships in each year, and these associations were significant at the $P < 0.05$ level in 2009, 2008, 2006, 2000, and 1970. Based on 2009 data, developed sites older than 20 years averaged 36.37% TCC, while sites that had been developed for less than 20 years old averaged 13.99% TCC. According to a two-proportion *z*-test, developed sites over 20 years old had significantly higher TCC ($P < 0.001$). Since the error introduced by assigning median ages to each category could not be quantified, significance of relationships should be interpreted with some caution.

DISCUSSION

Urbanization, agricultural legacies, and tree canopy cover

This study highlights the usefulness of historical air photos in documenting the long-term effects of urbanization on TCC along an urban-rural gradient. Observing a 16.3% overall increase in TCC during a time period when urban land increased by 47.4% suggests that regional urbanization had positive impacts on ecological benefits provided by TCC. However, these benefits come with attendant costs of urbanization (e.g., decreased agricultural production, increased urban heat island effects) that likely outweigh the ecological benefits of added TCC. The idea that urbanization may lead to increased TCC is not new, as Nowak (1993) showed that urban trees added TCC to an area naturally dominated by grassland and shrubs. In the TCMA, however, the pre-European landscape was largely wooded (Marschner 1974), so while Nowak et al. (1996)

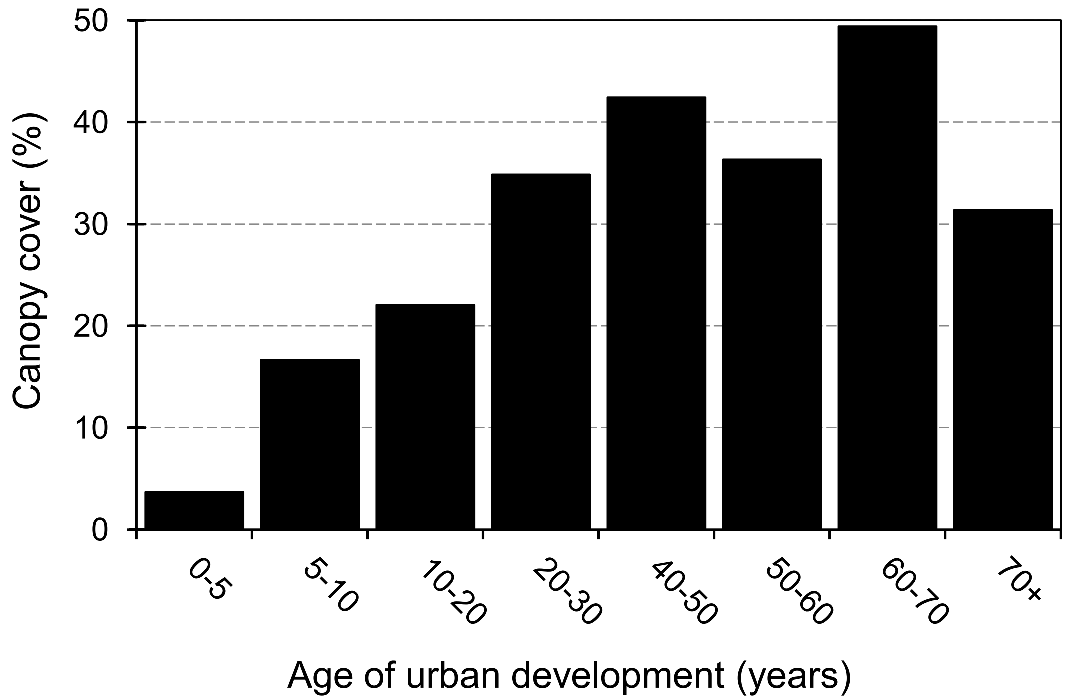

Figure 6. 2009 TCC by age of urban development, summarized for 2,858 urbanized canopy analysis points.

noted differences in TCC between cities in naturally forested vs. grassland and desert regions, this study suggests that past land use is at least as important as potential natural vegetation in influencing post-urbanization TCC dynamics. When considering long-term TCC trends, it may be appropriate in some regions to assume that urbanization will reduce TCC, but in much of the agricultural midwestern USA, urbanization may eventually lead to the highest TCC levels in the last century or more.

Spatial structure of tree canopy cover

TCC did not exhibit a strong linear relationship with distance from the urban core. Modern TCC is generally highest near the center of the transect, roughly 15-25 km from the urban core (Figure 4). High TCC in the middle of the transect is attributable to a high proportion of mature low-density residential neighborhoods. Low TCC in the urban core is likely a product of intense urbanization in the Minneapolis downtown. Low TCC at the peri-urban fringe is likely a combined effect of current tree-scarce agricultural LC and lagging tree growth in newer urban developments. Whereas some ecological indicators may be strongly related to linear distance from the urban core, these results agree with other studies (e.g., McDonnell et al. 1997) where simple linear relationships are not observed.

The temporal development of TCC's spatial structure supports the idea that mature residential neighborhoods support more TCC than other developed areas. When TCC was modeled as a function of distance from the urban core (Figure 4), all regressions prior to 1991 were linear and not significant (except 1960, where many observations were missing). From 1991-2009, all regressions were quadratic and significant, with the most variability explained in 2008. This can be explained by substantial canopy gains due to urban maturation in the near-urban suburbs (Figure 3; Figure 6), which were largely developed during the 1950s and 1960s. Similar future TCC increases may be seen in Lakeville's newly developed large-lot residential neighborhoods, which have ample pervious surface area for growing trees, though it may take decades for tree growth to produce expansive canopies.

On the other hand, complicating factors could affect future TCC outcomes in both new and old urban developments. For example, different residential tree species assemblages in the near-urban vs. peri-urban suburbs may lead to different TCC dynamics in the newer peri-urban neighborhoods (the author, unpublished data), especially in the face of newly arriving host-specific pests like the emerald ash borer. Differences in urban form may affect canopy development via the spaces available for trees. For instance, old neighborhoods with regularly gridded streets, small lots, and sidewalks may be able to accommodate trees differently than new developments with winding roads, large lots, and no sidewalks. Homeowner demographics and group identity could lead to varied planting decisions and tree maintenance across neighborhoods (Grove et al. 2006; Boone et al. 2010). Varying urban forest policies may cause differences in future TCC (Conway and Urbani 2007). For example, Apple Valley requires that new single-family residential homes have at least one front yard tree, while other municipalities have no such requirement. Continued TCC monitoring in newly developed neighborhoods could be used to compare canopy development through time to past canopy development in old neighborhoods.

Urban intensity was strongly correlated with TCC (Figure 5). The reliability of this metric for characterizing an indirect urban-rural gradient is in line with McDonnell and Hahs (2008), who recommend moving beyond simple distance-based conceptualizations of urban-rural gradients. TCC was significantly lower at more intensely urbanized sites, so while transect-wide TCC increased in the presence of widespread urbanization, densely developed areas experienced only small gains or losses in TCC. Indeed, the oldest urban category had lower TCC than all other categories over 20 years old (Figure 6), and most of these sites were located in the intensely developed urban core. Note that some of the TCC decline in the oldest urban category may be related to tree life spans, but this effect cannot be evaluated with the available data. Since TCC is already relatively high in older suburban neighborhoods and will likely increase over time in the newer suburbs, directing research and management efforts toward increasing TCC in areas with high impervious intensity may be the most effective strategy for boosting regional ecological benefits provided by urban forest canopy (e.g., urban heat island amelioration). Unfortunately, increasing TCC in densely developed urban centers is a serious challenge, as trees struggle to survive in urban centers due to factors such as limited soil volume, limited crown space, and pollution (Alvey 2006).

Conversion to urban land cover

Urban development—conversion to urban and transportation LC classes—resulted in the most substantial immediate net TCC losses among all LC classes. This demonstrates a historical failure to maintain TCC through the urbanization process, even in a region and time frame where the majority of urban development occurred in previously agricultural, canopy-poor areas. Although direct effects of LC change are important, most changes in TCC from one photo date to the next were observed without a coincident LC change (Table 3). This is likely a result of both real canopy change and analytical error attributable to slight mismatches in air photo georeferencing, air photo angle relative to tree canopies, and/or interpreter error. Observing many of the highest rates of canopy change in the 2000s when photo date intervals were small suggests the presence of some analytical error, although it is not necessarily surprising that canopy change occurred at a faster rate than change in underlying land use for many sites, given that LC change tends to be long-lasting and unidirectional (e.g., the transition for any given site from agriculture to urban happens just once and remains urban). Assuming that error was unbiased and not significant, urban land experienced the most frequent changes in TCC (both gains and losses) in the absence of LC change (Table 3). Moreover, urban LC had the second highest rate of net canopy gain without an associated LC change, trailing only forest LC. These results are consistent with the finding that older urban developments were likely to have higher TCC than newer urban areas (Figure 6). In

2009, urban land was second only to forest in percent TCC, in spite of the many recently urbanized areas where TCC had not yet formed.

Taken together, these findings indicate that the process of urbanization has had a negative immediate impact on TCC, but over time urban land has gained TCC relatively rapidly. TCC increases following urbanization are especially large in formerly agricultural areas, so it is important to recognize land use legacies in places like the TCMA, where agriculture commonly replaced forested areas prior to urbanization. While urban TCC will eventually level off, this region should expect further gains in TCC as recently developed sites afforest. This trend of increasing TCC will depend in part on the effects of destructive pests such as the newly arrived emerald ash borer, and land management decisions at scales from individual property owners to municipal or regional planning agencies.

Study limitations

This study's limitations may affect the conclusions. As mentioned earlier, errors introduced during air photo interpretation (e.g., those associated with shadows or interpreter error) likely have a minor impact on the results. Photo resolutions and qualities differed among photo dates, but reasonable findings across all years and consistent results from repeated estimates suggest that photos were of sufficient quality for TCC and LC interpretation.

The study was spatially restricted to a subset of the total TCMA. While TCMA-wide analysis would ultimately be more useful to land managers, the fine scale of the imagery made it unfeasible to analyze the entire metropolitan area across 14 photo dates. Future work may benefit from using broader-scale satellite imagery to study LC/TCC dynamics over entire metropolitan regions (Walton et al. 2008), although in most places satellite datasets lack the temporal depth of air photos. Nonetheless, by focusing on an urban-rural gradient instead of a single municipality, I demonstrated urbanization's effects on TCC in a range of settings from the relatively stable urban core to the suburbs developed in the mid-20th century to today's rapidly urbanizing peri-urban fringe. This is especially important because urban LC rose by only 10.41% within the central city of Minneapolis compared to a 63.42% increase in the rest of the study area, emphasizing the importance of studying more dynamic suburbs in addition to central cities (Medley et al. 1995). Some recent studies have considered potential TCC, or the amount of pervious surface where TCC could be increased (e.g., McPherson et al. 2011), and future research could track actual vs. potential TCC over time.

Conceptually, I assumed that increasing TCC was desirable. In reality, the situation was more nuanced because increasing TCC usually coincided with expanding urban LC. Urban land generates ecological problems, such as those associated with impervious surfaces. Additionally, urban land often replaced agricultural fields, so crop production and the ecological effects of agriculture were lost. An analysis of the tradeoffs among ecological and economic interests associated with each LC type is beyond the scope of this paper. These complexities aside, the study still accomplished the primary goal of assessing urbanization's effects on TCC over a long time frame and across an urban-rural gradient.

CONCLUSIONS

This study applied air photo analysis to document changes in TCC associated with urban-rural gradient position, urban intensity, LC change, and age of urban development. By documenting the spatiotemporal effects of urbanization on TCC over many decades, this paper adds to a growing body of literature seeking to develop a better understanding of urban environments. Urbanization's effects on TCC are more nuanced than can be gathered from summaries of overall TCC through time for the TCMA. Analyses revealed that TCC varies in nonlinear fashion along an urban-rural gradient, and this pattern changed through time, particularly as suburban sites matured and afforested. Urbanization caused relatively large immediate TCC losses, followed by relatively large net gains in TCC after the initial LC change. Although most of the study area was originally wooded, agricultural land clearing prior to urbanization resulted in TCC increases following urbanization; this contrasts other settings where urban areas directly replaced forests. TCC has an inverse relationship with intensity of urbanization, so while regional TCC rose from 1937-2009, increases were focused away from the densely developed urban core. Insights from this study provide a historical context for understanding the effects of urbanization on TCC across a metropolitan region, and may inform considerations of urban forest management in the future.

Chapter 3. Patterns in residential urban forest structure along a synthetic urbanization gradient

Overview. There is growing demand in the environmental sciences to understand the ecological effects of urbanization. This is especially true for the urban forest, a major component of the urban environment that is increasingly relied upon to provide ecosystem services such as air pollution removal and stormwater interception. The urbanization gradient is a popular organizing concept for assessing ecological response to varying urbanization intensity, and recent methodological improvements have moved beyond simple distance-based gradients to more sophisticated synthetic gradients based on urbanization indicators such as population density and impervious surface intensity. While these synthetic gradients provide a more complete picture of urbanization than any one indicator alone can provide, it is unclear how synthetic gradients relate to ecological structure. In this study, we collected field data on urban forest structure from 150 residential properties over a 40 km transect in Minnesota's Twin Cities Metropolitan Area. We then used factor analysis on a set of nineteen urbanization indicators, and extracted two primary urbanization trends strongly related to distance from the urban core and residential neighborhood density, respectively. Using polynomial regression models, we related the synthetic gradient to urban forest structure. The synthetic gradient explained 64.3 percent of the urban forest structural variables assessed, and improved upon a simple distance-based gradient by explaining patterns in tree canopy cover. Our findings demonstrate the need to consider secondary urbanization trends on ecological structure. These results support the continued application of synthetic gradient approaches to understanding the relationships between urbanization and ecological structure.

INTRODUCTION

Urbanization is a widespread and fundamental land change process with increasingly apparent relevance to the environmental sciences (Wang et al. 2012). In the United States, urban land area is expected to increase by 79 percent between 1997 and 2025 (Alig et al. 2004). This rapid urban expansion has important consequences for the structure of ecological systems within metropolitan regions, with impacts including diminished air and water quality, habitat destruction, and altered microclimatic patterns. These impacts in particular, and the linkages between urbanization and the environment more generally, need to be understood to maintain and enhance biodiversity, sustainability, and ecosystem services within urban areas (Alberti and Susskind 1996; McPherson 1998; Williams et al. 2009).

Two decades ago ecologists argued that gradient analysis, a classic ecological approach, was well suited to investigating urban areas because human impacts are generally greatest in the urban core and decrease with distance from the core (McDonnell and Pickett 1990). As urban ecology grew into its own distinct discipline, the urban-rural gradient approach was frequently applied to study the effects of urbanization on ecological systems (e.g., Medley et al. 1995; McDonnell et al. 1997; Porter et al. 2001). However, while gradients offer a useful organizing concept, simple linear transects from the urban core to the rural periphery inadequately capture crucial dynamics such as time lags and nonlinearities that are typical in complex human-environmental systems (Liu et al. 2007; McDonnell and Hahs 2008). Consequently, recent research has focused on what we term “character-based” synthetic gradients to describe urbanization intensity (Hahs and McDonnell 2006; du Toit and Cilliers 2011). Character-based gradients combine multiple urbanization indicators (e.g., population density, proportion of impervious surfaces, land cover diversity), in addition to linear distance from the urban core that defines simpler “distance-based” gradients.

One key application of character-based gradients is examining how urbanization affects ecological systems, yet this research area remains under-explored (McDonnell and Hahs 2008). The urban forest (UF)—defined here as all trees and woody shrubs within an urban area—is an appropriate subject for studying urbanization-ecological relationships, because it is a critical component of most urban ecological systems (Dwyer et al. 1992; McPherson et al. 1997; Nowak et al. 2001). For example, urban trees provide a suite of environmental benefits including stormwater interception, urban microclimate regulation, air pollution removal, and improved animal habitat (Nowak and Dwyer 2007). As we continue to learn more about the UF’s effects on ecosystems, it is increasingly important to understand how urbanization intensity relates to UF structure as defined by the number, size, and spatial configuration of trees and woody shrubs. Identifying how UF structure relates to primary trends along urbanization gradients would substantially improve conceptualizations of how urbanization impacts the UF.

Private lands are an important focus of study because only a small percentage of the UF is publicly maintained (McPherson 1998b), and residential areas in particular are critical because they can comprise about half of urban land area and over half of new urban growth (Akbari et al. 2003; Yuan et al. 2005). The residential UF has greater structural variability than commercial and industrial areas (Dorney et al. 1984), and is thus more challenging to characterize with respect to urbanization. Knowledge of fine-scale residential UF patterns can improve our understanding of urban ecosystem dynamics by isolating individual landowner preferences and behaviors within a broader social and environmental context (Grove et al. 2006; Boone et al. 2010; Greene et al. 2011). As the smallest coherent unit of land management, the property parcel scale is appropriate for assessing ecological effects of land use (Stone 2004; Manson et al. 2009). Given the importance of residential land in understanding metropolitan UF structure, this study is restricted to residential properties.

This chapter advances urban environmental geography by addressing two central questions regarding the effects of urbanization on UF structure. First, do patterns in UF structure vary along an urbanization gradient at the fine-scaled resolution of residential parcels? Apparent parcel-scale patterns would support the idea that urbanization intensity influences UF structure, while an absence of parcel-scale patterning would point to the overriding importance of other factors such as broader-scale controls. Second, can a character-based synthetic gradient outperform a distance-based gradient in identifying relationships between urbanization and UF structure at the property parcel scale? To address these questions, we generated both a character-based gradient using factor analysis and a standard distance-based gradient using Euclidean metrics, and then related UF data to both gradients to determine which one better explained UF structure. While this study draws on previous studies that have defined character-based urbanization gradients, this is among the first attempts to take the crucial next step of relating a character-based gradient to ecological structure. To our knowledge, it is also the first study to define a character-based gradient at the fine scale of property parcels. In doing so, this work generates new perspectives on emerging methodologies, contributes to urban ecological theory, and provides practical knowledge of UF structure at a fundamental scale of urban land management.

