# Change is Hard: Understanding Neighborhood Context and Socio-ecological Change with Time-series Remote Sensing

by

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## ABSTRACT

Quality of life in urban areas is strongly linked to land use and land cover, in part because green vegetation mitigates much of the negative consequences of urbanization and population pressures. However, the green vegetation of urban parks, forests, street trees, and landscaping is inequitably distributed in the urban environment. The social and economic processes that give rise to these uneven outcomes are not well-understood, while the rise in the availability of spatially explicit, fine-scale data on neighborhood conditions has created the conditions for an empirically rich investigation into neighborhood socio-ecological change. This dissertation assimilates new observations from different sources with new modes of inquiry to address persistent knowledge gaps: the dependence of socio-ecological relationships on scale and urban or metropolitan context; understanding the duration and significance of neighborhood improvement or decline; and the outstanding need for comparative analyses and novel analytical techniques for comparing neighborhood change between multiple metropolitan areas. Time-series satellite remote sensing of 30 years of vegetation cover is combined with population and housing market data to provide a comprehensive picture of the neighborhood environmental quality, demographic composition, and housing stock conditions. Three different metropolitan areas, Detroit, Los Angeles, and Seattle, are used to elucidate how our common assumptions of socio-ecological relations—and the underlying analytical approaches in which remote sensing plays a pivotal role—often fail to accurately capture the complexities and contradistinctions in the social and economic drivers of neighborhood-level biophysical changes. Results indicate that while population decline confounds conventional explanations for socio-economic differences in environmental quality, neighborhood advantages and disadvantages persist for multiple decades, with wealthier neighborhoods tending to resist cyclical declines in the housing market and accrue yet higher home values while preserving and increasing vegetated cover through irrigation and likely several policy tools. Historical conditions, particularly racial residential segregation, also yield surprising outcomes today, in some places reducing vegetation disparities and exacerbating them in others, depending on metropolitan-level population pressures and the balance of municipal political economies.

# CHAPTER I

# Introduction

As urban populations increase world-wide, the resource demands and environmental externalities of cities have become more apparent and more pressing. The relative affluence of urban residents leads to their increased consumption (Rees, 2009, Heinonen et al., 2011, Moran et al., 2018) and the concentration of economic activities that makes cities attractive also generates considerable pollution streams, disrupts energy and water balances, and alters biogeochemical cycling (Rees and Wackernagel, 1996). But urbanization has undeniable advantages, as a denser urban form mitigates carbon emissions from two of the most energy-intensive components of our modern economy: transportation and residential heating and cooling (Dodman, 2009, Kennedy et al., 2015, Holian and Kahn, 2015). Cities are therefore sites of the biggest challenges but also the most promising opportunities for sustainable transitions under global climate change (Solecki et al., 2013, Revi et al., 2014, Brelsford et al., 2017). While cities cover less than 3% of global ice-free land, they appropriate the land resources of a vast global hinterland, accounting for an estimated 70% of global energy use and 78% of global carbon emissions (Grimm et al., 2008, Seto and Ramankutty, 2016, Moran et al., 2018).

Local impacts of urbanization are often the most visible, however, and are felt most acutely by urban residents. These impacts can be understood in terms of *ecosystem services,* the class of ecosystem functions which people and society utilize to improve their economic conditions and quality of life (Breuste et al., 2013); chief among these are foods and fibers, clean air, drinking water, and the intangible but no less important recreational, social, and psychological benefits of nature. Ecosystem services depend on the integrity of ecosystems and particularly on exchanges between the atmosphere, hydrosphere, and the land surface (Crossman et al., 2013). Urbanization and related processes disrupt ecosystem services, exacerbating a number of *urban syndromes* that have become a ubiquitous part of urban living: air quality is impacted by the concentration of combustion activities (Nowak et al., 2006), including cars; water quality in local streams and lakes is degraded as an increase in pavement area concentrates the residual pollutants of the urban environment in a new "urban stream" (Paul and Meyer, 2001, Walsh et al., 2005, Alberti et al., 2007); and the increase in paved area and building mass has created an "urban heat island," where air temperatures noticeably increase with the density of the built environment (Oke, 1982, Kalnay and Cai, 2003, Zhou et al., 2004).

Despite the global urbanization trend, a variety of municipal population growth and decline regimes are underway, and the study of urban sustainability is complicated by the diverse trajectories of cities locked in a regional or global competition for talent and investment. We lack an understanding of the functional links between urban biophysical changes and diverging neighborhood fortunes (Bettencourt, 2013) including demographic turnover, the re-location of employment centers, increasing poverty and social and economic isolation in the suburbs, and changes in household financial burdens due to predatory, sub-prime mortgage lending (Kaplan and Sommers, 2009, Immergluck, 2011, Schafran, 2013). Economic restructuring in former industrial areas in the U.S. and abroad have led to declining populations and housing stocks, burdening these “shrinking” cities with large areas of vacant land, crumbling infrastructure, and high service costs (Martinez-Fernandez et al., 2012). This suggests that patterns of investment and population change can be read from the urban landscape itself. Indeed, the link between society and land surface conditions has already been established for night-time lights which, mapped from earth-observing satellites, are strongly associated with population size and gross domestic product (Doll and Muller, 2000, Doll, 2008, Henderson et al., 2012). To the extent that human activities alter the built environment and urban ecology, studying these neighborhood biophysical changes might help us to better understand how urban social and economic change drives divergent outcomes in sustainability. And context is key: while some of the economic consequences of vacancy and abandonment are similar to those of urban sprawl, both resulting in a loss of municipal revenue (Berkman, 1956), the social changes and the institutional conditions are very different (Galster, 2019).

Urban syndromes like the urban stream and urban heat island arise due to changes in *land cover,* or in the biophysical conditions of the earth surface (Turner II et al., 1995). **The reciprocal relationship between humans and their urban environment and the primacy of land in facilitating and mediating human-environment interactions makes *land-change science* a powerful toolkit for investigating the ecological consequences of social and economic changes** (Pickett et al., 2011, Verburg et al., 2015). Urban green vegetation, in the form of lawns, shrubs, and trees, plays a central role in regulating ecosystem services and mitigating urban syndromes (Pataki et al., 2011, Breuste et al., 2013, García Sánchez et al., 2018) by directly intercepting air pollutant particles, filtering runoff from the urban stream, and by shading or replacing impervious pavements. Though the services provided by green vegetation vary with the type, quality, and ownership (public or private green space), in general, greater vegetation density facilitates a higher quality of life for urban residents and a healthier urban ecosystem. This makes urban green space an important environmental amenity for urban residents; it is package of social and economic benefits subject to the same political economy that determines *who gets what, when, how, and why* (Grove and Burch, 1997, Locke and Baine, 2015). Too often, these benefits accrue to the residents that already enjoy significant socio-economic advantages and any attempt to create a more equitable arrangement of environmental amenities must reckon with trade-offs of economic development and housing costs when considering urban green space preservation or expansion (Wolch et al., 2014).

One implication of the social and economic determination of green space amenities is that the spatial arrangement and timing of changes in vegetated cover can serve as indicators of human activities and underlying socio-economic processes: land is cleared for new housing or retail development, areas already developed undergo changes in land management or vegetation phenology over time, and some areas are abandoned or redeveloped altogether (Wilson and Brown, 2014). By observing changes in urban land cover, we can draw inferences about changing patterns of wealth, public and private investment, and residential occupancy in cities—all of which influence neighborhood dynamics such as growth, decline, infill, or urban renewal (Hoalst-Pullen et al., 2011).

**This dissertation grapples with the challenge of understanding the social and economic changes that drive urban vegetation change in the hope of informing both policies and models of how urban growth and decline affect**

**the essential ecosystem services facilitated by green vegetation.** It is presented in three parts, Chapters II through IV, which are three stand-alone papers, each with its own introduction. This section is intended to speak to their common aim—understanding neighborhood socio-ecological change–and its merit, which I claim is based, in part, on the essential benefits green vegetation provides to neighborhood residents and how those benefits become more important as urban populations swell and climate change impacts exacerbate neighborhood inequalities. Yet, it is not my belief that nature is in thrall to human society, nor that human society and nature are separate; this false dichotomy should not be allowed to encourage a narrow, technocratic view of the ecosystem services that green vegetation provides. Rather, green vegetation is one prominent marker of how well our residential neighborhoods are designed to respond to and support human nature; a marker of the intangible but essential *natural-ness* of cities.

## 1.1 Knowledge Gaps Addressed

With this value in mind, my dissertation seeks to understand both the social and spatial distributions of green vegetation in residential landscapes and the neighborhood-level social and economic drivers of change in these distributions change over time. Ultimately, the objective of this research is to inform policy and planning related to improving urban environmental quality. One example of how social equity is considered in improving environmental quality comes from Haskell (2018), who describes how the New York City Parks Department compares maps of asthma rates to maps of their street tree canopy when considering new plantings. Because trees are long-lived, take many years to reach maturity, and face high mortality rates in urban areas, a better understanding of how social and economic change shapes a neighborhood's green vegetation can help with planning green interventions like these (Boone et al., 2010).

To that end, my dissertation seeks to address three key knowledge gaps in this area. One relates to the dearth of research on urban socio-ecological relations in a context of population decline. As much of the research on neighborhood vegetation has been conducted in cities and neighborhoods where green vegetation, as an environmental amenity, is highly valued (Hope et al., 2003, Mennis, 2006, Luck et al., 2009), there is a well-established view that "trees grow on money" (Schwarz et al., 2015). However, in declining neighborhoods, particularly in temperate climates where green vegetation is not water-limited, there is often a considerable amount of volunteer vegetation that takes hold on parcels of abandoned or demolished properties (Hollander, 2010, Nassauer and Raskin, 2014). In shrinking cities, the rate of abandonment may be considerable enough that there is a clear landscape expression of neighborhood decline (Hoalst-Pullen et al., 2011, Deng and Ma, 2015). How, then, do we explain this apparent paradox between the green lawn landscapes of some of the wealthiest U.S. neighborhoods and the emerging "urban prairie" (Gallagher, 2010) of declining neighborhoods? In Chapter II, the growing Detroit Metropolitan Area and shrinking City of Detroit, at its core, are contrasted to demonstrate how unevenness in neighborhood-level green vegetation does not always follow a pattern of socio-economic status.

The lack of research on uneven vegetation conditions between growing and declining neighborhoods, along with inadequate data on neighborhood conditions at fine time scales, has stymied any research into the relationship between dynamic socio-economic and biophysical changes in neighborhoods. This is the second knowledge gap I address in this dissertation: if we can explain observed differences between shrinking and growing neighborhoods, and if high socio-economic status still predicts high vegetation density in stable or growing housing markets, does continuous investment in a housing market make the neighborhood greener? A number of studies have sought to detect the link between parcel-scale land-management changes in declining housing markets (Minn et al., 2015, Deng and Ma, 2015); still other studies have pointed to the externalities of a parcel's decline (Morckel, 2013, Whitaker and Fitzpatrick IV, 2013, Leonard and Murdoch, 2009, Leonard, 2012). These studies suggest that some dynamic link may exist between neighborhood improvement or decline and visible biophysical changes, allowing for some time lag. In Chapter III, I investigate whether such a lagged relationship exists at the neighborhood scale between housing market conditions and vegetation density for three different metropolitan areas: Detroit, Los Angeles, and Seattle.

Finally, Chapter IV integrates the work of the first two chapters while addressing a third knowledge gap: how do the neighborhood-level social and economic drivers of vegetation change compare between different metropolitan areas with different historical contexts? There are multiple drivers that previous studies have implicated in the past production and on-going differentiation of uneven neighborhood vegetation conditions; those repeatedly identified include density and development gradients, socio-economic stratification or the "luxury" effect (Hope et al., 2003), and the "ecology of prestige" (Grove et al., 2006, Troy et al., 2007), which includes social contagion, norms, and reference group behavior. I could find no prior studies that compared these theoretical drivers between different cities or different historical or climatic contexts. In Chapter IV, I investigate whether or not these drivers can be identified from a panel of neighborhood social, economic, and housing market conditions; I also compare the drivers that are induced from the data, using a latent variable model, for their ability to explain both vegetation context and change over the period 1990-2017 for the same three study areas as before, Detroit, Los Angeles, and Seattle. These three metropolitan areas differ in their population growth regimes but also in climate.

The results of Chapters II and III were instructive for the design of the research in Chapter IV. Chapter II demonstrated that a neighborhood's metropolitan context is key to shaping the socio-ecological relationships between the neighborhood's residents and green vegetation density. Specifically, while socio-economic status (SES) is not a reliable indicator of green vegetation density in declining neighborhoods, housing market data do explain such variation between neighborhoods and also variation over time. The ability to use different measures of neighborhood conditions, whether from the Census or from housing market data, is necessary in light of the results of Chapter III, which indicated that no single metric for changing neighborhood conditions is sufficient to explain change in its biophysical conditions. Moreover, Chapter III indicates that a neighborhood's advantages or disadvantages are persistent and overwhelmingly determine long-term average vegetation conditions. The apparent persistence of neighborhood (dis)advantages is also consistent with sporadic shocks or cyclical changes they may experience (Galster et al., 2007), such as the 2007-2009 sub-prime mortgage crisis. As Rosenthal and Ross (2015) noted, it takes multiple decades of observation before a sustained change in neighborhood fortunes can be observed and, as I demonstrate in Chapter IV, this transition is subject to historical conditions which, for many neighborhoods, can instead lead to path dependency.

## 1.2 Epistemology

New empirical analyses of the social and economic determinants of uneven neighborhood outcomes are needed in light of both historical technical limitations and gaps in existing theory. Prior work on neighborhood change has relied on survey data from the decennial U.S. Census, which limits our insight into neighborhood conditions to 10-year intervals, with an unrealistic expectation of linear change between survey years. In addition, although the theoretical developments in the social sciences regarding neighborhoods have been substantial and varied, they do not sufficiently describe how individual-level or household-level changes give rise to meso-scale or neighborhood-level biophysical changes. **How do residents affect their environment?** Much more attention has been paid to how the environment affects residents (e.g., Wilson and Kelling, 1982, Lee et al., 1994, Sampson et al., 2002), how residents influence one another's environmental behaviors (e.g., Nassauer et al., 2009), or to the changing resident population irrespective of their links to the biophysical environment in which they live.

Conversely, in the land system sciences, those scholars concerned with land changes have been reluctant to theorize, preferring descriptive or statistical assessments of change consistent with a bottom-up or inductive approach to knowledge generation (Turner II, 2018, personal communication). Still other analyses have used simulation or agent-based models to test the bounds of available theories. In between bare, statistical descriptions of urban change and a relevant "grand narrative" of urban land change is *middle-range theory*, which has recently been promoted by prominent scholars in the land system sciences as a way of advancing our understanding of the drivers of land changes through "contextual generalizations" of specific causal chains (Meyfroidt et al., 2018).

Consistent with middle-range theory, the approach in this dissertation is to use statistical inference as a guide to identifying and understanding potentially novel socio-ecological changes occurring in multiple study systems. This exploratory, data-driven effort seeks to clarify how socio-economic change gives rise to biophysical changes at the neighborhood level, which necessitates large spatial scales and long times series records. Central to the approach of this research is the use of moderate-resolution, time-series satellite remote sensing of land-cover change, which brings significant benefits including a synoptic view of metropolitan landscape change over multiple decades (Wulder et al., 2012). Despite the limited spatial resolution and the blurring of distinctions between different types of vegetation and their different qualities relevant to ecosystem services, the value of earth observation for studies of landscape change, even in urban areas, has yet to be surpassed. Alternatives, including ground-level surveys or inventories generated from small-area, high-resolution commercial photography, are costly and do not provide the temporal coverage necessary to understand ecological change (Kennedy et al., 2014) nor the spatial coverage necessary for comparative studies.

There are, however, real limits to our ability to infer social and economic processes from observed physical changes and such inference is dependent on a number of factors:

- The spatial scale and metropolitan context of the changes that are thought to drive spatial variation in vegetated cover **(Chapter 2);**
- The historical trajectory and baseline conditions of a neighborhood undergoing socio-ecological change **(Chapter 3);**
- And the historical, structural conditions that led to the observed disparities

in urban vegetated cover today **(Chapter 4).**

Complementing the remotely sensed data are measures of neighborhood social and economic conditions. As discussed, the U.S. Census Bureau data are too infrequently collected to be useful in describing dynamic neighborhood changes; the spatial extent, too, is limited, in that they summarize over relatively large and arbitrarily defined neighborhood boundaries. Housing market data, specifically deed sale and tax assessor records, complement the U.S. Census data and provide much higher spatial and temporal resolution, but they are comparatively sparse descriptions of neighborhoods conditions. This research attempts to use the full potential of all three data sources.

# CHAPTER II

# Housing Market Activity is Associated with Disparities in Urban and Metropolitan Vegetation

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## 2.1 Introduction

Urban vegetation in the form of lawns, parks, and tree canopy cools neighborhoods, reduces stormwater runoff, cleans the air, and improves quality of life for urban residents. Yet urban vegetation is often distributed unevenly among residents, creating social disparities in access to these important benefits. In growing cities, higher household income or wealth enables residents to choose larger lots, purchase more extravagant landscaping, and live closer to green spaces, all of which signal higher prestige and further segregate access to scarce urban greenery. On the other hand, cities with declining populations and investments typically experience housing abandonment and the breakdown of the built environment, which in temperate climates often result in buildings covered or displaced by overgrown shrubs, grasses, and trees. Because of these countervailing influences, we cannot draw simple conclusions about the social and economic processes (for example, income segregation, sorting by lot size, neighborhood turnover) that lead to social disparities in urban vegetation without expanding the scope of cross-sectional studies of correlations between vegetation and income to include richer descriptions of the social environment and its changes through time.

Our aim is to improve understanding of the link between spatial patterns of urban vegetation and socio-economic change through new empirical work. First, we improve on existing measures of social conditions. Although socio-economic status (SES), particularly household income, has been shown repeatedly to relate strongly to the spatial distribution of environmental amenities like trees and parks (Patino and Duque, 2013, Schwarz et al., 2015), understanding the processes producing these associations requires direct observation of neighborhood social and economic conditions over time. However, decennial US Census or American Community Survey (ACS) data (commonly relied on for SES measures), although of great value to the study of multi-decadal neighborhood changes, have limited use for studies of gradual or highly dynamic neighborhood change due to their lack of temporal granularity. Here, we test new measures of social conditions that better characterize neighborhood biophysical conditions and can be linked to fine-scale, continuous measures of vegetation change from remote sensing.

We also assess how the relationship between urban vegetation and SES varies (1) across geographic scales and (2) between different urban contexts. Few studies have pursued these questions despite the recognition of both within-city and between-city differentiation in land management patterns (Pearsall and Christman, 2012, Polsky et al., 2014). We question whether the findings from existing studies of urban vegetation and SES in growing cities generalize to shrinking cities (cities with declining population) or legacy cities (cites experiencing deindustrialization or which experienced other severe economic restructuring). Although there is reasonably good theory to describe the effects of neighborhood change and vegetation in places undergoing urban growth, the ecological consequences of urban decline or revitalization in cities have received comparatively little attention (Großmann et al., 2013). Even within a single city, neighborhood socio-ecological conditions vary dramatically. We can hypothesize that, while well-established socio-ecological relationships—in particular, that vegetation density increases monotonically with SES measures—may hold at broad spatial scales, there is fine-scale heterogeneity that is masked in pooled, metropolitan-wide studies. As a result of the aforementioned conceptual and technical limitations, our understanding of the connection between vegetation and neighborhood conditions is tenuous, as is our understanding of the factors that drive changes in this association over time.

In this paper, we compare SES patterns with new measures of social conditions derived from real estate inventory data and other parcel-level sources: sale prices, tax foreclosures, new housing construction, demolitions, and the balance of construction and demolition. We expected that these more spatially, temporally, and semantically refined measures of neighborhood housing markets would also have stronger associations with the distribution of urban vegetation. We focused on Detroit, Michigan, a city that figures prominently in the sparse literature available on urban vegetation and decline (Emmanuel, 1997, Ryznar and Wagner, 2001, Hoalst-Pullen et al., 2011), but with a metropolitan area that had yet to be examined under the same lens. Although both the City of Detroit and its surrounding metropolitan area are shrinking (Figure 2.1), neighborhood conditions vary, with some neighborhoods experiencing net growth and new suburban development. To facilitate comparison with US Census measures, we investigated cross-sectional models of Census districts in three time periods and at two scales: between the City of Detroit and the wider metropolitan area, here defined as the three counties that include or are adjacent to the City of Detroit (Wayne, Oakland, and Macomb counties). We also investigated whether the new, property-level measures of social conditions demonstrate a stronger association with vegetation change than Census measures. Taken together, these contributions allow investigation of the mechanisms that drive the association between vegetation and neighborhood conditions and how those mechanisms might operate differently in different cities.

Our results demonstrate, first, that linear relationships between income or home values and urban vegetation, though evident at a broad metropolitan scale, do not explain recent patterns of vegetation density within the City of Detroit. Second, we find that the housing market and demolition rate measures demonstrate a stronger relationship with changes in vegetation density than corresponding changes in US Census measures like income, which suggests they hold at least as much interest for explaining the relationships between biophysical changes and neighborhood change processes.

### 2.1.1 A Framework to Integrate Social and Biophysical Changes

Spatial variations in urban vegetated area have long been associated with such social factors as population density, income, and prestige. In particular, home val-

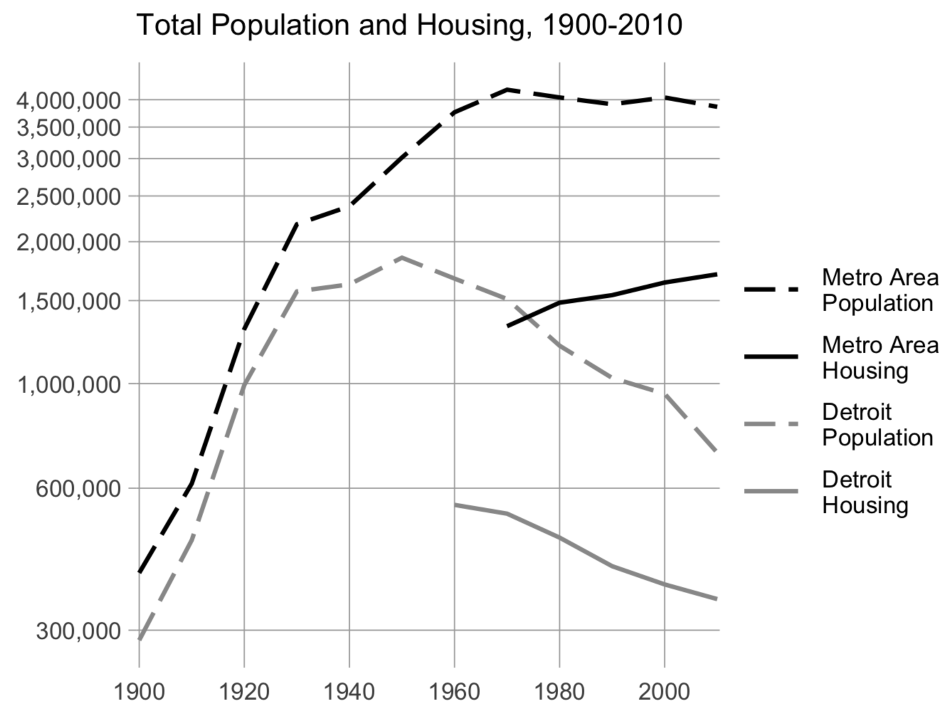


**Figure 2.1:** Population and housing totals taken from the US Census Bureau Decennial Census of Population and Housing, filled in with totals from Social Explorer (SocialExplorer.com) where necessary. Here, the Metro Area is defined as Wayne, Oakland, and Macomb counties. Dashed curves indicate population totals and solid curves indicate housing totals.

ues and socio-economic status (SES) have consistently been associated with higher vegetation densities (Patino and Duque, 2013) and a recent comparative study of tree canopy cover in multiple US cities summarized this well-established relationship as “trees grow on money” (Schwarz et al., 2015). This “ecology of luxury” has prompted concerns about green space access for certain socio-economic and demographic groups (Clarke and others 2013). The “ecology of prestige” (Grove and others 2006, 2014), by contrast, explains unevenness in the spatial distribution of urban vegetation as primarily due to differences in lifestyles or life stages between households or neighborhoods. Because trees are long-lived and a neighborhood’s income and demographic composition changes over time, a “legacy effect” on the amount and type of urban vegetation has also been documented (Locke and Baine 2015). A long and precise time series record of neighborhood conditions, as offered with the datasets used here, could allow for investigation of legacy effects in the links between social and vegetation patterns in ways that are not possible with Census data alone.

What SES measures like income fail to capture about neighborhood conditions are the associated housing market conditions and their dynamics that more directly reflect the value of properties that people occupy and manage. Income is a highly mobile quantity; it can move with residents in and out of neighborhoods; and its relationship with vegetation and the built environment is likely more complex than previous studies have acknowledged (as noted by Grove et al., 2014) High incomes facilitate high vegetation densities (for example, through larger parcel sizes, more extravagant lawns, and so on) but much of a neighborhood’s biophysical elements—building setbacks, street and sidewalk size and configuration, street trees—are essentially fixed once they are laid down. Large setbacks, large parcel sizes, close proximity to urban parks, and a dense urban tree canopy are all signals of wealth and prestige rather than those of incomes per se. Household income is also inadequate in describing wealth, as there is substantial heterogeneity within neighborhoods and between households, for a fixed level of income, in terms of the factors that determine wealth (including debts and generational wealth) and which make wealth itself hard to measure. Home values, to the extent that they are accurately reflected in sale prices, convey information about the physical condition of the housing stock, amenities and disamenities in the neighborhood, the residents (in terms of what they can afford), as well as market signals related to care and maintenance of properties.

Sale prices and other housing market variables therefore convey social, economic, and biophysical conditions in changing neighborhoods. These market variables are available on monthly or yearly intervals and can be tied to individual residential parcels. As high-resolution spatio-temporal data on neighborhood conditions, they enable us to investigate dynamic neighborhood changes in new ways and to link theories of neighborhood change to observed biophysical changes (Hoalst-Pullen et al., 2011). Census measures will continue to play a role in such studies, as it is not possible to understand the socio-ecological relations of a neighborhood without understanding the wider urban context. The exact socio-ecological relations in any one city may not generalize to others, particularly across climatic and cultural gradients, but the differences within a city are just as important as the differences between cities (Polsky et al., 2014). What these new variables provide are the data needed to understand multi-scale, dynamic neighborhood changes that may operate differently across neighborhoods and between cities.

## 2.2 Background and Study Area

Our study area, Detroit, Michigan, can be contextualized in a number of different ways. Detroit can be seen as an extreme case of Rust Belt deindustrialization, a so-called legacy city, or as part of a broader trend in shrinking cities across the USA. These two characterizations refer to different pathways with similar physical outcomes (for example, abandoned buildings, vacant lots, under-utilized infrastructure). They include different social and economic processes (Haase et al., 2014) that commonly involve the migration of human capital, financial capital, and/or economic opportunities from one neighborhood, city, region, or country to another. Some scholars have framed this migration as movement from the city center to the periphery, which is certainly true for much of Detroit's history. Present-day Detroit is also grappling with broader industrial and economic trends affecting the automobile industry.

We refer to Detroit as a shrinking city as it is embedded in a regional and state-wide context of population loss. The term "shrinking city" is favored here because the mechanisms we identify are related to population and housing loss, but also because the term refers to a widely recognized theme of research in the USA and particularly in Europe, where some cities exhibit shrinkage due to demographic changes that are not necessarily implied in the characterization of legacy cities. Our study is also multi-scalar, as measuring shrinkage itself is scale dependent (Franklin, 2017). In shrinking cities, some neighborhoods may be stable or growing, retaining their housing stock and maintaining or increasing home values, while others may be in decline, losing homeowners and even housing units to abandonment and eventual demolition. Detroit's decline can be traced to the relocation of manufacturing jobs in the mid-twentieth century to non-unionized Sun Belt cities, along with pernicious economic racism (Sugrue, 1996). Though centers of prestige in the urban core of Detroit were less affected, the recent subprime mortgage crisis has exacerbated neighborhood destabilization within the city while freezing or reversing growth in outlying suburban and exurban neighborhoods (Wilson and Brown, 2014). Even in the surrounding suburbs, population growth has stagnated for the past 40 years while housing development continued apace (Figure 2.1), demonstrating that population loss and urban sprawl are not mutually exclusive.

One of the most significant challenges for Detroit after the subprime mortgage crisis has been to identify where to maintain and improve its housing stock and where to transition residential neighborhoods to alternative uses. Although many of its residents have left, Detroit's housing stock—an uncommonly large number of detached, single-family homes—and much of its infrastructure remained behind. The economic vulnerability of the less-socially mobile residents who remain translates into housing foreclosure and abandonment when they can no longer afford to pay the mortgage or property taxes. Thus, Detroit's chief problem is one of entropy: the city is saddled with deteriorating foreclosed or abandoned properties scattered across too large an area for so few people. Demolition has been one of Detroit's strategies for tackling this problem since the early 1970s (Sternlieb et al., 1974). When a house is demolished, even if the foundation remains or is capped, there is more space and light available for vegetation to grow. Initially, vegetated area may be quite low, as the clearing of the parcel leaves areas of bare soil that recover vegetation at variable rates and with varying levels of vegetation quality, depending on planting and maintenance. Vegetation changes are also expected for foreclosed properties as owners may invest more or less effort in upkeep, depending on their capabilities and goals (Deng and Ma, 2015, Minn et al., 2015).

## 2.3 Data and Methods

In this study, we refer to the tri-county area of Oakland, Macomb, and Wayne counties as the "metropolitan area" and it forms the "metropolitan level" in our models. We also include the cities of Hamtramck and Highland Park, which are separate municipal entities surrounded by the City of Detroit proper, as part of the "Detroit level" in our models. The spatial extent of the metropolitan level includes that of the Detroit level.

### 2.3.1 Vegetation Abundance from Remote Sensing

Vegetated area was estimated from radiometrically and atmospherically corrected surface reflectance (SR) images from Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+). All "leaf-on" (summer-time) images matching a maximum cloud cover criterion (to facilitate interpretation of the spectral mixture space) in the years 1990 (4 images), 2000 (8 images), and 2010 (9 images) were acquired from the US Geological Survey and analyzed using linear spectral mixture analysis (LSMA). In this approach, the reflectance of any pixel in the scene—assumed to be a mixture of multiple land-cover types—is modeled as a linear combination of spectra from two or more "pure" surface materials, termed endmembers. While multiple scattering can lead to nonlinear interactions between endmembers for which LSMA is not suitable, this effect is widely thought to be of minor importance, especially in urban settings (Small, 2003, Wu and Murray, 2003). The result is a sub-pixel estimate of the vegetation abundance: the physical amount of vegetation within a pixel.