METHODS

Study Area

The study area is a transect—40 km long by 3 km wide—located in Minnesota's Twin Cities Metropolitan Area (TCMA; Figure 7). This area is ideal for examining the relationships between urbanization and ecological structure because it exemplifies the growth of the Northern Midwest region of the United States, where urban land area is projected to increase by 80 percent between 1997 and 2025 (Alig et al. 2004). The northern end of the transect is positioned in the urban core in the heart of downtown Minneapolis, the region's principal urban center. As the transect passes through the municipalities of Minneapolis, Richfield, Bloomington, Burnsville, Apple Valley, Lakeville, and Eureka Township, it generally transitions from urban to rural land cover types. This transect location was selected to capture a full range of urbanization intensities, include a wide variety of land cover types, minimize the occurrence of water bodies, and maintain consistent geospatial data availability. The Minnesota River runs

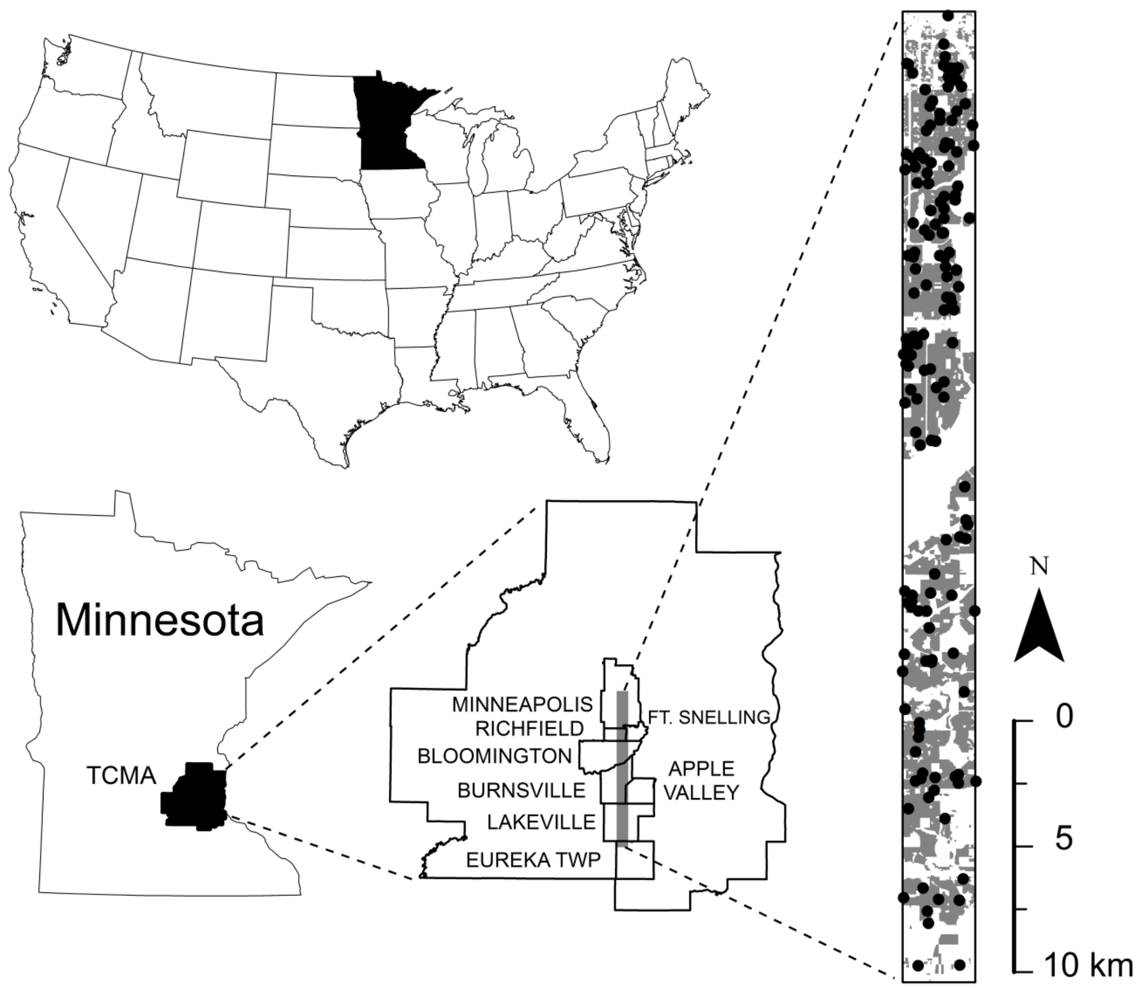

Figure 7. Location of the study transect within Minnesota's Twin Cities Metropolitan Area (TCMA). On the detailed transect map, black circles denote study parcels and gray represents all residential land.

through the transect near its center, and the transect contains a small portion of the Minneapolis-St. Paul International Airport property (see Ft. Snelling in Figure 7).

The study area is located within the 7,705 km^2 seven-county TCMA, which had a 2010 population of 2.85 million (U.S. Census Bureau). The study municipalities had a combined 2010 population of 667,618, and over half of those people resided in Minneapolis at the northern, most urban end of the transect (Table 4). In general, the oldest homes in the study were located in Minneapolis, and house age decreased with distance from the urban core (Table 4). Ongoing urbanization is concentrated toward the peri-urban fringe in the southern reaches of the transect, where new developments are primarily replacing treeless agricultural fields. This study was restricted to residential properties, which made up 51.7 percent of the study region by land area.

Field Data

This study used both field and digital data sets to assess UF attributes and land cover along the study transect. To collect field data, we sampled 150 residential parcels using the i-Tree Eco approach. We randomly selected the candidate study sites from 2008 county property tax databases (multiple-use properties were only eligible for inclusion if their primary use was residential) and visited sites from May to August 2009. When sampling permission was denied at one residence, we replaced it at random with a site in the same municipality to ensure fair spatial representation across the study transect. Study site UF characteristics were sampled following the i-Tree Eco (formerly UFORE) protocol (Nowak et al. 2008; i-Tree Eco 2011). This sampling approach has been widely

Table 4. Study area municipality characteristics

Municipality	Area in transect (km^2)	% of transect area	Pop density ($people/km^2$)[a]	Median house age (years)	Study sites
Minneapolis	27.89	23.24	2,574.12	85	58
Richfield	7.79	6.49	1,953.96	56	19
Ft. Snelling (Airport)	2.61	2.18	7.42	NA	0
Bloomington	16.98	14.15	834.61	54	22
Burnsville	27.88	23.23	863.06	30	24
Apple Valley	3.29	2.74	1,084.80	22	2
Lakeville	28.89	24.08	572.00	16	23
Eureka Township	4.67	3.89	15.38	6	2
TOTAL	120.00	100.00	1,128.26	55	150

[a] Municipality value, not necessarily representative of land within study transect (Source: U.S. Census Bureau).

applied in urban forestry research to quantify urban forest attributes and model associated ecosystem services (Yang et al. 2005; Escobedo et al. 2008; Nowak et al. 2008). While i-Tree Eco was not used here to estimate ecosystem service values, its well accepted sampling protocol was appropriate for meeting the study objectives. Most i-Tree studies randomly sample uniform circular plots, but we modified this and sampled 150 entire property parcels to better compare individual parcel characteristics to UF structure.

At each study site, we sampled for tree attributes, woody shrub attributes, and land cover information (i-Tree Eco 2011). Trees were defined as any woody vegetation >2.54 cm (1 in.) diameter at breast height (1.37 m; DBH). Shrubs were defined as woody vegetation >30.48 cm (1 ft.) tall and <2.54 cm DBH. For each parcel, we recorded the standard i-Tree measurements, which were used to generate the per-parcel UF variables for this study (Table 5). These included measures of tree distribution, tree size, woody shrub cover and abundance, municipal tree management, and opportunity for expanded tree cover. We also estimated site impervious surface cover (*imperv_site*), and later checked field estimates within a geographic information system (GIS) against air photo estimates using 2009 1 m resolution imagery from the National Agricultural Imagery Program (acquired from http://datagateway.nrcs.usda.gov/). For the eighteen sites where field and GIS-based impervious surface estimates disagreed by more than 5 percent, estimates were adjusted by averaging. Once field data were collected for 150 residential parcels, UF attributes were associated with parcels within a GIS.

Table 5. Description of urban forest structural attributes

Variable	Description	Min	Max	Median	Transform
Tree distribution					
tree_cover	Percent of parcel area covered by tree canopies. Estimated in the field at 5 percent intervals per i-Tree protocol.	3	83	28	Log
tree_count	Total trees (>2.54 cm DBH) on the property parcel.	1	137	6	Log
trees_ha	Trees per hectare.	6.18	343.41	53.97	Log
Tree size					
basal_area	Cross-sectional area of all tree stems in the parcel standardized by parcel area (m^2/ha).	0.01	25.05	5.84	Arcsinh
DBH_median	Median DBH (cm) for all trees on the parcel.	4.7	104.3	25.9	Log
DBH_max	Maximum DBH (cm) for all trees on the parcel. For individual trees with multiple stems, DBH is summed for up to the 6 largest stems.	6.2	239	67.6	Log
tree_ht_median	Median tree height (m) for all trees on the parcel.	2	14	6	Sqrt
tree_ht_max	Maximum tree height (m).	2	17	10	Sqrt
CB_ht_median	Median height to crown base (m).	0	8	2	Arcsinh
Shrub abundance					
shrub_cover	Percent of parcel area covered by shrubs. Estimated in the field at 5 percent intervals per i-Tree protocol.	0	43	8	Arcsine
shrub_count	Total shrub species on the property parcel, limited to twelve per i-Tree protocol.	0	12	5	Arcsinh
shrubs_ha	Shrub species per hectare.	0	196.63	40.83	Arcsinh
Management					
street_trees	Percent of parcel trees maintained municipally in the street right-of-way.	0	100	0	Arcsine
Expansion potential					
plantable_space	Percent of parcel unoccupied by tree canopies where trees could grow.	0	78	30.5	Arcsine

All variables were measured at the property parcel scale for 150 residences. DBH = diameter at breast height.

Digital Data

We used digital spatial data to define the urbanization gradient. For each study parcel, we derived nineteen urbanization indicators (Table 6). Most indicators were chosen because they were previously employed to characterize urbanization gradients (Hahs and McDonnell 2006; du Toit and Cilliers 2011). In fact, four measures—*index_census_tract*, *index_image_100ha*, *index_combined*, and *pop_urb_land*—have recently been introduced to improve definition of character-based urbanization gradients (Weeks 2003; Hahs and McDonnell 2006). Depending on the spatial data available, urbanization indicators were derived for individual study sites at the scale of the parcels themselves, at the U.S. Census tract, or within a 100 ha neighborhood. *Pop_density* and *pop_urb_land* were calculated at the U.S. Census tract level because more detailed data were not available. Census tracts are "designed to be homogeneous with respect to population characteristics, economic status, and living conditions" (U.S. Census Bureau), so their use is appropriate for characterizing neighborhoods in this study. The 100 ha neighborhood was defined as a circular buffer around each parcel centroid, and was employed for two reasons: (1) Minneapolis neighborhoods within the study area average approximately 120 ha, so 100 ha is within the same order of magnitude and reasonably approximates neighborhood size; and perhaps more importantly, (2) neighborhood variables were highly correlated at various spatial scales, so choosing a single scale did not bias results substantially. To assess any such effect, we calculated each neighborhood variable using 10, 25, 100, and 250 ha buffers around the centroids. We then scaled each variable by a factor to yield 100 ha equivalents, and assessed linear correlations between

Table 6. Description of urbanization indicator variables

Variable	Description	Min	Max	Median	Transformation
Site[a]					
urban_distance	North-south distance (km) from the urban core to the study site centroid. Urban core is defined as northern edge of study transect.	0.17	39.32	12.24	Log
house_age	Age of parcel development (years).	3	120	55	Log
parcel_size	Size of property parcel (m^2).	176	14,407	1,123	Log
value_total	Total parcel value (1,000s of $). Sum of property and building values.	89.00	1,120.00	232.05	Log
value_m²	Total parcel value per unit area ($\$/m^2$)	24.19	900.47	218.15	Log
imperv_site	Proportion impervious surfaces by parcel. Estimated from field surveys and high resolution air photos	0.07	0.95	0.42	Log
Neighborhood[b]					
dwellings_100ha	Count of residential property parcels within 100 ha.	5	1,305	602.5	Log
pop_density	People per ha. Based on 2010 U.S. Census tracts.	0.14	64.35	17.79	Log
pop_urb_land	People per unit urban land.[c] Calculated as people/proportion urban land. Population based on 2010 U.S. Census tracts. Urban land proportion based on 2007 impervious surfaces classification.[d]	0.88	64.93	19.48	Log
roads_100ha	Sum of road lengths (km) within 100 ha.	1.12	20.36	14.45	Log
imperv_100ha	Mean impervious surface intensity within 100 ha. Calculated as a percent of total land area. Based on 2007 impervious surfaces classification.[d]	1.63	80.00	35.77	Arcsine
Simpson_LC_100ha	Simpson's Diversity Index for land covers within 100 ha. Accounts for both richness and abundance of land covers. Based on 2007 classification of 30 m Landsat imagery.[d]	0	0.72	0.07	Arcsinh

Table 6. *(continued)*

Variable	Description	Min	Max	Median	Transformation
LSI_100ha	Landscape Shape Index within 100 ha. Indicates the degree of irregularity in landscape patch shapes.	1.26	1.44	1.28	Log
LPI_100ha	Largest Patch Index within 100 ha. The area of the largest patch in the surrounding 100 ha, based on 2007 land cover classification.[d]	0.06	0.20	0.19	Log
patches_100ha	Count of land cover patches within 100 ha. Based on 2007 land cover classification.[d]	1	62	9	Log
urban_pct_100ha	Percent urban land within 100 ha. Based on 2007 land cover classification.[d]	89	100	97	Arcsine
index_census_tract[c]	Total U.S. Census tract population multiplied by proportion of workers in non-agricultural work. Standardized metric between 0 and 100. Based on 2010 data (U.S. Census Bureau).	0	32.78	22.18	Arcsinh
index_image_100ha[c]	Index based on proportion impervious surfaces and bare soil within 100 ha. Standardized metric between 0 and 100. Based on a 2007 Landsat 30 m image.[d]	17.91	83.76	39.98	Log
index_combined[c]	Average value of *index_image_100ha* and *index_census_tract*. Standardized metric between 0 and 100.	8.95	51.24	31.41	Log

[a] Site variables measure attributes of the individual property parcel studied.
[b] Neighborhood variables describe characteristics of the area surrounding each study site parcel.
[c] For detailed index descriptions, see Weeks (2003) and Hahs and McDonnell (2006).
[d] Land cover and impervious surfaces classification available from University of Minnesota Remote Sensing and Geospatial Analysis Laboratory (http://land.umn.edu).

100 ha buffers and each of the other buffer distances (Figure 8). Since all correlations were highly significant ($p < 0.001$), we only used 100 ha neighborhoods for simplicity.

Digital spatial data were collected from several sources. Parcel data for the year 2008 were acquired from the Metropolitan Council (http://www.metrocouncil.org/), and included parcel size, value, and house age. A 2007 land cover classification, obtained from the University of Minnesota's Remote Sensing and Geospatial Analysis Laboratory (http://land.umn.edu), was the basis for landscape metrics and neighborhood impervious surface estimates. This classification is based on 30 m resolution Landsat imagery, has an assessed accuracy >93 percent, and contains the following five level-one classes: agriculture, forest, urban, water, and wetland/shrubland/grassland. It includes an impervious surfaces classification for the urban class only, which is based on the inverse relationship between impervious surfaces and the "greenness" component of a tasseled cap transformation (Bauer et al. 2008). Impervious surfaces are mapped as a percentage of each 30 m Landsat pixel. Finally, roads and population data were obtained from the U.S. Census TIGER data set (http://www.census.gov/geo/www/tiger/). Landscape metrics were calculated in Fragstats 3.3 (McGarigal et al. 2002), and all other GIS processes were completed in ArcGIS 10 (ESRI 2010).

Analysis

We conducted two analyses to assess UF structure along the urban-rural gradient. In the first, we compared UF structure to a simple distance-based gradient to emulate earlier urban environmental studies. In the second, we related UF structure to a more

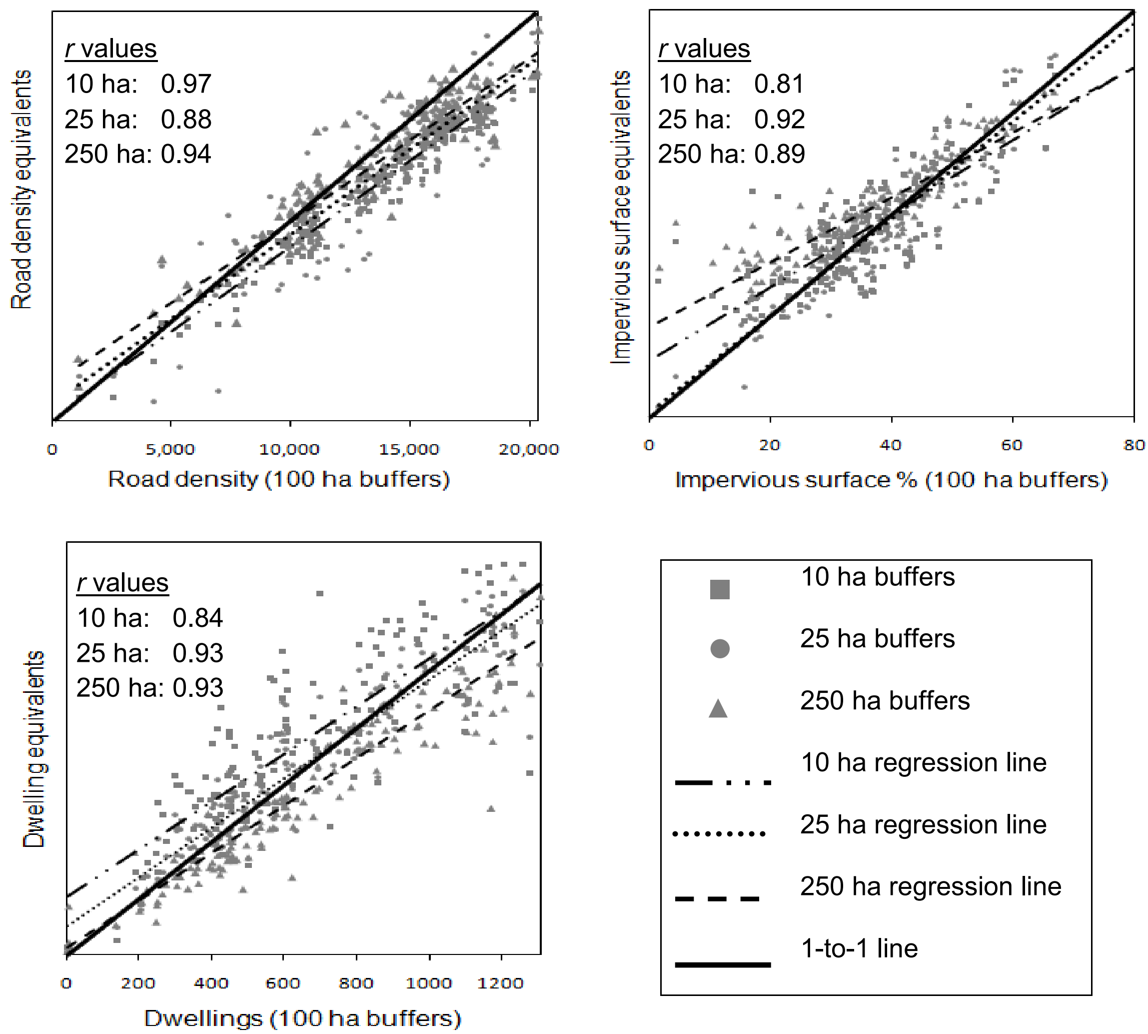

Figure 8. Pearson product-moment correlations between 100 ha study site buffers and 10, 25, and 250 ha buffers for select variables. For each buffer distance, the variables were multiplied by a factor to make them "equivalent" to 100 ha buffers (e.g., 10 ha buffer values were multiplied by 10; 250 ha buffer values were multiplied by 0.4). Results are displayed in scatterplots to show the scaling effects of various buffer distances. Linear curves were fit for each scatterplot, and a 1-to-1 comparison line is shown for reference. All correlations are significant at $p < 0.001$.

sophisticated character-based gradient. We used the same variables for both analyses, and variables were transformed as necessary to meet assumptions of linearity and normality for each method (Tables 5 and 6). The full data set included fourteen UF structural attributes (Table 5) and nineteen urbanization indicators (Table 6). The data set had no missing values over the 150 samples.

For the first analysis, assessing the distance-based gradient's relationship to UF structure, we used regression analysis to separately test the association between the logarithm of *urban_distance* and each UF structural attribute. Because UF structure does not necessarily exhibit linear responses to urban-rural distance (Berland forthcoming), we tested for significant linear and curvilinear relationships using polynomial regression models. We estimated linear, quadratic, and cubic regression models, and used F-tests to determine whether enhanced curve fitting afforded by a higher polynomial was statistically worth the reduction in degrees of freedom (after Walford 2011). In the end, we evaluated which curve, if any, best described urban-rural distance trends for each UF attribute. We corrected significance values for multiple simultaneous hypothesis tests with a false discovery rate adjustment (Benjamini and Hochberg 1995; Pike 2011).

For the second analysis, we related UF structure to a character-based urbanization gradient. This analysis drew on foundational research in defining character-based gradients with data dimension reducing techniques. In 2006, Hahs and McDonnell used principal components analysis (PCA) to isolate the variables that best explained non-redundant variability in a large set of urbanization indicators. PCA reduces data dimensionality within multicollinear data sets by generating linear combinations of input variables to maximize the total data set variability explained. More recently, du Toit and Cilliers (2011) argued that factor analysis (FA), as compared to PCA, provides a more appropriate means of reducing dimensionality in large urbanization data sets. FA only accounts for variance that is shared by multiple variables and excludes variance unique to a single variable (Sheskin 2007); this allows FA to more readily uncover latent variables, or underlying structures, in the data set that influence multiple urbanization indicator variables. The goal of FA, then, is to derive a small set of factors that explain substantial trends in a large set of urbanization indicators.

We conducted FA using principal axis factoring within the SPSS software package (IBM 2010). We started with the full set of nineteen urbanization indicators, but because FA is sensitive to excessive multicollinearity, we iteratively removed individual variables until the determinant of the variable correlation matrix was greater than 0.00001 (after Sheskin 2007). All factors with eigenvalues >1 were retained, as these account for more variance than would be expected of any one variable (Riitters et al. 1995; Sheskin 2007). The variables with loadings >0.71 were used to interpret the evident trend in each factor, as this benchmark represents 50 percent overlapping variance between the variable and the factor (du Toit and Cilliers 2011). Varimax rotation was used to enhance factor interpretability.

FA holds great promise for efficiently deriving urbanization gradients from complex assemblages of variables, but it is only one step toward understanding the relationships between urbanization gradients and ecological characteristics, given that the nature, direction, and magnitude of these relationships remain largely unknown. We used forward stepwise polynomial regression to take the next step of relating the urbanization gradient to UF structure. Specifically, we related transformed UF structural variables individually to the retained urbanization gradient factors. Forward stepwise polynomial regression is an extension of linear regression that facilitates testing for linear and curvilinear UF-urbanization relationships among all retained urbanization factors simultaneously. Urbanization factors providing significant improvements in the regression model (i.e., those yielding F-test p-values <0.05) were entered into the model in order of explanatory power. This approach ensured that we considered any and all key urbanization trends relating strongly to each UF structural attribute. We related UF structure directly to factor scores for each urbanization factor. Others have recommended using the variable with the highest loading to represent each factor (e.g., Riitters et al. 1995; Hahs and McDonnell 2006; du Toit and Cilliers 2011). However, because we were attempting to relate UF structure to underlying trends in the urbanization data set, factor scores offer the benefit of representing latent trends in the urbanization gradient that any single indicator variable cannot capture on its own. As before, a false discovery rate adjustment was applied to p-values (Benjamini and Hochberg 1995; Pike 2011). Outliers, defined as observations with Studentized residuals exceeding ±3.00, were removed from each analysis. We used Moran's I statistic to test for spatial autocorrelation among regression residuals.

RESULTS

We compiled UF and urbanization indicator variables for 150 sampled residential parcels. See Tables 5 and 6 for each variable's minimum, maximum, and median values. These variables were used to relate the distance- and character-based gradients to UF structure.

In the first analysis of the distance-based gradient, 64.3 percent (n = 9/14) of the UF structural variables were explained by the gradient (Table 7). Note that many UF response variables were dependent on one another (e.g., *tree_count* and *trees_ha*; *tree_ht_median* and *CB_ht_median*), so the total number of UF structural variables explained is less important than the number of structural categories explained. Urban-rural distance explained variables in the structural categories of tree size (e.g., *basal_area* and *DBH_max*), shrub abundance, and municipal street tree abundance, but did not explain measures of tree distribution and expansion potential. Curvilinear regression curves provided better fits than linear regression curves for 55.6 percent (n = 5/9) of the significant relationships. For UF structural attributes best explained by linear regression (e.g., *shrub_cover*), structural values decreased with increasing distance from the urban core. For UF structural attributes best explained by curvilinear regression (e.g., *basal_area*), structural values peaked at intermediate distances from the urban core.

The second analysis relied on a character-based urbanization gradient. In deriving the gradient using FA, we excluded seven of the nineteen candidate urbanization indicators due to high multicollinearity (Table 8). Using the remaining twelve urbanization indicators, we identified two factors explaining 65.50 percent of the shared variance in the data set (Table 8). Each factor had at least five variables with factor loadings greater than ±0.50, so we were satisfied that factors were not extracted on the basis of a single correlation (after du Toit and Cilliers 2011). Factor 1 explained 33.90 percent of the shared variance, and was most closely associated with *urban_distance* and *imperv_100ha*. Factor 2 explained 31.60 percent of the shared variance, and was most closely associated with *dwellings_100ha* and *index_census_tract*. Figure 9 shows the spatial structure of each factor. The Pearson product-moment correlation between factors 1 and 2 was -0.044 ($p = 0.591$), indicating that the factors described fundamentally different trends in the urbanization indicator data set.

Stepwise polynomial regression highlighted significant relationships between the urbanization factors and nine UF structural attributes (Table 9). 88.9 percent ($n = 8$) of these were previously related to the distance-based urbanization gradient; the only differences in the character-based gradient were the addition of *tree_cover* and the loss of *DBH_median* from the list of UF structural attributes significantly explained. *Tree_cover* was the only variable explained by factor 2 alone, and urbanization's relationship with *basal_area* was better explained by considering both factors. Most UF structural variables were positively associated with urbanization intensity, but two quadratic relationships—*DBH_max* and *tree_ht_max*—peaked at intermediate urbanization intensities (Table 9). Spatially autocorrelated residuals were not observed for any of the regression analyses.

Table 7. Polynomial regression results relating urban forest structural attributes to the distance-based gradient

Urban forest attribute	Curve[a]	Peak[b]	r^2	p-value[c]
tree_cover	--	--	0.002	0.560
tree_count	--	--	0.000	0.990
trees_ha	--	--	0.008	0.275
basal_area	cubic	mid	0.174	**< 0.001**
DBH_median	cubic	mid	0.124	**< 0.001**
DBH_max	cubic	mid	0.176	**< 0.001**
tree_ht_median	--	--	0.011	0.272
tree_ht_max	cubic	mid	0.036	**0.039**
CB_ht_median	linear	urban	0.068	**0.003**
shrub_cover	linear	urban	0.045	**0.020**
shrub_count	linear	urban	0.026	**0.049**
shrubs_ha	linear	urban	0.050	**0.014**
street_trees	quadratic	mid	0.374	**< 0.001**
plantable_space	--	--	0.024	0.062

[a] Indicates which polynomial regression best fit the data, if any.
[b] Describes the location of the curve peak relative to urban-rural distance (urban, mid, or rural).
[c] p-values were adjusted for multiple testing using the false discovery rate procedure (Pike 2011). Bold values indicate $p < 0.05$.

Table 8. Varimax rotated factor analysis results for urbanization indicators

	Factor	
	1	2
Rotation sums of squared loadings	4.068	3.792
Variance explained (percent)	33.899	31.598
Variable	Factor loadings	
urban_distance	**-0.935**	-0.159
house_age	0.511	0.442
parcel_size	-0.633	-0.483
value_total	-0.267	-0.443
imperv_site	0.537	0.270
dwellings_100ha	0.176	**0.935**
pop_urb_land	0.677	0.538
roads_100ha	0.519	0.703
imperv_100ha	**0.840**	0.348
patches_100ha	-0.581	-0.458
urban_pct_100ha	0.504	0.620
index_census_tract	0.340	**0.834**
value_m^2	excluded	
pop_density	excluded	
Simpson_LC_100ha	excluded	
LSI_100ha	excluded	
LPI_100ha	excluded	
index_image_100ha	excluded	
index_combined	excluded	

Excluded variables were removed due to excessive multicollinearity. Bold values indicate factor loadings >0.71.

Table 9. Stepwise polynomial regression results relating urbanization gradient factors to urban forest structural attributes. Regression models were not created when urbanization factors failed to enter the stepwise model, as indicated by dashes.

Urban forest attribute	Factor(s)[a]	Curve[b]	Peak[c]	r^2	*p*-value[d]
tree_cover	2	quadratic	urban	0.052	**0.043**
tree_count	--	--	--	--	--
trees_ha	--	--	--	--	--
basal_area	1,2	linear	urban	0.070	**0.023**
DBH_median	--	--	--	--	--
DBH_max	1	quadratic	mid	0.041	**0.049**
tree_ht_median	--	--	--	--	--
tree_ht_max	1	quadratic	mid	0.057	**0.038**
CB_ht_median	1	linear	urban	0.051	**0.043**
shrub_cover	1	linear	urban	0.064	**0.025**
shrub_count	1	linear	urban	0.045	**0.047**
shrubs_ha	1	linear	urban	0.069	**0.023**
street_trees	1	linear	urban	0.221	**< 0.001**
plantable_space	--	--	--	--	--

[a] Denotes which urbanization factors, if any, were used to construct the regression model.
[b] Indicates which polynomial curve best fit the data.
[c] Describes the location of the curve peak relative to the urbanization gradient (urban, mid, or rural).
[d] *p*-values were adjusted for multiple testing using the false discovery rate procedure (Pike 2011).

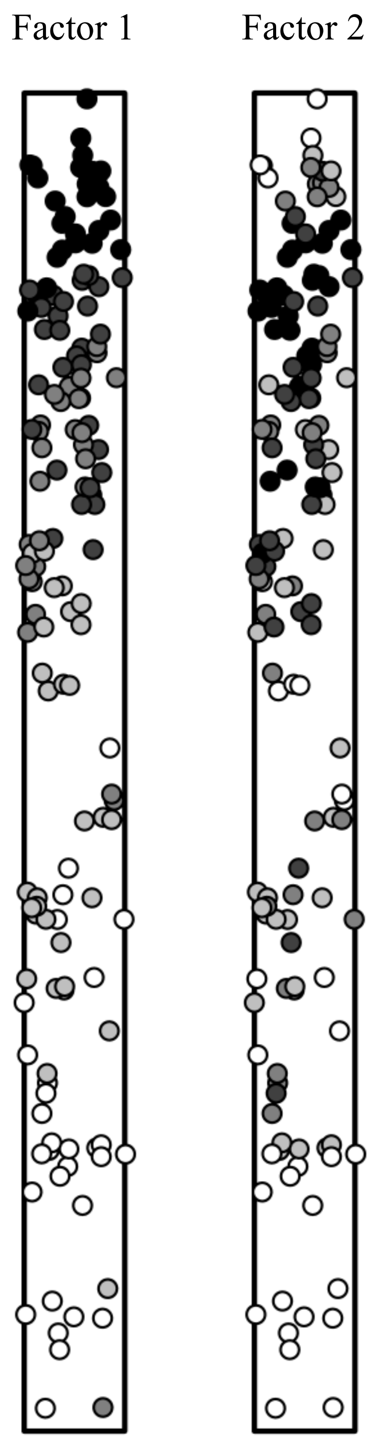

Figure 9. Urbanization factors at the 150 study parcels, categorized by quintiles from most urban (black) to least urban (white).

DISCUSSION

Urban forest structure relates to urbanization gradients

We analyzed the relationship between UF structure and two urbanization gradient characterizations. The distance-based urbanization gradient showed that parcel location relative to the urban core can explain trends in tree size, shrub abundance, and tree management. However, this gradient did not relate well to any measure of tree distribution, most notably *tree_cover*. While tree canopy cover may provide a limited view of the UF (Kenney et al. 2011), it is nonetheless a primary metric for assessing UF quantity, spatial distribution, and associated management goals (Nowak et al. 1996; Walton et al. 2008; McPherson et al. 2011). Given the significance of canopy cover in UF assessment and management, the inability to describe canopy cover with a simple distance-based gradient justified the use of more sophisticated character-based gradients.

Using FA to derive a character-based gradient was valuable in that it synthesized two primary trends in the urbanization indicator data set. Factor 1 showed a very strong urban-rural distance pattern (Figure 9), and thus evidenced many of the same relationships to UF structure seen in the distance-based gradient analysis (Tables 7 and 9). While factor 1 was also influenced by urbanization indicators such as *imperv_100ha* (Table 8), it is apparent that urban-rural distance best described the primary urbanization trend in the study area. Factor 2's strong association with *dwellings_100ha* and *index_census_tract* indicated a more nuanced urbanization trend based on residential neighborhood type. Factor 2 contrasted between highly residential and non-residential neighborhoods, even though non-residential neighborhoods were found at both the urban core and the peri-urban fringe (Figure 9). This distinction is noteworthy, as relevant trends in an urbanization data set do not necessarily need to reflect urbanization intensity in the traditional sense. The residential neighborhood density trend was pertinent here because landscape context may affect UF structure via physical space for planting trees, housing age and lagged tree growth, landowner demographics, and neighborhood group identity (Grove et al. 2006; Boone et al. 2010; McPherson et al. 2011; Berland forthcoming).

In addition to drawing out broad trends, the character-based approach and the addition of residential density considerations enabled the character-based gradient to capture trends in *tree_cover* that were not detected using the simple distance-based gradient. By extending explanatory power to the tree distribution category, the FA-derived character-based gradient offered a key improvement over the distance-based gradient. This enhancement in explanatory power suggests that using FA or related methods to derive character-based gradients is worthwhile when studying the impacts of urbanization on ecological structure. That said, aside from describing *tree_cover*, insights gleaned from the FA approach were similar to those taken from the distance-based analysis given the strong association of *urban_distance* with factor 1. This similarity in gradients suggests that urban-rural distance is adequate to describe basic urbanization-UF structural relationships, but considering the increasing availability of geospatial data and growing interest in urban ecological structure, FA and related approaches should continue to be refined and employed to search for patterns within and among metropolitan areas.

Both the distance-based and character-based urbanization gradients emphasized the importance of curvilinear relationships between urbanization and UF structure (Tables 7 and 9). Many UF attributes, particularly those associated with tree size, peaked at intermediate urbanization intensities. The primary cause is likely that older inner-ring suburbs had the tree maturation time and physical space to attain the largest tree sizes (Berland forthcoming), but more complicated factors may also be involved. On the oldest properties near the urban core, which were developed over one hundred years ago, the first generation of planted trees may have died and been replaced by smaller trees, while the original tree plantings in Richfield and Bloomington persisted at fully mature sizes because they were planted more recently. Since urban development in this region largely replaced agricultural fields, there were few existing trees prior to development, and trees planted in newer suburbs have yet to reach mature sizes. Such temporal lag effects are of growing interest in urban ecology (Ramalho and Hobbs 2012).

Urban planning and municipal UF management may also explain peak tree sizes in inner-ring suburbs, as older neighborhoods were planted to achieve a tree canopy over the narrow streets, while newer suburbs contain more ornamental and coniferous trees not conducive to creating substantial tree canopies. Several urban Minneapolis study parcels were recently converted from large single-family homes to apartments or townhomes, and this redevelopment favored small ornamental trees, potentially at the expense of large, mature trees. The near-urban municipalities of Minneapolis, Richfield, and Bloomington have also historically had the most active city tree planting programs (see *street_trees* in Table 9), whereas newer suburbs have less predictable tree cover due to increased landowner choice. Finally, biological factors such as Dutch elm disease (*Ophiostoma* spp.) may have substantially reduced the abundant mature American elm (*Ulmus americana*) trees in Minneapolis, while sparing common mature species in Richfield and Bloomington, most notably silver maple (*Acer saccharinum*) and Norway maple (*Acer platanoides*). Tracking tree sizes and UF management strategies through time along the urbanization gradient could help explain varying UF structure among municipalities by showing where, when, and why these changes occur.

Considerations for relating urbanization gradient factors to ecological structure

Character-based urbanization gradients show promise for demonstrating the effects of urbanization on ecological structure. This research supports Hahs and McDonnell (2006) in that data dimensionality reducing techniques provide an effective approach to objectively selecting a small set of measures to define urbanization gradients, yet we suggest careful consideration of four key qualifications. First, when attempting to represent underlying urbanization factors using a combination of urbanization indicator variables, FA is more appropriate than PCA because it emphasizes shared variance to identify those latent factors that cannot be captured by one indicator variable alone (du Toit and Cilliers 2011). PCA, on the other hand, is susceptible to the effects of specific variance in one indicator variable that is completely unrelated to the other variables (Sheskin 2007).

Second, although FA provides an appropriate technique for identifying latent urbanization factors, it is important to avoid excessive multicollinearity because FA can be sensitive to the shared variance among many highly correlated input variables. A useful heuristic is to iteratively remove input variables until the determinant of the variable correlation matrix is greater than 0.00001 (Sheskin 2007). Failure to properly implement data reduction techniques may lead to faulty conclusions when relating urbanization factors to ecological structure. When FA was applied to our data prior to reducing multicollinearity, four landscape metrics including *Simpson_LC_100ha*, *LSI_100ha*, *LPI_100ha*, and *patches_100ha* determined the first factor because they were highly multicollinear. Following the statistically appropriate exclusion of some landscape metrics from the FA, more intuitive urbanization indicators (i.e., *urban_distance* and *imperv_100ha*) arose to characterize the primary urbanization trend.

Third, ecological structure should be related directly to the factor scores associated with each urbanization factor. Past work has suggested using the variable with the highest loading on each factor to represent that factor (Riitters et al. 1995; Hahs and McDonnell 2006; du Toit and Cilliers 2011). However, the main point of using FA is to identify latent factors that no single urbanization indicator can fully capture, so the best approximation of that factor (i.e., factor scores) should be used to represent it. One potential difficulty in using the factors themselves to describe urbanization trends is a lack of interpretability, but in our analysis factor rotation enhanced interpretability so that we could describe the primary trends of urban-rural distance and residential neighborhood density.

Finally, FA can identify major trends in an urbanization data set, but it cannot determine whether those trends are ecologically relevant (Riitters et al. 1995; du Toit and

Cilliers 2011). At the same time, if additional variables are incorporated *ad hoc* following FA, then the original goal of objectively indentifying major latent urbanization trends to explain ecological structure is compromised. In our analysis, *house_age* was not closely associated with either urbanization factor, so it exerted only a weak influence on the factors used in the regression models predicting UF structure. However, *house_age* can influence UF structure (Grove et al. 2006; Berland forthcoming), so its inclusion could potentially help explain UF structural patterns. The tradeoffs between objectivity and subjectively identifying ecologically relevant urbanization indicators should be explored further in the future.