To reduce computational complexity and to improve data quality by mitigating band-to-band correlation, the minimum noise fraction (MNF, a dimension-reduction technique) is applied to the Landsat TM/ETM+ data prior to unmixing with LSMA. Sub-pixel land cover was estimated as being some fractional combination of substrate (impervious surface or soil), vegetation, and photometric shade (Small and Lu, 2006). A fully constrained least-squares (FCLS) inversion was conducted in which the abundance estimates of each land-cover type are constrained to be positive and to sum to one within each pixel. The abundance maps produced for each date were then combined in annual, pixel-wise composites by taking the median value for each abundance type. The median pixel-wise composite was found to reduce the error, described below, more than other compositing methods.

Sub-pixel vegetation abundance was validated against high-resolution aerial photographs in 2000 and 2010. In 1990, no high-resolution aerial photographs could be obtained. For 2000, a series of color-infrared digital ortho-rectified quarter-quad (DOQQ) images, taken in April of that year, were acquired from the USGS. For 2010, natural-color DOQQ images, taken in July of that year, were also acquired. 90-meter plots were randomly sampled where the available DOQQ images intersected the study area. In each sample plot, the proportion of vegetated area was estimated by manual interpretation. From the high-resolution DOQQ images, a single analyst traced polygons of all vegetated areas or all non-vegetated areas (depending on which required less drawing) within each 90-meter sample and divided the result by the total area to estimate the vegetated (or non-vegetated) proportion. The root-mean-squared error (RMSE) between the vegetation estimates manually derived and those from LSMA is used as an estimate of the error in vegetation abundance. For the 2000 composite image, the RMSE is 13.9%; in 2010, it is 11.8%. These can be interpreted as the amount of area within each 90-meter square plot by which LSMA under- or overestimates vegetation density.

### 2.3.2 Measures of Neighborhood Condition

Census data at the block-group level were acquired for 1990, 2000, and 2010. In 1990, data from the decennial US Census, Summary Tape File 3A were acquired from the Inter-University Consortium for Political and Social Research (ICPSR, 1999). In 2000, comprehensive data from the decennial US Census were acquired from SocialExplorer.com (2015). In 2010, because 2000 was the last year in which the long-form decennial census was conducted, data from the 5-year American Community Survey (ACS) in 2012, which represents an average of conditions from 2008 to 2012 (centered on 2010), were used in place of the 2010 decennial US Census. The 2012 ACS data were also acquired from Social Explorer.

In each year, only the Census variables that are commonly available across all three years were retained (namely, population density, age and sex structure, racial group proportions, housing size distribution, type of heating, and poverty rate). These measures, excluding median household income, then entered into a factor analysis in each year and at both spatial extents in order to derive minimally correlated factors to use as controls in the subsequent autoregression analyses. Variance inflation factors calculated for the weighted least-squares (WLS) models indicated no serious collinearity between Census factors and the additional contextual variables (county code, distance to central business district, and water-land ratio) nor the treatment variables.

Home sales, sale prices, notices of tax foreclosure, and year built were obtained from tax assessor and deed sales data purchased from RealtyTrac ("Assessor," "Recorder," and "Pre-Foreclosure" data in "DLP 3.0" format), a private company specializing in real estate data. Property addresses were geocoded using ESRI's ArcGIS Address Locator and spatially joined to Census block-group boundaries. As a measure for sale price, we used Census home values in 1990 but used deed sale prices in 2000 and 2010. We confirmed that deed sale prices, summarized by Census block group, have a very strong correspondence with home values measured by the Census (Pearson's correlations of 0.9 or higher). Sale prices in all years were escalated for inflation to 2010 US Dollars (USD) using the unadjusted Consumer Price Index (CPI) for housing for "all urban consumers" (Federal Reserve Bank of St. Louis, 2016). Deed sales within "arm's length" were removed from consideration. Among the recorded foreclosure events, notices of default were filtered out, leaving notices of tax sale as the primary identifier of a foreclosure event. Census block groups where no sale or foreclosure is recorded in a given year are assumed to have experienced none.

Demolitions in 2009 and 2010 were obtained from Data Driven Detroit, which, in turn, acquired the data from the Michigan Department of Environmental Quality's National Emissions Standards for Hazardous Air Pollutants (NESHAP) notification records (Data Driven Detroit, 2017). They are assumed to be a good proxy for demolitions in Detroit because they are required for virtually all types of structures, including residential homes demolished by the city. Although private homeowners may demolish their own home without a NESHAP notification, such a case is exceedingly rare. New housing starts were derived from the tax assessor data as the year of construction. Along with foreclosures, demolitions, and the balance of demolition and construction, block groups that contained no record were assumed to have experienced no event and all event totals were normalized by the total housing according to the US Census, in each block group in each year. Median home values from the 1990 decennial US Census was used in place of missing sale price data for that year. All address-level data described in this section were summarized at the block-group level in the R statistical computing environment (version 3.4.0).

### 2.3.3 Spatial Errors Models and Rank Correlations with Vegetation Change

We assumed and verified that spatial dependence is present in the vegetation density estimates at the Census block-group level. The forms of spatial dependence tested in the spatial errors models were selected by examining empirical variograms of the response and treatment variables. Our approach is to treat spatial dependence as a nuisance parameter (in a spatial errors model) rather than as a parameter of substantive interest (in a spatial lag model). This approach is justified by Lagrange multiplier tests (Anselin, 2007) conducted on the income, income-squared, and sale price models in all three years at both geographic extents, which consistently indicated that the spatial errors model was a better fit than a spatial lag formulation.

Because the spatial errors models use optimization in fitting, the covariates must be on a similar scale. As such, we transformed the median household income, median sale price, and the contextual variables outside the factor analysis (distance to the central business district and water-land ratio) to standard scores (Z-scores). The other treatment variables are all normalized by the number of housing units and are therefore numerically small. For each treatment variable, we tested several different forms of spatial dependence. The resulting models were compared in a multi-model inference using Akaike's information criterion (AIC) as the goodness-of-fit measure. Multiple testing was corrected for using Bonferroni correction. All weighted least-squares (WLS) models were fit using the linear regression function in R. All spatial errors models were fit in R using functions provided by the "`spdep`" package.

There are two parts to the central analysis. First, we determined the association between levels of vegetated area and neighborhood social conditions and housing market conditions at the city and metropolitan scales, accounting for neighborhood characteristics and spatial dependence. Second, we compared associations between change in vegetated area and change in neighborhood social and housing market conditions.

A central goal of the first analysis is to assess whether housing market variables, including data on the condition of the housing stock, better explain cross-sectional variation in vegetated area than do SES measures from the US Census, like household income. Before accounting for spatial dependence, the proportional abundance of vegetated area (summarized by Census block group) was regressed on each treatment variable, with 1- or 2-year lags as appropriate, using weighted least squares (WLS) with the total number of housing units as weights. Because of the importance of race in Detroit's housing history, we later examined potential disparities in green vegetation density between demographic groups by interpreting the loadings of Census variables onto our contextual factors and the directions and magnitudes of these effects.

To facilitate the calculation of change in Census statistics, the correlation tests between the natural logarithm of greenness change index (GCI) and Census, real estate, or demolition measures were carried out at the Census tract level, rather than block-group level (as block groups do not permit interannual comparisons). For this analysis, data from the 2000 decennial Census, described by 2000 Census tract boundaries, were cross walked to 2010 Census tract boundaries using the tract correspondence tables developed by Logan et al. (2016). Then, relevant Census measures in 2000 were subtracted from their 2010 counterparts. Differencing the real estate and demolition data were achieved by summarizing these address-level data by 2010 Census tract boundaries and then subtracting aggregates in each year or calculating derivatives. Spearman's rank correlation (Spearman's rho) was then calculated between log GCI and each variable of interest. Confidence intervals for Spearman's rho were calculated in R (version 3.4.0) using Fisher's z-transformation, available in the "`mada`" package in R.

## 2.4 Results

The initial WLS models demonstrated reasonably good fit to the data (adjusted $R^2$ values $\geq 0.56$ at the metropolitan level) using only contextual factors, which indicates a good baseline model (Table 2.1). Model fit is comparably lower at the city level (adjusted $R^2$ values ranging from 0.37 in 1990 to 0.25 in 2010). A list of the treatment variables, their effect sizes, and significance, averaged across the multiple SAR error models, can be found in Table 2.2.

### 2.4.1 Comparing Associations with Vegetated Area

Consistent with previous studies, our results indicate that sale prices and household incomes have strong, positive associations with vegetated area across neigh-

**Table 2.1:** Model fits from WLS models with the same-year median household income treatment. Here, the base model is the model with contextual variables only.

| Geographic Scale | Year | Base Adj. $R^2$ | Adj. $R^2$ with Income | Improvement (%) |
|---|---|---|---|---|
| Detroit | 1990 | 0.367 | 0.388 | 2.14% |
| Detroit | 2000 | 0.327 | 0.346 | 1.96% |
| Detroit | 2010 | 0.242 | 0.244 | n.s. |
| Metropolitan Area | 1990 | 0.637 | 0.682 | 4.46% |
| Metropolitan Area | 2000 | 0.571 | 0.609 | 3.85% |
| Metropolitan Area | 2010 | 0.560 | 0.578 | 1.76% |

borhoods (Table 2.2). At the metropolitan scale, household income is a stronger covariate than all other neighborhood measures in both 1990 and 2000. However, by 2010, models with contemporary or lagging sale prices performed best. In the City of Detroit, the declining importance of income and sale price is more pronounced: by 2010, neither household income nor sale prices are significant predictors of vegetated area. Instead, demolition rates are the best predictors of vegetated area in Detroit in 2010. Foreclosures and demolitions have often been hypothesized to directly affect vegetation amount and characteristics at the parcel scale in neighborhoods (Deng and Ma, 2015, Minn et al., 2015). We found that neighborhood-scale foreclosure rates are a significant (negative) effect on vegetated area only at the metropolitan level. As expected, higher demolition rates in Detroit (in 2010) are associated with higher vegetated area. Importantly, we find that if neighborhoods that do not experience any demolition are left out of the model, demolition rates have no association with vegetated area.

**Table 2.2:** Minimum, maximum, and mean Z-scores of effect sizes along with maximum p-values for each relevant treatment among all SAR errors models in the multi-model inference, organized by model geographic extent and year. The P values are marked as significant (*) if they are less than the Bonferroni-corrected threshold of $0.05/m = 0.00625$ where $m$ is the number of tests.

| Extent | Year | Treatment | Minimum Z | Mean Z | Maximum Z | Maximum p-value |
|---|---|---|---|---|---|---|
| Detroit | 1990 | Household Income | 5.875 | 5.948 | 6.060 | 0.00000* |
| Detroit | 1990 | Household Income Sq. | 6.346 | 6.391 | 6.435 | 0.00000* |
| Detroit | 1990 | Sale Price | 8.505 | 8.781 | 9.048 | 0.00000* |
| Detroit | 1990 | Sale Price Sq. | 7.680 | 7.832 | 8.102 | 0.00000* |
| Detroit | 2000 | 2009-2010 Construction Rate | -0.106 | 0.452 | 0.825 | 0.91549 |
| Detroit | 2000 | Household Income | 4.925 | 5.365 | 5.660 | 0.00000* |
| Detroit | 2000 | Household Income Sq. | 5.032 | 5.485 | 5.743 | 0.00000* |
| Detroit | 2000 | Sale Price | 2.796 | 3.069 | 3.551 | 0.00517* |
| Detroit | 2000 | Sale Price, 1-year Lag | 2.622 | 2.948 | 3.437 | 0.00873 |
| Detroit | 2000 | Sale Price, 1-year Lag Sq. | 2.951 | 3.157 | 3.453 | 0.00317* |
| Detroit | 2000 | Sale Price, 2-year Lag | 1.719 | 1.971 | 2.260 | 0.08567 |
| Detroit | 2000 | Sale Price, 2-year Lag Sq. | 1.847 | 2.159 | 2.391 | 0.06476 |
| Detroit | 2000 | Sale Price Sq. | 3.827 | 4.110 | 4.351 | 0.00013* |
| Detroit | 2010 | 2008 Foreclosure Rate | 0.982 | 1.057 | 1.313 | 0.32628 |
| Detroit | 2010 | 2009-2010 Construction Rate | 0.002 | 0.143 | 0.344 | 0.99855 |
| Detroit | 2010 | 2009-2010 Demolition Rate | 3.110 | 3.259 | 3.428 | 0.00187* |
| Detroit | 2010 | 2009 Demolition Rate | 0.316 | 0.532 | 0.743 | 0.75199 |
| Detroit | 2010 | 2009 Foreclosure Rate | 1.531 | 1.705 | 1.837 | 0.12569 |
| Detroit | 2010 | 2010 Demolition Rate | 3.329 | 3.443 | 3.569 | 0.00087* |
| Detroit | 2010 | 2010 Foreclosure Rate | -0.142 | 0.238 | 0.447 | 0.88702 |
| Detroit | 2010 | Household Income | 1.624 | 1.825 | 1.953 | 0.10440 |
| Detroit | 2010 | Household Income Sq. | 3.090 | 3.296 | 3.400 | 0.00200* |
| Detroit | 2010 | Net Change in Units | -3.359 | -3.215 | -3.065 | 0.00218* |
| Detroit | 2010 | Pre-2007 Foreclosure Rate | 0.932 | 1.460 | 1.726 | 0.35121 |
| Detroit | 2010 | Sale Price | -0.436 | 0.063 | 0.423 | 0.93870 |
| Detroit | 2010 | Sale Price, 1-year Lag | -1.107 | -0.484 | -0.246 | 0.80545 |
| Detroit | 2010 | Sale Price, 1-year Lag Sq. | -1.698 | -0.991 | -0.736 | 0.46198 |
| Detroit | 2010 | Sale Price, 2-year Lag | 1.119 | 1.440 | 1.692 | 0.26334 |
| Detroit | 2010 | Sale Price, 2-year Lag Sq. | 1.919 | 2.250 | 2.448 | 0.05505 |
| Detroit | 2010 | Sale Price Sq. | -1.467 | -0.933 | -0.541 | 0.58843 |

| Extent | Year | Treatment | Minimum Z | Mean Z | Maximum Z | Maximum p-value |
|---|---|---|---|---|---|---|
| Metro Area | 1990 | Household Income | 15.783 | 16.488 | 17.761 | 0.00000* |
| Metro Area | 1990 | Household Income Sq. | 12.552 | 13.331 | 14.623 | 0.00000* |
| Metro Area | 1990 | Sale Price | 14.352 | 14.983 | 16.166 | 0.00000* |
| Metro Area | 1990 | Sale Price Sq. | 9.379 | 10.038 | 11.206 | 0.00000* |
| Metro Area | 2000 | 2009-2010 Construction Rate | -0.900 | -0.722 | -0.584 | 0.55900 |
| Metro Area | 2000 | Household Income | 13.250 | 13.394 | 13.543 | 0.00000* |
| Metro Area | 2000 | Household Income Sq. | 10.862 | 10.988 | 11.124 | 0.00000* |
| Metro Area | 2000 | Sale Price | 9.160 | 9.284 | 9.504 | 0.00000* |
| Metro Area | 2000 | Sale Price, 1-year Lag | 8.992 | 9.155 | 9.345 | 0.00000* |
| Metro Area | 2000 | Sale Price, 1-year Lag Sq. | 8.038 | 8.173 | 8.280 | 0.00000* |
| Metro Area | 2000 | Sale Price, 2-year Lag | 9.616 | 9.791 | 9.992 | 0.00000* |
| Metro Area | 2000 | Sale Price, 2-year Lag Sq. | 8.982 | 9.118 | 9.262 | 0.00000* |
| Metro Area | 2000 | Sale Price Sq. | 8.609 | 8.744 | 8.931 | 0.00000* |
| Metro Area | 2010 | 2008 Foreclosure Rate | 0.646 | 0.902 | 1.094 | 0.51832 |
| Metro Area | 2010 | 2009-2010 Construction Rate | 0.461 | 0.546 | 0.647 | 0.64509 |
| Metro Area | 2010 | 2009 Foreclosure Rate | -2.666 | -2.368 | -2.113 | 0.03460 |
| Metro Area | 2010 | 2010 Foreclosure Rate | -3.738 | -3.534 | -3.426 | 0.00061* |
| Metro Area | 2010 | Household Income | 8.430 | 8.664 | 8.997 | 0.00000* |
| Metro Area | 2010 | Household Income Sq. | 7.798 | 8.068 | 8.301 | 0.00000* |
| Metro Area | 2010 | Pre-2007 Foreclosure Rate | 2.587 | 2.752 | 2.881 | 0.00968 |
| Metro Area | 2010 | Sale Price | 9.245 | 9.558 | 9.882 | 0.00000* |
| Metro Area | 2010 | Sale Price, 1-year Lag | 8.262 | 8.691 | 9.221 | 0.00000* |
| Metro Area | 2010 | Sale Price, 1-year Lag Sq. | 6.110 | 6.521 | 7.011 | 0.00000* |
| Metro Area | 2010 | Sale Price, 2-year Lag | 9.007 | 9.298 | 9.541 | 0.00000* |
| Metro Area | 2010 | Sale Price, 2-year Lag Sq. | 8.563 | 8.772 | 8.872 | 0.00000* |
| Metro Area | 2010 | Sale Price Sq. | 8.088 | 8.290 | 8.495 | 0.00000* |

We also fit models with a squared term for income or sale price (and lags) to see whether both high and low extremes in income or price were associated with high or low levels of vegetated area. Together with positive coefficients on the linear terms, significant and positive coefficients on the squared terms of household income and median sale price indicated that higher levels of vegetated area are, indeed, found at both the highest and the lowest levels of household income or sale price (Table 2.2). This quadratic relationship between income and vegetation is found in every year at both spatial scales. However, while sale price, squared or not, is consistently significant at the metropolitan scale, it is often not a significant predictor of vegetated area in Detroit. This suggests that although sale prices reflect broad patterns in vegetated area across the metropolitan area, local heterogeneity in neighborhood conditions within the city, time-dependent processes related to decline, or both can confound these broad trends.

We are interested in differences in effect sizes for the same model between the two geographic levels, as these would suggest scale-dependent effects on vegetated area and call into question generalizations to the metropolitan scale drawn from city-scale analyses. The average effects of household income and sale prices are relatively constant across years at the metropolitan level (Figure 2.2). In Detroit, however, the effect of income declines between 2000 and 2010 and the effect of sale price, including a 1-year lag, consistently declines between 1990 and 2010. This stark decline in effect size in Detroit is consistent with the aforementioned declining model fit, for these variables, over time and may reflect a decoupling of long-standing socio-ecological relationships as a city declines. At the metropolitan scale, these relationships persist because the contrast between the city and suburbs is so strong.

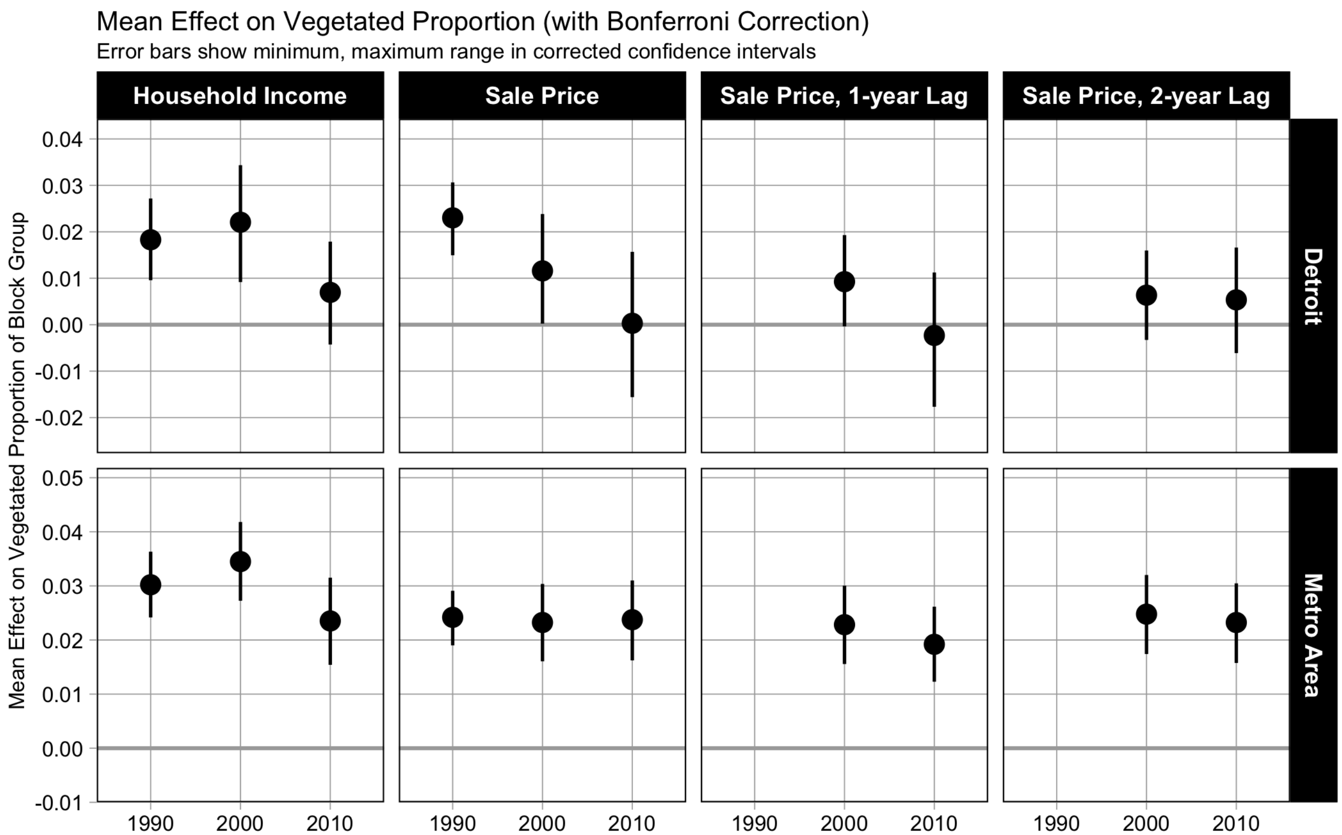


**Figure 2.2:** Mean effect sizes and minimum/ maximum confidence intervals for household income and lagged sale price from the multiple-model inference. Effect sizes are corrected for multiple testing with Bonferroni correction and can be interpreted as the change in the proportion of a block group's vegetated area for a one-standard-deviation increase in each treatment.

To facilitate meaningful comparisons, effect sizes are converted to an amount of vegetated area in acres (Figure 2.3), based on the average block-group size in each year and each spatial extent. For example, in Detroit in 2010, a one-standard-deviation increase in sale price is associated with 1.1-1.4 more acres of vegetated area in the average block group. Because foreclosures, demolitions, and new-construction-related treatments were not standardized, their effect sizes are expressed as the result of one more foreclosure, one more demolition, or one new housing unit than the average number in the average block group. Nonetheless, the magnitudes of a single parcel change in the average neighborhood, in terms of acreage of vegetated area, are only one order less than that of a one-standard-deviation increase in sale price or median household income (Figure 2.3).

In general, Detroit neighborhoods with high vegetation density but low incomes or sale prices are characterized by a high density of vacant lots (empty parcels where housing used to be) and high tree densities. High-vegetation, low-income neighborhoods increase in number in Detroit over this period. In 2000 and 2010, high-vegetation, low-income neighborhoods are increasingly found on the east side of Detroit. They generally have a high density of vacant lots but some, like Elmwood Park, also include large urban green spaces. Conversely, low-vegetation and high-value or high-income neighborhoods generally have intact housing stock (very few vacant lots). From aerial photographs, these neighborhoods appear to have slightly larger lot sizes, fewer trees, and intact housing stock. At the metropolitan scale, these neighborhoods are almost exclusively characterized by adjacency to business parks and large retail centers.

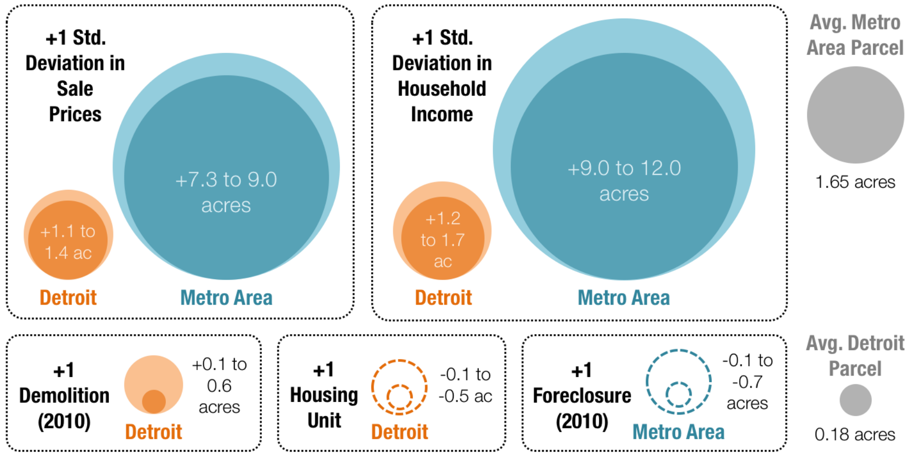


**Figure 2.3:** Range of average effect sizes across years on vegetated area, presented in terms of acres of vegetation, holding all else constant. Effect sizes are averaged in each year from across the multi-model inference. Acreage is calculated assuming the average block-group size in each year for either Detroit or the metropolitan area. Only effects that were consistently significant under all of the spatial dependence structures considered are presented here. Solid circles (and positive acreage) represent a positive effect on vegetated area; dashed circles (and negative acreage) represent a negative effect on vegetated area.

### 2.4.2 Comparing Associations with Change in Vegetated Area

Finally, we compared measures of *change* in socio-economic status (from the Census) with real estate and demolition records in regard to the strengths of their relationships with change in vegetation (the greenness change index, GCI). We calculated Spearman's rank correlation coefficients between change in the natural logarithm of GCI and three classes of neighborhood-level data: socio-economic measures differenced between the 2000 Census and 2012 American Community Survey (ACS); US Environmental Protection Agency (EPA) National Emission Standards for Hazardous Air Pollutants (NESHAP) notifications of demolitions; and the real estate inventory, including foreclosures and sale prices (Figure 2.4).

Overall, the measures derived from the demolition records and real estate inventory have stronger bivariate correlations with log GCI than Census-derived statistics. One notable exception is the change in housing density, which has the strongest relationship with log GCI for the City of Detroit and is a Census-derived statistic. Most measures exhibit much weaker correlations at the metropolitan level, which is likely due to the greater variation in neighborhood characteristics at that scale. However, we observe stronger correlations at the metropolitan level for housing increase (over the 2000 baseline), the change in the density of vacant housing, the number of new housing starts, and the first derivative of new housing starts. The foreclosure rates in any period are not strongly correlated, on their own, with log GCI at the metropolitan level, even though contemporary foreclosures had a consistent association with lower vegetation density at metropolitan scale in the multi-model inference.

How do specific neighborhoods in our study area fare differently in this period? We found that all neighborhoods in the study area increased in greenness, on average, between 2000 and 2010. Our finding of metro-wide vegetation growth is not surprising, as the construction rate in the City of Detroit is at this time is essentially zero and outside of Detroit, lower-density development patterns lead naturally toward vegetation growth and maintenance in a temperate climate. Changes in household income were not found to be significantly associated with greenness changes between 2000 and 2010 at any scale. Neighborhoods that experienced the most foreclosures between 2003 and 2010 and had the lowest increase in greenness are exclusively in Detroit and its closest suburbs. In general, these suburban neighborhoods are characterized by medium housing densities, high canopy cover, and an intact housing stock. With the exception of one Morningside neighborhood in Detroit, all of the City's neighborhoods with high foreclosure rates and low greenness change are located along the northern and eastern boundaries of Detroit

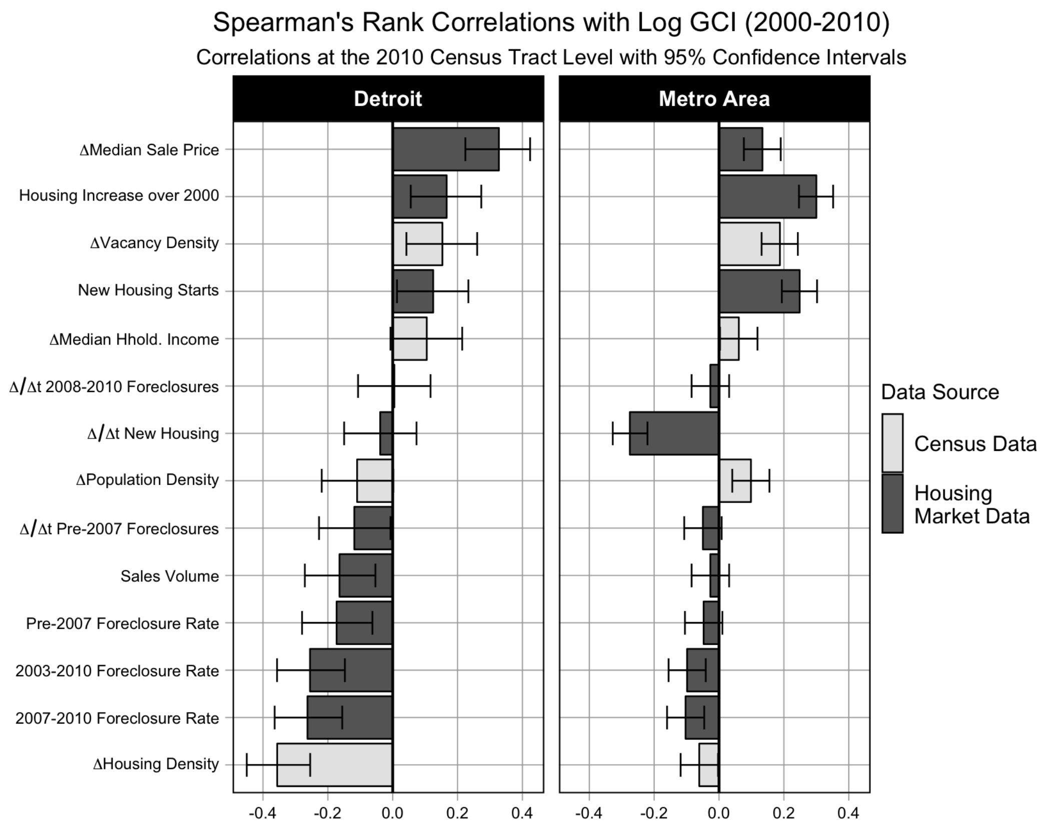


**Figure 2.4:** Spearman's rank correlations, shown with 95% confidence intervals, between log GCI and three classes of neighborhood-level measures at the Census tract level. The 2012 ACS class includes socio-economic measures that were observed in the decennial 2000 and 2012 5-year ACS surveys and then differenced. The Real Estate Inventory class includes counts of foreclosures, the number of sales, the number of new housing starts, or the change in median sale price. In general, these latter two classes have stronger correlations with log GCI. EPA NESHAP notifications are not available at the metropolitan level.

and have very few, if any, vacant lots.