Limitations, uncertainty, and future opportunities

Although this research supports the development of character-based urbanization gradients to assess UF structure, some limitations warrant consideration. For example, by focusing solely on residential land at the parcel scale, we did not assess patterns on non-residential lands or at broader spatial scales, although as argued above, this focus was driven by the distinct need for fine-scale analysis of private residential land. There may be error attributable to spatial data sets, field data collection, or data input, but no systematic biases were discovered during analysis. The decision to base neighborhood urbanization variables on 100 ha buffers was supported by robust variable scaling across multiple buffer distances (Figure 8), but it is unknown how this decision affected individual study parcels. Some variables were estimated at five percent intervals per i-Tree sampling protocol (i-Tree Eco 2011), and there is no straightforward approach for quantifying the effects of this estimation strategy on study findings. The fairly coarse land cover data set (30 m spatial resolution, five land cover classes) may have influenced the landscape metrics used as urbanization indicators (Wickham and Riitters 1995; Wu et al. 2002), but these data were used to calculate land use and urbanization indices at the scale of 100 ha, which is three orders of magnitude greater than the pixel size. Spatial errors in the underlying data would lead to very small variations in the derived neighborhood measures. By the same token, the five attribute categories were explicitly chosen to capture urban land use, and struck a balance between the number of classes and the goal of creating data with high overall accuracy (Yuan 2008; Yuan et al. 2008).

Some of the difficulty in predicting parcel-scale UF structure may stem from our reliance on neighborhood-scale urbanization indicators that describe patterns at scales much broader than the average parcel size. Although the available parcel data and field surveys provided several parcel-specific characteristics, more variables may be needed to improve analytical power. Since the parcel is the most basic unit of land management, improving parcel-scale data collection methodologies may improve our ability to predict fine-scale UF structure. Improved parcel-scale data could, in turn, be used to model the emergent effects of individual land management decisions on neighborhood- or regional-scale UF structure.

Beyond limitations imposed by study design and input data, some urbanization-UF structural relationships may have simply been overlooked, because UF structure is subject to complex aspects of coupled human-environmental systems (Alberti et al. 2003; Liu et al. 2007). Tree growth is temporally lagged such that present day UF structure may not reflect urbanization intensity (Dow 2000; Grove et al. 2006; Dean 2011). Similarly, urban growth in this region largely replaced agricultural lands, and legacies of this primarily treeless past are evidenced in present UF structure (Berland forthcoming). Finally, emergent patterns in UF structure only evident at broad scales may arise from fine-scale UF management across many individual parcels. Continued analysis of urbanization's effects on ecological structure through time and across space will improve understanding of these complexities.

CONCLUSIONS

We used gradient analysis to study the relationships between urbanization and UF structure. A simple distance-based gradient captured trends in 64.3 percent (n = 9/14) of the UF attributes assessed, spanning measures of tree size, shrub abundance, and municipal tree management. We then used FA to derive a gradient based on a suite of urbanization indicators, and extracted two key factors strongly related to urban-rural distance and residential neighborhood density, respectively. Like the distance-based gradient, the character-based gradient explained 64.3 percent (n = 9/14) of the UF attributes, and it improved upon the distance-based gradient by adding tree distribution to the types of UF structural attributes significantly explained. In addition, the character-based gradient provided a useful summative function in identifying the two key factors of urban-rural distance and residential neighborhood density. Many UF structural attributes peaked at intermediate degrees of urbanization, highlighting the need to consider curvilinear relationships in urban ecological settings. As this study is among the first to relate a character-based urbanization gradient to ecological structure, our findings are relevant to urban environmental geography in general, and urban forestry in particular. Continued advances in data availability and methodologies, along with better understanding of complex aspects of human-natural systems, will improve conceptualizations of how urbanization impacts ecological structure.

Chapter 4. A parcel-based land stratification approach for estimating urban forest structure, function, and value

Overview. Greater understanding of urbanization's impacts on the urban forest is needed to promote urban environmental sustainability. However, existing approaches for stratifying study areas for urban forest assessments do not adequately account for land use. We present a property parcel-based land use stratification approach that efficiently divides a study area into residential, non-residential developed, and undeveloped areas. We propose cluster analysis to further divide these broad land use classes into more detailed classes. This strategy is tested on UF data gathered at 300 sites along an urban-rural gradient in the Twin Cities Metropolitan Area of Minnesota. We compare UF structure, function, and value across both broad and detailed land use classes, and conclude that detailed land use stratification is most needed for undeveloped sites. Residential and non-residential developed sites exhibit less intra-class variability, and UF attributes at residential sites outpace those at non-residential developed sites. The findings improve our understanding of the relationships between land use and the urban forest, and provide a useful methodological approach for similar studies.

INTRODUCTION

Nature freely provides goods and services that are estimated to be worth more than global gross national product (Costanza et al. 1997). However, because many of these ecosystem services (ES), or benefits we derive from the natural environment, are not easily assigned monetary values, it is difficult to account for them explicitly in land management decisions, especially given our limited understanding of ecosystem service stocks and dynamics (Gatto and De Leo 2000; Daily and Matson 2008; Daily et al. 2009). So while fairly implementing ES perspectives in land management remains a key goal in sustainability science, inadequate scientific understanding of ES stocks and dynamics hampers our ability to meet this goal (Daily and Matson 2008).

Urban areas are prime places to advance ES science, partly because rapid urbanization has important effects on natural systems. The world's population is over 50 percent urban for the first time in history, and 82 percent of Americans now live in urban areas (UN Population Fund 2011). This rapid growth will continue, as developed land area in the U.S. is projected to increase by 79 percent from 1997-2025 (Alig et al. 2004). As the field of urban ecology has grown to address the sustainability challenges presented by urbanization (Grimm et al. 2008), many researchers have paid particular attention to ES associated with the urban forest (UF), defined here as all trees and woody shrubs within an urban area. The UF, a significant component of the urban ecological landscape (Dwyer et al. 1992), provides ES such as carbon storage and sequestration (McPherson 1998a; Nowak and Crane 2002) and air pollution removal (Scott et al. 1998; Nowak et al. 2006). Given the importance of these and other UF ES, various approaches and analytical tools have been developed to assess the UF. For example, the i-Tree suite of tools (http://itreetools.org/), perhaps the most widely applied toolkit for estimating UF characteristics, has greatly improved our ability to estimate UF structure, function, and value in diverse settings (Nowak et al. 2008a).

While the widespread application of i-Tree and other analytical techniques has improved understanding of UF ES, notable opportunities remain to advance the science. One major opportunity is to improve understanding of metropolitan UF ES beyond the boundaries of central cities. Previous i-Tree studies have largely focused on single, central cities (e.g., Yang et al. 2005; Nowak et al. 2006; Soares et al. 2011), but considering the persistent growth of suburban and peri-urban areas, this narrow focus limits our awareness of regional patterns and processes. For instance, in Minnesota's Twin Cities Metropolitan Area (TCMA), the Metropolitan Council coordinates planning and services across a 7,705 km^2 seven-county region, of which the central Twin Cities of Minneapolis and St. Paul occupy less than 4 percent of the land area. Furthermore, Minneapolis and St. Paul account for less than a quarter of the TCMA's population (U.S. Census Bureau 2010). These figures have two important implications for urban ecological studies in the region. First, the Twin Cities have a disproportionately high population density, so land use patterns (Yuan et al. 2005) and attendant urban ecological factors are potentially different in the Twin Cities compared to the greater TCMA. Second, focusing research on the Twin Cities alone overlooks >96 percent of the land area and >76 percent of the population in the TCMA.

The urban-rural gradient provides a leading framework for organizing urban ecological inquiry beyond central city boundaries (McDonnell and Pickett 1990; McDonnell and Hahs 2008). Assessing ecological structure and function along urbanization gradients from the intensely developed urban core to the sparsely developed peri-urban fringe can demonstrate urbanization's impacts on natural systems across a more complete range of metropolitan settings than is typically found in central cities alone. Such gradients need not be based solely on distance from the urban core, but may also incorporate indicators of urbanization such as impervious surface concentrations to describe degree of urbanization at a given location (Hahs and McDonnell 2006).

Many sampling approaches are available for distributing UF study sites within an urban area (Nowak et al. 2008a), and the ideal approach depends on project-specific goals. Because complete inventories are not feasible in most metropolitan settings, the landscape is often sampled using a stratified random design based on development history (Yang et al. 2005) or municipal service districts (Nowak et al. 2006). Such pre-stratification is useful for guaranteeing an adequate sample from each portion of the study area. However, while pre-stratifying on municipal service districts, for example, can highlight broad spatial patterns in the UF, it is of limited use for understanding direct relationships between land use and UF structure, function, and value. An alternative approach is needed to improve knowledge of these relationships, as this information will ultimately permit reliable projection of ES responses to future land use changes.

We believe that parcel-based sample stratification, while relatively underexplored, may provide the best pre-stratification approach for directly relating fine-scale land use to

UF character. The property parcel is the fundamental unit of urban land management (Manson et al. 2009), so observing UF characteristics on entire parcels allows for one-to-one comparison of UF characteristics and parcel attributes such as building age, value, and impervious surface intensity. So while the most popular existing methods for spatial pre-stratification by municipal districts may be quite useful for one city at one time, parcel-based stratification may offer the best means of explicitly associating UF characteristics with specific land uses, and this will help generate links between specific land use styles and UF ES.

Parcel-based stratification also has advantages over approaches using land cover classifications based on satellite imagery. Satellite-based land cover classifications often contain substantial error, particularly in urban areas (Homer et al. 2004; Walton 2008), and satellite pixels do not align perfectly with land use boundaries. Parcel datasets, on the other hand, can directly provide land use information with higher spatial and attribute accuracies than most satellite-based land cover classifications. Furthermore, fundamental differences in land use (e.g., the difference between residential and commercial land) may influence UF structure, but these differences can be difficult to detect using traditional satellite-based land cover classifications. In these cases, a parcel dataset has a distinct advantage because it contains land use attributes that effectively differentiate spectrally similar land covers.

This paper incorporates these considerations to assess the relationship between land use and UF structure, function, and value. Specifically, we employ an urbanization gradient approach to estimate UF character beyond the limits of a central city, and we compare central city and suburban UFs. We examine relationships between the UF and land use by comparing UF attributes across three broad land use classes derived from a parcel data set. Since parcel-based land use classes may be too broad to adequately represent within-class variability, we also compare UF attributes among more detailed land use classes derived using cluster analysis. The results are intended to improve knowledge of UF ES across urban-rural gradients, and to guide the design of future studies.

METHODS

Study area

The study was conducted along a transect (40 km long by 3 km wide) located in Minnesota's Twin Cities Metropolitan Area (TCMA; Figure 10). The northern end of the transect was positioned in the urban core at the heart of downtown Minneapolis, the region's principal urban center. As the transect passes through Minneapolis, Richfield, Bloomington, Burnsville, Apple Valley, Lakeville, and Eureka Township, it generally transitions from urban to rural land cover types. The Minnesota River Valley National Wildlife Refuge crosses through the transect near its center, and the transect contains a small portion of the Minneapolis-St. Paul International Airport property (see Ft. Snelling in Figure 10). This transect location was selected to maximize land cover types, minimize the occurrence of water bodies, and maintain consistent geospatial data availability in the study area. The study area is located within the 7,705 km^2 seven-county TCMA, which had a 2010 population of 2.85 million people (U.S. Census Bureau 2010). Together, the

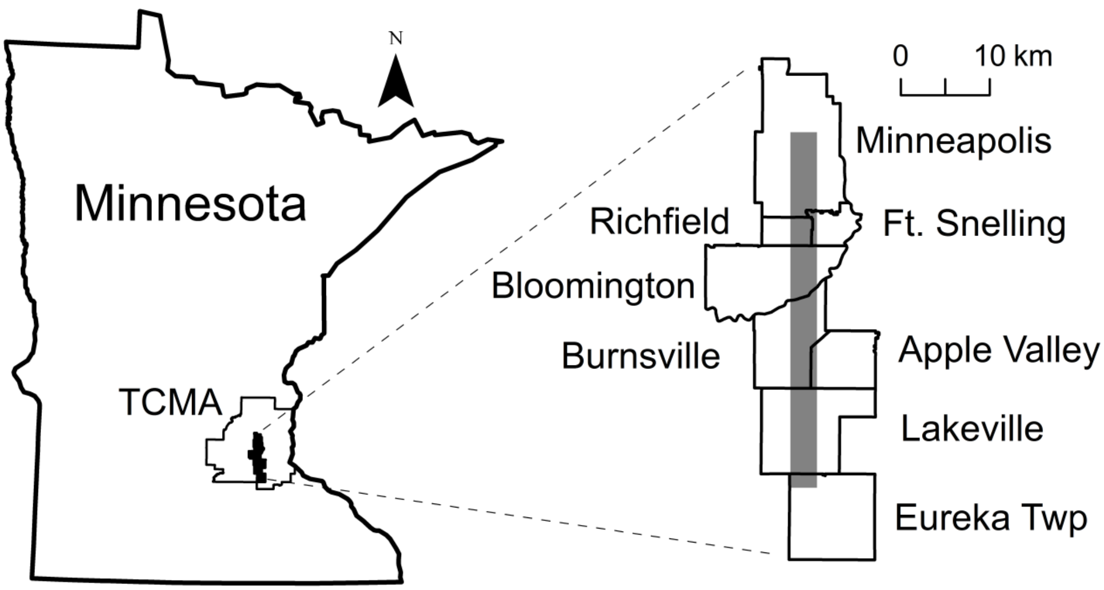

Figure 10. Study area map. The study transect (gray) is located within eight municipalities in the Twin Cities Metropolitan Area, MN.

central cities of Minneapolis and St. Paul comprised 23.4 percent of the TCMA's 2010 population. The study municipalities had a combined 2010 population of 667,618 (U.S. Census Bureau), but note that the study transect does not encompass the full extent of any municipality. Ongoing urbanization is concentrated toward the peri-urban fringe in the southern portions of the transect.

Land stratification and study site selection

A primary goal of this study was to analyze UF characteristics with respect to land use. We were particularly interested in determining whether a broad, parcel-based land use classification could adequately capture UF variability among land uses, or if more detailed land use information was required to represent variability within each broad land use class. This was accomplished via analysis of both broad (*level-1*) and more specific (*level-2*) land use classes.

Land use stratification was based on a multi-step procedure within a geographic information system (GIS). 2008 county property tax databases were used to stratify the study area into the following four level-1classes: residential properties (*res)*; non-residential developed parcels (*nonres*) such as businesses, churches, and schools; undeveloped areas (*undev)* including agricultural areas, parks, golf courses, cemeteries, playgrounds and athletic fields (divided from developed school parcels where applicable), airfields, forests, wetlands, grasslands, and major highway and utility right-of-ways (ROWs); and open water. Parcels listing more than one land use were classified according to the primary use. Parks with modest visitor centers or restrooms were considered entirely undeveloped, in spite of these proportionally small built structures. To make all study region land area eligible for study site selection, we allocated the entire mid-street to mid-alley area to the nearest property parcel or undeveloped area. Level-1 stratification yielded a study area that was 51.7 percent *res*, 13.3 percent *nonres*, 29.8 percent *undev*, and 5.2 percent open water.

Following level-1 stratification, we selected 300 study sites. Open water was not eligible for study site selection due to its low capacity for UF ES. 150 *res* sites were selected from a randomly ordered list of study area parcels. This original sorting was used to establish *res* study site quotas for each municipality. We sought sampling permission at each parcel on the list, and any location where sampling permission could not be obtained was crossed off the list and replaced by the next parcel in that municipality. We continued sampling until we reached each municipality's quota. Then fifty *nonres* parcels were selected in the same way. Finally, 100 *undev* sites were selected by randomly distributing points in the undeveloped portion of the study area. Points were buffered to 0.04 ha (0.1 acre) circular area, and visited in order based on a random identifier. We obtained permission to sample *undev* sites on private land. This distribution slightly underrepresented *res* sites based on land area, but the increased numbers of *nonres* and *undev* sites improved sample depth and spatial coverage of these classes. Qualitative observations of participant demographics alleviated concerns about potential study participant bias toward groups who were home during the day, such as the retired.

Level-2 post-stratification was based on detailed parcel characteristics of study sites. *Res* sites were divided into three level-2 classes via *k*-means clustering. Three classes were selected to mirror qualitative field observations of the following common *res* types: small *urban* parcels near the urban core with high impervious surface concentrations; medium-sized *middle suburban* parcels with older, modest homes near the center of the transect; and *far suburban* parcels with bigger, newer homes in the neighborhoods furthest from the urban core. With these considerations in mind, clustering was based on the following five parcel variables: house age, distance from the urban core, parcel size, total value, and impervious surfaces (percent of parcel). Clustering data were standardized so variables with large values would not dominate the procedure. Two multi-family residential parcels were identified as outliers and removed from the clustering data set, leaving 148 *res* sites; note that these two sites were included in the modeling of transect-wide UF structure, function, and value.

Nonres sites were clustered via *k*-means clustering to extract *urban* vs. *suburban* property types, reflecting a qualitatively observed dichotomy between compact, densely developed parcels near the urban core and newer, more sparsely developed parcels toward the rural end of the transect. Clustering relied on the following four site-specific variables: building age, distance from the urban core, parcel size, and impervious surfaces (percent of parcel). Parcel value was not used here due to missing values for several sites.

Undev sites were clustered according to land cover into four level-2 classes based on observed site characteristics rather than a statistical technique. Landscaped sites were typified by manicured turf grass, and included parks, athletic fields, cemeteries, golf courses, and school playgrounds. Natural areas included park areas with natural ground covers (i.e., not landscaped or covered by turf grass), wetlands, grasslands, and vacant/abandoned lands. ROWs consisted of major utility and transportation corridors. Transportation ROWs were limited to corridors buffering major highways, as defined by the Minnesota Department of Transportation. Agricultural sites included agricultural fields and pastures, as well as hedgerows and buffer strips between fields. Three *undev* sites spanned multiple clusters, and were assigned to the dominant land use type.

Field observations

We visited sites from May-November 2009, and sampled using the i-Tree Eco approach (Nowak et al. 2008a; formerly UFORE). For *res* and *nonres* sites, we sampled the entire property parcel from mid-street to mid-alley. For *undev* sites, we sampled 0.04 ha (0.1 acre) circular plots. Following i-Tree Eco protocol, we documented tree, woody shrub, and land cover information (i-Tree Eco 2011). Trees were defined as any woody vegetation >2.54 cm (1 in.) diameter at breast height (1.37 m; DBH). Shrubs were defined as woody vegetation >30.48 cm (1 ft.) tall and <2.54 cm DBH. For each tree, we recorded the species, DBH, total height, height to leaf crown base, crown width along north-south and east-west axes, percent canopy missing, dieback, percent of canopy over impervious surfaces, percent of canopy over shrubs, crown light exposure, distance to buildings, and whether or not the tree was a municipal street tree. Shrub attributes, for a maximum of twelve species per site, included species, height, percent of total shrub area occupied by each species and height combination, and percent shrub mass missing. Trees and shrubs were identified to the species level, aside from the notable exceptions of some *Malus* (apple), *Taxus* (yew), *Prunus* (cherry), *Populus* (poplar), and *Rhododendron* (rhododendron) specimens, which were identified to the genus level when species/variety could not be distinguished. In addition to UF data, we estimated site impervious surface cover in the field, and later checked field estimates against 2009 high-resolution air photos in a GIS. GIS impervious estimates were aided by site sketches made in the field. For the twenty-four sites where field and GIS-based impervious surface estimates disagreed by more than 5 percent, estimates were adjusted by averaging.

Analysis

Field data were entered into the i-Tree Eco software program (v. 4.1.3) and processed by the USDA Forest Service Northeast Research Station. i-Tree Eco estimates several aspects of UF structure, function, and value based on sample data across land use strata (Nowak et al. 2008a). In this study, we focused on i-Tree Eco structural estimates of tree density, leaf area density, and leaf biomass, and supplemented these by calculating basal area. UF function estimates included carbon storage, annual carbon sequestration, and monthly air pollution removal values for carbon monoxide, nitrogen dioxide, ozone, sulfur dioxide, and particulate matter ≤10 microns. Finally, i-Tree Eco estimated structural value as the cost of replacing existing trees with similar trees (Nowak et al. 2008a). To provide a transect-wide estimation of UF structure, function, and value, i-Tree Eco was applied to the 300 site sample based on the level-1 land use stratification.

The same UF attributes were also estimated by individual study site in i-Tree Eco. This was achieved by submitting each site as its own land use stratum, whereas typical i-Tree projects use many sites per stratum to estimate UF characteristics across broad areas (e.g., municipal service districts or entire cities). We specified the study parcel area as the total land use stratum area, so per area estimates reflected parcel sizes. Raw estimated air pollution removal quantities for five pollutants are not easily compared across sites, so we summed each site's annual pollution removal benefits in dollar values to facilitate straightforward comparison. Monetary values were based on 2007 U.S. median externality values for each pollutant (i-Tree Eco 2011). All variables were considered on a per area basis due to varied parcel sizes.

Following i-Tree Eco processing, UF characteristics were compared across land use strata using the Kruskal-Wallis test (K-W), a nonparametric analog to one-way analysis of variance testing. K-W indicates whether at least one of the clusters tends to yield larger observations than one or more of the other clusters (Conover 1999). Since K-W does not indicate which clusters are significantly different, we applied Dunn's multiple comparisons post test (Dunn 1964) when K-W was significant. Dunn's test determines which pairs of clusters differ from one another, and it accounts for the total number of comparisons made when ascribing statistical significance. This correction for the total number of comparisons is important, because the chance of making a type I error, or false positive, increases with the number of comparisons made.

We first compared level-1 classes against one another to assess whether UF structure, function, and value varied across these broad land use strata. We then compared level-2 clusters to observe the frequency of within- versus across-level-1 class differences in UF characteristics. A low proportion of within-class differences would suggest that level-2 classification may not be necessary to represent the variability among sites in a given level-1 class. Alternatively, higher proportions of within-class differences would indicate that level-2 site stratification is prudent for that level-1 class. This analysis was exploratory in nature, so we did not set *a priori* criteria for deciding when level-2 stratification is necessary. Rather, results will help establish heuristics to guide future land use stratifications.

Finally, to assess whether the central city's UF is comparable to the suburban UF, we used the Mann-Whitney *U*-test to compare level-1 estimates for Minneapolis sites to estimates from all other municipalities. This test is similar to K-W, but provides a rank-based comparison of just two groups—in this case Minneapolis versus all other municipalities. Significant differences between the Minneapolis and suburban UFs would indicate that central city UF estimates are not applicable to suburban municipalities in this study area, and would suggest the need for greater emphasis on understanding UF characteristics across the complete range of metropolitan settings.

RESULTS

Transect-wide urban forest characteristics

We analyzed data from 300 sites distributed across eleven i-Tree Eco land use categories (Table 10). Appendix A provides a detailed urban forest data summary. According to i-Tree Eco estimates for level-1 land use stratification, the entire study transect contained approximately 998,000 trees (83.2 trees/ha). Estimated tree canopy cover was 25.0 percent. The top ten species, according to the sum of species relative abundance and percent of total leaf area, were green ash (*Fraxinus pennsylvanica*), box elder (*Acer negundo*), silver maple (*Acer saccharinum*), common buckthorn (*Rhamnus cathartica*), eastern cottonwood (*Populus deltoides*), white spruce (*Picea glauca*), northern hackberry (*Celtis occidentalis*), Norway maple (*Acer platanoides*), American elm (*Ulmus americana*), and bur oak *(Quercus macrocarpa*).

Transect-wide UF function varied by ES. The UF provided an estimated air pollution removal benefit of $1.83 million/yr ($152/yr/ha). Similarly, it provided carbon storage and sequestration benefits of $3.05 million ($254/ha) and $127,000/yr ($11/yr/ha), respectively. On the other hand, the UF imposed a net building energy cost of $72,600/yr ($6/yr/ha), and it generated additional carbon emissions valued at $61/yr (<$0.01/yr/ha). The structural value of the UF was estimated at $670 million ($55,859/ha).

Land use strata comparisons

For all eight measures compared, K-W indicated highly significant differences among level-1 land uses (Figure 11). Dunn's test demonstrated that, for each measure, *res* and *undev* sites significantly outpaced *nonres* sites, but did not differ from one another. Note that although *res* and *undev* strata were not statistically different, the median value for *undev* measures was 0 for each measure, while *res* median values were always >0 (Figure 11).

Table 10. Study site distribution according to i-Tree Eco field observation categories (columns) and level-2 land use stratification (rows).

	Residential[a]	Commercial / Industrial	Park	Cemetery	Golf course	Agriculture	Vacant	Institutional	Utility	Water / Wetland	Transportation	Total
Res[a]												
Urban	57	-	-	-	-	-	-	-	-	-	-	57
Middle suburban	64	-	-	-	-	-	-	-	-	-	-	64
Far suburban	27	-	-	-	-	-	-	-	-	-	-	27
Nonres												
Urban	-	37	-	-	-	-	-	-	-	-	-	37
Suburban	-	13	-	-	-	-	-	-	-	-	-	13
Undev												
Landscaped	-	-	30	2	4	-	-	4	-	2	-	42
Natural	-	-	16	-	-	-	2	-	-	4	-	22
ROW	-	-	-	-	-	-	-	-	1	-	14	15
Agriculture	-	-	-	-	-	21	-	-	-	-	-	21
Total	148	50	46	2	4	21	2	4	1	6	14	298

[a] Two multi-family residences were identified as outliers. They were not included in the level-2 stratification.

Clustering level-1 strata to more detailed level-2 land use clusters followed expected patterns (Table 11; Figure 12). For example, most far suburban *res* sites were located in municipalities far from the urban core. Exceptions occurred in locally less common neighborhood types, such as compact townhome parcels in suburban Lakeville. *Nonres* clusters were distinctly separated by urban-rural distance into urban and suburban sites (Figure 12). Landscaped *undev* sites were distributed throughout the study area, natural and agricultural sites were concentrated toward the rural end of the study area, and transportation/utility ROWs were slightly more common in the more rural municipalities (Figure 12).

As with level-1 comparisons, level-2 K-W tests indicated highly significant differences ($P < 0.001$) for each measure. However, at this level under half (101 of 208, or 48.6 percent) of level-2 comparisons across level-1 strata were significantly different (Table 12). No level-2 comparisons showed differences among *res* clusters or among *nonres* clusters. 42 percent of *undev* cluster comparisons indicated differences (Table 12). All measures except leaf biomass showed some differences among level-2 *undev* clusters, and the most notable differences were between level-2 clusters with high UF values (landscaped, natural) and low valued ROW and agricultural clusters (Figure 13).

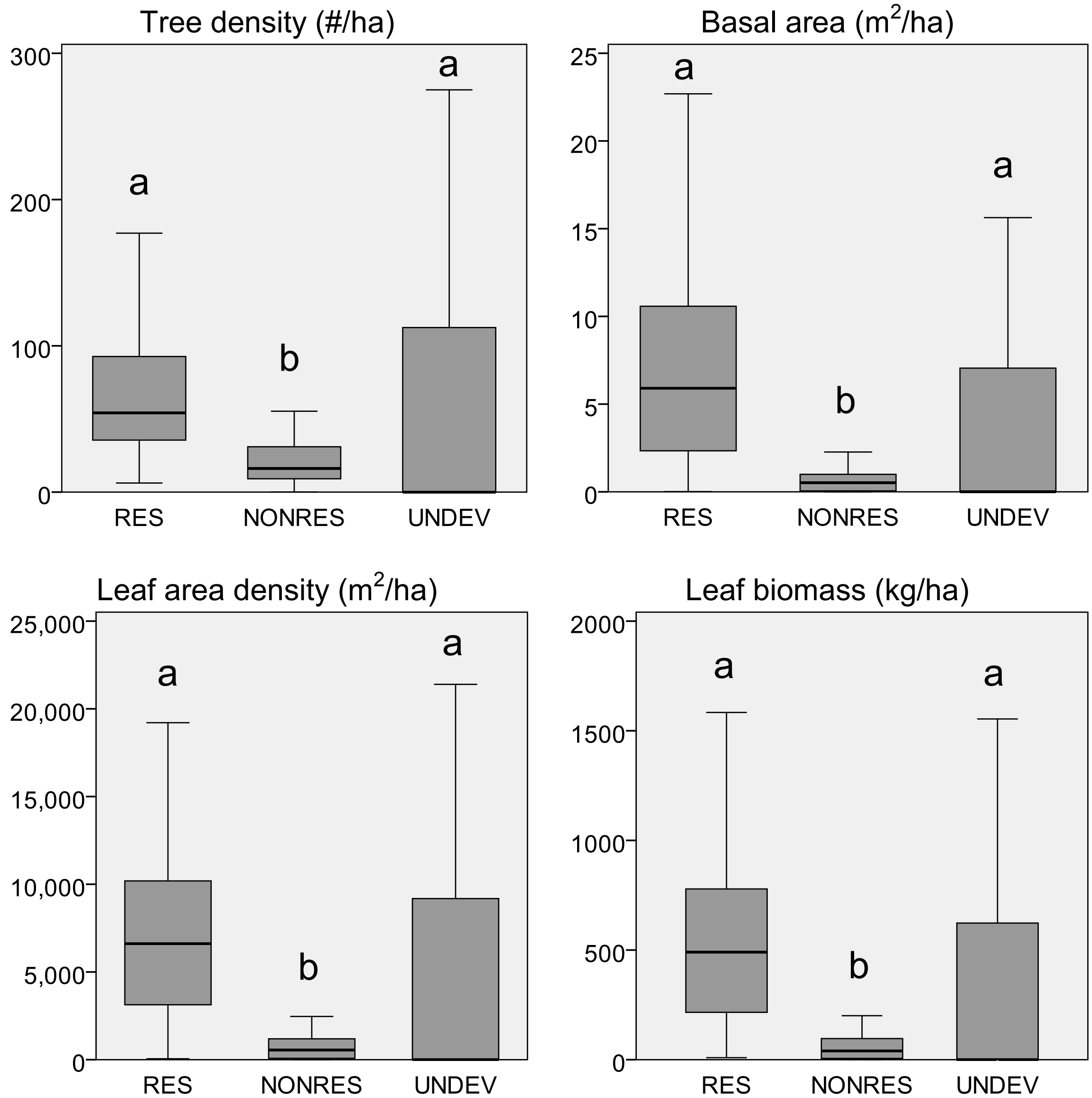

Figure 11. Urban forest structure, function, and value by level-1 land use. Box plots show minimum and maximum values with whiskers, lower and upper quartiles with boxes, and median lines inside boxes. Different letters indicate significant differences, as identified by Dunn's test.

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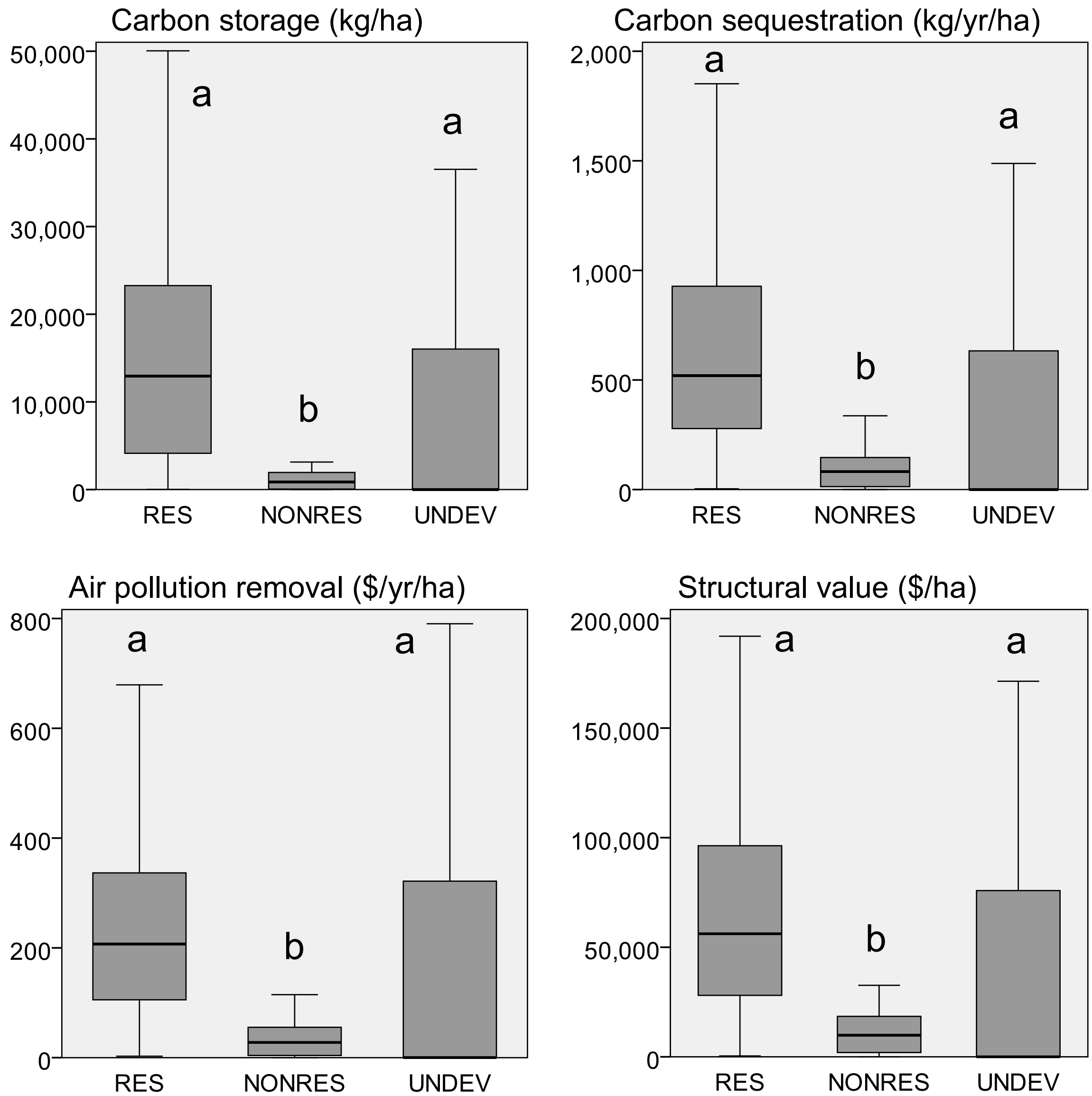

Figure 11. (*continued*)

Table 11. Distribution of study sites among land cover clusters and municipalities. Municipalities are listed in order from urban to rural.

Land Cover Stratification		Municipality					
Level-1	Level-2	Mpls	Rich	Bloom	BV/AV	LV/Eur	Total
Residential		*57*	*19*	*22*	*25*	*25*	*148*
	Urban	31	8	9	5	4	57
	Middle suburban	23	11	11	11	8	64
	Far suburban	3	0	2	9	13	27
Non-residential		*31*	*3*	*5*	*6*	*5*	*50*
	Urban	31	3	3	0	0	37
	Suburban	0	0	2	6	5	13
Undeveloped		*20*	*6*	*10*	*25*	*39*	*100*
	Landscaped	16	1	3	9	13	42
	Natural	0	0	3	14	5	22
	Right of way	4	5	4	2	0	15
	Agriculture	0	0	0	0	21	21
Total		108	28	37	56	69	*298*

Abbreviations: *Mpls* = Minneapolis; *Rich* = Richfield/Ft. Snelling; *Bloom* = Bloomington; *BV/AV* = Burnsville/Apple Valley; *LV/Eur* = Lakeville/Eureka Township.

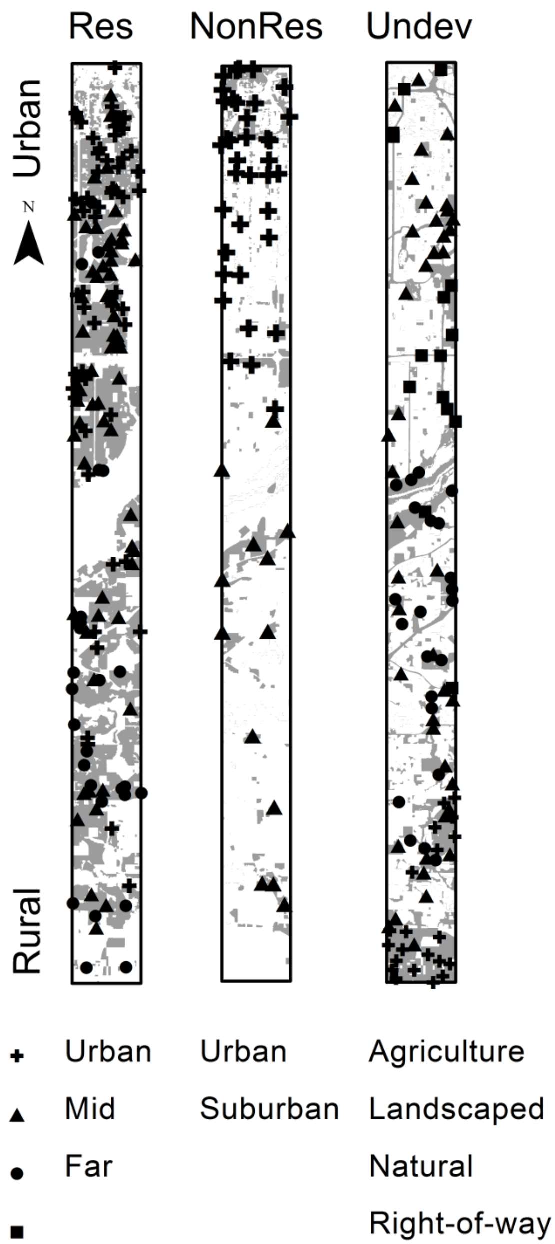

Figure 12. Spatial distribution of study sites by level-2 land use. Gray shading represents the spatial distribution of each land use stratum.

Central city versus suburban forest characteristics

When *res*, *nonres*, and *undev* sites in Minneapolis were compared to their counterparts in suburban municipalities, the following two significant differences were observed: Minneapolis *res* sites had greater carbon storage and air pollution removal values (Figure 14). No differences were observed for *nonres* or *undev* sites. Although no statistical differences were indicated, Minneapolis *res* sites had higher per area median values than suburban sites for tree density, basal area, leaf area density, leaf biomass, carbon sequestration, and structural value (Figure 14). Similarly, Minneapolis *undev* sample sites had higher median values than suburban sites for all eight UF attributes compared. In contrast, suburban *nonres* sample sites had higher median values than Minneapolis sites for all eight attributes compared.