Areas where sale prices increased or only slightly decreased (top quartile of home value change between 2000 and 2010, which includes both losses and gains) and that also experienced the lowest increase in greenness (lowest quartile of log GCI) include neighborhoods in Mexicantown in Detroit, Hamtramck, and neighborhoods west and north of Highland Park. Conversely, areas where sale prices increased or only slightly decreased and with the greatest increased in greenness in Detroit between 2000 and 2010 include neighborhoods situated relatively close to downtown Detroit and, with the exception of the Springwells neighborhood (which includes a very large outdoor green space), with very high vacant lot densities. Outside of Detroit, neighborhoods that maintained value and increased in greenness are exurban neighborhoods in western and northern Oakland County; these feature very large lots mixed among golf courses and forested wetlands. Previous research on exurban developments in southeast Michigan indicate they increase in greenness over time—to the extent that they are carbon sinks over the long-term—due to their large lot size and land management behaviors (Visscher et al., 2014).

### 2.4.3 Demographics and Vegetated Area

In 1990, at the metropolitan scale, neighborhoods that scored high on the factor associated with white and Asian populations (eigenvalue of 16.29) had higher vegetation densities (median model t-statistic of 4.0); this same factor was associated with high single-family and owner-occupied housing and low poverty rates. In the City of Detroit, high vegetation densities are associated with a very similar factor (eigenvalue of 10.75) but these neighborhoods have mixed white and black populations; neighborhoods that scored high on the factor(s) associated with white population proportion exclusively (eigenvalue of 2.18) or mixed white and Asian populations (eigenvalue of 1.29) actually tend to have *lower* vegetation densities in Detroit (t-statistics of -4.9 and -2.6, respectively). From this template in 1990 emerges a consistent, scale-dependent pattern in the associations of vegetation density with white and black populations that persists in 2000 and 2010. The example of 2010 proves the rule: high-black population neighborhoods in Detroit have *higher* vegetation densities (eigenvalue of 8.87, t-statistic of 4.4), whereas similar neighborhoods at metropolitan scale have *lower* vegetation densities (eigenvalue of 6.02, t-statistic of -8.7). Mixed white and Asian neighborhoods in Detroit have *lower* vegetation densities (eigenvalue of 8.37, t-statistic of -2.8), whereas similar neighborhoods at the metropolitan scale have *higher* vegetation densities (eigenvalue of 15.48, t-statistic of 4.4). Because the metropolitan model extent includes the City of Detroit, we might conclude that the unexpected (compared to previous studies) negative association between high white population scores and vegetation density is driven in large part by the pattern in Detroit. This pattern, in turn, may reflect a spatial concentration of the majority-black City's non-black residents in the more dense and more central areas. It is also apparent that, unlike socio-economic status, demographics are consistent in their associations with vegetation density over this 20-year period.

## 2.5 Discussion and Conclusions

Understanding dynamic neighborhood change processes is important because they influence how disparities in human health and well-being are created and enforced through socio-ecological interactions. Increasingly precise spatial and temporal data are available to study these dynamics (Sampson et al., 2002). Incorporating new annual, parcel-level data from real estate inventories into studies of urban socio-ecological disparities requires understanding how well these new measures of social conditions compare to US Census data, which are well established for broad, cross-sectional studies of neighborhood conditions. For these reasons, we compared how well these different measures of neighborhood conditions and neighborhood changes explain urban vegetation disparities across space and changes in urban vegetation over time.

Our analysis focused on two questions: (1) How do well-established measures of socio-economic status (SES) compare in their associations with vegetated area and vegetation change with new measures of social conditions focused on the housing market? (2) How do these associations hold up in the context of a shrinking metropolitan area and at multiple scales? We discuss the implications of our findings below.

### 2.5.1 Parcel-level Measures Link Social and Biophysical Conditions

Although household income often exhibits the strongest association with vegetated area at the metropolitan level, home sale prices are a close second. Sale prices are a good proxy for home values, which convey the physical condition of the housing stock and its neighborhood. As owning a home is often a significant portion of household equity in the USA, home values also convey some information about the wealth of a neighborhood's residents and could affect a homeowner's interest in investing in and maintaining the house and surrounding landscape. As such, home sale prices are a strong link between neighborhood socio-economic and biophysical conditions (Figure 2.3).

Demolition rates (in the City of Detroit) and foreclosure rates (at the metropolitan level) are also significant effects structuring vegetated area. Demolition has been a policy instrument in Detroit since the early 1970s (Sternlieb et al., 1974), used in neighborhoods with abandoned and deteriorated housing stock. We found that demolitions are occurring in neighborhoods with higher levels of vegetation and are associated with growth in vegetated area. Demolitions are therefore another link between neighborhood social and biophysical conditions. When we examined specific neighborhoods, we found that those with an intact housing stock (i.e., few, if any, vacant lots) tended to have low vegetation densities and high incomes, low vegetation growth (low increase in greenness), and high cumulative foreclosure rates between 2000 and 2010. This implies that stable housing stock is associated with high incomes and also that foreclosures in the Detroit area are used strategically in areas where the housing stock has not declined to the point of abandonment and demolition.

Comparing the associations of tax foreclosures with vegetation levels and vegetation change, we found that tax foreclosures typically occur in low-vegetation neighborhoods and also in neighborhoods with very little vegetation growth (in this period). However, a bivariate correlation over this length of time says nothing about whether foreclosures precede or follow vegetation change. It should be recognized that feedbacks in the urban socio-ecological system mean that many variables correlated with log GCI may be seen either as drivers of vegetation change or as driven by vegetation change. Therefore, we do not make a distinction here as to the direction of causality. In future studies, the high-frequency, parcel-level data we have introduced here will be essential for discerning the processes driving neighborhood vegetation change and the feedbacks involved.

### 2.5.2 Socio-Ecological Relationships Differ Across Scales

Our results provide new evidence of scale-dependence in urban socio-ecological relationships, highlighting important differences in the spatial patterns of vegetation between the City of Detroit and the wider metropolitan area. Although we observed consistently positive and stable associations between vegetated area and both higher incomes and higher home values across the metropolitan area, these associations are inconsistent within the City of Detroit.

Why should the well-established, invariably positive and mutually reinforcing relationship between SES and vegetated area, which persists at the metropolitan scale, be different in the City of Detroit? In some ways, Detroit neighborhoods are exceptional within the metropolitan area. Sale prices may be artificially lower in Detroit than in neighborhoods right across the city line: for instance, the same sharp discontinuities in prices can be seen across the southern and eastern boundaries that separate Detroit from neighboring municipalities.

We also find that the shape of the relationships of income and sale price with vegetated area differs between scales. At the city level, vegetated area is highest in both high-income and low-income areas (a quadratic relationship), whereas at the metropolitan level, vegetated area generally only increases with income. This finding comports with both the well-documented, mutually reinforcing relationship between social conditions and vegetation density (Patino and Duque, 2013) and the observed trend of increasing vegetation in declining neighborhoods (Hoalst-Pullen et al., 2011). In Detroit, this is clearly suggestive of the challenge in explaining the processes establishing and maintaining disparities in urban vegetation—simultaneously a luxury effect that can capitalize on larger lawns or nearby parks and the effect of ambient, possibly unwanted, vegetation that appears with increasing abandonment and demolition rates. The latter effect is evident in the association of neighborhoods that have high demolition rates with lower household incomes.

With the increasing vacant land burden due to rising demolitions, high incomes are not required to capitalize on more vegetated area, as in a classic metropolitan growth scenario. Detroit's land burden is higher than for similarly situated urban areas, and its disposition of vacant land is often considerably delayed or prevented under the current law (Dewar, 2006). Tax foreclosure also operates differently in Detroit than in surrounding municipalities and has systematically discouraged the reuse of tax-foreclosed homes by would-be owner-occupants (Dewar et al., 2014). There may also be less incentive to pursue mortgage foreclosures in Detroit due to the real or perceived quality of the housing stock and the lower demand for housing. At the metropolitan level, tax foreclosures are found to have a negative association with vegetated area, yet they exhibit no significant association with vegetated area in the City of Detroit.

This suggests that foreclosures are not consistently associated with certain biophysical conditions in Detroit neighborhoods. Lawn management practices for parcels in foreclosure have been thought to range from neglect (and overgrowth) to conspicuous maintenance (frequent mowing and trimming to maintain attractiveness). Although these processes operate at the parcel level, where the effect of neglect has been previously detected (Deng and Ma, 2015), our results suggest that either: lawn management practices associated with foreclosure cannot be detected at the neighborhood level; that both processes are operating and cancel out in the aggregate; or that there are confounding effects on vegetated area associated with other, unobserved processes. Many of these apparent idiosyncrasies may be found in other major cities, particularly shrinking cities, as property laws, the efficacy of local institutions, and local housing market activity will always vary across the metropolitan area.

### 2.5.3 Socio-Ecological Relationships May Change Over Time

There is also evidence in Detroit that income and home prices have declined as correlates of vegetation density over time (Figure 2.2), such that we might expect they no longer exhibit any relationship with vegetated area in the near future. By 2010, neighborhood demolition rates and the net change in housing are better predictors of vegetated area in Detroit than household income or home sale prices. This suggests that widely theorized, wealth-related processes for allocating urban vegetation—the consumption of landscaping or larger lawns by private homeowners, the development of public green spaces in wealthier areas—play a diminishing role in shrinking cities. Though we only have demolitions data for the Census year 2010, it is evident that more demolitions are strongly related to increased vegetated area in Detroit neighborhoods.

This declining association between socio-economic status, as measured by income or home value, and vegetated area in Detroit (Figure 2.2), is inconsistent with the suggestion of Lowry et al. (2012) that the passage of time would strengthen income-vegetation relationships. It can be understood, however, in the context of a declining city like Detroit, where both population size and the capability to maintain residential land are declining. Urban neighborhoods can be theorized as complex adaptive systems, characterized by feedback loops: home value appraisals are based on recent sales nearby, low home values present a barrier to accessing credit for home improvements, and municipal (dis)investment in services is both a driver and a consequence of the available tax base. As social and economic feedback loops break down due to population loss and declining investment, the reproduction of certain socio-ecological relationships will also inevitably decline. This is more consistent with the hypothesis of Watmough et al. (2013) that correlations between socio-economic status and land cover are weaker in rural areas because local population-and-environment links are more complex. Luck et al. (2009) also suggested that socio-economic factors have less influence in less established neighborhoods. In general, this result suggests that socio-economic status is unreliable as a predictor of the vegetation distribution for all cities and all spatial scales. In particular, relationships of vegetation patterns to socio-economic condition in declining cities and at the metropolitan scale may not be well-approximated by studies of growing cities at the city scale. Additionally, it points to the need for more spatially and temporally detailed investigations of neighborhood change that can support process-based explanations of socio-ecological change in urban neighborhoods. Such studies can be supported by the new measures presented here.

# CHAPTER III

# Comparing Associations between Residential Neighborhood Change and Vegetation Growth across U.S. Metropolitan Housing Markets

## 3.1 Introduction

Urban areas arise from multiple coordinated or competing social and economic activities to satisfy human needs (Batty, 2008). The connection between these activities and the local environment is clearly expressed through zoning, residential land management, and the siting of environmental amenities and disamenities (Chowdhury et al., 2011). In the United States (U.S.), where a separation of land uses has been the norm, there are clearly visible differences between urban lands designated for residential, industrial, or commercial uses. This spatial separation of urban land uses and associated differences in the types and amounts of land cover (e.g., trees, lawn, pavement) have demonstrated, though inconsistent, associations with neighborhood socio-economic status, household lifestyle or life stage, education levels and racial composition, as well as the age of the housing stock and residential vacancy rates (Grove et al., 2014, Schwarz et al., 2015, Endsley et al., 2018).

Similarly, the spatial arrangement and timing of changes in urban land cover, such as in built area or vegetation cover, can serve as indicators of human activities and underlying socio-economic processes: land is cleared for new housing or retail development, areas already developed exhibit changes in land management or vegetation phenology over time, and some areas are abandoned or redeveloped (Wilson and Brown, 2014). By observing changes in urban land cover, we can draw inferences about changing patterns of wealth, public and private investment, and residential occupancy in cities—all of which influence neighborhood dynamics such as growth, decline, infill, or urban renewal (Hoalst-Pullen et al., 2011). New information about neighborhood dynamics is critical for understanding the on-going spatial differentiation of housing conditions and quality of life—particularly the quality of the urban residential environment and its sustainable development—in contemporary cities in the U.S.

Despite a wealth of hedonic pricing, environmental justice, and urban geography studies that demonstrate strong associations between neighborhood socio-economic and biophysical conditions, considerably less attention has been paid to neighborhood change, particularly over multiple decades (Galster et al., 2007, Williams et al., 2013, Delmelle, 2016), and to associations between socio-economic change and biophysical change. Moreover, available socio-ecological theories on the subject of neighborhood change, such as homophily, broken windows theory, or "cues to care," are concerned only with the changing demographic or socio-economic profile of a neighborhood's residents, not with the landscape or the built environment. Such theories either fail to engage with the physical changes in neighborhoods most relevant to urban sustainability (e.g., in vegetation condition, in air and water quality) or are concerned with too small a scale to be generalizable across and between metropolitan areas.

Understanding the social and economic factors that give rise to certain neighborhood biophysical changes is essential to bounding expectations for sustainable residential development (Batty, 2008, Brelsford et al., 2017). The effect of social and economic change on the amount of green vegetation should be of particular interest, as vegetation provides numerous benefits to an urban population. Trees and shrubs of urban parks and residential landscapes improve air and water quality by directly intercepting air pollutants, delaying run-off from precipitation, and filtering run-off from the urban stream. Shade from trees can cool buildings directly and, through evapotranspiration, reduce the urban heat island effect. Urban green spaces also provide psychological and social benefits to residents, chiefly in the form of recreation opportunities but also through the passive consumption of eye-pleasing, green views. For all of these reasons, urban trees in the U.S. have been estimated to provide a $3.8 billion ecosystem service (Nowak et al., 2006). The preferences of homeowners and retailers for a particular kind of green space, turf grass lawns, have made it the top irrigated crop in the U.S. by area (Milesi et al., 2005), despite the high water inputs required to maintain it and the extensive urban sprawl it accompanies.

Thus, growing and maintaining urban vegetation is essential for sustainable transitions in our residential landscapes (Ripplinger et al., 2017). Yet, over the past several decades, metropolitan neighborhoods have been subject to dramatic fluxes both in and out of residents and investment capital. In the U.S., this has taken the form of capital flight and urban sprawl in the mid-twentieth century and more recent reversals to this historic pattern in the forms of gentrification and suburban poverty. **How has neighborhood vegetation density changed with**

**these reversals in neighborhood fortune?** This study investigates the association between neighborhood decline or improvement and change in vegetation density over multiple decades and is concerned with the questions:

**Q1.** Can we distinguish between declining, stable, and improving neighborhoods by their different land-cover change trajectories?

**Q2.** Do upward-transitioning (improving) or downward-transitioning (declining) neighborhoods tend to become greener or less green over time?

While satellite remote sensing has long been used to study urban land changes related to development and environmental conditions, it is only recent improvements in technology and new data policies that have made possible studies of land surface changes over multiple decades at fine spatial and temporal scales (Chowdhury et al., 2011, Wulder et al., 2012). At the same time, new parcel-level datasets are becoming available for neighborhood studies at fine spatial and temporal scales, both through the curation and licensing of administrative records by private companies (such as Attom Data Solutions or CoreLogic) and through the publication of records obtained in processes such as Freedom of Information Act (FOIA) requests. This study combines the long-term, continuous monitoring of urban land cover from the Landsat program with high-resolution deed sale and tax assessor records for three metropolitan areas across the U.S.: Detroit, MI; Los Angeles, CA; and Seattle, WA. These three areas differ not only in the timing and extent of their growth and development but also span different climate and precipitation regimes.

### 3.1.1 A Conceptual Model of Continuous Neighborhood Socio-Ecological Change

This study seeks to provide an empirical link between neighborhood socio-economic change and vegetation change at neighborhood scale. It complements efforts by demographers to identify common pathways of neighborhood or municipal change (Delmelle, 2017, Franklin, 2017) and builds on previous land system science studies that use changes of the land surface and built environment to infer changing patterns of wealth or development (Seto and Kaufmann, 2003, Weeks et al., 2007, Robinson et al., 2009, Wilson and Brown, 2014). There are also important contributions in neighborhood change from urban sociology, though few theories have described a link specifically between social and physical changes. An "inextricable" and "developmental" link between physical disorder (e.g., graffiti, litter, abandonment) and social disorder (e.g., crime) originated in the eponymous "broken windows" theory of Wilson and Kelling (1982) but has since been elaborated in conceptual models of informal social control and seemingly invisible, collective efforts by residents to impose both physical and social order in their neighborhoods (Johansen et al., 2015). Crime is frequently the target of theories of neighborhood change, and the deleterious filtering of neighborhood housing stock is seen as another process of physical disorder that inevitably gives rise to social disorder and crime (Hipp et al., 2018).

Urban vegetation plays a key role in these studies, for it has been taken both as a sign of physical order and disorder. Again, informal social control is often the aim of some neighborhood greening programs, particularly those that espouse well-manicured turf grass lawns, which, at the opening of the twenty-first century had become the top irrigated crop in the U.S. by area (Robbins, 2007, Polsky et al., 2014). In such landscapes, conspicuously maintained vegetation is one of many "cues to care" (Nassauer et al., 2009) communicating social norms through environmental indicators and is seen as part of maintaining order in communities (Troy et al., 2016). Yet, dense canopy and shrub cover have historically been blamed for increasing crime rates because they purportedly give cover to criminals. More recent scholarship, particularly in disadvantaged neighborhoods where signs of physical disorder are rampant, has found that high vegetation density is typically associated with lower crime (Troy et al., 2012, 2016) and that deliberate neighborhood greening on the part of residents directly catalyzes efforts to combat crime (Sadler et al., 2017). Regardless of their conclusions, what all of these studies have in common is the premise that vegetation cover and social conditions are inter-dependent.

The most extreme examples of coupled neighborhood socio-ecological change from a U.S. metropolitan context come from declining neighborhoods in the "Rust Belt" (Burkholder, 2012), which—due to a host of factors including economic racism, systematic disinvestment, and deindustrialization—have seen significant losses in the housing stock of many neighborhoods due to neglect, abandonment, and demolition. Conversely, most studies of urban land-cover change have historically been concerned with urban growth, i.e., the conversion of undeveloped land into residential, commercial, or industrial buildings. Spatially differentiated growth and decline occur simultaneously, and the flows of people and development capital both *into* and *out of* neighborhoods are the social and economic changes that are most strongly connected to land conversion (Smith et al., 2001). That growth and decline are twin processes is evident in divergent metropolitan fortunes, where even in shrinking cities certain neighborhoods are hit much harder by an economic downturn than others (Couch et al., 2005, Hollander, 2010), and where the housing stock itself becomes an instrument of speculative financial capital (Akers, 2017).

Although stocks and flows of human, financial, and social capital are implicated in theories of change at neighborhood scale (Delmelle and Thill, 2014), the aforementioned theoretical developments only implicate processes that operate on the small scale: from a single parcel to a single neighborhood block; they do not readily generalize to describe socio-ecological changes that can be compared across neighborhoods and between metropolitan areas. One theoretical model of neighborhood change that has been adopted for the study of associated biophysical changes at *neighborhood scale* is Hoover and Vernon's (1959) life cycle model (Hoalst-Pullen et al., 2011), and this model has also been used as a starting point for investigating long-term, sustained changes in neighborhood fortunes (Delmelle, 2016). As Figure 3.1 illustrates, a certain amount of (unspecified) land-cover change might be associated with the distinct phases of the neighborhood life cycle; as the capital investment of a neighborhood (e.g., the value of the housing stock) changes, lagged or leading land-cover changes can be observed. For example, in the "thinning out" stage, a neighborhood's loss of its housing stock (through abandonment and demolition) may be accompanied by a net increase in pervious surface and vegetated covers (Endsley et al., 2018, Chapter II, this volume). Recent work in Detroit has shown, similarly, that different rates of impervious surface change can be attributed to different socio-economic conditions (Wilson and Brown, 2014).

Thus, there are multiple pathways for neighborhood change to influence vegetation change, as well as the reverse. **In this study, the pathway expected**

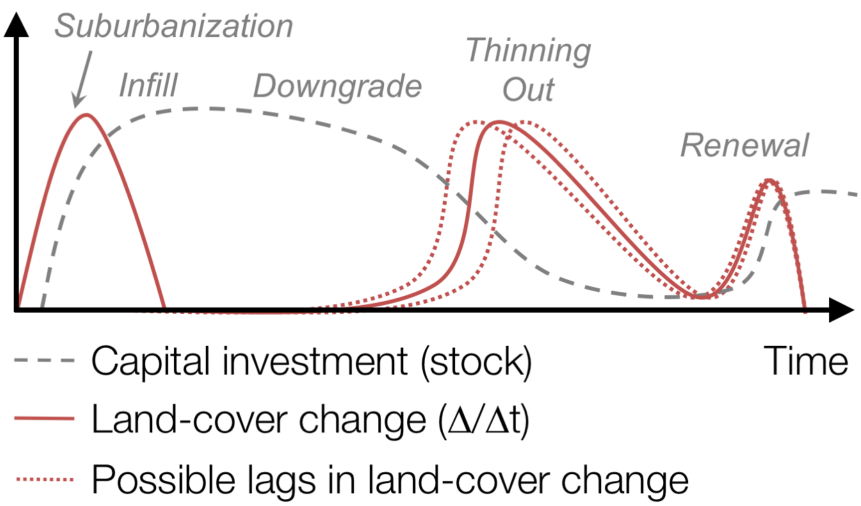


**Figure 3.1:** A conceptual diagram showing the land-cover change (in absolute terms) potentially associated with different phases of Hoover & Vernon's (1959) neighborhood life cycle.

**to predominate depends on the scale of the analysis.** At neighborhood scale, the flows of people and development capital between neighborhoods is expected to change the balance of land cover over time. At parcel scale, it is price feedbacks from green vegetation amenities that are expected to contribute (positively) to change in home values. From this conceptual model and our knowledge of urban socio-ecological systems, **we can formulate a few hypotheses about coupled vegetation and socio-economic changes in residential areas across the three metropolitan areas of this study:**

**H1.** In the arid climate of Los Angeles, as people and capital flow into improving neighborhoods and out of declining neighborhoods, human-vegetation relations that sustain green vegetation density will strengthen in improving neighborhoods and weaken in declining neighborhoods. This will result in lagged increases in vegetation density in improving neighborhoods and lagged decreases in vegetation density in declining neighborhoods.

**H2.** Conversely, in the temperate climates of Detroit and Seattle, the weakening of human-vegetation relations in declining neighborhoods will lead to lagged increases in vegetation density that are either indistinguishable from the lagged investments in vegetation growth of improving neighborhoods or exceed the rates of vegetation growth in improving neighborhoods (i.e., vegetation growth will be *faster* in declining neighborhoods).

**H3.** Home values tend to appreciate just as vegetation tends to expand over time. The amenity value of green vegetation will give rise to a positive association between increases in greenness and increases in price, except within the City of Detroit, where a high degree of abandonment and demolition has fundamentally changed the hedonic calculus with regards to green vegetation.

### 3.1.2 Defining Metropolitan Neighborhood Change

While monthly to annual observations of neighborhood vegetation conditions can be obtained through satellite remote sensing, measures of population and housing changes are difficult to obtain at a similar frequency. The U.S. Census Bureau provides a wealth of information on neighborhood conditions, but only every 5 to 10 years. This necessitates the use of unconventional datasets. This study uses deed sale and tax assessor records, which provide information on changes in neighborhood home values at a monthly or annual rate, and defines the median price-per-square foot of housing as a proxy for the condition of a neighborhood's housing stock condition. Normalized for the built area of the house, it is expected that, while prices do respond to demand for housing, differences in the rate of change of home values across a metropolitan area will reflect changes in local demand.

As current and prospective home-buyers are likely to be more socially mobile, it is assumed that they will respond to the condition of the housing stock, in addition to location characteristics, when making a choice to buy housing. Furthermore, since Frederick Law Olmstead first noted that properties adjacent to New York's Central Park appreciated faster than others farther away (Herrick, 1939), it has become widely established through hedonic pricing studies that home values are strongly associated with vegetation cover as one of many locational attributes of housing stock (Geoghegan, 2002, Irwin, 2002). This study investigates whether or not growth in vegetation cover, as a locational attribute, is also associated with change in home values.

## 3.2 Data and Methods

To test the hypotheses laid out and more generally detect an association between continuous neighborhood socio-economic and vegetation changes: 1) Unsupervised clustering methods are used to derive a data-driven neighborhood change typology that can be compared to vegetation change outcomes (i.e., is there a relationship between neighborhood change typology and vegetation change?); 2) A formal, spatially explicit, repeat-sales model is developed to test whether local changes in residential sale prices can be explained, in part, by local changes in greenness. Part 1 addresses question Q1 and tests hypotheses H1 and H2 by examining correlations between lagged price and greenness trends across canonical neighborhood change types. Part 2 addresses question Q2 and hypothesis H3, assuming that upward-transitioning and downward-transitioning neighborhoods increase and decrease in sale value, respectively.

### 3.2.1 Study Areas

The metropolitan areas featured in this study were chosen for a variety of reasons. Detroit, MI is perhaps the most severe example of a “legacy” or “shrinking” city in the U.S.; despite growing to almost 2 million people by 1950, it has since lost more than half of its peak population and the unusually high density of single-family homes within its borders has dwindled considerably due to abandonment and demolition. Los Angeles, CA, in contrast, has grown steadily throughout its history and, due to natural physical barriers and municipal fragmentation in the twentieth century, has a higher development density than Detroit. It is also an arid, precipitation-limited climate, where green, photosynthetic vegetation is scarce. The City of Los Angeles has grown much more slowly in recent years than in its past but Seattle, WA, which experienced a downturn in population 40 years ago, is today one of the fastest growing major U.S. cities.

Climate differences between these areas are salient to the motivation and analysis of this research. While Los Angeles receives less than half an inch of rainfall during a typical northern hemisphere summer, Seattle typically gets 3 or more inches and Detroit more than 9 inches of rainfall in the same season, according to the National Oceanic and Atmospheric Administration’s 1981-2010 climate normals. The cities are much more similar in temperature, with Los Angeles and Detroit ranging from a summertime minimum of about 62 degrees F to 81 degrees F; Seattle is slightly cooler, ranging from 56 to 74 degrees F.

In this study, I consider not just the urban core but the wider metropolitan area. While any urban system boundary definition is somewhat subjective, this choice allows us to consider a full urban-to-rural gradient around each city and therefore includes a wide range of parcel sizes and housing characteristics. In Los

Angeles and Seattle, I examine neighborhoods within the Metropolitan Statistical Areas (MSAs), as defined by the U.S. Census Bureau; due to a lack of deed record coverage in part of the Detroit-Warren-Dearborn MSA, I use the "tri-county" area of Wayne, Macomb, and Oakland counties as Detroit's "metropolitan area," instead. The Detroit metropolitan area does span a similar range of development to the Seattle and Los Angeles MSAs and also contains the vast majority of the housing stock in the wider Detroit-Warren-Dearborn MSA.

Neighborhoods are widely understood to be socially constructed units whose boundaries vary with the multiple subjective viewpoints of residents and scholars (Lee et al., 1994). Administrative units and Census enumeration districts are commonly used but result in neighborhoods with a considerable range of sizes and shapes that may bias landscape measures obtained in those areas. Here, the underlying deed sales are point-level data, which gives us the flexibility to define neighborhood boundaries in a rigorous way; although, ultimately, it is no less arbitrary than the majority of population enumeration districts that have been proposed. I chose to define neighborhoods on a regular grid, with a grid spacing chosen so as to minimize the spatial autocorrelation between neighborhoods. This boundary definition proceeds from plotting the semivariogram of individual home sale values. As expected, the distance over which home sale values are correlated differs between metropolitan areas according to their relative development densities. I chose a 1-km grid spacing for the Los Angeles MSA, 1.5-km for the Seattle MSA, and 2-km for the Detroit metropolitan area.

### 3.2.2 Median Value of Neighborhood Housing Stock

Data on neighborhood median home values, new construction, and tax foreclosures are obtained from deed sale and tax assessor records collected and licensed by CoreLogic, Inc., based on the administrative records that are publicly available through the various municipal and county offices of each study area. Home values are defined based on eligible residential property sales rather than assessed values, as the latter are often subjective and based on inconsistent valuation criteria (Correll et al., 1978). Eligible property sales are defined as "arm's-length" sales, i.e., sales where both parties (buyer and seller) are resolved to obtain the best deal possible because they are not related by blood or marriage and the property's tax or mortgage status is not in question. To this end, certain deed types associated with next-of-kin transfers, foreclosure, or repossession by the lender were excluded. Suspect deed types are evaluated with respect to the norms for each metropolitan area; for instance, quit-claims are likely to represent foreclosures in the Detroit housing market but are a more general form for conveying real estate in the Western U.S. In addition, I disregard sales in the top and bottom 0.1% of adjusted price in each market as well as those sales which are flagged as foreclosures or non-arm's length sales by CoreLogic's proprietary methods. These flags correspond well with other indicators of foreclosures and non-arm's length sales, such as the deed type. Sale prices were adjusted for inflation to 2010 U.S. dollars (USD) using the unadjusted Consumer Price Index (CPI) for housing for "all urban consumers" (Federal Reserve Bank of St. Louis, 2016). To account for differences in the structural characteristics of housing, I calculate home values as price-per-square foot of built area, which also somewhat normalizes the distribution of housing prices; a long right tail or right skew in the distribution of price-per-square foot is still found in some markets.

Where estimates of median home value summarized at the neighborhood level are needed for analysis, I used ordinary kriging to interpolate missing neighborhood price-year observations. This essentially provides an optimal weighted average of neighborhood median value based on estimates in surrounding neighborhoods (McCluskey et al., 2000). An exponential model of spatial dependence was used, which is common in housing studies (e.g., Hoshino and Kuriyama, 2010), although there was little difference in the cross-validation statistics between an exponential, spherical, or Gaussian model. Neighborhoods in which there was not a single price-year observation during the study period were not interpolated and were dropped from further consideration.

### 3.2.3 Remote Sensing Measures of Vegetation Cover

Ideally, we want to derive a physically based measure of vegetation cover, i.e., the amount of land that is covered by vegetation, from a long satellite time series record. The Landsat program's Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+), together, provide a continuous time series record of earth surface changes from 1985 to 2015 and later. These sensors provide, at 30-meter spatial resolution, visible, near-infrared, and short-wave infrared measurements every 8 to 16 days.