Although this analysis revealed few significant differences among Minneapolis and suburban sites, there were noteworthy dissimilarities between the two areas. For all eight measures, suburban *undev* sites had median values of 0, yet suburban sites had higher maximum values than Minneapolis for four of eight measures. Further analysis using a two-sample Kolmogorov-Smirnov test did not indicate different distribution shapes between Minneapolis and the suburbs. It was unclear how varying means and medians within a category affected the analysis; for example, mean and median tree densities for *undev* suburban sites were 149.4 trees/ha and 0.0 trees/ha, respectively, while Minneapolis *undev* sites were less variable (mean = 65.0 trees/ha, median = 50.0 trees/ha).

Table 12. Summary of within- and across-level-1 land use class distributional differences. Values indicate the number of significant differences out of the total number of comparisons made. Significance was evaluated using Dunn's multiple comparisons test following a Kruskal-Wallis test. Across-class comparisons note differences among *res*, *nonres*, and *undev* classes for level-1 and level-2 land uses. Within-class comparisons summarize differences between level-2 classes within the same level-1 class.

	Across-strata comparisons		Within-strata comparisons (Level-2)			
Measure	Level-1	Level-2	*Res*	*Nonres*	*Undev*	Total
Structure						
Tree density	2/3	11/26	0/3	0/1	3/6	3/10
Basal area	2/3	13/26	0/3	0/1	3/6	3/10
Leaf area density	2/3	11/26	0/3	0/1	2/6	2/10
Leaf biomass	2/3	12/26	0/3	0/1	0/6	0/10
Function						
Carbon storage	2/3	13/26	0/3	0/1	3/6	3/10
Carbon sequestration	2/3	14/26	0/3	0/1	3/6	3/10
Air pollution removal	2/3	14/26	0/3	0/1	3/6	3/10
Value						
Structural value	2/3	13/26	0/3	0/1	3/6	3/10
Column mean	2/3 (67%)	12.6/26 (49%)	0/3 (0%)	0/1 (0%)	2.5/6 (42%)	2.5/10 (25%)

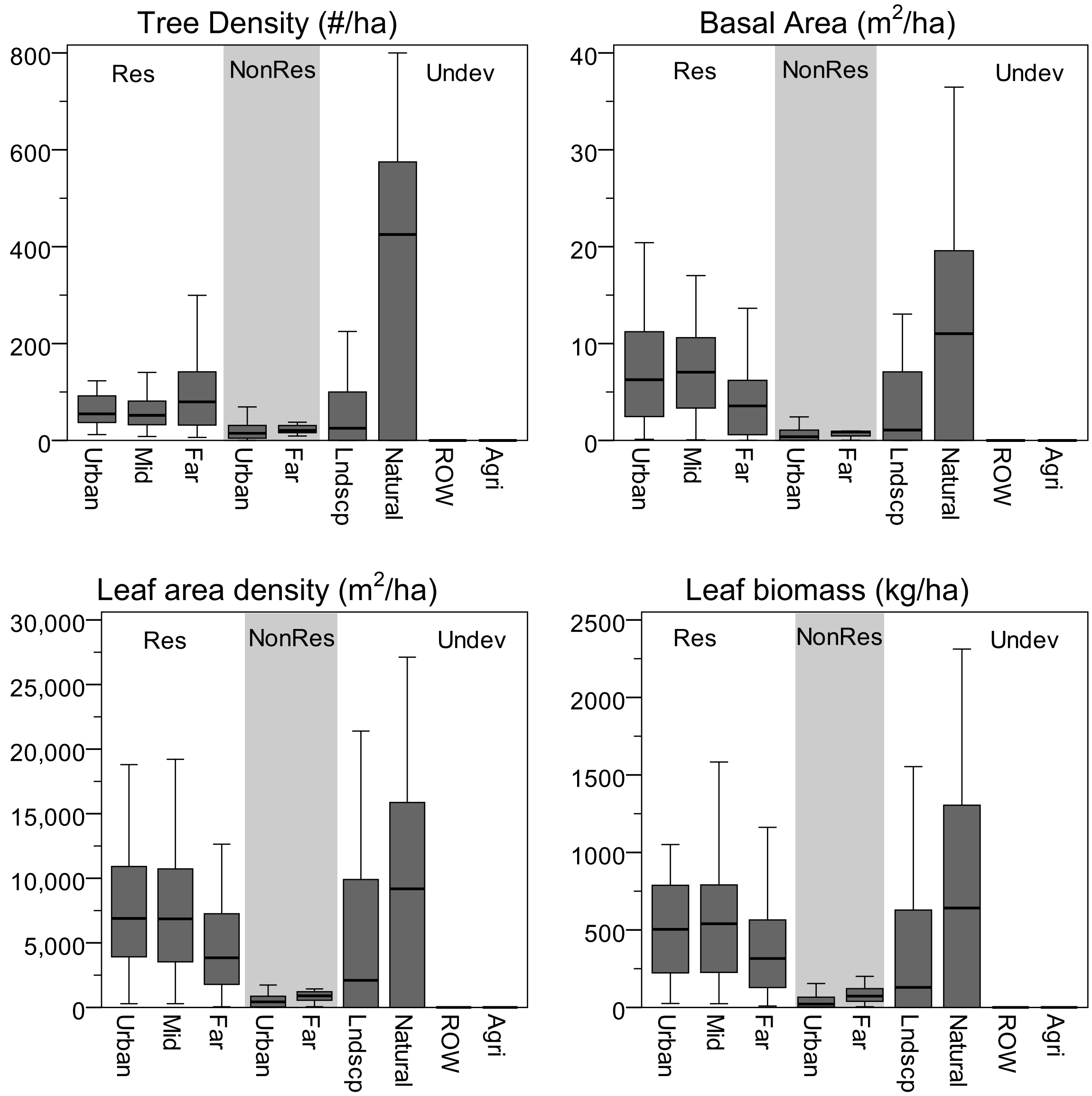

Figure 13. Urban forest structure, function, and value by level-2 land use strata. Box plots show minimum and maximum values with whiskers, lower and upper quartiles with boxes, and median lines inside boxes.

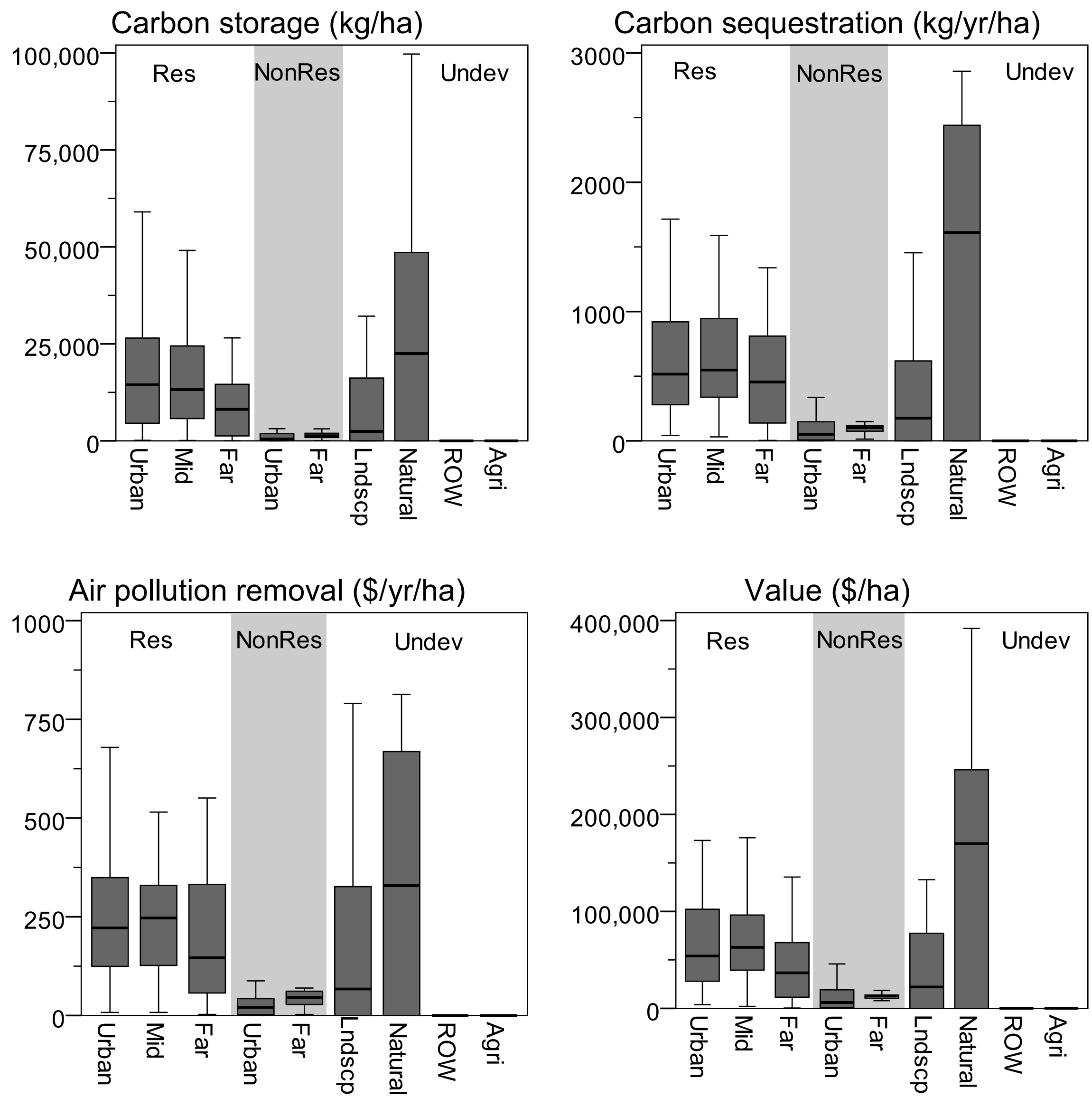

Figure 13. (*continued*)

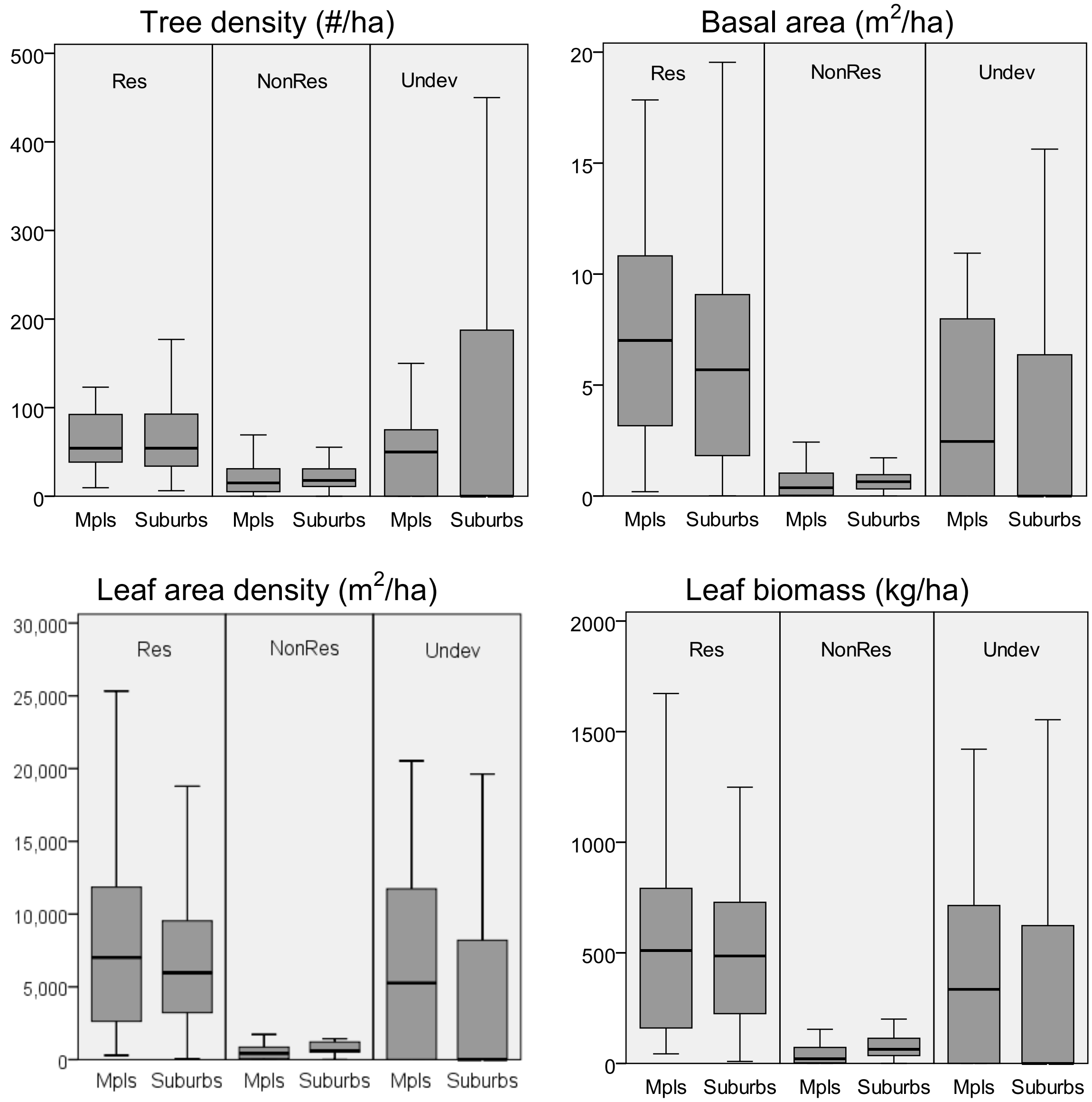

Figure 14. Comparison of Minneapolis vs. suburban forest attributes, by level-1 land use classes. Box plots show minimum and maximum values with whiskers, lower and upper quartiles with boxes, and median lines inside boxes. Asterisks indicate significant differences ($P < 0.05$).

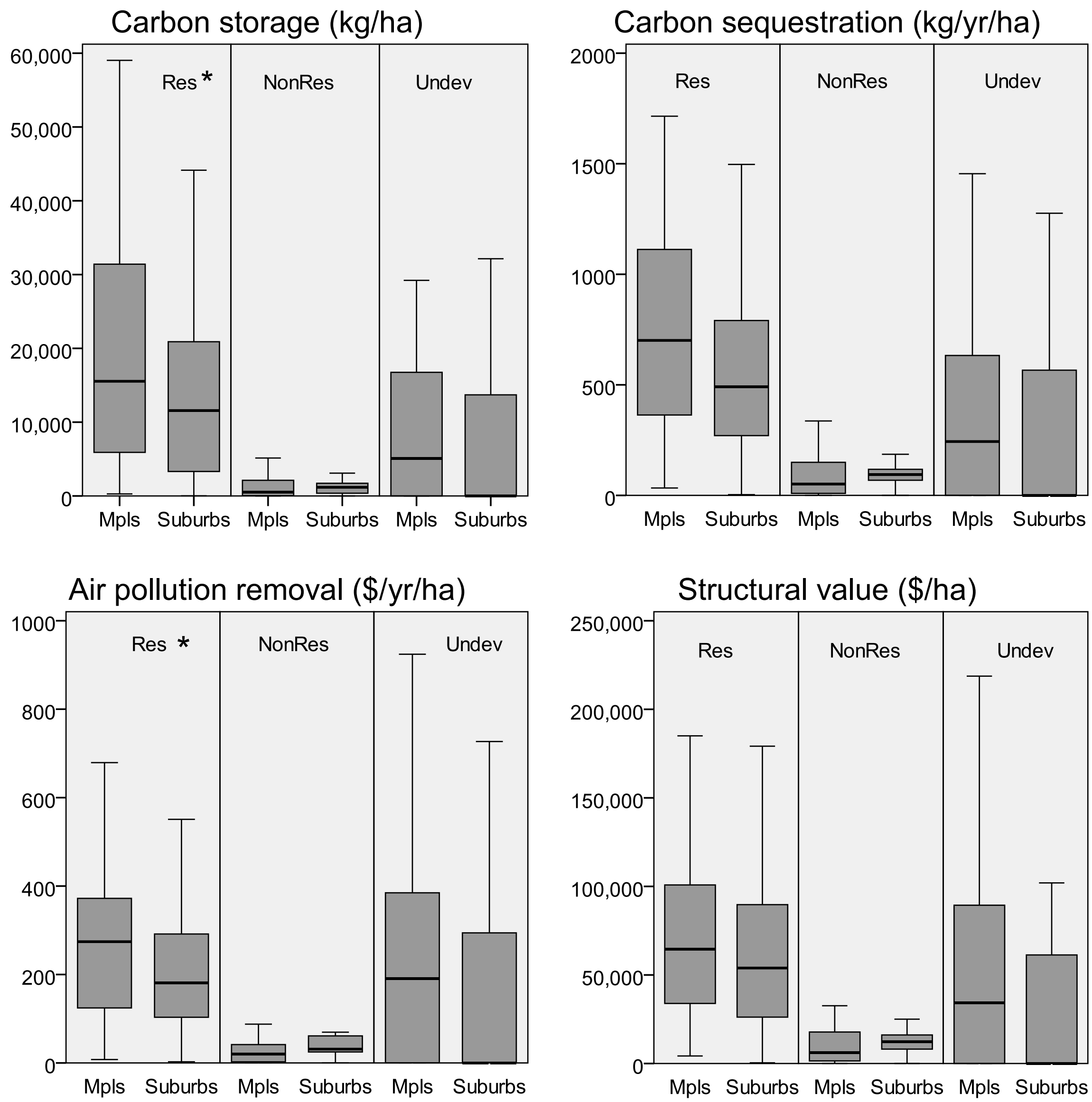

Figure 14. (*continued*)

DISCUSSION

Parcel-based land use stratification

Parcel-based stratification provided an efficient means of selecting study sites and comparing UF attributes across land use categories. Given fine-scale urban heterogeneity attributable to landowner decision making, sampling individual parcels provides a strong basis for directly relating parcel characteristics to UF data, while avoiding the issue of random circular plots intersecting multiple properties. Depending on the study goals, this approach may be preferable to other stratification techniques, such as those based on municipal administrative boundaries or satellite-based land cover classifications.

Administrative boundaries may have management implications, but may not be ecologically relevant. Land cover classifications can distinguish ecologically dissimilar areas (e.g., forests vs. grasslands vs. urban areas), but may not be able to differentiate between spectrally similar land uses, such as residential and commercial urban areas, where UF management may diverge substantially over time. Parcel-based stratification, on the other hand, directly and accurately accounts for land use and thus offers clues regarding both land cover and management. While sampling parcels is not a new approach (Nowak 1994b), we believe it deserves increased consideration among urban foresters to improve knowledge of land use's impacts on the UF at the smallest coherent scale of urban land management. The approach used here—distributing study parcels among municipalities based on a randomized list of parcels—provided a straightforward method of identifying random sites among various land uses.

The most important limitations of the parcel-based stratification technique are related to level-2 land use stratification. One concern was that undeveloped land could not be divided into subclasses prior to sampling. For example, a park containing landscaped and natural areas was contained in the GIS data set as one single park polygon. This is an important issue because post-sampling stratification resulted in fairly low sample sizes for some land use classes. The i-Tree developers recommend a minimum of 20 sites per land use stratum because low sample sizes increase the standard error of estimates (i-Tree Eco 2011). Stratifying level-2 undeveloped sites prior to sampling with existing spatial data could improve sample depth. For example, a satellite-based land cover classification could be used to distinguish among landscaped parks, forests, and agricultural areas, and spatial data from transportation agencies and utilities could be used to identify ROWs.

Analysis of UF structure, function, and value according to level-1 land use classes highlighted the importance of distinguishing between *res* and *nonres* developed sites. *Res* sites had significantly higher values than *nonres* sites for all eight UF attributes we assessed. While Dunn's test did not indicate any differences between *res* and *undev* sites, visual inspection of box plots (Figure 11) shows a key difference between the two. Namely, the median for *undev* sites is 0 for each measure, while the first quartile for *res* sites is always >0. This suggests two very different styles of land use. *Res* sites typically fell within a relatively moderate range for most UF estimates, whereas *undev* sites were commonly treeless but those with trees often had highly developed UF structure.

The differences among *undev* sites suggest that a level-2 classification is particularly important for these sites. Indeed, 42 percent of comparisons among *undev* level-2 categories were significantly different, compared to 0 percent of comparisons within the *res* and *nonres* categories. Level-2 *undev* within-class comparisons were almost as likely to be different as level-2 comparisons across level-1 class boundaries. This is not surprising, given the wide range of land uses contained in the *undev* class.

On the other hand, it may not be necessary to distinguish among *res* and *nonres* sites beyond a level-1 classification. The lack of level-2 per unit area differences within level-1 developed classes suggests that these types of parcels have less variable UF structure, function, and value than *undev* sites, and indicates relative uniformity of developed parcels compared to undeveloped areas. Relative consistency across developed sites was attributable to regular municipal plantings along streets, and limited private planting space imposed by building footprints and impervious surfaces.

Another possible factor is that the rank-based statistical test applied here was not sensitive to extreme values, so very large properties with extensive UF cover did not factor heavily into the analysis. Thus, differences among developed level-2 classes may have been overlooked, particularly regarding the frequency of parcels with exceptionally high UF attribute values. So while no significant differences were revealed in this analysis, there may be subtle but potentially meaningful variations across developed level 2-classes. For example, box plots show that far suburban *res* sites had the highest maximum tree density, but the lowest maximum basal area (Figure 13). If additional sampling and analysis confirmed this observation, the contrasting UF structure—namely, abundant small trees in the far suburbs versus fewer large trees in the urban and near suburban areas—could point to important UF functional gradients over space and through time. Further study is needed to determine whether level-2 clustering is necessary to adequately characterize per unit area UF structure, function, and value on developed sites.

Urban versus suburban forest attributes

Assessing UF structure, function, and value along an urban-rural gradient highlighted perspectives not observed in studies focused on just one city. Most notably, we explored whether UF estimates for the central city are applicable to suburban areas. Additionally, understanding current UF structure and function for parcels with varying characteristics (e.g., size, house age) provides important baseline data for modeling future ES potential across a metropolitan region. These perspectives could represent early steps in the development of regional UF management strategies across the TCMA. Similarly, these data could be used by suburban UF managers to more appropriately manage their UF resources.

The urban-rural gradient approach also has important limitations. First, sampling across entire municipalities was unfeasible due to limits on time and funding. Thus, comparisons among municipalities were based on portions of those municipalities, and may not provide a fully representative view of each city. Second, we oriented the study transect due south from downtown Minneapolis primarily to minimize open water area, but it is unknown how parcel characteristics and UF attributes would vary along a different transect placement within the TCMA, or in a different metropolitan area. Continued exploration of UF attributes along urban-rural gradients will improve generalizations regarding the impacts of land use on the UF.

We observed few differences between level-1 classes in Minneapolis and suburban municipalities. The Mann-Whitney *U* test is not sensitive to extreme values, so sites with exceptionally high UF attributes may have been underappreciated. That being said, for all but two comparisons (*res* carbon storage and *res* air pollution removal), values at a random Minneapolis site had an equal chance of being larger or smaller than those of a random suburban site. These two *res* differences contrast findings from the level-2 analysis above, where urban *res* sites did not differ from near suburban and far suburban sites; this may be because the urban-suburban analysis was based strictly on spatial location, while level-2 stratification was based on additional parcel characteristics. Note that suburban *undev* sites had a median value of 0 for all eight metrics, largely attributable to treeless agricultural sites toward the rural end of the transect. So while most comparisons failed to reject the null hypothesis that samples were drawn from the same population, bear in mind that more subtle differences between Minneapolis and the suburbs may have been present and could have important consequences for UF structure, function, and value. Additional research is needed to fully understand the similarities and differences between urban and suburban forest resources.

Although there may be underlying complicating factors, it seems appropriate to use per unit area UF estimates from Minneapolis as a rough approximation for suburban municipalities in the TCMA, in the absence of municipality-specific UF data. This assumes level-1 land use stratification as described above, as the proportion of each land use class will influence UF estimates for the municipality as a whole. These findings support the historical trend in UF ES science to primarily focus on central cities, with two important caveats. First, the lack of evidence indicating differences between Minneapolis and the suburbs does not mean that consequential differences do not exist; additional UF data and alternative statistical tests with sensitivity to extreme values may reveal important differences. Second, suburban municipalities should not rely on central city estimates to make detailed assumptions about their own UF resources, if it can be avoided. For example, while transect-wide UF estimates are comparable to estimates for Minneapolis alone for some variables (e.g., tree canopy cover, carbon sequestration), relying on central city estimates to approximate other suburban UF attributes such as tree density could encourage misguided policies. To avoid these issues, researchers in a few suburban municipalities have already generated UF ES assessments (e.g., Dorney et al. 1984; McPherson 1998a). Such local estimates are ultimately needed to generate reliable UF estimates for a given municipality. This is especially important where locally common land use classes are underrepresented in the central city, or where UF management policies and tree species preferences are distinctly different in the central city compared to the suburban municipality of interest.

CONCLUSIONS

Understanding the effects of land use on urban forest structure, function, and value is a research priority in the field of urban ecosystem service science. Prior to urban forest assessments, property parcel databases can be used to provide an accurate and efficient means of stratifying landscapes by broad land use classes, and clustering techniques can be used to identify more detailed land use classes. We compared eight measures of UF structure, function, and value across residential, non-residential developed, and undeveloped sites in the TCMA. UF attributes were higher on residential and undeveloped lands as compared to non-residential areas. In this study, more detailed level-2 clustering did not highlight level-1 intra-class differences in UF attributes for either residential or non-residential sites, but it did demonstrate stark contrasts among various undeveloped land uses. Testing indicated few differences between Minneapolis and suburban UF attributes, suggesting that central city UF assessments may provide a useful, yet rough approximation of suburban forest structure, function, and value. Statistical analyses with greater sensitivity to extreme values are needed to confirm the results of this study. The parcel-based land use stratification approach developed here provides a relatively simple and effective method for selecting study sites in other UF assessments along urban-rural gradients.

Chapter 5. Conclusions and synthesis

MAJOR FINDINGS AND SYNTHESIS

This dissertation assessed the urban forest along an urban-rural gradient in Minnesota's Twin Cities Metropolitan Area (TCMA), paying particular attention to the spatiotemporal effects of urbanization on urban forest structure, function, and value. The first study (Chapter 2) used historical air photos to assess the effects of land cover changes, and especially urbanization, on tree canopy cover over the past 70+ years. As urban land expanded regionally, tree canopy cover was initially reduced, but urban areas accrued tree canopy cover relatively rapidly after the urbanization event. In fact, urban land cover was second only to forests in percent tree canopy cover in 2009. This demonstrates that mature urban neighborhoods can support substantial tree canopy cover, but densely developed areas supported substantially less tree canopy cover.

In Chapter 3, I used factor analysis to derive a synthetic character-based urbanization gradient incorporating nineteen urbanization indicator variables. This is important because no single measure can fully capture urbanization intensity on its own. The character-based gradient was defined by two primary factors. As expected, factor 1 was strongly associated with distance from the urban core and impervious surface concentrations. Factor 2 represented a more subtle, yet important trend related to residential neighborhood density, with high values in inner-ring suburban residential areas, and low values in the non-residential urban core and the more sparsely developed suburbs near the peri-urban fringe. This study is likely the first to relate such a gradient to urban ecological structure, and thus generated novel perspectives on the relationships between urbanization intensity and urban forest structure in residential areas. The character-based gradient provided an improvement over a simple distance-based gradient because it was able to account for the spatial distribution of tree canopy cover. This analysis pointed to the need to consider secondary urbanization patterns in order to expand our understanding of urbanization's effects on ecological structure.

Chapter 4 described a study in which I modeled urban forest structure, function, and value according to land use. I outlined a new parcel-based approach for stratifying study areas prior to ground-based sampling, because existing strategies do not provide the most effective means for relating urban forest attributes directly to land use. Under this approach, I stratified the study area into three broad land use classes: residential developed land, non-residential developed land, and undeveloped land. I then divided my study sites into more detailed land use classes using cluster analysis, and assessed whether this additional level of land use classification detail was necessary. For developed land, differences among detailed land use clusters were not significant, so basic stratification into residential and non-residential land may be adequate. On the other hand, there was considerable variability among undeveloped sites, so detailed stratification is highly recommended in these areas. I also compared the Minneapolis urban forest to that of the suburban municipalities, and found few statistically significant differences in structure, function, or value. While this suggests that central city urban forest estimates may be generally applicable to the suburban forest, further study is needed to confirm these findings.

Taken together, these studies emphasize three important considerations regarding the urban forest in the TCMA. First, the urban forest is an important and dynamic source of ecosystem services in the region. The final study estimated key urban forest functions and structural value. For the entire study area, the 83.2 trees/ha generated approximately $411/yr/ha of air quality and carbon benefits, not to mention numerous additional social and environmental benefits beyond the scope of this study. Replacing the study area trees with similar trees would cost $670 million ($55,859/ha). The distribution of these benefits changes over time with urban forest structure, and as the landscape context evolves. For example, trees in densely developed urban areas may provide more urban heat island reduction than similar trees in large suburban lawns. Indeed, Chapter 2 highlighted the need to improve urban forest structure in those areas with the highest impervious surface coverage, but this is challenging because highly urban environments are not hospitable to trees.

Second, urban forest structure often peaks at intermediate urbanization intensities. While many factors may play a role, the basic message is simple—urban forest structure is well developed where there is ample room to grow, and where urban development is old enough that trees have reached mature sizes. Highly developed areas such as the urban core do not have enough growing space to generate rich urban forest structure. Newly developed areas with ample growing space have limited urban forest structure because planted trees have not had time to achieve mature sizes, especially in the TCMA and the greater Midwestern U.S., where urbanization typically replaces treeless agricultural areas. The concepts of plantable space and temporally lagged tree growth complicate urban forest studies, but researchers are increasingly aware of these issues.

More broadly, my third key point relates to complex aspects of human-environmental systems in general. Beyond temporal lags, there are additional complexities that prevent straightforward assessment of the urban forest. One complex aspect is nonlinearity, which arose in multiple facets of this research. For example, in Chapter 3 I demonstrated that urbanization intensity does not follow a linear gradient from city center to peri-urban fringe, and by combining multiple indicators of urbanization, I was able to better characterize urbanization's relationships to urban forest structure. I increased my ability to capture nonlinear urban forest responses to urbanization by including polynomial terms in my regression models. In addition, I found preliminary evidence suggesting that a residential parcel's capacity for urban forest structure increases in a nonlinear fashion for exceptionally large parcels, and as mentioned in Chapter 4, additional analyses are needed to adequately understand the role of these exceptionally large parcels in providing urban forest ecosystem services.

FUTURE RESEARCH PRIORITIES

Completing this research project motivated me to address additional questions in the future. My next project will use modeling techniques to simulate future urban forest structure and function under various scenarios of tree planting, mortality due to exotic pest invasions, and management strategies. These projections will permit me to compare neighborhoods across the urban-rural gradient on an equal temporal playing field; in other words, I will project urban forest attributes in newly developed neighborhoods to compare urban development styles while controlling for the interrelated effects of time since development and lagged tree growth. This type of modeling is ultimately necessary to promote urban sustainability in land use decision making. As researchers have only recently paid serious attention to the complexities associated with the urban forest, I will continue to refine approaches such as character-based urbanization gradient derivation to generate realistic perspectives on urbanization's relationship to ecological structure. Related to this, I plan to collaborate with others to consider a broader range of urban forest ecosystem services (e.g., biodiversity, cultural benefits), and also to document the tradeoffs associated with gains in urban forest cover, such as lost agricultural production. Since constraints on time and money limited the spatial scope of my dissertation research, I am interested in determining whether my conclusions can be generalized across a broader set of metropolitan areas. Finally, one underlying goal of my research is to increase public awareness of urban ecology. For example, study participants received a letter outlining my research goals (Appendix B), and several participants contacted me to find out what I concluded about their yards and communities. Study participants as a whole had a surprisingly keen awareness of their trees and some of the disamenities they bring, but were usually surprised to hear about the associated air and water quality benefits. Moving forward, I will continue to share my findings with urban forestry professionals and citizens to promote stronger ties between the research community and the general public.

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Appendix A. Summary of urban forest data collected

Table A1. Trees[1] encountered, by species

Latin name	Common name	Count
Abies balsamea	Balsam fir	18
Acer ginnala	Amur maple	41
Acer negundo	Box elder	272
Acer nigrum	Black maple	9
Acer platanoides	Norway maple	95
Acer rubrum	Red maple	21
Acer saccharinum	Silver maple	126
Acer saccharum	Sugar maple	23
Aesculus glabra	Ohio buckeye	1
Aesculus hippocastanum	Horse chestnut	3
Aesculus pavia	Red buckeye	1
Amelanchier arborea	Common serviceberry	3
Betula nigra	River birch	32
Betula papyrifera	Paper birch	39
Carya cordiformis	Bitternut hickory	3
Carya glabra	Pignut hickory	1
Catalpa speciosa	Northern catalpa	7
Celtis occidentalis	Common hackberry	116
Cercis canadensis	Eastern redbud	5
Cornus alternifolia	Alternate-leaf dogwood	2
Cornus florida	Flowering dogwood	7
Cotinus coggygria	Purple smoke tree	1
Cotinus obovatus	American smoke tree	4
Euonymus alatus	Winged burning bush	1
Fraxinus nigra	Black ash	16
Fraxinus pennsylvanica	Green ash	285
Ginkgo biloba	Maidenhair tree	5
Gleditsia triacanthos	Honey locust	41
Juglans nigra	Black walnut	9
Juniperus communis	Common juniper	2
Juniperus virginiana	Eastern redcedar	10
Larix laricina	Tamarack	1
Lonicera canadensis	American fly honeysuckle	1
Magnolia stellata	Star magnolia	1
Malus spp.	Apple	114
Morus alba	White mulberry	34
Ostrya virginiana	Ironwood	14
Picea abies	Norway spruce	9

Table A1. (*continued*)

Latin name	Common name	Count
Picea glauca	White spruce	154
Picea mariana	Black spruce	1
Picea pungens	Colorado blue spruce	70
Pinus nigra	Austrian pine	25
Pinus resinosa	Red pine	24
Pinus strobus	Eastern white pine	29
Pinus sylvestris	Scots pine	8
Platanus occidentalis	American sycamore	1
Populus alba	White poplar	1
Populus balsamifera	Balsam poplar	3
Populus deltoides	Eastern cottonwood	53
Populus grandidentata	Bigtooth aspen	2
Populus spp.	Poplar	3
Populus tremuloides	Quaking aspen	105
Prunus americana	American plum	3
Prunus serotina	Black cherry	44
Prunus spp.	Cherry	31
Prunus virginiana	Chokecherry	19
Prunus x cistena	Purpleleaf sandcherry	2
Pyrus calleryana	Callery pear	1
Quercus alba	White oak	42
Quercus bicolor	Swamp white oak	14
Quercus ellipsoidalis	Northern pin oak	59
Quercus macrocarpa	Bur oak	42
Quercus rubra	Northern red oak	41
Rhamnus cathartica	Common buckthorn	201
Rhamnus frangula	Glossy buckthorn	4
Rhamnus lanceolata	Lanceleaf buckthorn	1
Rhus glabra	Smooth sumac	2
Rhus typhina	Staghorn sumac	11
Robinia pseudoacacia	Black locust	1
Salix discolor	American willow	1
Salix matsudana	Chinese willow	1
Salix nigra	Black willow	29
Sorbus americana	American mountain ash	2
Syringa patula	Manchurian lilac	1
Syringa reticulata	Japanese tree lilac	6
Syringa vulgaris	Common lilac	25
Taxus canadensis	Canadian yew	2
Thuja occidentalis	Arborvitae	151
Tilia americana	American linden	75

Table A1. *(continued)*

Latin name	Common name	Count
Tsuga canadensis	Eastern hemlock	1
Ulmus americana	American elm	63
Ulmus davidiana	David elm	1
Ulmus parvifolia	Chinese elm	2
Ulmus pumila	Siberian elm	11
Ulmus rubra	Slippery elm	63
Ulmus spp.	Elm	11
Ulmus thomasii	Rock elm	6
Viburnum lentago	Nannyberry	1
	TOTAL	**2823**

[1] Trees were defined as woody vegetation >2.54 cm (1 in) DBH.