As a proxy for vegetation cover, I use the modified soil-adjusted vegetation index, MSAVI, as presented in Equation 3.1, where R and NIR refer to the red and near-infrared reflectance bands (Qi et al., 1994). MSAVI is an improvement upon other "greenness" indices such as the normalized difference vegetation index (NDVI), which is affected by background contamination, particularly soil brightness and color (Bannari et al., 1995, Fensholt et al., 2006); these issues are more pronounced in sparsely vegetated areas, such as semi-arid Los Angeles. MSAVI is therefore a better index for comparison between the Los Angeles MSA and the temperate areas of Seattle and Detroit (Rondeaux et al., 1996). MSAVI also has a linear relationship with sub-pixel vegetation fraction—the fractional amount of area covered by green vegetation (Qi et al., 1994).

$$\text{MSAVI} = \frac{2\,\text{NIR} + 1 - [(2\,\text{NIR} + 1)^2 - 8(\text{NIR} - \text{R})]^{\frac{1}{2}}}{2} \tag{3.1}$$

All eligible Landsat 5 TM and Landsat 7 ETM+ images from 1995 to 2015 are used in deriving greenness (MSAVI) estimates. Table 1 lists the considerations for eligibility in each metropolitan area. For all areas, only a single Landsat path is used to prevent look-angle differences across estimates for a single ground resolution cell. In addition, only Tier 1 surface reflectance (SR) images with less than 40% land cloud cover are considered. In each image, areas of cloud, cloud shadow, and water are masked using the provided quality assessment band produced by the USGS CFMask protocol. Finally, to account of variations in scene-specific brightness over time than can occur due to variations in cloud cover, each image is relatively radiometrically normalized to the annual Landsat 7 ETM+ SR composite with the highest dynamic range (Hall et al., 1991). Due to the superior radiometric calibration properties the Landsat 7 ETM+ sensor, only ETM+ SR composites are considered for the reference image.

To automate the relative radiometric normalization, “bright” and “dark” pseudo-invariant features are found by first calculating the multi-temporal variance across all images in the study period (1995-2015). Those areas below an empirically selected variance threshold are considered as potential rectification targets. The "tasseled cap" transform (Kauth and Thomas, 1976) is then used to project these pixels into their "brightness" and "greenness" coordinates (Crist and Kauth, 1986). Those pixels with a brightness below the 1st percentile are then used as "dark" targets while those with a brightness above the 95th percentile are considered "bright" targets. Both bright and dark targets are also required to fall below the 20th percentile of greenness. For some scenes, there are too few dark targets that meet this criterion. For these scenes, the threshold is raised to the 50th percentile of greenness. With these targets, relative normalization is performed as described by Hall et al. (1991). Following relative normalization, in theory, the Landsat 5 TM SR values are projected onto the ETM+ SR scale.

Finally, images are seasonally composited (once per year in Detroit, twice per year in Seattle and Los Angeles MSAs) so as to facilitate comparison with an annual panel on neighborhood conditions. Compositing does sacrifice important information on phenology but does reduce the noise, as well, and has been found to provide more accurate and more conservative estimates of greenness trends (Forkel et al., 2013). Compositing is done a little differently in each metro area. While in Detroit, the warm and wet seasons coincide with the northern hemisphere summer (May through September), the Los Angeles and Seattle MSAs are situated along the Pacific coast and have disjoint warm and wet seasons (Table 3.1). In both areas, based on a cursory examination of precipitation and temperature normals, I have decided to composite the images in separate "cool, wet" (November through April) and "warm, dry" (May through September) seasons. This ensures that we have a chance to measure vegetation signals of residential landscape change that would otherwise be limited by either temperature or precipitation.

After examining the MSAVI time series produced through both median-value and maximum-value compositing and with versus without radiometric normalization, it was apparent that maximum-value, non-normalized composites produce the most consistent estimates of greenness over time. This was based on an analysis of the variation in MSAVI over the study period in pseudo-invariant forested areas near Detroit. These areas were identified from the National Land Cover Dataset (NLCD) product (Wickham et al., 2014) in multiple years and from high-resolution imagery as mature forest stands with no disturbance and no appreciable change in vigor or leaf-area index over the 20-year period. A plot of greenness in these "stable" areas should therefore show little variation (Figure 3.2); indeed, the greenness is mostly flat over time, except when the scene count is low at the beginning and end of the time series, when only one Landsat platform is available. Figure 2 also shows that radiometric normalization does little to improve the overall consistency of the estimates and is actually worse when scene counts are low. In other words, we may be underestimating seasonal maximum MSAVI when few images are available.

For some analyses, long-term greenness trends were smoothed using a zero-phase digital filter with finite impulse response (FIR). The filter computes a moving average, but unlike a simple moving average, the filter is designed so that no phase offset is induced in the smoothed data, which is critical to accurate interpretation of the time series. Gustafsson's (1996) method for padding the time series is used to ensure that the start and end points are also smoothed appropriately.

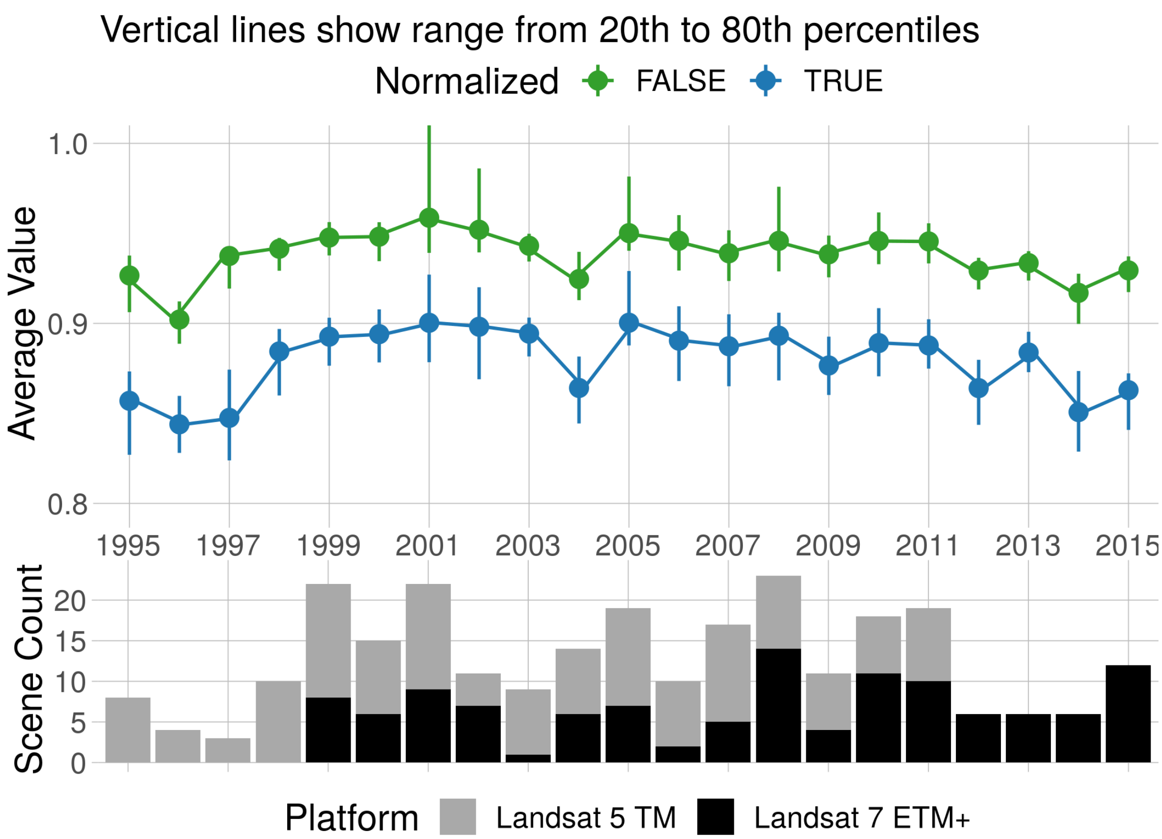


**Figure 3.2:** Average greenness (MSAVI) in pseudo-invariant or "stable" forested areas of Detroit, with and without radiometric normalization (top) shown with the count of Landsat 5 TM and Landsat 7 ETM+ scenes (bottom). In the top image, vertical lines show the 20th to 80th percentile range.

**Table 3.1:** Selection criteria and processing details for Landsat image time series in each of the three study areas.

| | **Detroit Metro** | **Low Angeles MSA** | **Seattle MSA** |
|---|---|---|---|
| **WRS2 Path, Rows** | Path 20, Rows 30 and 31 | Path 41, Rows 36 and 37 | Path 46, Rows 26-28 |
| **Scene Critera** | L1TP or L1GT SR images with <40% land cloud cover | L1TP or L1GT SR images with ¡40% land cloud cover | L1TP or L1GT SR images with ¡40% land cloud cover |
| **Compositing** | One “leaf-on” season, May 1 - September 30 | “Dry” season (May 1 - October 31) and “Wet” season (November 1 to April 30) | “Warm, Dry” season (May 1 - October 31) and “Cool, Wet” season (November 1 to April 30) |
| **Other Criteria** | Areas with >25% cultivated area consistent in 2001, 2006, and 2010 NLCD years are masked | Areas above 518 meters (1700 ft) masked in the wet season | Areas above 457 meters (1500 ft) masked in the wet season; above 1500 meters (4921 ft) in the dry season |
| **Total No. of Individual Images** | 265 | 416 in wet season; 550 in dry | 109 in cool-wet season, 196 in warm-dry |

### 3.2.4 Defining Neighborhood Change Typologies

The housing markets in the Detroit, Los Angeles, and Seattle metropolitan areas show strikingly similar trends in home values across neighborhoods (Figure 3.3). Despite wide variation in the mean value over time—the gulf between the most prestigious, high-value suburban neighborhoods and older, often denser neighborhoods with declining housing stock and low housing demand—almost every neighborhood sees an increase in sale prices during the housing boom and a subsequent, steep decline in home sale prices. And yet, static differences between low-value and high-value neighborhoods persist over time. When neighborhood price curves are standardized within neighborhoods, such that a Z-score or standard score is obtained in each year, differences in baselines are largely eliminated, as each neighborhood’s price curve now varies around its long-term mean. A principal components analysis (PCA) conducted on this standardized panel reveals loadings profiles that seem to emphasize changes common to all the neighborhoods: a secular trend in increasing prices over time (in the Los Angeles MSA) and a spike in values associated with the peak of the recent housing boom, along with delayed or earlier spikes.

As an *a priori* definition of neighborhood decline or improvement would depend on population and housing data that are not available at this time scale, this similarity in neighborhood value trends over time presents a challenge for identifying canonical neighborhood change sub-types that may correspond with vegetation change. Thus, an empirical approach to induce canonical groups in the home price time series is used to *discover* neighborhood groups with similar temporal patterns of change. Here, I use two approaches with a similar underlying premise: **locational advantages and disadvantages in a booming regional housing market will result in slight differences in the timing of peak home value appreciation.** The two approaches differ in whether or not they allow these differences in timing to impact the clusters that are formed, i.e., whether or not they consider timing to be important.

The first technique, whole time-series clustering with a dynamic time warping (DTW) distance function (Aghabozorgi et al., 2015), does not consider differences in timing; it does not assume that neighborhood price time series are aligned, which provides a flexible approach to clustering on similar attributes that don't occur at the same time index. Second, I used change-point detection to identify the timing of the peak of the housing boom and the start of the recovery for a neighborhood with the aim of clustering neighborhoods on the duration and timing of their response to the business cycle. In the first approach, the neighborhood

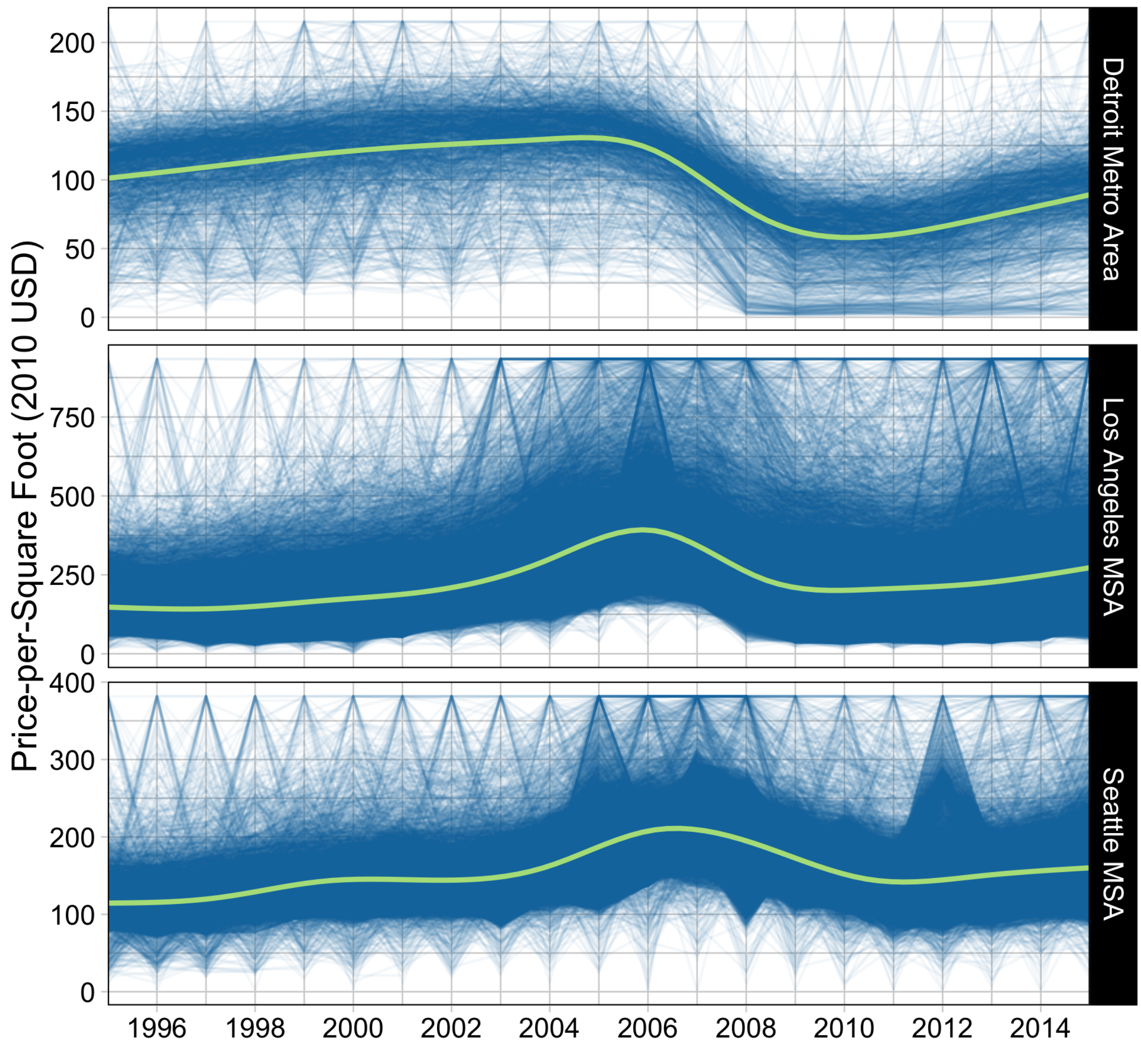


**Figure 3.3:** Time profiles of neighborhood median home sale prices, as price-per-square foot of built housing, over time, for the Detroit Metro, Los Angeles MSA, and Seattle MSA neighborhoods. Each neighborhood's price curve, in blue, is top-coded at the 98.5 percentile. The yellow line is a generalized additive model smoother fit across all neighborhoods. We see that, despite considerable volatility in price, every neighborhood experiences the boom and bust in prices associated with the recent sub-prime mortgage crisis.

change typology (as an alternative to "decline" or "improvement") is discovered by the clustering algorithm; in the second, the year of the peak of the housing boom or the year of the recovery is used as the typology.

The second clustering approach used requires change-point detection; each neighborhood's price trajectory is differenced with a lag of 1 year, i.e., the last year's price is subtracted from the current year's price for all years. This differencing results in a number of change points—time points where the change in price crosses the zero line; these correspond to the peaks and troughs of a price trajectory. In addition, the price and greenness time series of different neighborhoods can be aligned by their peak years, which provides a way to test whether greenness change and housing market growth are synchronized. Prior to change-point detection, the price trajectories are smoothed to make it easier for local maxima and minima (peaks and troughs) to be detected in the presence of noise. In a price time series based on deed sale records, "noise" refers to volatility—sales that are considerably above or below what would commonly be considered the market price for the local neighborhood. Apparent volatility may also arise due to the arbitrary neighborhood boundaries used: dissimilar housing units may be grouped together. As with the long-term greenness trends, a zero-phase digital FIR filter is used to smooth the price trajectories. After experimenting with different window sizes, a moving window of 4 years was used for smoothing.

### 3.2.5 Testing Price and Vegetation Associations

In addressing question Q2, I examined whether price changes in each metropolitan area could be explained by changes in greenness. There are reasons to believe that changes in home sale prices and changes in vegetation density or vigor drive one another, i.e., that their relationship is bi-directional. In asking what effect neighborhood improvement or decline (in price terms) has on vegetation, we are essentially inverting a classical hedonic valuation of a unit change in an environmental amenity. The repeat-sales model described by Harding et al. (2009) was developed in response to the shortcomings of cross-sectional hedonic models, chief of which is omitted variable bias. The repeat-sales model corrects for this bias through differencing consecutive sales of each property. By using only repeat sales of the same property, we control for property-level differences in, e.g., the size of the property, the number of bedrooms or bathrooms, they style of the architecture, and numerous other housing characteristics that don't vary over time but have a significant impact on price. Han (2014) updates this approach by also weighting a property's sale by the inverse of the length of time elapsed since the last sale.

When there are more than two time periods, it is not easy to extend a panel model like the repeat-sales model to consider spatial autocorrelation and other violations of the assumption of independent and identically distributed (or "spherical") random errors because each subject (property) is represented more than once in the data. One must also make a substantive decision as to whether a first-difference or fixed-effects approach more accurately describes the relationship between the dependent and independent variables. However, when only two time periods are observed, the fixed-effects and first-difference models are equivalent (Halaby, 2004), and we are able to control for omitted variable bias with either approach. By taking the first-difference approach, it is easy to extend the model to allow for non-spherical errors or lagged predictors, as the design matrix for this model is structurally identical to that of a cross-sectional (non-longitudinal) approach.

As it is well-established that spatial dependence in housing prices exists, I extend the repeat-sales model by relaxing the assumption of independent observations, using a spatial auto-regressive framework, and testing whether lagged predictors, correlated errors, or a combination of the two produces a superior fit to the data. Specifically, I consider three possible model formulations: a spatially lagged dependent variable (i.e., sale price spillovers) model, spatial errors model, and the combination of the two (the spatially autoregressive moving average, SARMA); this approach has precedent in hedonic models of non-structural housing characteristics (for instance, Cohen and Coughlin, 2008). While a model with spatially lagged price (dependent variable) and greenness (independent variable) is more consistent with our conceptual model and prior work in hedonic modeling of home values, Lagrange multiplier tests indicated that a spatial errors (alone) model provided a better fit to the data. In addition, technical limitations in the best available software for spatial modeling made it impossible to calculate the adjusted effect sizes in the lag models (so-called "impact measures"). Thus, a spatial errors model was used. As for the connectivity allowed between "close" parcels, while row-standardized spatial weights matrices are often used in studies of non-market valuation of environmental amenities (e.g., Cohen and Coughlin, 2008), these weighting schemes tend to emphasize sparsely-connected spatial units; I used, instead, a variance-stabilizing scheme (Tiefelsdorf et al., 1999), which puts a similar weight on parcels whether they have rich or sparse connections. Spatial dependence was defined based on proximity, with the cut-off for spatial dependence being chosen from a semivariogram plot of the change-in-price residuals (after Bivand et al., 2013).

$$
\begin{aligned}
&[\Delta\text{Price}]_i = \lambda W[\Delta\text{Price}] + (\Delta X_i)\beta_{(1)} + W(\Delta X_i)\beta_{(2)} + t_i^* + \varepsilon_i \\
&\varepsilon_i \sim \mathbf{N}(0, \sigma^2) \\
&t_i^* = \sum_{j \in (b_0, b_1, \dots)} \begin{cases} t_i - j, & t_i \geq j \\ 0, & t_i < j \end{cases}
\end{aligned}
\tag{3.2}
$$

It should also be noted that no model formulation—whether with lagged dependent or independent variables, with non-spherical errors, or some combination—succeeded in eliminating residual spatial autocorrelation. Because of this persistent residual spatial autocorrelation, and because a small number of different spatial connectivities thought to model this autocorrelation were tested, the level for significance is raised from $\alpha = 0.05$ to $\alpha = 0.05/6$ (for 3 model types and 2 connectivities), resulting in approximate 99.5% confidence intervals on the point estimates.

In all three metropolitan areas, the majority of sales are repeat sales, i.e., most sales are for properties that have sold at least once before. To reduce the computational complexity and allow the spatial models to converge, a small sample of repeat sales was taken in each study area. In the Los Angeles and Seattle MSAs, a 1% sample of properties with repeat sales is taken, corresponding to 17,000 and 14,000 properties, respectively. For consistency, in the Detroit Metro area, a similar number of properties was sampled, 13,000, however, because this study area is smaller, this number corresponds to an approximate 5% sample. For each randomly sampled property, 2 sales were randomly selected within the period 1995-2015. The dependent variable in the repeat sales model, then, is the percentage change from the first sale to the second sale. The dates of these sales were used to join the contemporary greenness time series, which was also first-differenced, i.e., the change in greenness is the change between the greenness at the time of the first sale and the greenness at the time of the second sale.

## 3.3 Results

### 3.3.1 Greenness Trends and Canonical Neighborhood Change Typologies

Both of the clustering approaches used to discover canonical neighborhood change types, DTW and change-point detection, yielded insight into the dynamics of residential home values and, in particular, the uneven nature of growth and decline both within and across metropolitan areas. However, neither approach yielded neighborhood groups that had any interesting association with vegetation change. DTW clustering produced clusters that predominantly differ in the average value of the housing stock over time: neighborhoods are clustered together by how expensive they are. When the cluster membership is mapped across the metropolitan area, very reasonable housing sub-markets can be identified, such as in Figure 3.4, the map for Detroit, where the housing sub-markets of the Cities of Detroit and Pontiac can be clearly seen as part of cluster 4, which corresponds to the lowest-value housing cluster time series, as shown in Figure 3.5; again, we can see that each cluster is stratified by its average value over time, that every cluster experiences a housing boom and bust, and also, more interestingly, that some clusters experience a larger recovery in value than others.

To eliminate the effect of baseline, average-value differences across clusters, we can standardize the housing price trajectories by scaling the price for a given neighborhood at any time to a Z-score, based on that neighborhood's long-term price, as shown in Equation 3.3, where $y$ is the price for neighborhood $i$ at time $t$. This has the effect of shifting the curves up and down on the vertical axis until the overlay one another, diminishing this chief source of variation. In the Los

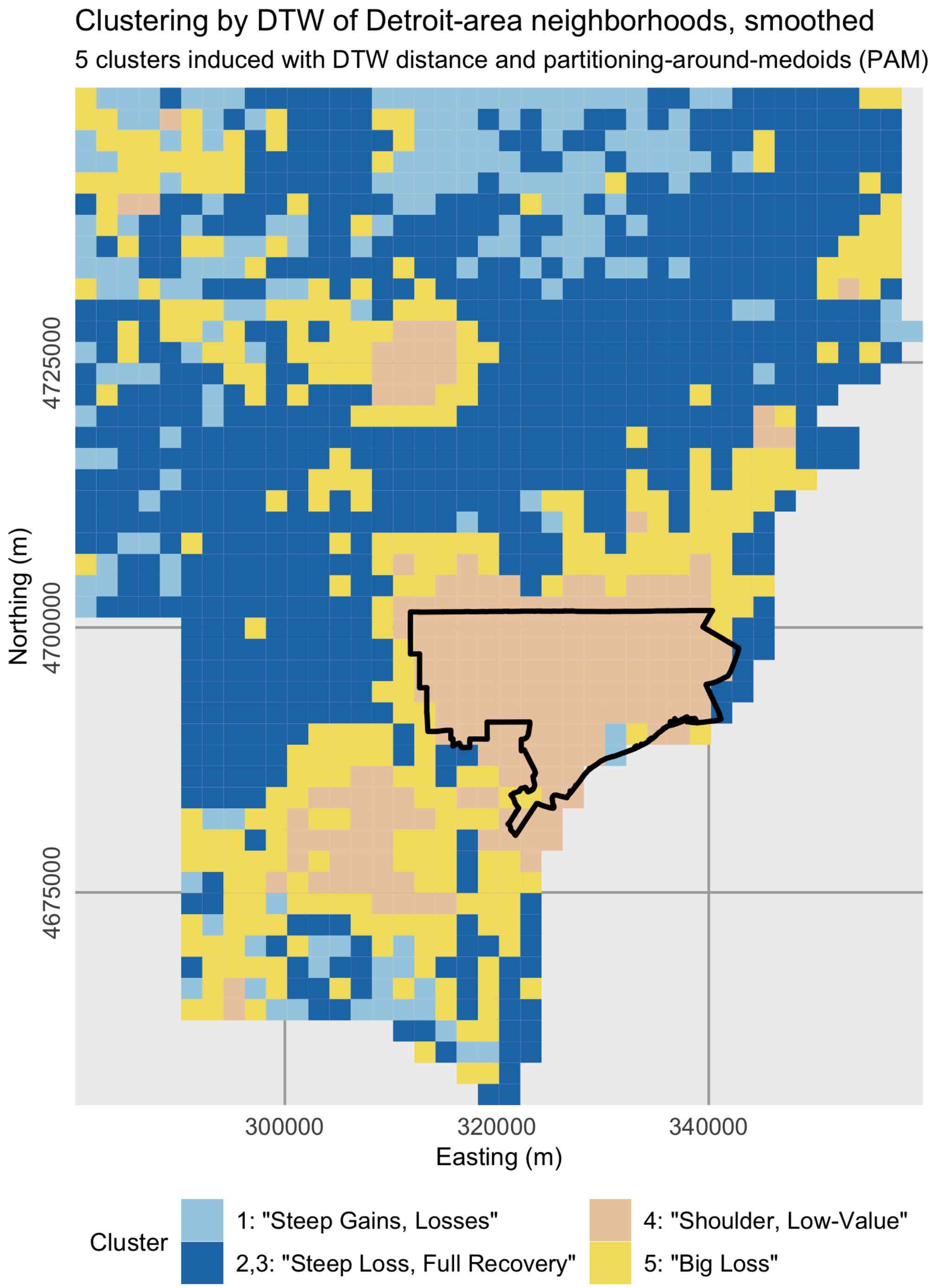


**Figure 3.4:** Map of the locations of each cluster's member neighborhoods in the Detroit metropolitan area; the City of Detroit is outlined in black.

Angeles and Seattle MSAs, standardizing the curves also highlights their second greatest source of variation: the magnitude of the recovery. The sorting of Los Angeles MSA clusters by average value is preserved in this standardization: the highest-value cluster has the highest recovery, the second-highest value cluster the second-highest recovery, and so on. In Seattle, sorting is not preserved, but the same neighborhoods, those of Seattle and Bellevue, appear in the highest-value cluster (non-standardized clustering) and the highest-recovery cluster (standardized clustering). In Detroit, no price trajectory medoid shows signs of a recovery, which may indicate few neighborhoods experience a recovery.

$$Z(i,t) = \frac{y(i,t) - \bar{y}_i}{\sigma_y(i)} \tag{3.3}$$

None of the clusters induced in any metropolitan area displayed any variation with greenness change. However, the Los Angeles MSA clusters, with or without standardization, do vary with greenness levels, specifically with the long-term maximum MSAVI. As Figure 3.6 shows, Los Angeles neighborhoods with higher average values (and higher value recovery) have higher greenness, on average; in the wet season, the highest-value neighborhoods have a median greenness 2.5 times higher than that of the lowest-value neighborhoods. Again, sorting is preserved: the next highest-value neighborhoods have the next-highest average greenness, and so on. A Tukey's honestly significant differences (HSD) test, which corrects for multiple testing across all pair-wise differences in means, indicates that each cluster's mean greenness is significantly different from all others (p-value $<< 0.001$)

The second approach used to discover a canonical neighborhood change typology, change-point detection, produced neighborhoods organized by the year of

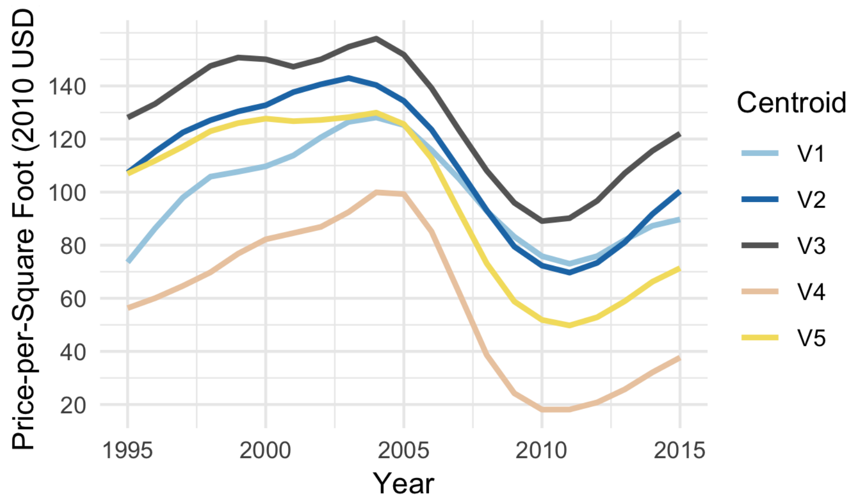


**Figure 3.5:** Average price trajectory curves or "medoids" of each DTW cluster for metropolitan Detroit; cluster numbers V1, V2, etc. correspond to cluster numbers in Figure 3.4.

their peak in the housing boom or the year in which they started to recover after the housing bust. A plot of the change points detected in each metropolitan area can be seen in Figure 3.7. The change points detected for the Detroit Metro region are limited compared to Seattle and Los Angeles as Detroit deed sales data are not reliable prior to 1995; this effectively truncates the detection of the start of the housing boom. However, the peak of the housing boom and the start of the recovery are well-defined across each metropolitan area and interesting inter-metropolitan patterns are apparent. While Seattle and Los Angeles MSA neighborhoods generally reach their peak value in 2006-2007, Detroit Metro neighborhoods peak much earlier and with wider variation, anywhere from 2001 to 2006. This is, in part, because the price trajectories for Detroit Metro neighborhoods reach a plateau; prices are generally stable for 2-4 years after reaching the peak, prior to the housing bust. The narrow distribution of both start and peak years of the Los Angeles MSA housing boom are indicative of that area's generally steep increase in housing prices. Conversely, Seattle MSA neighborhoods have a wide distribution of starting years, indicative of that area's long and steady appreciation in housing val-

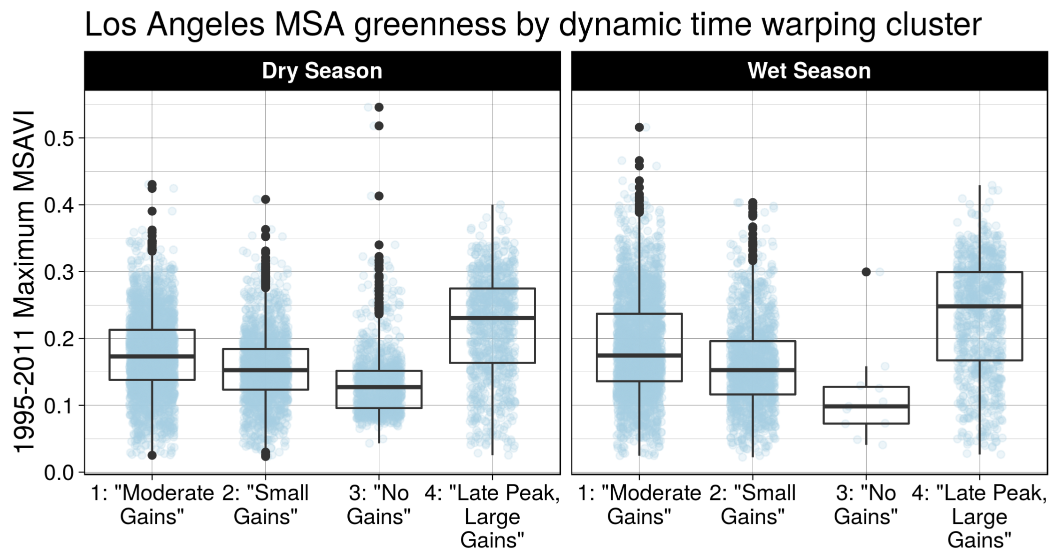


**Figure 3.6:** Long-term maximum MSAVI varies across clusters in the Los Angeles MSA, shown here for non-standardized DTW clustering.

ues; while many neighborhoods start growing after the early-1990s recession (the prior business cycle), many have seen steady appreciation since 1985 (the earliest year with available data).