Table A2. Common tree species by municipality

Overall		(300 study sites, 2823 trees)	
Rank	**Species**	**Count**	**Relative abundance (%)**[1]
1	*Fraxinus pennsylvanica*	285	10.10
2	*Acer negundo*	272	9.64
3	*Rhamnus cathartica*	201	7.12
4	*Picea glauca*	154	5.46
5	*Thuja occidentalis*	151	5.35
6	*Acer saccharinum*	126	4.46
7	*Celtis occidentalis*	116	4.11
8	*Malus* spp.	113	4.00
9	*Populus tremuloides*	105	3.72
10	*Acer platanoides*	95	3.37
Minneapolis		(101 study sites, 578 trees)	
Rank	**Species**	**Count**	**Relative abundance (%)**[1]
1	*Fraxinus pennsylvanica*	74	12.80
2	*Acer platanoides*	46	7.96
3	*Celtis occidentalis*	46	7.96
4	*Ulmus americana*	33	5.71
5	*Acer saccharinum*	30	5.19
	Thuja occidentalis	30	5.19
7	*Acer negundo*	29	5.02
8	*Tilia americana*	26	4.50
9	*Prunus* spp.	25	4.33
10	*Gleditsia triacanthos*	23	3.98
	Malus spp.	23	3.98
Richfield / Ft. Snelling		(28 study sites, 132 trees)	
Rank	**Species**	**Count**	**Relative abundance (%)**[1]
1	*Fraxinus pennsylvanica*	26	19.70
2	*Acer saccharinum*	14	10.61
3	*Acer platanoides*	9	6.82
	Thuja occidentalis	9	6.82
5	*Ulmus americana*	7	5.30
6	*Betula papyrifera*	6	4.55
7	*Picea glauca*	6	4.55
8	*Celtis occidentalis*	4	3.03
	Morus alba	4	3.03
	Tilia americana	4	3.03

Table A2. *(continued)*

Bloomington		(35 study sites, 352 trees)	
Rank	**Species**	**Count**	**Relative abundance (%)**[1]
1	*Fraxinus pennsylvanica*	47	13.35
2	*Celtis occidentalis*	40	11.36
3	*Acer saccharinum*	34	9.66
4	*Ulmus rubra*	19	5.40
5	*Picea glauca*	14	3.98
	Syringa vulgaris	14	3.98
7	*Thuja occidentalis*	12	3.41
8	*Malus* spp.	11	3.13
9	*Acer platanoides*	10	2.84
	Ostrya virginiana	10	2.84
	Prunus virginiana	10	2.84
Burnsville/Apple Valley		(53 study sites, 905 trees)	
Rank	**Species**	**Count**	**Relative abundance (%)**[1]
1	*Rhamnus cathartica*	129	14.25
2	*Acer negundo*	93	10.28
3	*Thuja occidentalis*	75	8.29
4	*Fraxinus pennsylvanica*	65	7.18
5	*Malus* spp.	40	4.42
6	*Picea glauca*	37	4.09
7	*Populus tremuloides*	31	3.43
8	*Populus deltoides*	28	3.09
9	*Quercus ellipsoidalis*	24	2.65
10	*Acer saccharinum*	23	2.54
	Quercus rubra	23	2.54
	Tilia americana	23	2.54
Lakeville/Eureka Township		(62 study sites, 916 trees)	
Rank	**Species**	**Count**	**Relative abundance (%)**[1]
1	*Acer negundo*	142	15.50
2	*Picea glauca*	91	9.93
3	*Fraxinus pennsylvanica*	73	7.97
4	*Populus tremuloides*	64	6.99
5	*Rhamnus cathartica*	61	6.66
6	*Picea pungens*	39	4.26
7	*Malus* spp.	36	3.93
8	*Ulmus rubra*	32	3.49
9	*Quercus ellipsoidalis*	27	2.95
10	*Acer saccharinum*	25	2.73
	Betula nigra	25	2.73
	Thuja occidentalis	25	2.73

[1] Relative abundance = percent of total trees represented by each species

Table A3. Common tree species by land use class

Residential developed		(150 study sites, 1723 trees)		
Rank	**Species**	**Count**	**Rel. abund.[1]**	**% of sites[2]**
1	*Acer negundo*	159	9.23	14.67
2	*Fraxinus pennsylvanica*	143	8.30	44.00
3	*Picea glauca*	105	6.09	20.67
4	*Acer saccharinum*	103	5.98	40.00
5	*Rhamnus cathartica*	86	4.99	9.33
6	*Celtis occidentalis*	77	4.47	14.67
7	*Malus* spp.	73	4.24	32.00
8	*Populus tremuloides*	71	4.12	1.33
9	*Thuja occidentalis*	68	3.95	14.67
10	*Acer platanoides*	60	3.48	30.67
Non-residential developed		(50 study sites, 570 trees)		
Rank	**Species**	**Count**	**Rel. abund.[1]**	**% of sites[2]**
1	*Fraxinus pennsylvanica*	94	16.49	50.00
2	*Thuja occidentalis*	82	14.39	20.00
3	*Picea glauca*	43	7.54	18.00
4	*Malus* spp.	40	7.02	20.00
	Tilia americana	40	7.02	18.00
6	*Acer platanoides*	32	5.61	18.00
7	*Acer ginnala*	30	5.26	8.00
8	*Prunus* spp.	25	4.39	8.00
9	*Gleditsia triacanthos*	24	4.21	14.00
10	*Celtis occidentalis*	21	3.68	16.00
Undeveloped land		(100 study sites, 530 trees)		
Rank	**Species**	**Count**	**Rel. abund.[1]**	**% of sites[2]**
1	*Rhamnus cathartica*	114	21.51	11.00
2	*Acer negundo*	98	18.49	11.00
3	*Fraxinus pennsylvanica*	48	9.06	16.00
4	*Populus deltoides*	34	6.42	8.00
5	*Populus tremuloides*	25	4.72	5.00
6	*Quercus macrocarpa*	19	3.58	8.00
7	*Celtis occidentalis*	18	3.40	7.00
8	*Pinus resinosa*	17	3.21	1.00
9	*Fraxinus nigra*	15	2.83	4.00
	Quercus rubra	15	2.83	6.00

[1] Relative abundance = percent of total trees represented by each species
[2] % of sites = percent of study sites at which the species was found

Table A4. Largest and smallest tree species by DBH[1,2]

Rank	Species	DBH	Count
Largest			
Rank	**Species**	**DBH**	**Count**
1	*Populus alba*	102.50	1
2	*Platanus occidentalis*	96.00	1
3	*Ulmus parvifolia*	59.75	2
4	*Pyrus communis*	56.10	1
5	*Acer saccharinum*	55.07	126
6	*Aesculus pavia*	48.60	1
7	*Aesculus glabra*	43.50	1
8	*Larix laricina*	41.70	1
9	*Catalpa speciosa*	41.56	7
10	*Robinia pseudoacacia*	40.8	1
11	*Quercus macrocarpa*	40.72	42
12	*Quercus alba*	39.94	42
13	*Acer saccharum*	38.65	23
14	*Quercus ellipsoidalis*	37.40	59
15	*Populus deltoides*	36.71	53
Smallest			
Rank	**Species**	**DBH**	**Count**
1	*Syringa patula*	3.10	1
2	*Syringa reticulata*	7.12	6
3	*Rhamnus frangula*	7.23	4
4	*Amelanchier arborea*	7.43	3
5	*Juniperus communis*	7.80	2
6	*Carya glabra*	8.50	1
7	*Rhus typhina*	8.90	11
8	*Ostrya virginiana*	9.19	14
9	*Rhamnus cathartica*	9.50	201
10	*Cornus alternifolia*	10.70	2
11	*Acer nigrum*	11.46	9
12	*Cercis canadensis*	11.46	5
13	*Salix discolor*	11.80	1
14	*Prunus x cistena*	12.30	2
15	*Rhus glabra*	12.40	2
	AVERAGE/TOTAL	**23.63**	**2823**

[1] Average DBH, in cm.
[2] For multi-stem individuals, all stems >2.54 cm DBH were summed.

Table A5. Largest and smallest tree species by height[1]

Rank	Species	Height	Count
Largest			
Rank	**Species**	**Height**	**Count**
1	*Quercus ellipsoidalis*	9.86	59
2	*Populus deltoides*	9.81	53
3	*Pinus resinosa*	9.79	24
4	*Quercus alba*	9.38	42
5	*Quercus rubra*	9.27	41
6	*Aesculus glabra*	9.00	1
	Picea abies	9.00	9
	Platanus occidentalis	9.00	1
9	*Quercus macrocarpa*	8.98	42
10	*Populus grandidentata*	8.50	2
	Ulmus parvifolia	8.50	2
12	*Prunus serotina*	8.18	44
13	*Acer saccharum*	8.17	23
14	*Aesculus pavia*	8.00	1
	Larix laricina	8.00	1
Smallest			
Rank	**Species**	**Height**	**Count**
1	*Viburnum lentago*	2.00	1
	Ulmus davidiana	2.00	1
	Rhus typhina	2.00	11
	Prunus x cistena	2.00	2
	Magnolia stellata	2.00	1
	Juniperus communis	2.00	2
7	*Cornus florida*	2.14	7
8	*Taxus canadensis*	2.50	2
	Rhamnus frangula	2.50	2
10	*Syringa vulgaris*	2.64	25
11	*Prunus virginiana*	2.84	19
12	*Prunus* spp.	2.90	31
13	*Tsuga canadensis*	3.00	1
	Syringa patula	3.00	1
	Rhus glabra	3.00	2
	Cercis canadensis	3.00	5
	Cotinus obovatus	3.00	4
	AVERAGE/TOTAL	**5.92**	**2823**

[1]Height measured from ground to top of tree, to the nearest meter.

Table A6. Common shrub species[1,2] by municipality

Overall		(300 study sites, 116 shrub species)
Rank	**Species**	**% of sites[3]**
1	*Thuja occidentalis*	20.33
2	*Rhamnus cathartica*	18.33
3	*Syringa vulgaris*	15.67
4	*Spiraea japonica*	14.33
5	*Berberis thunbergii*	12.67
6	*Acer negundo*	12.33
7	*Euonymus alatus*	10.67
8	*Taxus* spp.	10.00
9	*Juniperus virginiana*	9.67
	Morus alba	9.67
Minneapolis		(101 study sites, 86 shrub species)
Rank	**Species**	**% of sites[3]**
1	*Thuja occidentalis*	19.80
2	*Celtis occidentalis*	17.82
3	*Syringa vulgaris*	16.83
4	*Morus alba*	13.86
5	*Berberis thunbergii*	12.87
	Ulmus americana	12.87
7	*Ribes alpinum*	10.89
	Taxus spp.	10.89
9	*Acer negundo*	9.90
	Hydrangea spp.	9.90
	Rhamnus cathartica	9.90
	Spiraea japonica	9.90
Richfield / Ft. Snelling		(28 study sites, 43 shrub species)
Rank	**Species**	**% of sites[3]**
1	*Thuja occidentalis*	28.57
2	*Syringa vulgaris*	25.00
3	*Taxus* spp.	21.43
4	*Spiraea japonica*	17.85
	Weigela florida	17.85
6	*Berberis thunbergii*	14.29
	Rhododendron spp.	14.29
	Ribes alpinum	14.29
	Spiraea betulifolia	14.29
10	10 species tied	10.71

Table A6. *(continued)*

Bloomington		(35 study sites, 52 shrub species)
Rank	**Species**	**% of sites**[3]
1	*Thuja occidentalis*	28.57
2	*Rhamnus cathartica*	25.71
3	*Morus alba*	22.86
	Spiraea japonica	22.86
	Syringa vulgaris	22.86
6	*Berberis thunbergii*	17.14
	Juniperus virginiana	17.14
8	*Lonicera canadensis*	14.29
	Rhododendron spp.	14.29
	Weigela florida	14.29
Burnsville/Apple Valley		(53 study sites, 62 shrub species)
Rank	**Species**	**% of sites**[3]
1	*Rhamnus cathartica*	43.40
2	*Acer negundo*	28.30
3	*Euonymus alatus*	22.64
	Spiraea japonica	22.64
	Thuja occidentalis	22.64
6	*Lonicera canadensis*	16.98
	Syringa vulgaris	16.98
8	*Berberis thunbergii*	15.09
	Juniperus virginiana	15.09
10	*Fraxinus pennsylvanica*	13.21
Lakeville/Eureka Township		(62 study sites, 67 shrub species)
Rank	**Species**	**% of sites**[3]
1	*Thuja occidentalis*	17.74
2	*Rhamnus cathartica*	16.13
3	*Acer negundo*	12.90
	Spiraea japonica	12.90
5	*Berberis thunbergii*	11.29
	Euonymus alatus	11.29
7	*Potentilla fruiticosa*	9.68
	Syringa vulgaris	9.68
9	*Cornus sericea*	8.06
	Picea pungens	8.06
	Taxus spp.	8.06

[1] Shrubs defined as woody vegetation >0.30 m (1 foot) tall and <2.54 cm (1 inch) DBH.
[2] The most abundant species, up to a maximum of 12, were recorded at each study site.
[3] % of sites = percent of study sites at which the species was found.

Table A7. Common shrub[1,2] species by land use class

Rank	Species	% of sites[3]
Residential developed		(150 study sites, 100 shrub species)
Rank	**Species**	**% of sites[3]**
1	*Thuja occidentalis*	33.33
2	*Syringa vulgaris*	30.00
3	*Spiraea japonica*	22.67
4	*Rhamnus cathartica*	22.00
5	*Berberis thunbergii*	20.67
	Euonymus alatus	20.67
7	*Morus alba*	17.33
8	*Acer negundo*	16.00
9	*Taxus brevifolia*	14.67
10	*Cornus alba*	12.00
	Fraxinus pennsylvanica	12.00
	Ulmus rubra	12.00
Non-residential developed		(50 study sites, 49 shrub species)
Rank	**Species**	**% of sites[3]**
1	*Juniperus virginiana*	24.00
2	*Thuja occidentalis*	22.00
3	*Spiraea japonica*	20.00
4	*Berberis thunbergii*	14.00
5	*Celtis occidentalis*	12.00
6	*Acer negundo*	10.00
	Potentilla fruiticosa	10.00
	Ribes alpinum	10.00
	Spiraea betulifolia	10.00
	Taxus canadensis	10.00
Undeveloped land		(100 study sites, 32 shrub species)
Rank	**Species**	**% of sites[3]**
1	*Rhamnus cathartica*	19.00
2	*Acer negundo*	8.00
3	*Zanthoxylum americanum*	4.00
4	*Lonicera canadensis*	3.00
	Rubus occidentalis	3.00
6	*Morus alba*	2.00
	Ribes cynosbati	2.00
	Salix nigra	2.00
9	24 species tied	1.00

[1] Shrubs defined as woody vegetation >0.30 m (1 foot) tall and <2.54 cm (1 inch) DBH.
[2] The most abundant species, up to a maximum of 12, were recorded at each study site.
[3] % of sites = percent of study sites at which the species was found.

Table A8. Urban forest structural attributes by land use cluster[1], with standard error values in parentheses

	RESIDENTIAL			NON-RESIDENTIAL		UNDEVELOPED			
Cluster	**Urban**	**Mid**	**Far**	**Urban**	**Far**	**Landscaped**	**Natural**	**ROW**	**Agriculture**
n	57	64	27	37	13	42	22	15	21
Trees/ha									
Mean	72.1 (7.2)	69.1 (7.2)	109.8 (20.0)	22.5 (4.3)	23.8 (3.6)	88.7 (23.1)	388.6 (85.9)	3.3 (3.3)	44.0 (28.1)
Minimum	12.0	8.1	6.2	0.0	9.1	0.00	0.0	0.0	0.0
Maximum	254.9	303.8	343.5	112.8	55.3	600.0	1725.0	50.0	575.0
Leaf area (m^2/ha)									
Mean	7734 (702)	7669 (600)	4943 (830)	973 (314)	884 (122)	5779 (1184)	9417 (1897)	111 (111)	2873 (1411)
Minimum	288	289	52	0	54	0	0	0	0
Maximum	25322	19209	17729	10556	1435	30822	27117	1664	19625
Leaf biomass (kg/ha)									
Mean	579 (57.8)	557 (46.7)	392 (65.4)	73 (21.9)	92 (17.4)	419 (85.6)	732 (150.4)	18 (17.8)	239 (116.6)
Minimum	26	24	9	0	4	0	0	0	0
Maximum	2211	1584	1249	598	201	1965	2312	267	1759
Basal area (m^2/ha)									
Mean	7.3 (.08)	7.2 (0.6)	4.8 (1.1)	1.1 (0.3)	0.9 (0.2)	7.3 (2.2)	10.9 (2.3)	0.0 (0.0)	2.3 (1.6)
Minimum	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum	25.0	22.5	22.7	9.0	3.1	76.9	36.5	0.5	33.8
Tree species/ha									
Mean	48.0 (4.7)	37.3 (2.7)	38.4 (4.3)	9.0 (1.6)	6.7 (1.3)	33.3 (6.1)	84.1 (15.3)	1.7 (1.7)	11.9 (5.9)
Minimum	7.8	4.7	0.7	0.0	1.1	0.0	0.0	0.0	0.0
Maximum	181.8	140.6	95.5	37.7	16.4	175.0	200.0	25.0	100.0

[1] See Chapter 4 for clustering methodology.

Table A9. Estimated urban forest structural value and functions by land use cluster[1], with standard error values in parentheses

	RESIDENTIAL			NON-RESIDENTIAL		UNDEVELOPED			
Cluster	**Urban**	**Mid**	**Far**	**Urban**	**Far**	**Landscaped**	**Natural**	**ROW**	**Agriculture**
n	57	64	27	37	13	42	22	15	21
Structural value (1,000s of $/ha)									
Mean	68.17	68.12	56.27	14.64	12.98	78.91	143.58	0.62	19.66
	(7.00)	(5.42)	(11.73)	(3.72)	(1.60)	(20.41)	(27.48)	(0.62)	(13.69)
Minimum	3.83	2.10	0.39	0.00	1.33	0.00	0.00	0.00	0.00
Maximum	256.42	191.90	254.23	108.14	25.04	590.58	391.87	9.37	285.78
Carbon storage (1,000s of kg/ha)									
Mean	18.16	17.34	12.79	2.10	1.62	20.88	26.93	0.06	5.68
	(2.23)	(1.81)	(3.48)	(0.64)	(0.40)	(6.66)	(6.03)	(0.06)	(4.28)
Minimum	0.14	0.09	0.01	0.00	0.04	0.00	0.00	0.00	0.00
Maximum	80.41	71.30	76.44	19.03	5.63	211.78	99.73	0.93	90.07
Carbon sequestration (kg/yr/ha)									
Mean	703.3	673.4	668.1	116.0	102.5	578.4	1346.0	11.1	231.5
	(73.1)	(62.2)	(142.2)	(27.2)	(11.9)	(143.9)	(245.5)	(11.1)	(159.3)
Minimum	41.9	30.7	3.4	0.0	13.3	0.0	0.0	0.0	0.0
Maximum	2779.0	2368.7	2913.7	765.5	186.0	3468.6	2858.6	166.1	3321.6
Air pollution removal ($/yr/ha)									
Mean	245.8	248.0	179.5	35.6	47.0	195.0	372.2	0.0	159.3
	(39.9)	(29.0)	(37.6)	(16.1)	(12.8)	(63.6)	(109.3)	(0.0)	(88.2)
Minimum	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum	1047.4	964.4	739.8	455.5	134.8	1220.2	1220.2	0.0	1220.2

[1] See Chapter 4 for clustering methodology.

Appendix B. Study participant informational letter

UNIVERSITY OF MINNESOTA

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Date:

Thank you for your willingness to participate in the research study I am conducting through the Department of Geography at the University of Minnesota. The project seeks to understand how tree cover varies from the city center to the urban fringe, and determine what this variation means for *ecosystem services*. Ecosystem services are benefits we receive from the environment, such as food, shelter, and clean water. Trees in urban areas provide many services—they remove pollutants and carbon from the atmosphere, slow the rate of storm water runoff and soil erosion, reduce air conditioning bills by shading homes, absorb sound to reduce noise levels, beautify our neighborhoods, and the list goes on. Comparing the benefits trees provide to the costs of planting and maintaining them can help our communities better manage their tree resources.

Today we gathered data on vegetation and land cover on your property. For each tree and shrub, we recorded attributes such as species, size, and health. Land cover includes categories such as grass, buildings, cement, and mulched landscaping. This set of data will be used to generate estimates of the ecosystem services provided by trees on your property. Comparing these estimates across many parts of the Twin Cities metropolitan area will help us better understand how ecosystem service provision varies across space as a result of landowner choices, public policy, and many other factors.

To protect your privacy, I will omit identifying information such as your name and address from any reports generated during this research study. Maps of the study area will not show exact locations of study participants. If you have any further questions or concerns, feel free to contact me via the phone number or email address listed below.

Thanks again!

Sincerely,

Adam Berland

Email: berl0038@umn.edu
Phone: (651)785-5713