As with the clusters defined by DTW distance, however, there was not a strong association between greenness trends and the timing of business cycles. In metropolitan Detroit, neighborhoods that initiated their housing boom later (2001 or later) generally experienced much more positive greenness trends than other neighborhoods in that study area. Examining these neighborhoods on a map reveals that they are generally neighborhoods located within the City of Detroit and in outlying suburban or exurban areas, i.e., areas where housing densities or low (in the City of Detroit, this is due to thinning of the housing stock). In the Seattle MSA, neighborhoods that peak later (2008 or 2009) generally have more negative greenness trends in the wet season than other neighborhoods. However, these neighborhoods are widely dispersed, with no particular spatial patterns.

Robust trends fit to the neighborhood-specific housing booms, based on the

**Table 3.2:** Model fits from WLS models with the same-year median household income treatment. Here, the base model is the model with contextual variables only.

| | Appreciation rate during housing boom (approx. 1995-2005) | Depreciation rate during housing bust (approx. 2000-2009) |
|---|---|---|
| **Detroit Metro** | 5.5% | -9.2% |
| **Los Angeles MSA** | 39.0% | -9.3% |
| **Seattle MSA** | 16.6% | -6.5% |

change-point analysis, were analyzed to see if greenness trends might be *synchronized* with the local housing market, e.g., in the concomitant patterns of land development. The robust trends calculated provide annual rates of growth and decline that can be summarized across metropolitan areas (Table 3.2).

### 3.3.2 Parcel-Level Repeat-Sale Associations with Greenness Change

In order to implement the repeat sales model in a spatially explicit framework, it was first necessary to model the effect of time on change in repeat sale price (the dependent variable). Although including sale-year or sale-month factors would allow for a flexible, non-linear response of price to time, such factors were not compatible with the spatially explicit repeat sales model (they cannot be manually time-demeaned). Therefore, a time plot of repeat-sale prices in each month was examined in order to select change points for a piece-wise linear approximation of the business cycle. This time profile analysis revealed patterns very similar to those seen in Figure 3.3, i.e., sale prices exhibited the characteristic boom-bust business cycle of the wider housing market. In each study area, two change points were used, one to describe the peak of the housing boom and one to describe the trough of the housing bust. Using a baseline, ordinary least squares (OLS) model with time covariates only, adjusted R-squared values revealed that the piece-wise linear approximation was a fair substitute for the more flexible, sale-year and sale-

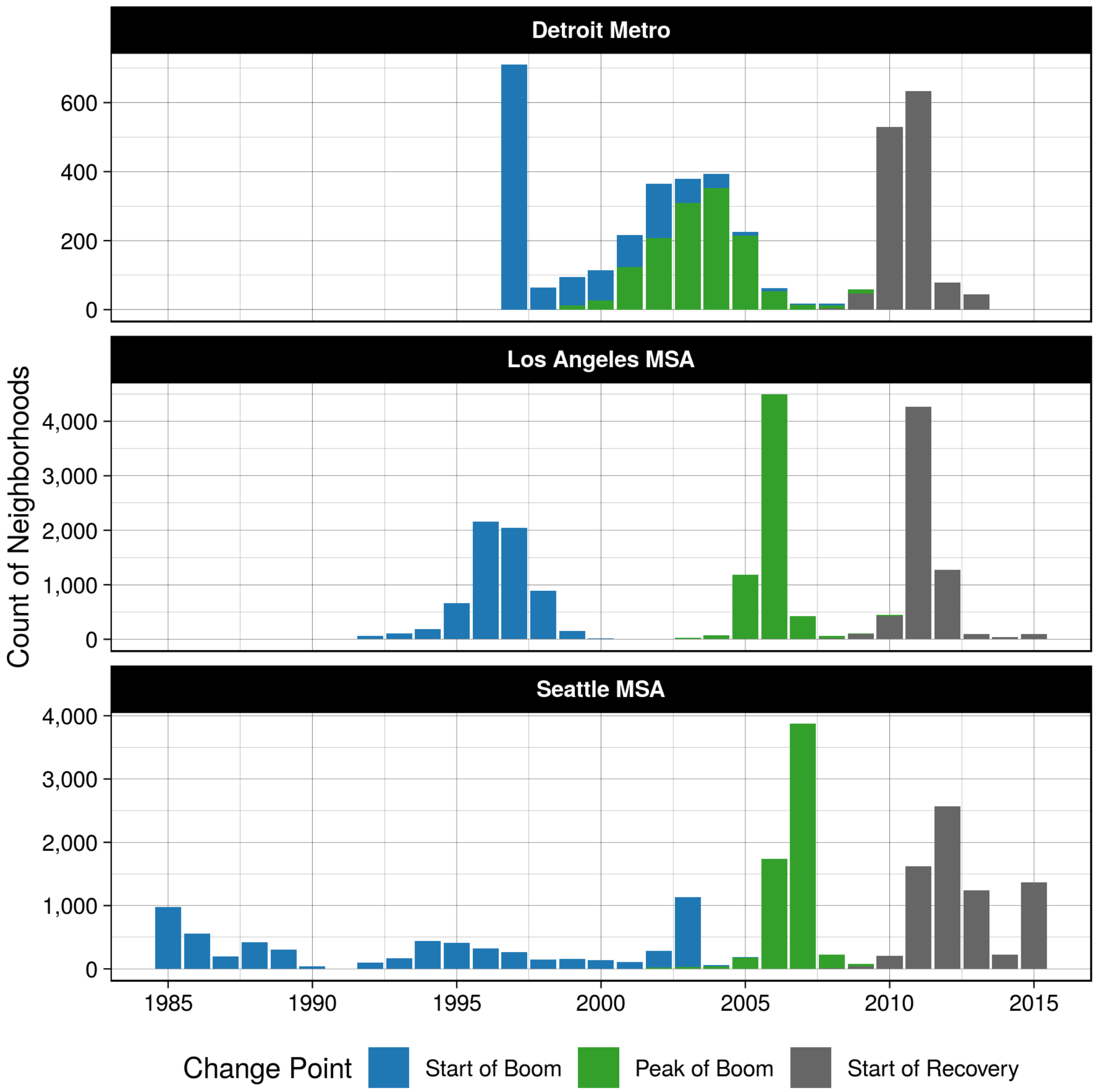


**Figure 3.7:** Change points detected for each metropolitan area: the start of the housing boom (when prices first began to rise), the peak of the housing boom (when the highest price is reached), and the start of the recovery (when prices begin to rise after the housing bust).

**Table 3.3:** Adjusted R-squared values from the OLS estimation of the repeat-sales model using either sale-year and sale-month factors or a piece-wise linear approximation.

| | **Sale-Year & Sale-Month Factors: Adjusted $R^2$** | **Piece-wise Linear Approximation: Adjusted $R^2$** |
|---|---|---|
| **Detroit Metro** | 0.403 | 0.398 |
| **Los Angeles MSA** | 0.318 | 0.283 |
| **Seattle MSA** | 0.091 | 0.074 |

month factors model (Table 3.3), with decreases in goodness-of-fit not exceeding 3.5%. In the Detroit Metro and Los Angeles MSA models, the overall goodness-of-fit is satisfactory, with time covariates, alone, explaining between 30-40% of the variation in change in repeat sale prices. It is not clear why the Seattle MSA model has a poor fit to the time series; the time profile shows a similarly strong business cycle. However, as noted, Seattle MSA neighborhoods have been appreciating for a much longer time period than in the other two study areas.

The effect of change in greenness on change in price was estimated for sales occurring during the housing bust or at any other time; the latter effect is estimated as an interaction with a housing-bust indicator variable. Unlike the unsupervised clustering and change-point detection work described earlier, here, the housing bust is defined in the same way for all study areas. Repeat sales that occur during or after December 2007 are considered to be sales during or after the housing bust; this is based on the National Bureau of Economic Research's timing of business cycles (NBER, 2019). However, because the timing of the recovery, if any, is extremely different between neighborhoods and metropolitan areas, no attempt to define "business as usual" *after* the housing bust is made.

The point estimates and approximate 99.5% confidence intervals for the effect of change in greenness on change in price is presented in Figure 3.8. The effect of an increase in the average maximum MSAVI (greenness) by 0.1 points within a 100-m or 500-m radius is shown; this value corresponds to a moderately large, though realistic, increase in greenness (MSAVI typically ranges from 0.1 to 0.5 across these study areas). First, we can see that repeat sales during the housing bust do not differ markedly from those that occurred outside of the housing bust, except for those sales in the City of Detroit. These sales, which are few in number (hence, the large confidence intervals), vary widely in the estimated effect of increasing greenness on change in price, an effect which appears to be positive and significant except for sales during the housing bust.

Given the uncertainty in the underlying data and the residual spatial autocorrelation, it seems that the effect of an increase in greenness on change in price is insignificant in every metropolitan area at every season or time period except for the Detroit Metro area, where it is a moderately large, positive effect. In the Detroit Metro area, an increase in greenness within a 100-m or 500-m radius is estimated to contribute to an increase in sale price ranging from 10-25%. In the Seattle MSA, there is essentially no relationship between change in greenness and change in price. In the Los Angeles MSA, the relationship is only evident during the cool and wet season (northern hemisphere winter) where, except during the housing bust, it provides a sale price premium comparable to that seen in the Detroit Metro area, between 5% and 30%.

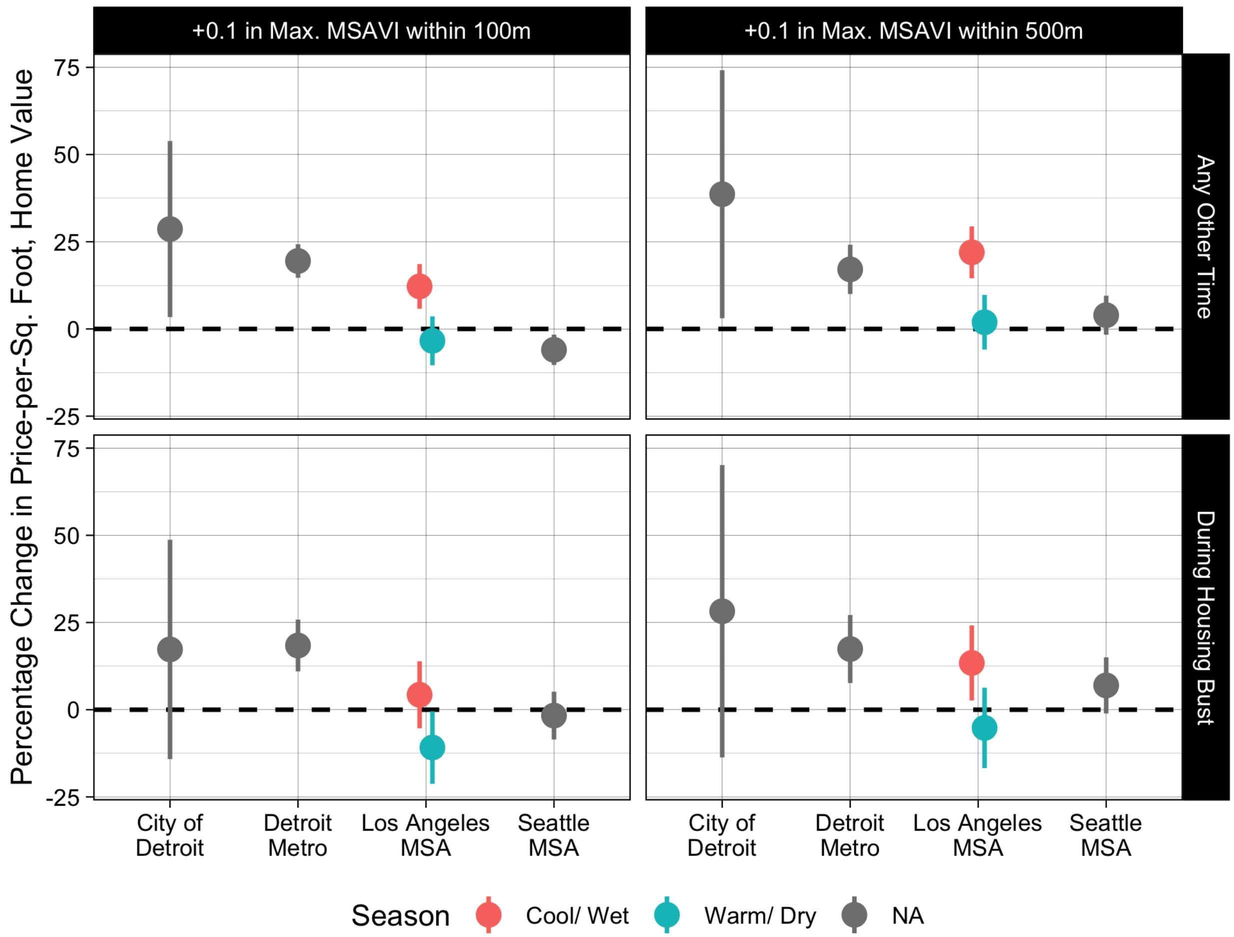


**Figure 3.8:** From the spatially explicit repeat sales model, point estimates and approximate 99.5% confidence intervals for the effect of change in greenness on change in price are shown for each metropolitan area. The bottom row shows these for properties with a repeat sale that occurred during the housing bust; the top row shows these for properties that sold at any other time.

## 3.4 Discussion and Conclusions

### 3.4.1 Greenness Trends and Neighborhood Improvement or Decline

Regarding my hypotheses, the clustering approaches, dynamic time warping and change-point detection did not yield any insight into differences in vegetation (greenness) change. However, they do lend weak support to both H1 and H2 when differences in vegetation (greenness) levels are examined. **Specifically, the strong correspondence between average home values, recovery in price, and average greenness levels in Los Angeles MSA neighborhoods suggests that green vegetation is a strong signal of socio-economic status in this water-limited environment (H1).** In concordance with H1 and H2, we do not see this correspondence in Seattle MSA or Detroit metropolitan neighborhoods, where green vegetation is not water-limited and, particularly in the case of the City of Detroit, where green vegetation may be found in abundance in less affluent and less prestigious neighborhoods (Endsley et al., 2018, Chapter II, this volume). The socio-ecological significance of green vegetation may also be more visible in semi-arid Los Angeles MSA neighborhoods because the region is currently undergoing severe water stress, as indicated by the decline in dry-season greenness over the last 10 years.

There is apparently no association between price trends and greenness change, allowing for up to 2-year lags, and it seems that vegetation trends, alone, do not tell us much about changing neighborhood fortunes (Q1). The greenness time series may be of limited value in such an analysis due to high uncertainty, low spatial resolution, inter-annual process noise, or some combination of these factors. The uncertainty in the greenness time series is inherent in the problem of trying to estimate gradual, continuous change in surface vegetation with a remote sensing-derived time series. While studies of deforestation or land-use change are typically marked by sudden and dramatic land conversions, which lead to sharply defined changes in surface reflectance, vegetation change in residential landscapes that is thought to be indicative of social and economic processes (e.g., changes in lawn maintenance, landscaping, or changes in individual housing units) are much harder to accurately detect using moderate resolution datasets such as the 30-m Landsat data in this study. **The 30-year, interannual greenness records produced in this study reveal wide variation between neighborhoods over time; it is possible this wide variation is due to time-invariant neighborhood differences in average greenness that is estimated, in each year, with an uncertainty that is larger than the signal of neighborhood socio-ecological change we are trying to detect.** While finer spatial resolution—which may lead to useful distinctions between vegetation types and private versus public land ownership—could be obtained with different platforms, including commercial satellite imagery, the record of observation in these platforms is currently not long enough to be useful in a multi-decadal study such as this one.

When examined separately, the price trends and greenness trends do offer interesting insight into each metropolitan area. The 30-year greenness trends of the Detroit Metro and Seattle MSA areas, both temperate with high available water throughout the year, reveal no long-term change in average greenness. In Los Angeles MSA neighborhoods, both the wet-season and dry-season greenness show recent declines. The wet-season (November-April) greenness in the Los Angeles area appears to have been in slight decline from 1995 to 2015. The dry-season (May-October) greenness shows even steeper, more recent declines, with the average maximum dry-season MSAVI declining by about 28% between 1998 and 2015 and by about 24% between 2011 and 2015, alone. These recent declines in metro-wide average greenness correspond to severe recent droughts in the area, particularly in year 2014.

The price trend analysis—again, though not revealing of any interesting associations with vegetation or greenness trends—does provide insight into the different housing market dynamics. The average home value appreciations in the Detroit Metro, Los Angeles MSA, and Seattle MSA housing markets, based on robust trend analysis, showed wide variation, ranging from 5.5% to 39.0% (Table 3.2). The high mean rate of growth in the Los Angeles MSA is largely due to spectacular growth in downtown and Hollywood and new growth in northern Los Angeles County east of Lancaster. The comparatively anemic growth rate of Detroit Metro neighborhoods is seen in the typically slow rate of growth of its high-population suburbs; it is actually new exurban development and speculation in southeast municipal Detroit that is leading growth rates in that area. Conversely, the rates of decline were more homogeneous across the metropolitan areas, ranging from -6.5% to -9.3%. A narrower range of annual depreciation rates may be reflective of a nation-wide, coordinated decline in value. This would be expected due to the widespread attention the sub-prime mortgage crisis received, however, with only three metropolitan areas included in this analysis, this is merely speculative.

### 3.4.2 Greenness Change and Change in Repeat Sale Prices

The neighborhood-level analysis just described may suffer from some serious technical limitations. The greenness time series may be too noisy, the underlying signal of gradual vegetation change subsumed by the uncertainty that is inherent in the coarse spatial resolution and that is introduced through further spatial and temporal aggregation. Does a parcel-scale analysis reveal any association with between greenness change and changes in price? The results from the spatially explicit repeat sales models are mixed, but it seems that, in general, areas with rising home values may be getting greener (Q2).

A consistent, significant, and positive association between parcel-level greenness change and change in sale price was found for Detroit Metro properties as a whole; this association did not persist for properties within the City of Detroit during the housing bust, which was partially consistent with our hypothesis that home values will grow with green space, except when that green space is already exceptionally abundant due to neighborhood decline (H3). Among Los Angeles MSA properties, a similar, positive association was found only during the cool and wet season and also did not persist for sales during the housing bust. Seattle MSA properties exhibited no association between changes in parcel-level greenness and in sale price for sales at any time. These inter-metropolitan differences were unexpected and do not cleave along the climatic or economic divisions that were hypothesized to affect residential socio-ecological relations (H1, H2). The failure to detect an association during the housing bust is unsurprising given that sales during the housing bust are almost certainly artificially low, i.e., negative changes in price, relative to the previous sale price. If an increase in ambient greenness does lead to an increase in sale price through feedbacks in the valuation of environmental amenities, then this driving relationship would be confounded by the steep discount applied to prices for sales during the housing bust. However, this driving relationship is not strongly evident for sales that did not occur during the housing bust, given that it is only seen for Detroit Metro properties and for Los Angeles MSA properties during the cool-wet season.

The significance of cool-wet season vegetation for Los Angeles MSA properties is surprising; we expected dry season vegetation to display a stronger relationship with social and economic conditions because irrigation is more likely to be used at that time. The cool-wet season signal suggests that growth in precipitation-limited natural vegetation, that which is not planted or managed by residents, is implicated in the appreciation of home values in this area. Indeed, natural vegetation is found in abundance at higher elevation on the margins of the Los Angeles neighborhoods that experienced the steepest gains in value during the housing boom. These neighborhoods also have the highest overall greenness levels in the Los Angeles MSA (Figure 3.6). It is surprising, however, that an irrigation signal was not detected as a significant price-greenness association during the warm and dry season.

It is interesting that the model from the Detroit Metro area most unambiguously affirms an association between greenness change and change in price, given that this study was inspired by prior work in that study area (Endsley et al., 2018, Chapter II, this volume) and that the area is so different from the other two metropolitan areas, Seattle and Los Angeles. Metropolitan Detroit is comparatively small and predominantly composed of the medium- to low-density housing developments characteristic of suburban and exurban U.S. landscapes. The properties sampled in metropolitan Detroit might then constitute an unusually salient sample of parcels with a high degree of green, vegetated cover in close proximity, likely in the form of lawns, parks, and tree canopy. An improvement on the repeat sales model in this study might therefore include additional data on the type of parcel that is sold. While the first-difference approach used here controls for parcel characteristics that do not change over time, there may be important sub-groups in the population repeat-sale parcels that need to be acknowledged, e.g., detached single-family homes versus condominiums. In particular, controlling for homeownership rates seems critical, as areas with low homeownership rates likely have weaker price-greenness associations due to, among other factors, split incentives between landlords and renters.

Many time-varying neighborhood conditions that could be measured were not included in the parcel-level analysis due to structural inconsistencies in the data, however, these may have immense value for understanding the dynamic evolution of individual parcels or neighborhoods. These include the new construction rate, foreclosure rate, and school closings. More generally, an improvement to this analysis should more explicitly investigate the causal pathways between social and economic changes at the parcel or neighborhood scale and corresponding growth or decline in vegetated cover. If price feedbacks from environmental amenities do exist, there are many potential confounders that could be masking this relationship in addition to housing stock heterogeneity and low homeownership rates. The fine spatial scale of the repeat-sales analysis builds on a well-established foundation of non-market valuation. Future studies may benefit from combining such an analysis with the insights of ethnographic studies that can identify household-level and neighborhood-level drivers of change in vegetated cover which were not accounted for here and are not strongly correlated with home values.

### 3.4.3 Neighborhood Persistence and Change

In addition to the technical challenges raised above, it must also be acknowledged that our definition and proxy for neighborhood change may be inadequate. The apparent lack of association between changes in neighborhood home values and greenness may simply be because home values are not a reliable metric for the wider neighborhood social and economic conditions we wish to measure. In this study, home values were chosen as a proxy because they are easily and consistently obtained across multiple metropolitan areas. It is assumed that home values, in addition to representing the characteristics of the house (e.g., number of bedrooms, quality of construction), represent environmental amenities indicative of wider, neighborhood-level conditions. Indeed, multiple hedonic pricing studies bear out a strong association between home value and contemporary neighborhood greenness. This study, too, reproduces the static associations between average neighborhood home values and average neighborhood greenness (Figure 3.6). Neighborhood change, however, is multi-dimensional; some aspects of change may have stronger effects on neighborhood vegetation cover than others and some aspects of change may not be implicated in vegetation change at all.

Because of the durability of the housing stock, long sweeps of time are likely necessary in order to observe a sustained change in neighborhood fortunes (Rosenthal and Ross, 2015) and it is possible that the 20-year time series of home values used in this study is not sufficiently long. The lack of an association between lagged trends or anomalies in greenness and home values casts doubt on whether flows of population and capital between neighborhoods are evident in land change trends. Instead, the static associations between home values and average greenness in the Los Angeles and Detroit metropolitan areas and, in particular, in the three-way association between the strength of the recovery, the overall housing value, and the average greenness in Los Angeles neighborhoods, suggest that neighborhoods have persistent advantages and disadvantages that prime them for accelerated growth or decline.

Thus, it seems that these advantages and disadvantages strongly determine the biophysical outcomes of neighborhoods, specifically which neighborhoods enjoy the multiple benefits of green vegetation. As Pulido (2004) noted, Los Angeles neighborhoods are "constellations of opportunities;" the higher-value neighborhoods are greener, appreciate more in home values, and recover more value after a crisis. The persistence of neighborhood (dis)advantages over time is not inconsistent with sporadic shocks or cyclical changes (Galster et al., 2007), including the recent sub-prime mortgage crisis. We do not know, however, the extent to which different neighborhood baselines lead to path dependence (Rosenthal and Ross, 2015), nor whether there are similar, self-stabilizing dynamics in green vegetation density.

# CHAPTER IV

# A Comparison of the Factors Driving Change in Neighborhood Green Vegetation across U.S. Metropolitan Areas

## 4.1 Introduction

Green vegetation in residential landscapes mitigates many of the environmental consequences associated with urbanization. Vegetation cover—in the form of trees, lawns, and gardens, on public or private property—facilitates clean air and water, recreation opportunities, and relief from rising urban air temperatures, yet these ecosystem services are not shared equally by urban residents (Talarchek, 1990, Lo and Faber, 1997, Heynen et al., 2006). This uneven nature of urban vegetation and ecosystem services has long been understood to arise from urban form and residents' different capabilities to create and claim urban green space (Heynen and Lindsey, 2003, Mennis, 2006), particularly through street trees, public parks, and larger parcel sizes. Though less attention has been paid to the dynamics of *change* in green vegetation in residential landscapes than to the different quantities and qualities between neighborhoods, pressing questions of how to improve the equitable facilitation of urban ecosystem services through neighborhood green space

(Wolch et al., 2014) require a better understanding of how changes in the resident population and in housing conditions drive changes in green vegetation.

Recently, scholars of the social and economic drivers of vegetation change have converged on the idea that the distribution of vegetated cover in residential landscapes is determined by a few broad factors (Giner et al., 2013): gradients of population or development density in the built environment determine how much area is available for green vegetation; economic stratification (or the "luxury effect," as described by Hope et al., 2003) drives differences in both public and private investment in landscaping and the urban tree canopy; and social stratification or "prestige" factors (Grove et al., 2006, Troy et al., 2007), related to lifestyles and life stages, describe how residents' preferences and decisions about landscaping depend on their household size, the presence of children, or whether they feel compelled to keep up with neighborhood norms. Some syntheses see social and economic stratification as a single, broad set of mechanisms arising from household preferences and a wider political economy: households communicate social norms through landscape-level "cues to care" (Nassauer et al., 2009); socially mobile residents can capitalize on public green spaces and larger lot sizes in deciding where to live; and wealthier residents can afford extravagant landscaping and potentially costly irrigation to maintain private green spaces (Locke and Grove, 2016, Chuang et al., 2017). But if we separate the effects of income and wealth from those of reference group behavior and social contagion, we can identify three factors: density, luxury, prestige; this three-factor model (density, luxury, prestige) has been repeatedly used to explain the spatial distribution of green vegetation in numerous study areas, primarily in the continental United States (U.S.).

To date, the studies that have informed the three-factor model have generally examined only one or two factors in a specific place and/or at a specific time (Chuang et al., 2017). Other studies tend to imagine two of the tiers, economic stratification and social stratification, as competing, rather than complementary, narratives (Grove et al., 2014). Social stratification or prestige certainly plays a role in explaining neighborhood-level variation in green vegetation; many studies note that measures of lifestyle or life stage (e.g., family formation, education, type of employment) better explain spatial variation in neighborhood- and particularly parcel-level vegetation than socio-economic status (Grove et al., 2014, Visscher et al., 2014). Of course, there are many contemporary studies that point to economic stratification or the "luxury effect" as the dominant organizing principle of urban vegetation disparities (Clarke et al., 2013, Li et al., 2015, Schwarz et al., 2015, Steenberg et al., 2015). Yet it also seems likely that differences in vegetation ownership and qualities—between public and private green space and between tree canopy and other parcel-level green vegetation—are more directly related to an ecology of prestige, or to social contagion and residents' lifestyles (Heynen et al., 2006). One limitation of prior work on the analysis of prestige and lifestyle factors in the U.S. has been the repeated reliance of such studies on a single proprietary dataset, namely the Claritas Potential Rating Index for Zipcode Markets (PRIZM) dataset, which suggests that prestige hasn't been explicitly operationalized for future study. It begs the question: can the the three factors of density, luxury, and prestige not be identified directly from resident profiles and neighborhood conditions? These data limitations notwithstanding, the mixed evidence in the literature indicates that luxury effects (e.g., landscaping, investment) and prestige (e.g., lawn-care behaviors, housing setbacks) both partially explain neighborhood-level vegetation differences and change.

The three-factor model also raises questions about parts of socio-ecological theory that may be left behind. In particular, though studies of uneven neighborhood greenness have also identified that both time lags and legacy factors are important (Bigsby et al., 2014, Locke and Baine, 2015, Grove et al., 2018), they are often ignored by researchers looking to explain present-day vegetation disparities. Yet, certain spatial patterns in the built environment may signal a legacy of disinvestment, economic racism, and land-use legacies such as environmental contamination from polluting industries or brownfields. There are several methodological and data availability challenges to adequately incorporating time lags in socio-ecological research; yet neighborhood legacies, often persisting through the current day, can be measured in a variety of ways, reflecting how disinvestment, racism, and a spatial fix for undesirable industrial activity are intertwined (Wyly et al., 2004). Extensive demolition (Endsley et al., 2018, Chapter II, this volume) or targeted redevelopment (Wilson and Brown, 2014) are two examples where neighborhood legacies yield specific processes that shape neighborhood-level vegetation changes. In the U.S., neighborhoods have also been differentially improved or harmed by the introduction of building codes and also by Progressive-era social movements to promote the general welfare through the development of urban parks. The on-going legacies of racially targeted disinvestment or speculation in neighborhood housing markets, including foreclosure, may also be related to vegetation change (Deng and Ma, 2015, Minn et al., 2015).

This study responds to an outstanding need for comparative analyses of how the effects of density, luxury, or prestige drive vegetation change in different urban contexts (Chowdhury et al., 2011, Jenerette et al., 2013), exemplified by the sometimes surprising results from studies of cities differentiated by their climate

(Ripplinger et al., 2017) or demographic changes (Endsley et al., 2018, Chapter II, this volume). Comparative studies can also generate synergistic or counterfactual examples, enabling new theories. Most salient to the discussion of urban green space is the observation that while growing cities often have insufficient green vegetation due to population pressure, shrinking cities, at least in temperate climates, often have an abundance (Herrmann et al., 2016); identifying common drivers of disparate outcomes in growing versus shrinking cities could inform place-specific policy interventions.

While case studies at or within the city or neighborhood scales proceed from well-contextualized observations (e.g., Heynen et al., 2006), metropolitan-scale or cross-metropolitan comparative studies require an approach that scales well and is still interpretable. Here, I use a data-driven approach to describing the common factors of neighborhood social and economic variation over the past 27 years for three metropolitan areas diversified by their climate and population growth regimes: the Detroit Metropolitan Area and the Los Angeles and Seattle Metropolitan Statistical Areas (MSAs). These factors are compared to the well-documented structural factors of density, luxury, and prestige, in their ability to explain change in neighborhood-level vegetated cover. As I will demonstrate, this comparative, statistical approach still requires attention to the historical context and neighborhood legacies that shape relations between population, housing, and vegetation.

Identifying common factors of neighborhood change and how they vary between urban contexts is also an important goal of demographers, urban planners, and social scientists engaged in studying residential populations and urban places (Abel and White, 2015, Hochstenbach and van Gent, 2015). As recent studies demonstrate, empirical patterns of neighborhood change can be used both to validate theories of change but also to spur questions and identify gaps in understanding (e.g. Delmelle, 2016). The objectives of this study respond to two outstanding questions about the social and economic drivers of neighborhood vegetation change:

**Q1.** How do the patterns of social and economic change discovered in Census and housing market data correspond to those of density, luxury, and prestige, which are theorized to have created uneven neighborhood vegetation conditions?

**Q2.** How do these ongoing social and economic changes relate to change in vegetated cover and vigor at neighborhood scale in different metropolitan areas?

**Q3.** How do historical legacies confound or complicate this data-driven approach to understanding relationships between contemporary neighborhood social or economic changes and vegetation change?

## 4.2 Data and Methods

I use neighborhood-level social and economic variables to identify common factors of neighborhood change and how they relate to observed patterns of vegetation change. Tract-level data from the U.S. Census Bureau are combined with housing market data and pooled together in four periods: 1990, 2000, 2010, and 2015. The common factors—possibly including density, luxury, and prestige—are modeled as *latent variables* and are induced directly from a panel of inter-related measures of neighborhood conditions. Finally, the relationships between change in these latent variables and change in vegetation conditions are estimated using mixed models developed separately for each metropolitan area.

### 4.2.1 Study Areas

The cities of Detroit, Los Angeles, and Seattle and their surrounding communities are illustrative of three broad patterns in other U.S. metropolitan areas. Detroit, with its shrinking core and growing suburbs, reflects the historic decentralization of U.S. cities and ongoing population decline. Seattle, in stark contrast, is growing rapidly, in large part due to growth in its economies of scale and in a young, working population that increasingly desires density and its corresponding urban amenities. Los Angeles, too, is growing, but must of its development in the last decade of the twentieth century follows that of other Sunbelt cities, accommodating population growth with a much smaller rise in housing costs than Seattle. Though the specific insights about social and economic changes in these cities are most relevant to other U.S. cities, the methodology used to investigate the socio-ecological relations of these cities is certainly transferable to metropolitan areas world-wide.

In Los Angeles and Seattle, the U.S. Census Bureau's defined metropolitan statistical area (MSA) is used. In Detroit, the study area encompasses only Wayne, Oakland, and Macomb counties, but this spans an entire urban-to-rural gradient and contains the vast majority of its population and structures. The three study areas differ importantly in their climatic conditions. The Los Angeles MSA is warm and arid: mean May-through-July precipitation over the period 1981-2010 was 0.33 inches for the city of Los Angeles but 4.2 and 14.2 inches for Seattle and Detroit, respectively (NOAA, 2019). Average temperatures were more similar for this same period, ranging from 60.7 F in Seattle to 66.4 F in Los Angeles.

In all study areas, tracts that contained a significant amount of cultivated (agricultural) lands were excluded from the analysis (Figure 4.1). This determination was made by identifying areas that were classified as “cultivated” in all three available years of the National Land Cover Dataset (NLCD): 2001, 2006, and 2011; tracts with a large amount of land consistently classified as cultivated were removed. The thresholds for removal were determined empirically for each metro area, judging by the number of tracts removed and the spatial pattern created. In the Detroit Metro study area, tracts with more than 11% of their area cultivated were excluded. In the Los Angeles and Seattle MSAs, the thresholds were 1.3% and 6.0%. In the Seattle MSA, tracts with considerable National Forest or National Park area were also removed; this led to the exclusion of a small number of large-area tracts in the east of the MSA. Finally, in the Los Angeles MSA, because a small number of tracts in southeast Orange County were located on a separate Landsat path from the rest, these tracts were excluded.

**Neighborhood Social and Economic Indicators**

Measures of social and economic conditions by Census tract were taken from the decennial U.S. Census in 1990, 2000, and 2010 as well as from the American Community Survey (ACS) 5-year summaries in 2012 and 2017. The 5-year summaries average conditions over 2008-2012 and 2012-2017 and they can be considered as describing neighborhood conditions in a window that is centered on 2010 and 2015, respectively. I selected any social and economic measures that have been found to significantly co-vary with vegetation in prior studies of neighborhood social, economic, and vegetation relations. Mennis (2006), Luck et al. (2009), and Patino and Duque (2013), in particular, include tables of the relevant variables that have repeatedly been implicated in such studies; our list is presented in Table 4.1, along with the source of the data.

Most of the decennial Census and ACS variables were obtained from the U.S. Census Bureau through Social Explorer (SocialExplorer.com). Median household income was obtained, unadjusted from the IPUMS National Historical Geographic Information System or NHGIS (Manson et al., 2018) and is adjusted for inflation to 2015 USD using the harmonized, seasonally unadjusted CPI for all items. All population and housing unit counts were converted to percentages relative to appropriate totals. The count of persons having attained a graduate degree varies between Census years; later years enumerate separate counts of professional, master's, and doctoral degrees, all of which are lumped together as graduate degrees for consistency. Similarly, the 65-and-over age distribution is obtained by summing multiple age bins.

In addition to the self-identified population shares of white, black, Asian, or Hispanic residents, I include measures of racial and ethnic segregation: black-white unevenness and Hispanic/ Non-Hispanic unevenness. These measures are related to the dissimilarity index or DI (White, 1983), but are calculated slightly differently. Whereas the DI drifts over time with the changing metropolitan racial or ethnic composition, this measure of unevenness—which can be interpreted as the proportion of the population that would have to move into or out of a neighborhood to achieve two-group racial or ethnic parity—is insensitive to changes in the overall population sizes over time as it depends only on the relative shares of each group within a single neighborhood. Equation 4.1 shows how unevenness is calculated for any two groups, $P_1$ and $P_2$.

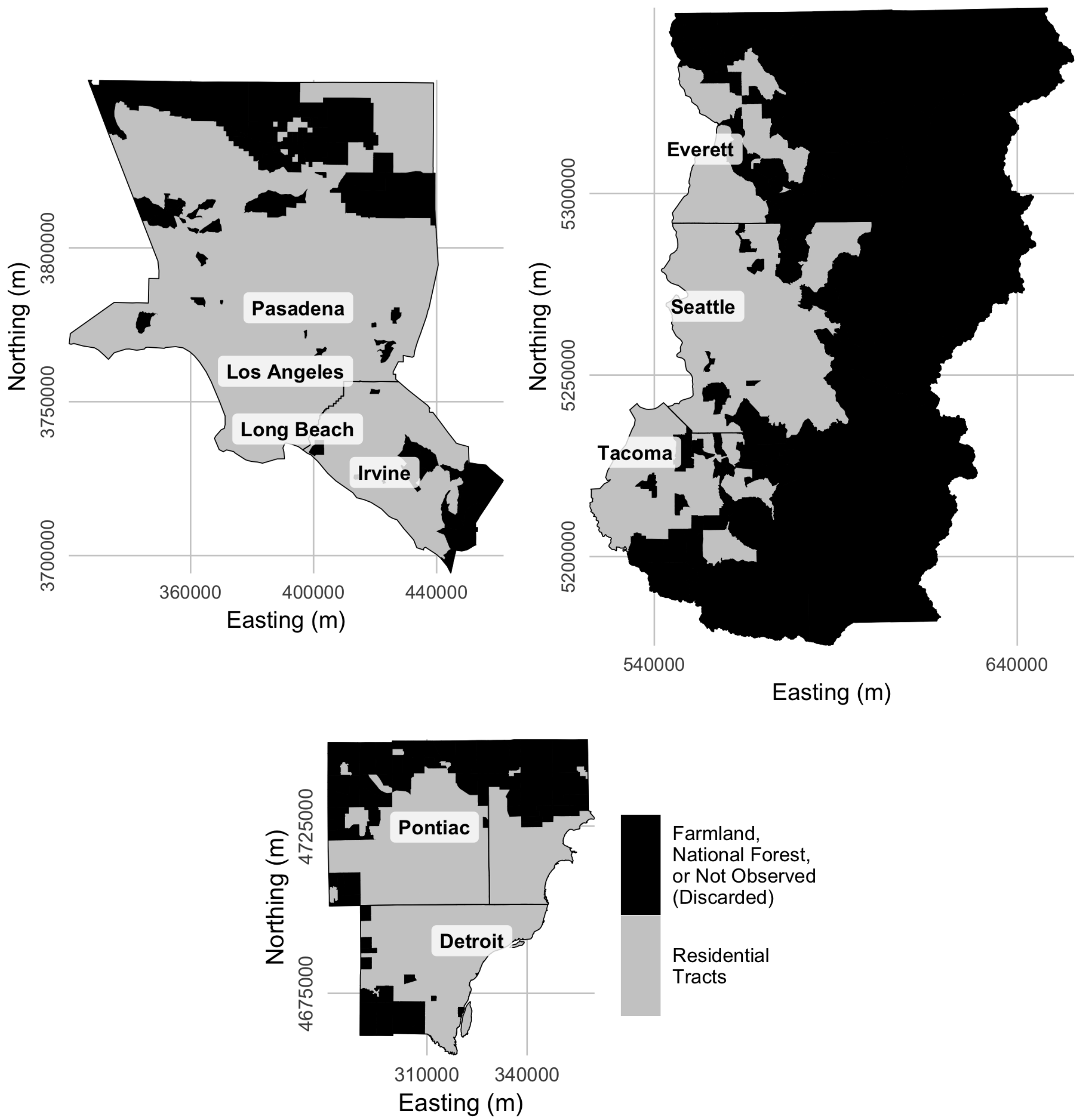


**Figure 4.1:** The three study areas, shown at approximate scale, in UTM projection. From top-left, clockwise: Los Angeles MSA (UTM 11N), Seattle MSA (UTM 10N), Detroit Metro (UTM 17N). The counties that make up each metropolitan area or MSA are outlined in black. Census tracts that were dropped from each study region's panel, due to considerable cultivated or National Forest area, or which otherwise had missing data, are filled in with black.

**Table 4.1:** Measured variables of neighborhood conditions and their sources.

| **Variable** | **Data Source** |
|---|---|
| Population density | Decennial U.S. Census; Social Explorer |
| Housing density | Decennial U.S. Census; Social Explorer |
| Population 17 years of age and under | Decennial U.S. Census; Social Explorer |
| Population 65 years of age and over | Decennial U.S. Census; Social Explorer |
| Population self-identified as white alone | Decennial U.S. Census and ACS; Social Explorer |
| Population self-identified as black alone | Decennial U.S. Census and ACS; Social Explorer |
| Population self-identified as Asian alone | Decennial U.S. Census and ACS; Social Explorer |
| Population self-identified as Hispanic | Decennial U.S. Census; Social Explorer |
| Persons married | Decennial U.S. Census and ACS; Social Explorer |
| Persons attained a Bachelor's degree | Decennial U.S. Census and ACS; Social Explorer |
| Persons attained a Graduate degree | Decennial U.S. Census and ACS; Social Explorer |
| Owner-occupied housing rate | Decennial U.S. Census; Social Explorer |
| Vacant housing rate | Decennial U.S. Census; Social Explorer |
| Median household income (2015 USD) | Decennial U.S. Census and ACS, Social Explorer and IPUMS NHGIS |
| Median home value (2010 USD) | Decennial U.S. Census and ACS, Social Explorer and IPUMS NHGIS |
| Median sale price (2010 USD) | Deed sales, CoreLogic Inc. |
| New housing starts/ construction | Tax assessor's records, CoreLogic Inc. |
| 2-year mortgage foreclosure rate | Deed sales, CoreLogic Inc. |
| Cumulative mortgage foreclosure rate | Deed sales, CoreLogic Inc. |
| Share of housing that is single-family | Tax assessor's records, CoreLogic Inc. |
| Median year built | Tax assessor's records, CoreLogic Inc. |
| Median parcel size | Tax assessor's records, CoreLogic Inc. |
| black-white unevenness | Decennial U.S. Census; Social Explorer |
| Hispanic/ Non-Hispanic unevenness | Decennial U.S. Census; Social Explorer |
| Elevation (meters) | USGS National Elevation Dataset |

$$\text{Unevenness}(P_1, P_2) = \frac{1}{2}\left|\frac{P_1}{\sum P_i} - \frac{P_2}{\sum P_i}\right| \tag{4.1}$$

**Housing Market Measures of Neighborhood Change**

Median sale price-per-square foot is obtained in most years from the deed sale records of qualified residential properties, obtained from CoreLogic, Inc. However, in 1990, about half of Detroit Metro Census tracts do not have a recorded sale. In addition to median sale price, multiple imputation is used to recover missing neighborhood-year observations of median year built, median household income, and median parcel size in all metro-area panels. The approach used is implemented in the Amelia II software (Honaker and King, 2011) for the R statistical computing environment. Prior to imputation, all variables, including those with no missingness and those for which some missingness is tolerated, are transformed, as needed, so that all variables are approximately normally distributed. Over-imputation diagnostics and a comparison of the kernel density estimates of the distributions of observed versus imputed values indicated the imputed values were a very good match.

The percentage of missing tract-year observations for any of the four imputed variables was no higher than 3.3% in any study area, except for median sale price in the Detroit Metro area (16.1%). Median sale price-per-square foot in these tracts is computed using multiple imputation based on the other panel variables but also on the median home value as estimated by the 1990 Census, which is interpolated to 2010 Census tract boundaries using the population and area weights established by Logan et al. (2016). The interpolated 1990 home values are used solely for multiple imputation. Prior to imputation, the 1990 home value estimates are adjusted for inflation to 2010 USD using the unadjusted CPI-U (for all urban consumers) for housing from the Federal Reserve Bank of St. Louis. Missing data were imputed separately in each year for each study area. The mean value across 30 imputed estimates was used to replace missing values in each case for only the median sale price, median year built, median household income, and median parcel size variables.

**Green Vegetation**

Most prior studies of neighborhood vegetation patterns have relied on greenness indices (e.g., Mennis, 2006, Jenerette et al., 2013, Deng and Ma, 2015) such as the normalized difference vegetation index (NDVI). These proxies for green vegetation have the advantages that they are easy and fast to compute and generally comparable throughout a study area. However, as mere proxies of green vegetation, they are difficult to interpret as a modeled outcome of social or economic change and are frequently biased in certain climatic settings. NDVI, in particular, and related greenness indices, are affected by background contamination, particularly soil brightness and color (Fensholt et al., 2006); these issues are more pronounced in sparsely vegetated areas, such as semi-arid Los Angeles.

I employ a physically based measure of a neighborhood's green vegetated area derived from linear spectral mixture analysis (LSMA) of Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) surface reflectance (SR). LSMA is particularly well-suited to urban studies because of the problem of mixed pixels in moderate resolution satellite imagery, i.e., the tendency for a single pixel to contain multiple different ground covers, due to the relatively large size of Landsat pixels compared to that of ground features. Landsat SR data were obtained from the U.S. Geological Survey (USGS) EROS Science Processing Architecture (ESPA) along with pixel-level quality assessment (QA) data. In each study area, a determination of the “leaf-on” or green leaf-cover season was made based on climatic data. In the Detroit Metro and Seattle MSA areas, in particular, seasonal snow cover is present for part of the year. The Los Angeles and Seattle MSAs are situated along the Pacific coast and have separate warm and wet seasons. In the Los Angeles MSA, this separation can lead to different signals of green vegetation in wet versus dry seasons. However, to facilitate comparison across all study areas, we used only Landsat images in the months of May through September, inclusive.

All Tier 1 Landsat 5 TM and Landsat 7 ETM+ images with less than 60% land cloud cover, in these months, were utilized, though some images were thrown out due to haze and clouds that could not be masked based on the flags in the QA band. Landsat 8 OLI data were not used, although they are available for part of the study period, as the OLI sensor characteristics are quite different from TM and ETM+. Only images in a single World Reference System 2 (WRS2) path were used in each study area to avoid error that may be introduced from different look angles in overlapping paths. Finally, to account of variations in scene-specific brightness over time than can occur due to variations in atmospheric conditions and cloud cover not otherwise corrected for or masked, each image in a study area’s time series is relatively radiometrically normalized using the approach described by Hall et al. (1991), where the metro-specific reference image is selected for having the highest dynamic range in either 2000 or 2010. Each radiometrically normalized image was unmixed using a fully constrained least-squares approach identical to that described by Endsley et al. (2018, Chapter II, this volume); the final vegetation abundance images were composited annually at the pixel level into a single image representing the median summer-time vegetation density. Validation of this approach in previous work by the author indicates that vegetated area is estimated with $\pm 11.8 - 13.9\%$ root mean squared error (Endsley et al., 2018).

### 4.2.2 Modeling Latent Social and Economic Variables

In evaluating the contribution of social and economic change to vegetation change, then, we are confronted with a suite of neighborhood social and economic conditions that vary over time and space and cannot be evaluated independently from one another. Certain neighborhood change processes may only be detected, outside of the lived experience of residents, as subtle shifts in neighborhood income, age, or racial or ethnic composition (as with gentrification, e.g., Abel and White, 2015) or in the combined movement of these indicators along with housing market measures (Smith, 1987). Yet, common variation in indicators of neighborhood conditions may reveal the social and economic factors driving neighborhood differentiation. These common factors may then be modeled as latent variables (Pett et al., 2003) which influence or are constituted by a number of inter-related measured variables (Fabrigar and Wegener, 2012), such as neighborhood conditions measured during the decennial U.S. Census.

Based on initial assessments of the correlation structure of the combined Census and housing market data panel, for a single metropolitan area in all years, a confirmatory factor analysis (CFA) was conducted to model the latent variables that were represented by the pooled neighborhood indicators. The CFA model was implemented as a structural equation model and fit using the `lavaan` library in the R statistical computing environment (Rosseel, 2012). The CFA model was constrained such that both the loadings and the intercepts of the measured Census and housing market variables are the same in every year of the study panel (1990, 2000, 2010, 2015). This establishes *strong invariance,* i.e., that any two neighborhoods with the same score on one of the latent variables will have the same expected values in the measured variables in every year (Beaujean, 2014) and can therefore be meaningfully compared across the years.

Between 4 and 6 latent factors were considered, based on an examination of screeplots (Fabrigar and Wegener, 2012) from the principal components analysis but also from different oblique rotations of the initial factors. All factors were allowed to have non-zero covariance, i.e., they were not constrained to be independent of or orthogonal to one another; allowing correlation between factors may result in a more realistic model of neighborhood, as, for example, age structure is not necessarily independent of education levels. Some of the measured variables listed in Table 4.1 had to be dropped because their co-variation was too difficult to model in a particular metropolitan area. Sometimes, more than one stable CFA model was found, typically by exchanging one measured variable for another moderately correlated variable. The comparative fit index (Beaujean, 2014) and residual error metrics were used to determine which model was a better fit to the variance structure overall. In both the Seattle MSA and the Detroit Metro models, in order to achieve a stable solution, the intercepts for white population share were allowed to vary between years. All other measured variable intercepts and all loadings were constrained to be identical across years in each metropolitan area's model.

### 4.2.3 Modeling the Context and Drivers of Vegetation Change

It is essential, in evaluating the social and economic drivers of neighborhood vegetation change, to understand the context in which these changes occur. Thus, the statistical model developed in this study is one that simultaneously estimates both a contextual effect and a within-neighborhood effect of common social and economic factors on vegetated cover. This is achieved with a mixed-effects model commonly known as the within-between (WB) random effects model (Allison, 2009), shown in Equation 4.2. Specifically, the contextual effect, $\beta_B$ for a given variable, say, household income, on a neighborhood's vegetation density, $y_{it}$, is the effect of a neighborhood's long-term mean household income; it is a between-neighborhood effect. The within-neighborhood effect, $\beta_W$, in this example, is the effect that a growth in income in the average neighborhood would have in changing vegetation density.

$$
\begin{aligned}
&y_{it} = \beta_0 + \left(X_{it} - \bar{X}_i\right)\beta_W + \bar{X}_i\,\beta_B + \gamma_i + \varepsilon_{it} \\
&\gamma_i \sim \mathbf{N}\left(0,\, \sigma^2_\gamma\right)
\end{aligned}
\tag{4.2}
$$

The within estimates, $\beta_W$, are identical to those of a classic fixed effects (FE) estimator (Allison, 2009) and therefore do not suffer from the bias introduced by a random effects model when the random effects assumption is unjustified. In Equation 4.2, $\gamma_i$ is the random neighborhood intercept term. The WB random effects model is fit in the R statistical computing environment with the `lme4` library using restricted maximum likelihood (REML). Statistical significance at the 99% confidence level is calculated using Sattherthwaite's approximation of p-values (Kuznetsova et al., 2017), which have been shown to achieve the correct

Type-I error rates for mixed models when REML is used (Luke, 2017).

In each metropolitan area (modeled separately), both contextual effects and within effects of each common factor from the CFA were initially considered. In addition, certain metro-area models included additional variables that directly represent well-identified neighborhood change processes, such as segregation or between-group unevenness (Equation 4.1), the construction rate (in all three study areas), and the mortgage foreclosure rate (in Los Angeles MSA, only, for lack of complete data in the others). As previous studies point to the exceptional socio-ecological relations of the City of Detroit (Hoalst-Pullen et al., 2011, Endsley et al., 2018), in the Detroit Metro model, a dummy variable for City neighborhoods is interacted with most of the covariates.

Finally, both contextual and within effects for key climate variables were added: the current and one-year lagged total summer precipitation and the mean July temperature for the given year. These variables were aggregated within Census tracts each study year from data provided by Oregon State University's PRISM Climate Group (Daly et al., 2004). To estimate these variables within Census tracts, the average value was estimated after resampling the original 2.5 arc-minute data to 90-meter spatial resolution. Multicollinearity was assessed by calculating variance inflation factor (VIF) scores from an ordinary least squares (OLS) model that reproduces the mean structure of the WB random effects model.

## 4.3 Results

### 4.3.1 Common Factors of Neighborhood Change

Though factor invariance between metropolitan areas was not pursued or investigated, the common factors identified (Table 4.2) are remarkably similar across all three study areas; they also compare very well with other studies that have reduced the dimensionality of similar data panels (Abel and White, 2015, Delmelle, 2016, Chuang et al., 2017). F1 is interpreted as "Residential stability" in the sense of twentieth-century U.S. housing market norms: low housing densities, the ideal of home-ownership (as opposed to renting), and the ideal of the single-family, detached house are represented in the positive loadings on these conditions in all three metropolitan areas. In addition, high marriage rates and high incomes are also determined by F1. This suggests that home-ownership, long seen as a financial vehicle for building equity and inter-generational wealth, is strongly associated with certain housing characteristics but also with certain socio-economic advantages, namely marriage and high household incomes.

**Table 4.2:** Empirical factors from the confirmatory factor analysis (CFA) and their loadings for each metropolitan area.

| Factor interpretation | Loadings: Detroit Metro | Loadings: Los Angeles MSA | Loadings: Seattle MSA |
|---|---|---|---|
| **F1: Residential stability** | Owner-occupied rate (1.00), Marriage rate (0.34), Under-17 rate (0.22), Single-family rate (0.13), Housing density (-0.10), Household income (0.10) | Owner-occupied rate (1.00), Single-family rate (0.22), Housing density (-0.19), Vacancy (-0.19), Marriage rate (0.19), Over-65 rate (0.14), Household income (0.09) | Owner-occupied rate (1.00), Housing density (-0.70), Marriage rate (0.35), Single-family rate (0.24), Vacancy (0.11), Household income (0.11), Median year built (0.10) |
| **F2: Relative black-white population share** | Black pop. proportion (1.00), White pop. proportion (-0.80), Vacancy rate (0.20), Under-17 rate (0.08), Year built (-0.03), Marriage rate (-0.02), Single-family rate (-0.01) | White pop. proportion (-1.24), Black pop. proportion (1.00), Marriage rate (-0.19), Home sale price (-0.03) | Black pop. proportion (1.00), White pop. proportion (-0.68) |
| **F3: Economic advantage of child-less "Creative Class"** | Graduate degree attainment (1.37), Bachelor's degree attainment (1.00), Under-17 rate (-0.18), Household income (0.05) | Graduate degree attainment (1.43), Bachelor's degree attainment (1.00), Household income (0.09), Home sale price (0.07) | Graduate degree attainment (1.39), Bachelor's degree attainment (1.00), Under-17 rate (-0.52), Owner-occupied rate (0.46), Household income (0.17) |
| **F4: Hispanic residents** | Hispanic pop. proportion (1.00) | *(No stable solution)* | Hispanic pop. proportion (1.00) |
| **F5: Families with children** | Asian pop. proportion (1.00), Owner-occupied rate (-0.35), white pop. proportion (0.11), Marriage rate (0.09) | Under-17 rate (1.00), Marriage rate (0.45), Over-65 rate (-0.28) | Housing density (1.01), Under-17 rate (1.00), Vacancy rate (-0.88), Marriage rate (0.41) |

F2 is strongly related to the shares of self-identified white and black residents. As such, neighborhoods that score high on F2 are generally highly segregated, majority-black neighborhoods; over time, a neighborhood's increasing F2 score could indicate a majority-white neighborhood that is integrating. This is inevitable where either some white residents are displaced by incoming black residents or black in-migration is higher than white in-migration. In Detroit Metro and Los Angeles MSA neighborhoods, related loadings on high vacancy rates, low marriage rates, and an older housing stock indicate that economic disenfranchisement is associated with black residential segregation.

F3 can be understood as the effect of the "creative class," as described by Florida (2002). In all three metropolitan areas, this factor determines high levels of post-secondary education and high household incomes; the latter follows from the higher wages demanded by higher levels of education. In Seattle and Detroit neighborhoods, childlessness also loads onto this factor, as highly educated working professionals in these neighborhoods may have delayed or opted-out of child-rearing. Creative class households enjoy related socio-economic advantages, including higher home values and higher rates of homeownership.

F4, which loads onto only one variable, is essentially the proportion of Hispanic residents or, over time, the growth in the neighborhood's Hispanic population. No stable CFA model for any metropolitan area allowed any other variable to be co-determined by this factor. The instability of the Hispanic population proportion variable may be due to potentially high estimation errors in the 2017 ACS 5-year sample; this variable in the 2017 survey in the Detroit metropolitan area shows significant and unrealistic negative spatial autocorrelation across Census tracts, a pattern that is considerably different from the previous three decennial surveys. If not due to error, then the Hispanic population proportion variable may have a particular set of covariances that we have not been able to reproduce with the current model structure.

F5 is the most heterogeneous factor between the metropolitan areas and not really comparable between study areas. F5 is commonly associated with a high under-17 rate and a high marriage rate, indicating that family formation is a distinct factor of neighborhood-level variation. However, stable solutions for the variance structure also had to contend with the influence of the Asian population share variable, which was highly correlated with the first three factors in each study area, particularly in Detroit, where this factor contributed to substantial variance inflation in the regression model. In the Seattle and Los Angeles MSA areas, the factor represents all families with children.

### 4.3.2 Trends in Green Vegetation Density

Figures 4.2, 4.3, and 4.4 shows robust linear trends of vegetation density over the 1990, 2000, 2010, and 2015 annual vegetation composites in each area. In general, most neighborhoods are getting greener in the temperate climates of the Detroit and Seattle metropolitan areas. In particular, vegetation trends within the City of Detroit are consistent with the "greening of Detroit" observed in previous studies (Ryznar and Wagner, 2001, Hoalst-Pullen et al., 2011); we observed strong growth in vegetation on the east and northeast sides of the City of Detroit, likely due to extensive abandonment and demolition in those neighborhoods (Endsley et al., 2018, Chapter II, this volume). In the Seattle MSA, almost every Census tract has experienced growth in green vegetation since 1990, consistent with changing land uses due to deindustrialization (Abel and White, 2015), but none more so than those within the “Emerald City” of Seattle (outlined in black in Figure 4.4). The lush, moderate-density, single-family home neighborhoods of north Seattle, including the Woodland Park and Green Lake areas, have seen the strongest growth in vegetation. In contrast to these temperate regions where water is generally in high availability, semi-arid Los Angeles MSA neighborhoods have generally lost vegetation cover since 1990. Neighborhoods at higher elevations, such as in the Malibu and Bel Air Hills or Verdugo Mountains, have moderately increased in green cover, likely because there is more tree cover in these areas (McPherson et al., 2011) and wealthier neighborhoods in these areas invest more in irrigation of landscaping (Clarke et al., 2013, Mini et al., 2014, Clarke and Jenerette, 2015). The overall decline in warm-season green vegetation cover elsewhere in the Los Angeles MSA is likely due to rising temperatures and more frequent drought conditions; indeed, from 2006 through 2010, single-family water use in L.A. declined steadily along with the greenness of irrigated residential lands from 2006 through 2010 (Mini et al., 2014).

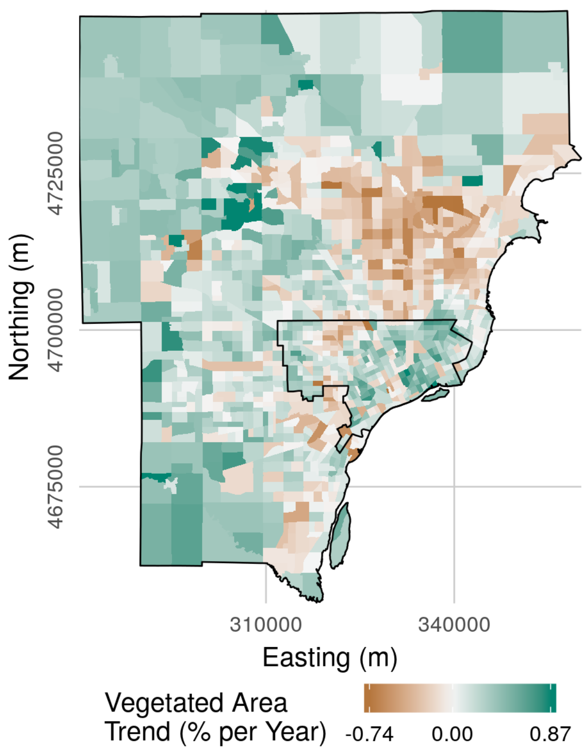


**Figure 4.2:** Robust vegetation change trends for the Detroit Metro area, summarized by 2010 Census tracts. The City of Detroit is outlined in black.

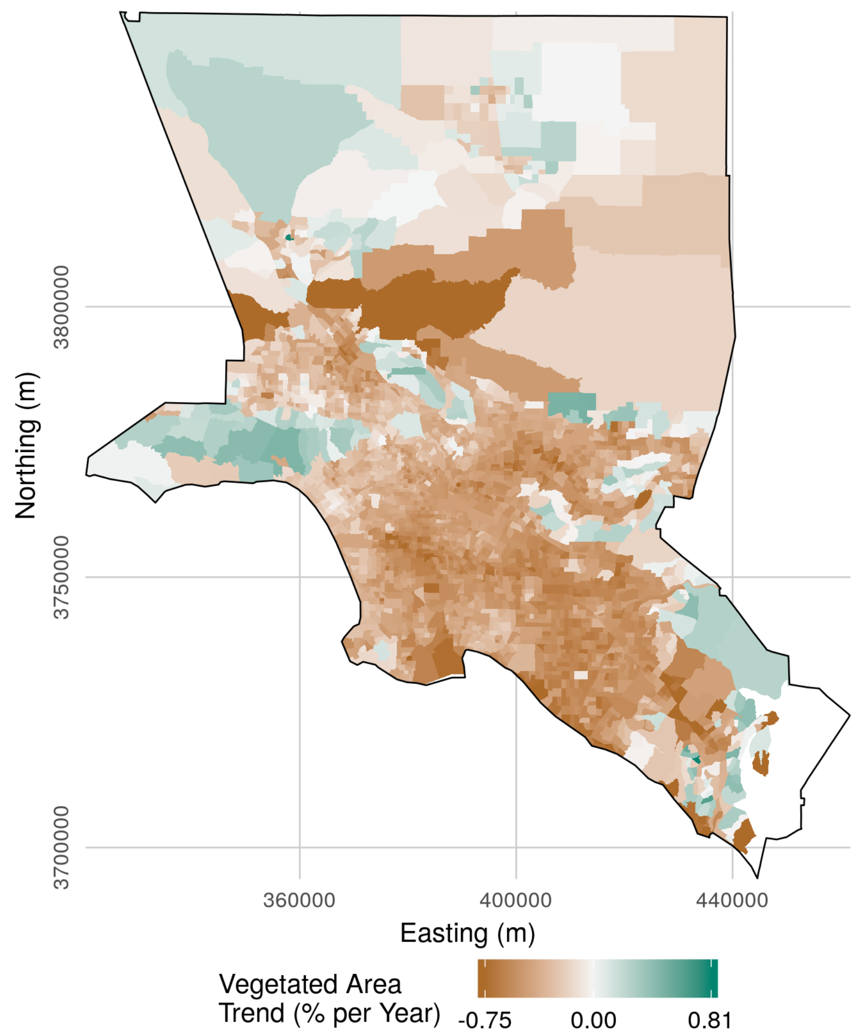


**Figure 4.3:** Robust vegetation change trends for the Los Angeles MSA, summarized by 2010 Census tracts.

### 4.3.3 Within-Between Random Effects Model

In the Detroit Metro within-between (WB) random effects model, inclusion of common factor F5 led to severe multicollinearity with multiple other factors and so was dropped from the model. Likewise, the contextual effects that were interacted with the City-of-Detroit dummy variable had very high VIF scores in the OLS model and were subsequently dropped. In all models, black-white unevenness was highly correlated with F2 and had to be dropped. In the Seattle MSA model, F1 and F5 are highly correlated, so two separate models were estimated for Seattle MSA neighborhoods, exchanging F1 for F5 and vice-versa.

Robustness checks included visual interpretation of the residuals for heteroscedasticity and spatial autocorrelation. A plot of the model residuals against the fitted values showed no apparent deviation from constant variance across the domain. Spatial autocorrelation was assessed by calculating the distance from each Census tract's centroid to the central business district (CBD) of each metropolitan area. A generalized additive model smoother fit to the residuals plotted by distance to the CBD showed an almost completely flat relationship, i.e., no dependence on distance to the CBD.

In all three study areas, high long-term neighborhood stability (F1) is a context for high vegetation density (Table 4.3) In the Seattle MSA, both residential stability (F1) and the presence of families with children (F5) are contexts for greener neighborhoods; though modeled separately, they are both strong effects on long-term vegetation cover. In the Los Angeles MSA, creative class enclaves (F3) are also typically greener, whereas these same neighborhoods in the Seattle MSA are typically less green, controlling for families with children. In the Detroit Metro model, a surprising result (given the tendency for high vegetation density

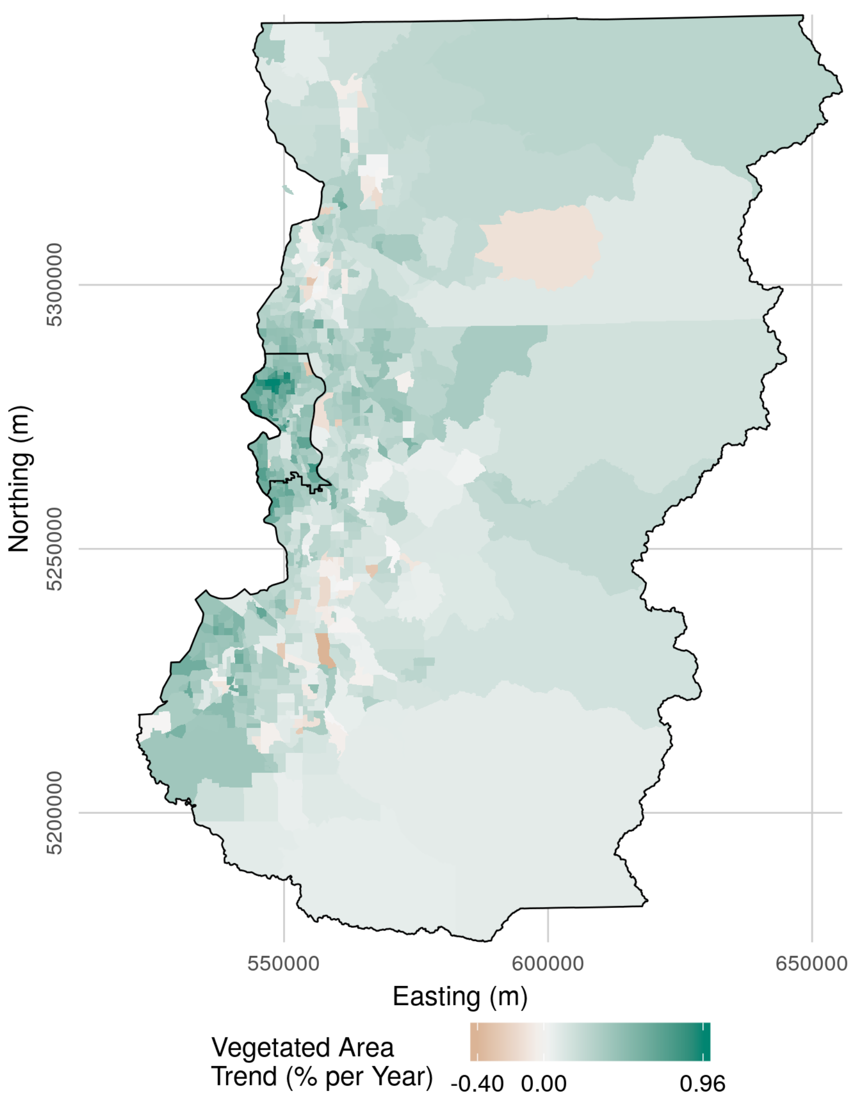


**Figure 4.4:** Robust vegetation change trends for the Seattle MSA, summarized by 2010 Census tracts.

to follow high socio-economic status) is that neighborhoods with a high share of black residents and their associated economic disenfranchisement (F2) have high vegetation densities, net of residential stability.

The factors driving *change* in vegetation density (Table 4.4) seem to be very different between metropolitan areas. Although declines in residential stability (F1) are significant drivers of vegetation growth within the City of Detroit (not the wider Metro Area) and in the Los Angeles MSA, this effect is a weaker driver of vegetated cover *loss* in the Seattle MSA. Increasing black population proportions in the Seattle MSA and in suburban Detroit neighborhoods is a significant driver of vegetation loss, but this kind of change has no significant effect on vegetated cover in the Los Angeles MSA. The significant driving effects of growth in the creative class (F3) in the Los Angeles and Seattle MSAs, but not in the Detroit Metro area, may be due to the greater concentration of highly educated people in those areas, relative to Detroit. However, the concentration of these highly educated, high-income populations seem to have differing effects; in the Los Angeles MSA model, growth in F3 drives growth in vegetation cover, whereas in the Seattle MSA model, growth in F3 drives loss in vegetation cover. Growth in families with children (F5) also has a different effect: it is a driver of vegetation loss in the Los Angeles MSA but of gain in the Seattle MSA. In the Los Angeles MSA, where we have additional data on mortgage foreclosures unavailable in the other study areas, we see that an increase in the 2-year mortgage foreclosure rate is the strongest driver of growth in vegetation density in that area.

**Table 4.3:** Contextual effects, and standard errors in parentheses, estimated by the within-between random effects model. Response variable is proportion of neighborhood area (ranging from 0 to 1) that is vegetated. Foreclosure and construction rates are the number of events normalized by the total housing units. Satterthwaite approximate p-values denoted: *** p-value $< 0.0001$; ** p-value $< 0.001$; * p-value $< 0.01$.

| Covariate | Detroit Metro | Los Angeles MSA | Seattle MSA (with F1) | Seattle MSA (with F5) |
|---|---|---|---|---|
| **Climate: Annual Precipitation (mm)** | **-0.00114** | **0.00221** | **0.00036** | **0.00044** |
| | (0.00021)*** | (0.00024)*** | (0.00006)*** | (0.00007)*** |
| **Climate: July Mean Temperature (deg C)** | **-0.09803** | **0.00239** | **0.00071** | **0.00346** |
| | (0.00694)*** | (0.00128) | (0.00759) | (0.00774) |
| **Construction Rate** | **0.20807** | **-0.09049** | **-0.06129** | **-0.04663** |
| | (0.16436) | (0.02748)* | (0.07589) | (0.07737) |
| **Elevation (by 100m)** | | **0.00656** | | |
| | | (0.00116)*** | | |
| **F1: Residential stability** | **0.05163** | **0.03990** | **0.09843** | |
| | (0.00330)*** | (0.00190)*** | (0.00385)*** | |
| **F2: Relative Black-White population share** | **0.01490** | **0.01386** | **0.01062** | **-0.01402** |
| | (0.00152)*** | (0.00440)* | (0.00397)* | (0.00386)** |
| **F3: Economic advantage of child-less “Creative Class”** | **0.00367** | **0.02159** | **0.01901** | **-0.05362** |
| | (0.00400) | (0.00229)*** | (0.00799) | (0.00806)*** |
| **F4: Hispanic residents** | **-0.00745** | | **-0.00166** | **-0.02864** |
| | (0.00230)* | | (0.00845) | (0.00839)** |
| **F5: Families with children** | | **-0.01152** | | **0.19665** |
| | | (0.00452) | | (0.00799)*** |
| **Hispanic/Non-Hispanic Unevenness** | | **0.05022** | | |
| | | (0.01093)*** | | |
| **Median Price-per-Square Foot ($100s)** | | **0.00142** | **-0.01096** | **-0.01159** |
| | | (0.00082) | (0.00257)*** | (0.00262)*** |
| **Mortgage Foreclosure Rate** | | **-1.07708** | | |
| | | (0.27010)*** | | |

**Table 4.4:** Within effects, and standard errors in parentheses, estimated by the within-between random effects model. Response variable is proportion of neighborhood area (ranging from 0 to 1) that is vegetated. Foreclosure and construction rates are the number of events normalized by the total housing units. Satterthwaite approximate p-values denoted: *** p-value $<$ 0.0001; ** p-value $<$ 0.001; * p-value $<$ 0.01.

| Covariate | Detroit Metro | Los Angeles MSA | Seattle MSA (with F1) | Seattle MSA (with F5) |
|---:|---|---|---|---|
| **Climate: Annual Precipitation (mm)** | **0.00060** | **0.00114** | **-0.00004** | **-0.00003** |
| | (0.00001)*** | (0.00003)*** | (0.00001)* | (0.00001) |
| **Climate: July Mean Temperature (deg C)** | **0.00244** | **-0.00155** | **-0.00056** | **-0.00086** |
| | (0.00054)*** | (0.00042)** | (0.00070) | (0.00069) |
| **Construction Rate** | **-0.02455** | **-0.03557** | **0.01261** | **0.00954** |
| | (0.02548) | (0.00375)*** | (0.01191) | (0.01174) |
| ***. . . (within City of Detroit)*** | **-0.07865** | | | |
| | (0.83142) | | | |
| **F1: Residential stability** | **-0.00133** | **-0.01340** | **0.01061** | |
| | (0.00233) | (0.00102)*** | (0.00364)* | |
| ***. . . (within City of Detroit)*** | **-0.01067** | | | |
| | (0.00298)** | | | |
| **F2: Relative Black-White population share** | **-0.00435** | **-0.00201** | **-0.01623** | **-0.01921** |
| | (0.00118)** | (0.00135) | (0.00171)*** | (0.00166)*** |
| ***. . . (within City of Detroit)*** | **0.00609** | | | |
| | (0.00182)** | | | |
| **F3: Economic advantage of child-less "Creative Class"** | **-0.00043** | **0.00970** | **-0.01389** | **-0.02906** |
| | (0.00304) | (0.00112)*** | (0.00426)* | (0.00498)*** |
| ***. . . (within City of Detroit)*** | **0.00325** | | | |
| | (0.00364) | | | |
| **F4: Hispanic residents** | **0.00142** | | **-0.00515** | **-0.00678** |
| | (0.00104) | | (0.00225) | (0.00217)* |
| ***. . . (within City of Detroit)*** | **-0.00269** | | | |
| | (0.00126) | | | |
| **F5: Families with children** | | **-0.01122** | | **0.03911** |
| | | (0.00145)*** | | (0.00616)*** |
| **Hispanic/Non-Hispanic Unevenness** | | **-0.04189** | | |
| | | (0.00482)*** | | |

| Covariate | Detroit Metro | Los Angeles MSA | Seattle MSA (with F1) | Seattle MSA (with F5) |
|---|---|---|---|---|
| **Median Price-per-Square Foot ($100s)** | | **0.00074**<br>(0.00012)*** | **0.00055**<br>(0.00041) | **0.00039**<br>(0.00041) |
| **Mortgage Foreclosure Rate** | | **0.76683**<br>(0.03489)*** | | |

## 4.4 Discussion

### 4.4.1 Neighborhood Change Trends

The social and economic trends of these three metropolitan areas include changes common across U.S. communities: declining marriage rates, filtering of the post-war suburban housing stock, and the rise of a highly educated urban elite. Part of the decline in residential stability (F1) can be attributed to nation-wide declines in marriage rates and family formation (Cohn et al., 2011) as well as in inflation-adjusted incomes. The recent decline of post-war inner-ring suburbs is well-documented (Molina, 2016) and is seen in all three metropolitan areas of this study. Neighborhood scores on F3, enclaves of the creative class, have generally increased in the Los Angeles and Seattle MSAs, reflecting an increase in degree credentials for many city-dwelling Americans.

While residential stability has declined, the share of black residents has generally increased in most neighborhoods, though this rising integration is spatially uneven within each metropolitan area. In Detroit, this reflects both neighborhood segregation and integration, as more socially mobile black residents migrate outward from the margins of the City of Detroit and into inner-suburban neighborhoods and southern Macomb County. Detroit-area neighborhoods with the fastest growth in the F2 score are in Redford (west of Detroit) and Eastpointe (northeast of Detroit); in nearby Warren, MI, black residents accounted for less than 1% of the population in 1990 but over 18% in 2017, according to the U.S. Census Bureau. F1 and F2 scores are generally anti-correlated in each study area, as white households with greater inter-generational wealth are more likely to own their home than black households.

As in the other study areas, residential stability (F1) in the Seattle MSA has generally declined, yet the spatial pattern here is more striking. In the cities of Seattle, Redmond, and Renton, residential stability has been maintained or increased; it has declined everywhere else. Also striking is the pattern of change in relative black-white population share (F2) and in the Hispanic population share (F4); in the cities of Seattle and Tacoma, neighborhood scores on these factors have declined while they have risen almost everywhere else (Figure 4.5). In the Los Angeles MSA, areas of high long-term residential stability (F1) are spatially disjoint from the areas of highest growth in mortgage foreclosures.

### 4.4.2 Correspondence of Common Factors to the Literature

There does not appear to be a one-to-one mapping between the empirically derived common factors and density, luxury, or prestige. F1, residential stability, does correspond closely to the theorized luxury effect, which impacts vegetation through a set of related neighborhood conditions that create opportunities for greening, including single-family homeownership and parcel size (Giner et al., 2013), and that preserve neighborhood green space through potentially costly irrigation, particularly in arid regions (Jenerette et al., 2013), or through political advocacy for green space or zoning codes. As Chuang et al. (2017) also noted in Baltimore, long-term stability of a neighborhood, in wealth terms, predicts higher green vegetation density.

The socio-economic advantage of a rising creative class (F3) is consistent with elements of both luxury and prestige. Highly educated, high-income households have more resources to spend to capitalize on urban green space (Heynen et al., 2006) but their education may also predispose them towards certain socially

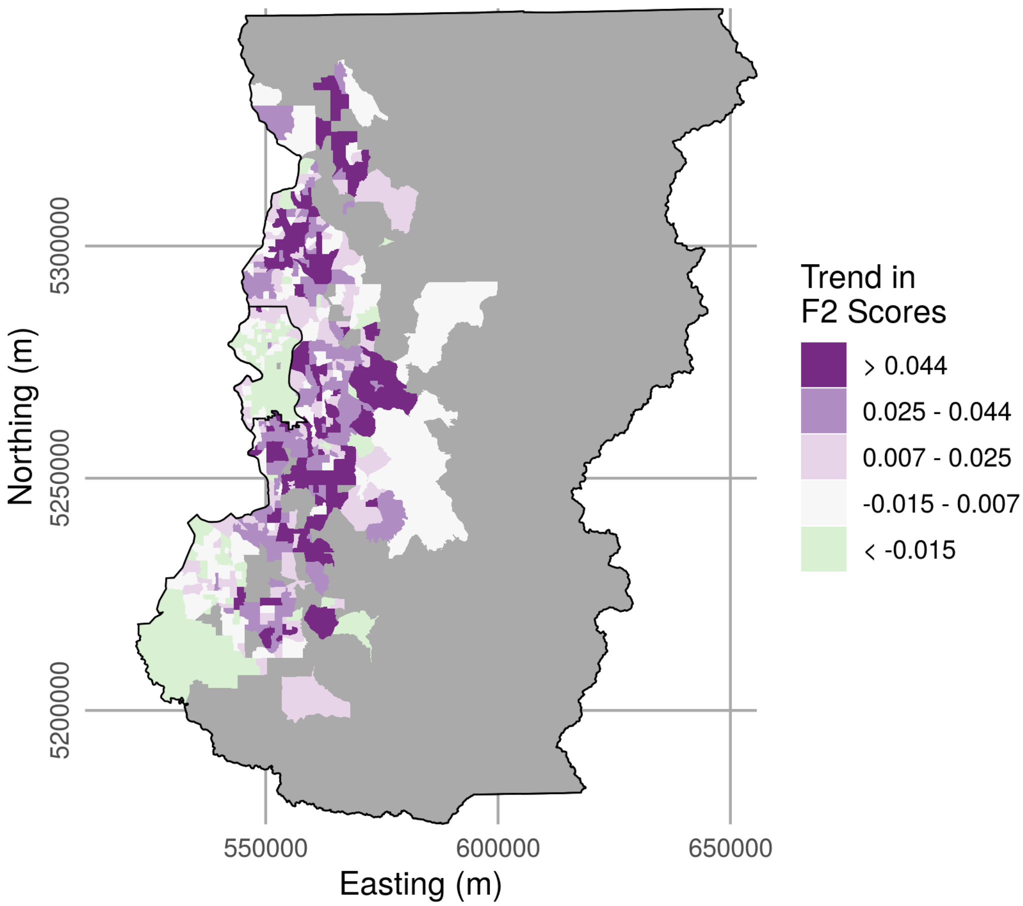


**Figure 4.5:** Map of trends in neighborhood F2 scores across the Seattle MSA; increasing trends can be interpreted as a rise in the black share of residents and therefore, given a majority-white baseline, of increasing integration. The City of Seattle is outlined in black.

learned lawn and tree management behaviors (Clarke et al., 2013). This combination of processes, implicating both an ecology of luxury and an ecology of prestige, is apparent in the marginal effect of F3 when F1 is or is not controlled for: when a context of residential stability (F1) is controlled for, marginally highly educated neighborhoods are greener; without residential stability (F1) controlled for, the marginal effect of a highly educated population is less-green neighborhoods (Table 4.4). The latter might reflect a tendency for highly educated households to live in denser neighborhoods with more amenities but less green space; in these neighborhoods, they may be more likely to rent and are yet unmarried.

Families with children (F5) also implicates luxury, lifestyle, and life stage: marriage rates have recently declined at a much faster rate for lower-income groups (Pew Research Center, 2010, Cohn et al., 2011). This may explain why the contextual effects of F1 and F5 mask one another; higher-income, more highly educated individuals have a stronger inclination and capability to get married and raise children. Married families have been thought to prefer lower housing densities, where there is more green space available for children to play and housing units are large enough to accommodate growth in the family (Boone et al., 2009, Giner et al., 2013). However, in the Seattle MSA, families with children occupy higher housing densities, and this may account for the different contextual and within effects of this factor compared to the Los Angeles MSA. More generally, the different measured variables influenced by this factor (F5) limit cross-metropolitan comparison. The more comparable demographic factors, F2 and F4, do not correspond with prevailing theories about structural effects on urban vegetation (e.g., density, luxury, prestige); however, they do suggest that populations facing economic disenfranchisement or public disinvestment in neighborhood conditions—*legacies* of discrimination or segregation—do experience changes in neighborhood greenness regardless of neighborhood socio-economic status. Indeed, neighborhoods with a greater long-term Hispanic population share are less green overall in all three metropolitan areas (this is not obvious for the Los Angeles MSA from Table 4.4, but the positive effect of Hispanic/ Non-Hispanic unevenness seems to arise from greener majority Non-Hispanic neighborhoods). In Seattle MSA neighborhoods, controlling for the presence of children with families, growth in the Hispanic population seems to drive losses in green vegetation. As Heynen et al. (2006) suggested, this could be a result of this group's rapid growth (and concomitant growth in the built environment), their lawn management behaviors, or public disinvestment in the tree canopy of majority-Hispanic neighborhoods.

### 4.4.3 Drivers of Vegetation Change

#### Climatic Drivers

The measure of vegetation density in this study is influenced mostly by visible vegetated cover area or the leaf-area index but also by plant vigor; both are sensitive to temperature and available water during the growing season. Water availability and temperature during the growing season are the two primary constraints on green vegetation's productivity in these study areas. Neighborhood green vegetation in the Los Angeles MSA is clearly limited by water availability (Tables 4.3 and 4.4), which is not the case for Detroit Metro and Seattle MSA neighborhoods.

Temperatures have a weaker association with levels of and change in vegetated cover. With the exception of Detroit Metro neighborhoods, mean July temperatures have no effect on long-term vegetated cover. In the Los Angeles MSA, an increase in mean July temperatures of 1 deg C drives a decline in percent vegetated area of 1.5 points, but there is no apparent effect of rising temperatures on vegetated cover in Seattle MSA neighborhoods. The Detroit area appears to be quite different in the effect of temperature on vegetated cover (Tables 4.3 and 4.4). However, it should be noted that the temperature gradient across the Detroit Metro area is very small and has the same spatial pattern as building density in the region. Thus, the estimated size of the contextual effect of mean July temperatures in Detroit Metro neighborhoods (9.8 percentage points of vegetated area per 1 deg C increase in temperature) is likely inflated by this urban-to-rural development gradient. The range of temperatures along this gradient is only about 1 deg C. Unlike the Los Angeles and Detroit areas, Seattle MSA neighborhoods exhibit no significant relationship between vegetated cover and temperature and the effects of water availability are virtually zero. It appears that vegetated cover in Seattle-area neighborhoods is limited neither by water nor temperature, likely because the region enjoys moderate temperatures and ample water availability throughout the year.

**Detroit Metropolitan Area**

Within the City of Detroit, a decline in residential stability (F1) is the greatest driver of vegetation growth, and this can be understood as the effect of the joint processes of neighborhood decline: declining single-family owner-occupancy, marriage rates, and incomes due to extensive out-migration has led to the thinning-out of neighborhoods and the replacement of the built environment with pervious and vegetated cover (Endsley et al., 2018, Chapter II, this volume). Change in residential stability does *not* drive vegetation change outside of the City, however, indicating that the suburbs' rising housing densities and sharply declining homeownership rates since 2000 have not yet made a measurable difference in neighborhood greenness. Indeed, most neighborhoods in the Detroit area have become greener over the past 25 years even as the number of housing units has increased, suggesting that, at least since the mid-2000s, the dominant form of new development has been infill, which is likely taken up more by renters than owners.

At metropolitan scale, rising black-white integration drives a loss in vegetation density, likely due to population pressures. However, the driving direction here may be reversed, as integration has proceeded in certain neighborhoods, previously denied to black households, that are more built-up and less green than some suburban black enclaves. The suburban cities of Southfield and Warren serve as excellent examples; the former is a majority-black city characterized by lush, low-density, single-family neighborhoods while the latter is a majority-white city with extensive commercial and industrial development, including two General Motors plants and multiple rail lines. Both cities have been in transition for some time (Zenk et al., 2005); Southfield's black residents increased from a tract-level median of 23% of residents in 1990 to 73% by 2017. Although we might expect Southfield's lower housing density to lead to housing affordability for black residents in southeast Michigan, the city's median home value in 1990 was 12% lower than the Metro-area median home value at the time; in 2017, it was 30% lower. Relative affordability may have been one driver of black in-migration to Southfield, but socially mobile, aspiring black homeowners also likely faced few attractive alternatives for places to live, and may have been disinclined or discouraged from moving to nearby Warren, where black residents were fewer than 1% of the city's population in 1990.

Thus, residential segregation and housing market discrimination may have

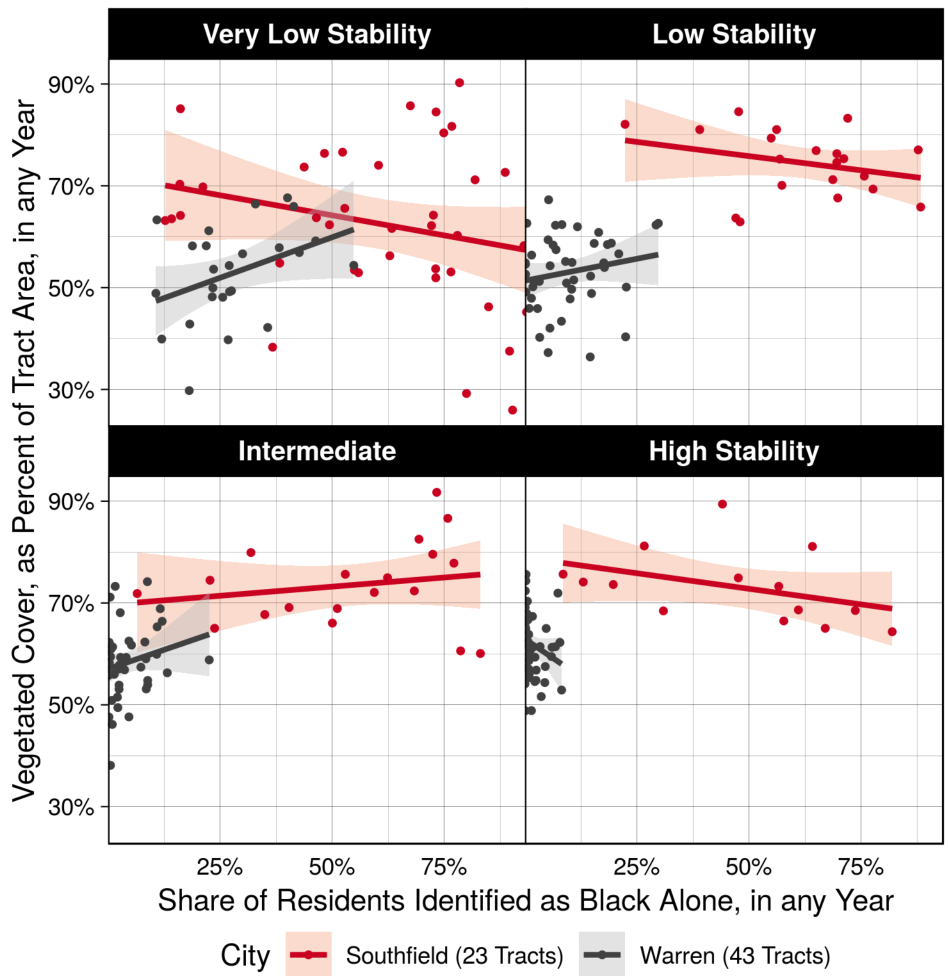


**Figure 4.6:** Plot of vegetation density, in any year, against a neighborhood's self-identified black population share, in each quartile of residential stability (F1), for the cities of Warren and Southfield. Linear trend line with 95% confidence interval is plotted.

in fact driven black residents away from more developed, industrialized centers in the Detroit metropolitan region, like Warren (Downey, 2005). Indeed, a recent review of the literature reveals that green space inequities related to race or ethnicity are more visible in less segregated areas (Watkins and Gerrish, 2018). This explains the otherwise surprising result that a neighborhood context characterized by a large black population and high residential segregation also has a high vegetation density (Table 4.3 and Figure 4.6), not just in the vacant neighborhoods of Detroit but across the metropolitan area. In Warren, too, the neighborhoods in 2010 and 2015 with the greatest shares of black residents are greener (top-left panel of Figure 4.6); these are located at the border with the City of Detroit at 8 Mile Road and include parks and extensive urban tree canopy that has been well-preserved, though a couple of derelict structures have been demolished, as well. However, as a neighborhood's F2 score increases, vegetated cover declines (Table 4.4), even in majority-black Southfield. Because an increase in F2 reflects not only an increase in the black share of residents but of associated economic disadvantages, we might suspect that a model of concentrated disadvantage predicts a decline in green vegetation. From aerial photographs, however, it is apparent that the rapidly integrating neighborhoods of Warren near 8 Mile Road which, in addition to their proximity to the City of Detroit also contain the least expensive housing stock of Warren, have preserved extensive tree canopy over the past 20 years. Thus, it seems more likely that either redevelopment or filtering of suburban neighborhoods leads to changes in residents or in their preferences, willingness to pay, or political power pursuant to advocating for and maintaining urban tree canopy.

### Los Angeles MSA

In Los Angeles MSA neighborhoods, though a context of high residential stability (F1) is associated with high vegetation density (Table 4.3), the model indicates that further growth in residential stability as well as construction are driving losses in green vegetation (Table 4.4). This is consistent with Lee et al. (2017), who observed that the expansion and redevelopment of single-family homes was driving a loss in urban tree canopy; specifically, they found that single-family homes in the area have been rebuilt larger since 2000, despite the need for more dense, higher-occupancy development. In addition to housing expansion, change attitudes towards trees as they grow may also explain tree removal by home-owners (Conway, 2016).

The Los Angeles area also has a large number of highly educated, high-income residents, like other cosmopolitan metropolises world-wide. These residents are found in and seem to contribute toward greener neighborhoods. Indeed, a map of the two highest quintiles of the long-term average F3 score corresponds exactly to the greenest neighborhoods of the Los Angeles MSA: all of the high-elevation neighborhoods as well as Santa Monica and Los Alamitos. These neighborhoods have extensive urban parks but also seem to have maintained a high density of urban trees throughout the study period. Conversely, families with children (F5), already in relatively green areas such as the Santa Monica Hills, Central L.A., and Pasadena, seem to be driving losses in green vegetation, which could be explained either by the aforementioned increase in hardscaping (Lee et al., 2017) or by shifting preferences in this group toward less water-demanding, more xeric landscaping (Larson et al., 2017).

The strong effect of mortgage foreclosures on green vegetation requires further analysis. While a comparison of maps of simple linear trends shows a strong anti-correlation between areas of the highest growth in foreclosure rates and areas of least decline in greenness, the data indicate that when neighborhoods have above-average foreclosure rates they tend to have above-average greenness. This suggests some possible responses to widespread foreclosure in an arid climate; 1) Owner-occupants of nearby properties are pursuing a landscaping and irrigation strategy on their own property that boosts greenness in an effort to offset any visible decline in foreclosed properties; 2) Landlords and other investors in foreclosed properties in these areas may be pursuing a rehabilitation or holding strategy (Molina, 2016) by maintaining a property's ornamental vegetation; or 3) Properties in mortgage foreclosure defer the housing additions described by Lee et al. (2017) and therefore retain more tree canopy cover during high foreclosure periods.

**Seattle MSA**

With the exception of a few neighborhoods north of Northgate, City of Seattle neighborhoods have lost black residents (falling F2 scores), with an average decline in the tract-level black share of residents of 2.4 percentage points over 1990-2017. Over this period, City of Seattle neighborhoods, particularly in north Seattle, south of Northgate, and central Tacoma neighborhoods along Nisqually Reach, have become both whiter (in residents) and greener (in vegetation). Abel and White (2015) identify gentrification as one of the primary drivers of Seattle's demographic change over this period, and in north Seattle this is characterized by replacement or an increase in younger, higher-income households, both as renters but also as homeowners; their ability to pay is consistent with the large increase in housing costs in these neighborhoods.

While an increase in greenness is shared by most Seattle MSA neighborhoods, there is a spatial correspondence between the areas of fastest vegetation growth and the areas of fastest decline in the black share of residents (or, equivalently, fastest growth in the white share of residents; see Figure 4.5). From an examination of aerial photographs, these Seattle and Tacoma neighborhoods seem to have preserved a maturing urban tree canopy; on some parcels, new trees have been planted and all visible trees seem to have grown over this 27-year period. Conversely, outside Seattle and Tacoma, in integrating cities like Kent (71% white alone in 2000, 52% by 2017), there is extensive new housing and retail development. This is consistent with the pattern of new development observed at the urban fringe, despite the Seattle area's urban growth boundary that was implemented in 1990 (Morrill, 2008).

Increasing F3 scores are a sign of neighborhoods in transition or under gentrification, and it is no surprise that growth in this factor is strong for neighborhoods along Puget Sound both in Seattle and Tacoma. This growth in the creative class (F3) seems to be driving a decline in green vegetation, even in wealthy suburbs like Mill Creek and its environs, where a growing population is inducing new housing development that has replaced much of the forested areas near the Garhart Reservoir. Lake Stevens, WA is another example, where a growth rate of over 300% between 2000 and 2010 has led to extensive infill on former agricultural lands. Bonney Lake, WA has also seen extensive tract-home development in formerly forested areas east of the Puyallup River. An additional consideration is that new housing developments have always been motivated by a desire to attract high-income buyers (Smith, 1987), which may also explain high F3 scores in these areas.

Given that communities with an increasing black share (increasing F2 scores) have also seen extensive development, we can surmise that in the face of population pressure, the neighborhoods that have best defended against development have created conditions, possibly rising housing costs, that are less desirable for minority residents. This has shifted both the balance of new development and racial integration to the suburbs. Similarly, where families with children (F5) have grown or declined the least, in the City of Seattle and east of the I-405 freeway near Bellevue and Redmond, we see low-density neighborhoods with extensive tree canopy cover that have completely avoided redevelopment for the past 27 years.

## 4.5 Conclusions

The conceptual aim of this study was to evaluate how empirically defined factors of neighborhood social and economic change compare to those identified in the prior literature in their ability to explain vegetation change in three different metropolitan contexts. There is a related methodological aim, as well; comparative metropolitan-scale studies require an approach amenable to large populations and which remains interpretable. However, the surprising and sometimes counter-intuitive statistical results evident in this study (such as the high greenness of majority-black neighborhoods in Detroit's inner suburbs) also indicate that knowledge of historical context is key to correctly interpreting the sociospatial patterns of neighborhood-level vegetation change. When limited time or data availability prohibit a more grounded study of the factors driving vegetation change, the statistical approach used in this study can effectively point the researcher where to look within the metropolitan frame and its high-dimensional panel of changing neighborhood conditions.

The statistical model used presents an alternative description to the three-factor model of how social and economic conditions shape neighborhood vegetation conditions. The empirical factors of this study are more nuanced and implicitly acknowledge the interdependence of (and correlations between) density, luxury, and prestige. Comparing three different metropolitan areas, I find evidence of broad trends consistent with the luxury effect. In all three study areas, residential stability (high owner-occupancy and marriage rates) creates a context of high green vegetation density. Married families with children are highly correlated with residential stability but exhibit a more complex relationship with neighborhood vegetation, possibly because the neighborhood change processes related to their life stage are better observed at finer spatial scales.

The varying effects of *change* in these patterns of neighborhood variation on green vegetation are partially explained by differences in metropolitan context and in historical legacies, particularly legacies of racial residential segregation. Racial segregation and integration are twin processes that strongly correspond to changes in neighborhood vegetation because they involve large shifts in the metropolitan population. In the Detroit Metro area, even discounting the highly segregated City of Detroit, a legacy of housing discrimination created surprisingly green neighborhoods for black suburban residents; the slow erosion of that legacy through integration is reducing disparities in vegetation in the inner suburbs. Conversely, a concentration of white residents in the cities of Seattle and Tacoma is benefiting from, and perhaps aiding in, the preservation of single-family homes and urban tree canopy at the cost of increasing development pressure elsewhere. Although most Seattle-area neighborhoods have become greener since 1990, the unrealized gains of neighborhoods outside Seattle and Tacoma can be explained by their increased population pressures and new housing development. Both within and around Seattle, the most socially vulnerable residents are still disproportionately exposed to polluting industries, as well (Abel and White, 2015).

Over the past 27 years, an interaction between residential preferences (e.g., for or against tree canopy and for detached, single-family homes) and population pressures have shaped the socio-spatial distribution of green vegetation in U.S. metropolitan areas. Though a panel of three study areas is hardly definitive, the comparisons between these metropolitan areas has compelling implications for environmental justice (EJ) studies. I hypothesize that the uneven distribution of environmental amenities arises differently under a regime of population growth than one of decline. Specifically, in rapidly growing cities like Seattle and Los Angeles, the most economically and socially advantaged residents are able to capitalize, even to hoard, environmental amenities such as parks and greener neighborhoods. But in stable or declining areas, like the City of Detroit and its stable metropolitan population, it is primarily historical legacies that shape the socio-spatial distribution of environmental amenities, sometimes in ways that are counter-intuitive to EJ scholarship (Grove et al., 2018).

This study's data-driven approach is primarily limited by the spatial scale and collection frequency of the Census Bureau datasets. But the spectral and spatial resolutions of the Landsat satellite data platform also limit our ability to describe neighborhood biophysical conditions in more detail than aggregate green vegetation density. While the multi-decadal legacy of Landsat is key to a neighborhood-scale analysis, long periods of separation between study periods may be required to overcome the high uncertainty associated with gradual neighborhood biophysical changes. As they are defined by differences from the mean, the effects of change in social or economic conditions on vegetation are likely to be relatively small. Where fine-scale data on vegetation type and quality, in addition to public versus private ownership, can be combined with data on neighborhood conditions at a similar scale, this methodological approach looks very promising as a way of synthesizing disparate patterns of social and economic change and discovering their relationship to the biophysical changes that ultimately drive long-term differences in neighborhood environmental quality.

# CHAPTER V

# Conclusion

Our tacit understanding of neighborhood socio-ecological change based on statistical patterns between socio-economic status and land cover belies a complexity that is multi-scalar, sensitive to initial conditions, and dependent on the metropolitan and climatic contexts. This complexity has not been acknowledged in much of the research on the drivers of uneven environmental amenities, such as green space, in urban areas. Statistical pattern-based approaches to studying neighborhood-level change are common. Some of the shortcomings of theses approaches, which served as the inspiration for this dissertation, can be addressed with better data (by "pixelizing" rich and accurate social or economic datasets, e.g. Geoghegan et al., 1998): more semantically refined data at smaller spatial scales (e.g., household- or parcel-level) and collected with greater frequency (e.g., monthly or annually). Spatial scale is chief among the technical limitations of my dissertation. Yet some of the limitations are conceptual, particularly related to the measurement of neighborhood social and economic conditions, the definition of the neighborhood, and our conceptualization of neighborhood change. Here, I describe these limitations in detail and make recommendations for future work on the social and economic drivers of neighborhood vegetation change, with the aim of informing the equitable provision of ecosystem services for as many residents as possible. Despite these real limitations, I also summarize the important contributions of this dissertation to the literature and, separately, to our practical understanding of metropolitan population change and its effect on neighborhood green vegetation.

## 5.1 Contributions to the Literature on Socio-Ecological Change

In the first paper of my dissertation, Chapter II in this volume, I worked with an interdisciplinary group of faculty wrestling with the problem of understanding neighborhood change. Part of the inspiration for our approach came from both scholarly studies working to infer social and economic conditions based on satellite views of urban or rural landscapes (e.g., Weeks et al., 2007, Stow et al., 2013) as well as private companies tracking stocks or corporate valuations against retail parking lot car densities or the heights of crude oil storage drums. Night-time lights data, too, due to their strong correlations with urban form and the built environment, were being regularly used to validate macro-economic assessments of regional or national wealth (e.g., Elvidge et al., 2007, Henderson et al., 2012, Pinkovskiy and Sala-i Martin, 2014) in a "Census from heaven" (Sutton et al., 2001). These black-box, statistical learning approaches required no grounded theory to deliver "insights" into the relationships between urban form or biophysical conditions and the social or economic conditions that demographers and social scientists are keenly interested in observing.

Yet it soon became clear that these approaches don't allow us to identify the mechanisms of socio-ecological change. Decades of scholarly work on the topic had already gone far to elucidate the connection between metropolitan populations and their environment. Whether these approaches originated in econometrics and hedonic price models, in planning or environmental justice, the general consensus was that neighborhood-level variation in green vegetation was largely explained by a positive association with socio-economic status (Heynen and Lindsey, 2003, Heynen et al., 2006, Mennis, 2006) due to the capitalization of urban green space and lawn landscapes by wealthier home-owners with the political power to maintain and advocate for public parks and tree canopy; and with preferences informed by the behavior of similar home-owners in their neighborhood. We investigated the limitations of this association in explaining neighborhood-level variation in vegetation density in metropolitan Detroit, where extensive thinning of the housing stock due abandonment and demolition has created an "urban prairie" (Gallagher, 2010) in what should be the region's dense urban core.

We found that neighborhood median sale price was a good indicator of a neighborhood's socio-economic status (SES) and hypothesized that it was also a good proxy for the condition of the housing stock, more generally. Moreover, the positive, mutually reinforcing relationship between green vegetation and SES did not hold up for neighborhoods in the City of Detroit. In some ways, Detroit is exceptional; an abundance of single-family homes built during the Fordist era has gradually disappeared as economic racism and capital flight precipitated severe population loss. Yet Detroit serves as an example of how the "luxury effect" (Hope et al., 2003) on green vegetation (the ability of wealthier or higher-income households and neighborhoods to move into or to buy a greener environment) is fundamentally dependent on context; there may be other metropolitan contexts or conditions under which this otherwise well-established relationship is confounded.

**Chapter II indicated that socio-ecological relations, such as the luxury effect, depend on the social and economic context.** In growing cities, these relations may strengthen over time as the urban landscape is continuously modified and the spatial distribution of environmental amenities is reinforced along gradients of socio-economic status (luxury), home-owner preferences (prestige), or land-use demands (Lowry et al., 2012). In cities with declining populations, however, socio-ecological relations may decline in strength (Hoalst-Pullen et al., 2011); the links between the remaining population and its environment have either become more complex (Watmough et al., 2013) and therefore harder to identify or have broken down such that human influences on the landscape are no longer reinforced, as in a newly constructed or emerging neighborhood (Luck et al., 2009). Indeed, we found that the effect of SES on neighborhood green vegetation substantially weakened over time in the City of Detroit, such that by 2010, there is no luxury effect; it persists at the metropolitan scale, but not for the City of Detroit.

**Chapter II also proved the utility of housing market data, specifically deed sale and tax assessor records, for tracking neighborhood biophysical conditions; the successful use of these data and the finding that socio-ecological relations differ for declining neighborhoods led to the notion that flows of people and investment capital might affect neighborhood biophysical conditions.** This led to my investigation in Chapter III of housing market *dynamics* and whether these flows, quantified by an inter-annual panel of neighborhood median home values, were associated with continuous changes in neighborhood vegetation density. The data-driven approach of Chapter III failed to detect any association between housing market and vegetation dynamics in the Detroit, Los Angeles, and Seattle metropolitan areas. Despite our intuition that home values are a good proxy for neighborhood conditions (based on Chapter II), it is clear that as a single measure, they are not at all sufficient to understand neighborhood biophysical change, even over long time periods. This is, in large part, because of the strong influence of baseline conditions.

**Chapter III indicates that neighborhood (dis)advantage is persistent, and the biophysical conditions are overwhelmingly dependent on the structural conditions that gave rise to uneven neighborhood outcomes.** We did not observe a transformation in any neighborhood's fortunes: low-value neighborhoods maintained low home values while high-value neighborhoods, particularly in the Seattle and Los Angeles Metropolitan Statistical Areas (MSAs), continued to appreciate in value. As Pulido (2004) noted, Los Angeles neighborhoods are "constellations of opportunities;" the higher-value neighborhoods are greener, appreciate more in home values, and recover more value after a crisis (such as the sub-prime mortgage crisis in 2006-2007). The differences between metropolitan areas are also stark and indicate that population pressures—along with the contest for talent and growth—drive further differentiation both between and within metropolitan areas.

**Chapter IV reinforces the idea that information about the historical, social, and economic context is essential to understanding divergent outcomes between and within metropolitan areas.** For instance, the effect of change in residential stability (change in single-family home-ownership rates, marriage rates, housing density, and income) on neighborhood green vegetation differs based on the historical and present-day actions of homeowners. In the City of Detroit, a widespread decline in residential stability is driving growth in green vegetation as single-family homes are abandoned and eventually demolished. In the Los Angeles MSA, maintenance of residential stability seems to encourage housing additions and expansion that reduce the area of green vegetation, though recent drought conditions may also be to blame. In the Seattle MSA, it is homeowners' defense of a neighborhood's tree canopy and low-density, single-family housing stock that is apparently necessary for preserving green space in the face of a fast-growing metropolitan population; residents in these Seattle and Tacoma neighborhoods have found a spatial fix in the suburbs, which have absorbed much of the metro-area population growth.

**Chapter IV therefore casts doubt on the idea of generalizable links between population or economic growth and vegetation change and critiques the prevailing theory of socio-ecological relations in general.** I compared the key factors of neighborhood variation induced in neighborhood panel data with the well-documented effects of density, luxury, and prestige. Luxury and prestige, in particular, are not orthogonal dimensions of neighborhood variation or change when measured in terms of the neighborhood characteristics and resident population. Rather, they are highly correlated neighborhood-level factors arising due to shared processes at both the neighborhood and household levels, including migration and turnover, investment in landscaping or irrigation, changing home-owner preferences, and changes in public investment in green space, with or without neighborhood advocacy in a wider political economy. Though they remain useful for describing the effects of population changes on green vegetation, the story is incomplete without consideration of historical or *legacy* effects that give rise to uneven green space allocated among different demographic groups.

**Finally, Chapter IV makes an important contribution toward our understanding of the relationship between urban green spaces and racial identity,** an area of substantial controversy (Watkins and Gerrish, 2018). Scholars have struggled with identifying the different contributions to neighborhood green space from income or wealth inequality versus racial segregation; racial discrimination in housing and employment, along with other social ills, cause these factors to be correlated. In many areas, the correlation between income segregation and racial segregation is so high that, when aggregate socio-economic advantage is controlled for, differences along racial lines can be identified in metropolitan areas with historic (e.g., Detroit) or on-going racial segregation (e.g., Seattle), which is also where the correlations between residential stability and segregation are highest (Table 5.1). The correlation is strong in all three study areas, and one of the most surprising results of Chapter IV—insofar as the empirical factors can be compared between different metro areas—is that predominantly black neighborhoods (scoring high on factor F2) are greener than predominantly white neighborhoods (scoring low on factor F2) with equal residential stability. In the Seattle MSA, it is clear that when residential stability is *not* controlled, predominantly black neighborhoods are less green (Table 4.3). Though the technical approach of Chapter IV permits identification of this marginal difference between neighborhoods with higher black or higher white shares of residents, the specific reason for this difference must be located in a close reading of local context, aided by grounded knowledge. In Detroit, it was studies by environmental justice scholars (e.g., Downey, 2005) that pointed to an idiosyncratic history of residential segregation and more recent neighborhood integration as the reason why “black neighborhoods” are greener than similarly situated “white neighborhoods.” What the models of Chapter IV also make clear is that rising integration can mitigate these disparities, as in the Detroit area while rising segregation will exacerbate them, as in the Seattle area (Table 4.4).

**Table 5.1:** Correlations (standardized covariances) between residential stability (F1) and black-white segregation (F2), based on the confirmatory factor analysis (CFA), in each metropolitan area.

| Study Area | Year | F1 & F2 Correlation |
|---|---|---|
| **Detroit Metro** | 1990 | -0.744 |
| | 2000 | -0.730 |
| | 2010 | -0.736 |
| | 2015 | -0.775 |
| **Los Angeles MSA** | 1990 | -0.580 |
| | 2000 | -0.495 |
| | 2010 | -0.446 |
| | 2015 | -0.508 |
| **Seattle MSA** | 1990 | -0.668 |
| | 2000 | -0.618 |
| | 2010 | -0.544 |
| | 2015 | -0.456 |

## 5.2 Contributions to Policy on and Planning of Neighborhood Green Space

An important lesson from this dissertation for the planning of equitable green space provision in cities is that the social and economic determinants of uneven green space vary between different metropolitan areas. Chapter IV, in particular, contains several observations as to how these determinants vary between the Detroit, Los Angeles, and Seattle metropolitan areas. While both the Los Angeles and Seattle metropolitan areas have experienced steady population growth over the period 1990-2017, the consequences of that growth for neighborhood green space are very different. Neighborhoods throughout the Los Angeles MSA neighborhoods have seen growth in highly educated residents; while it is not clear how much is due to new residents versus new credentials for existing residents, the growth in the so-called creative class (Florida, 2002) promotes growth in greenness in the Los Angeles area. In the Seattle MSA, however, growth in the creative class is almost certainly a result of in-migration—due to the growth in local economic opportunities associated with the internet and new technologies—and is associated with a loss in neighborhood green space, clearly as a result of the soaring demand for housing for this group.

There is an interesting lesson in contrasting the Seattle and Detroit metropolitan areas, as well. Detroit bears the legacy of egregious racial residential segregation and capital flight, having transitioned from 16% black alone to 83% black between 1950 and 2010, according to the U.S. Census Bureau. By comparison, Seattle transitioned from about 3% black in 1950, to 10% black in 1990; the self-identified black share of the population then *contracted* to 8% by 2010. Both urban core areas are, in some ways, greener than their suburbs. In Seattle, this is because the majority-white neighborhoods have preserved a single-family housing stock and dense street tree canopy. In Detroit, this is because the majority-black neighborhoods, unable to stem the tide of population loss and disinvestment in the housing stock, have lost much of the built environment due to abandonment and demolition, with volunteer shrubs and trees filling in the empty spaces. The different processes that gave rise to these superficially similar outcomes speak to the relative power and influence of the respective demographic groups.

Changes in the Seattle area highlight the need for city planning to explicitly consider green space provision in the face of on-going urbanization. Neighborhoods in the cities of Seattle and Tacoma seem especially resistant to redevelopment and have preserved a dense street tree canopy. Median home values in Seattle and Tacoma are not very different from the rest of the MSA, according to the 2017 American Community Survey (ACS); housing is expensive everywhere and yet the development these neighborhoods avoid has been shifted to the suburbs. Moreover, the increasing white segregation of the cities of Seattle and Tacoma (11.4%

black alone in 1990 to 9.9% in 2017) pose a challenge not just for policies to promote a well-integrated and pluralistic society but also for the goal of joint economic and environmental equity.

It's not just growing areas that need to pay attention to equitable green space provision. In Seattle MSA and Los Angeles MSA neighborhoods, socioeconomic status (SES) still largely determines access to neighborhood green amenities. This isn't the case in Detroit-area neighborhoods, but the high residential mobility of highly educated, wealthy Americans today suggests that the green neighborhoods of Detroit's inner suburbs—where a significant number of black residents reside and which are relatively close to the City of Detroit's stadiums, restaurants, and other amenities—could become sites of displacement and turnover in the near future. Either the greenness of these relatively low-cost neighborhoods is undervalued or there are other local conditions that have discouraged the in-migration of high-income, high-mobility outsiders (Smith, 1987). This also raises the question of whether recent trends in integration of Metro Detroit's inner suburbs can be attributed more to the migration of black households than of white households.

As Chapter III indicated, neighborhood advantages and disadvantages are remarkably persistent. Growing cities like the core cities of Los Angeles and Seattle, have the uncommon opportunity to promote positive and sustainable neighborhood transitions by capitalizing on the influx of socially mobile residents (Delmelle, 2015, Hochstenbach and van Gent, 2015). And yet, these areas have, so far, failed to spread the benefits of this investment equitably (Abel and White, 2015). This is harder still for cities across metropolitan Detroit, which under a changing climate must transition a durable urban environment that does not foster as much green space as it should (nor the right kind of green space), in some areas, despite comparatively anemic growth in the tax base. In any metropolitan area, the ultimate consequence of attention to sustainability without attention to equity (Dale and Newman, 2009) is that unsustainable land development, transportation, and energy use patterns in the suburbs and exurbs will continue as metropolitan residents seek higher environmental quality without sacrificing economic opportunities and cultural amenities.

## 5.3 Limitations and Needed Improvements

One of the strengths of this dissertation is its synthesis of multiple data sources: satellite remote sensing of vegetation, Census measures of neighborhood composition, deed sales, tax assessor records, and climate re-analysis data. However, these different sources are not equally reliable and their different spatial scales and collection intervals have required me to make compromises in the modeling of neighborhood socio-ecological change.

In particular, the satellite remote sensing data are limited in their spatial resolution and in the accuracy with which they allow us to estimate green vegetation. Although the Landsat TM/ETM+ legacy, spanning 35 years as of this writing, offers unprecedented long-term observation of metropolitan landscapes, the ground resolution is 30 by 30 meters, roughly the inside area of a baseball diamond. Within a pixel of this size we might find multiple parcels, multiples houses and multiple households within them. The sub-pixel approach of linear spectral mixture analysis (LSMA) allows us to estimate the area of that pixel that contains green vegetation, and this approach has high internal consistency and is based on a physical-theoretical model of the satellite sensor's integration of reflected light data. However, it also has high uncertainty, with an estimated error of

$\pm 11.8 - 13.9\%$ of pixel area in these papers. This error rate is improved by spatial aggregation to the neighborhood scale and long baselines between images (5-10 years) improves our confidence in model estimates based on these measures.

There is no substitute for the Landsat program's long record of observation. Nonetheless, alternative approaches to estimating change over shorter periods are becoming available. High-resolution aerial and satellite photography, combined with supervised statistical learning approaches like maximum likelihood or random forest, is likely to provide superior accuracy. While the class labeling accuracy of these approaches could be improved, image segmentation can further enhance the overall accuracy of land-cover estimation in urban areas by enforcing rules about the shapes and sizes of ground areas determined to be, e.g., impervious surface versus green tree canopy. High-resolution data are costly, however, and prohibitively expensive for a comparative study that aims to cover multiple metropolitan areas over multiple decades.

Higher spatial resolution will necessarily improve the accuracy of neighborhood-level aggregations; even if the accuracy rate isn't improved, the absolute amount of vegetated area that is over- or under-estimated will be smaller. Thus, a key recommendation for future neighborhood-level studies is to utilize higher-resolution data where possible, even if the data will only be aggregated. The effect of scale is not limited to its influence on overall accuracy of vegetated cover area, however; it also potentially impacts our ability to describe vegetation type and quality. High-resolution images therefore also permit a *semantic* refinement of green vegetation into classes like tree canopy, shrub, and lawn cover, which is not possible using LSMA with moderate-resolution imagery.

The semantic refinement of green vegetation permitted by approaches with higher spatial resolution is key to unravelling some of the complexity of residential socio-ecological relations. Though multiple lines of evidence point to this complexity, it is generally unacknowledged in my work and that of many prior scholars: there are differences between landscaping choices in the front yard versus back yard (Pham et al., 2013) and between the drivers of investment in public and private green spaces (Grove et al., 2006, Pham et al., 2012); the durability of the built environment and the long life of urban trees indicates that temporal lags between socio-economic and biophysical conditions need to be explicitly modeled (Locke and Baine, 2015). The potential benefits to my dissertation of a more semantically refined estimate of green vegetation are considerable. In Chapter II, differentiating between tree canopy cover and other green vegetation would have helped to determine the impacts on ecosystem services (given the relative levels of provision offered by different vegetation types) of abandonment and demolition. In Chapter IV, differentiating between public and private green space would have helped to discriminate between the effects of aggregate population pressures (i.e., new development) and changes in the preferences and practices of a neighborhood's residents, based on changing neighborhood profiles. How and why property changes hands is also key to understanding socio-ecological changes. The observation that population growth in the creative class is driving extensive new development in the Seattle MSA, for instance, would be more policy-relevant if we could distinguish between new development of forests and riparian areas from that of infill.

### 5.3.1 Future Studies of Neighborhood Socio-Ecological Change

As Geoghegan et al. (1998) observed two decades ago, the chief challenge for modeling neighborhood change processes has been to overcome the differences in data characteristics and their relevance for questions of social and ecological changes, which were previously seen as a separate but are now clearly interdependent; what is required is not simply the integration of diverse datasets but a model that selectively and functionally incorporates the relevant household-level, neighborhood-level, and governance-level drivers of both sudden and gradual biophysical change. Observations of neighborhood social, housing, and biophysical conditions at higher spatial and semantic resolution might fundamentally change some of the conclusions in this dissertation and the wider literature on neighborhood socio-ecological change. Nevertheless, moderate-scale remote sensing data on neighborhood-level conditions have a role to play in verifying neighborhood-level theories and in enriching case histories. Contrasting Chapters II and IV makes this clear: Based on decades of formal or informal observations of the changes underway in Detroit's residential landscapes, we understood that neighborhood decline, housing abandonment, and ultimately demolition were steps in the primary causal chain through which Detroit neighborhoods were transformed. Consequently, we included a key indicator for this process, the demolition rate, in our model.

Some theories or case histories may require key indicators to be measured that are not available through well-known, publicly available datasets like the U.S. Census decennial surveys. Future interdisciplinary studies may therefore benefit from the participation of sociologists, demographers, and others who are familiar with richer, alternative data sources. Two examples are the Los Angeles Family and Neighborhood Survey (LAFANS) and the Project on Human Development in Chicago Neighborhoods (PHDCN).

LAFANS contains, among other indicators, "careful" observations of the "physical and social characteristics" of communities as small as a single Census block (Peterson et al., 2007). These observations include a rich set of descriptors directly related to hypothesized mechanisms of resident's behaviors influencing their environment, including descriptions of the physical order of a neighborhood, which are relevant both to "broken windows" theory (Wilson and Kelling, 1982) and "cues to care" (Nassauer et al., 2009) and are therefore an opportunity to formally link neighborhood sociological theory with the literature on landscape design. In addition, the LAFANS observations describe the housing stock in detail, including the type of housing, the number and arrangement of units (e.g., duplex, low-rise versus high-rise), and local amenities including parks and types of retail services. Despite this rich set of indicators, the LAFANS data are only available for Los Angeles-area neighborhoods; they do not allow for comparison against other cities and the metropolitan and climatic contexts are fixed.

The LAFANS data could, however, be compared in some aspects to the PHDCN data, which are fixed on Chicago neighborhoods. The PHDCN dataset aims to provide "a detailed look at the environments in which...social behaviors [such as juvenile delinquency, adult crime, substance abuse, and violence] take place" (ICPSR, 2019). Both the "community surveys" and the "systematic social observations" (SOS) offer opportunities similar to LAFANS to study informal social control and social cohesion which, again, are very relevant to theories about neighborhood-level processes and residential behaviors that affect environmental quality. Both datasets therefore provide a rich opportunity to formally specify and test hypotheses related to ecologies of luxury and prestige.

These examples, LAFANS and PHDCN, underscore a final point about the nature of quantitative studies of neighborhood socio-ecological change, particularly when disparate sources from multiple metropolitan areas are needed: the collection, management, cleaning, and analysis of data require tremendous effort. To the extent that my analysis routines are re-useable and reporducible, I have already made them available on the internet throught Github. It is my hope that future scholars of neighborhood change may find the following resources useful.

- Python library I created for calculating sub-pixel vegetated area from Landsat surface reflectance: https://github.com/arthur-e/unmixing
- Google Earth Engine scripts for creating radiometrically normalized time series of modified soil-adjusted vegetation index (MSAVI): https://github.com/arthur-e/ee-python-notebooks/
- Utilities, with examples, for subsetting, cleaning, and managing parcel-level data like that provided by CoreLogic: https://github.com/arthur-e/parcel-analysis

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