Green Gentrification in Washington, D.C.

A methods study of how GIS can be used to assess the effects of parks on city-wide gentrification

A thesis submitted by

Alyssa Kogan

in partial fulfillment of the requirements for the degree of
Master of Science
in
Environmental Policy and Planning

Tufts University

May 2018

Adviser: Barbara Parmenter
Readers: Sumeeta Srinivisan and Isabelle Anguelovski

Abstract

Urban green space is widely regarded as a valuable resource and a key part to a healthy and sustainable city, yet there are large disparities in the distribution of and access to green space, which reflect already existing income and socio-economic disparities. Using green space data and census data, this study assesses the impact of green space on gentrification in Washington, D.C., both spatially and temporally. Via GIS, descriptive statistics and spatial regression as the methods of analysis, the study's primary conclusion is that the change in non-Hispanic Black population is the most statistically significant predictor of distance to green space. Of all the models, using a multivariate model with distance to green space as the outcome variable is the most noteworthy and compelling model because it controls for other sociodemographic variables and is conducive to a lucid interpretation. The results show an eastward movement of green gentrification over the study period of 1990-2015. Furthermore, examining how GIS can be used to quantify gentrification induced by green spaces reveals considerable limitations, both with data availability and contextual factors. Suggested future research attempts to remedy some of these limitations by classifying green spaces by usage, using alternative data sources as proxies for gentrification, and delving into qualitative research.

Acknowledgements

I am tremendously thankful to my advisor, Barbara Parmenter, whose knowledge, dedication, support and patience is greatly appreciated. I would be hard pressed to find another advisor who is willing to offer GIS help and technical support at 10 pm on a Sunday night. Another enormous thanks goes to both my readers, Sumeeta Srinivasan and Isabelle Anguelovski. Both of their wisdom and input helped to shape my final thesis into what it is today.

I would also like to thank my parents and brother for their steadfast love and support during all my years of education. Thanks also to my UEP family for so much love, community and support during our time here.

Table of Contents

List of Tables ... vi

List of Figures ... vii

Chapter 1: Introduction ... 1
- **Research Questions** ... 3
- **Chapter Breakdown** ... 3

Chapter 2: Background ... 5

Chapter 3: Green Gentrification – a Literature Review ... 13
- **Introduction** ... 13
- **Background** ... 13
- **Measuring Gentrification** ... 19
- **Disparities in Access and GIS** ... 21
- **Green Gentrification** ... 27
- **Conclusion** ... 30

Chapter 4: Data and Methods ... 31
- **Introduction** ... 31
- **Data Description** ... 31
- **Distance to Green Space** ... 36
- **Descriptive Statistics** ... 38
- **Exploratory Spatial Data Analysis** ... 39
- **Regression** ... 40

Chapter 5: Results ... 42
- **Introduction** ... 42
- **Descriptive Statistics** ... 42
  - Overall context ... 42
  - Sociodemographic and Housing Variables ... 42
  - GeoDa and Spatial Autocorrelation ... 44
  - Individual Park Buffers ... 45
  - Summarized Park Buffers ... 46
- **Regression Results** ... 48
  - Distance to Parks as Independent Variable ... 48
  - Distance to Parks as Dependent Variable ... 51

Chapter 6: Discussion Section ... 54
- **Introduction** ... 54
- **Green Gentrification Discussion** ... 54
  - Political and Economic Context ... 56
- **Research Challenges** ... 57
  - Difficulties of Measuring Green Gentrification ... 57
  - Data Discussion ... 59
  - Methods Discussion ... 60

Chapter 7: Conclusion 63
Policy Implications of the DC Study 63
Data Recommendations 64
Methods Recommendations 65
Appendices 68
References 98

List of Tables

Table 1: Variable Description ... 32
Table 2: Methods for Calculating Distance to Green Space ... 37
Table 3: Average Change Around Parks by Distance ... 68
Table 4: Local Univariate Moran's I: 1990-2000 ... 69
Table 5: Local Univariate Moran's I: 2000-2010 ... 70
Table 6: Local Univariate Moran's I: 2010-2015 ... 71
Table 7: Local Bivariate Moran's I: 1990-2000 (with distance to parks as independent variable and Queen's Contiguity) ... 72
Table 8: Local Bivariate Moran's I: 2000-2010 (with distance to parks as independent variable and Queen's Contiguity) ... 73
Table 9: Local Bivariate Moran's I: 2010-2015 (with distance to parks as independent variable and Queen's Contiguity) ... 74
Table 10: Results of OLS and GWR Models for core gentrification indicators (with Distance to Parks as independent variable) ... 75
Table 11: Results of OLS and GWR Models for core gentrification indicators (with Distance to Parks as dependent variable) ... 76
Table 12: Moran's I values for all variables ... 45
Table 13: Changes for ages 18-34 around individual parks ... 77
Table 14: Changes for Bachelor's degree or higher around individual parks (bold denotes changes towards green gentrification) ... 79
Table 15: Changes in median house value around individual parks ... 81
Table 16: Changes in median family income around individual parks ... 83
Table 17: Changes in non-Hispanic Black around individual parks ... 85
Table 18: Changes in poverty rate around individual parks ... 87

List of Figures

Figure 1: Washington, D.C. 5
Figure 2: Green space in DC (includes national parks, community gardens, and parks and recreation centers) 10
Figure 3: Green spaces acquired post-1990 34
Figure 4: Change in Non-Hispanic Black Population 89
Figure 5: Change in Population with Bachelor's Degree or Higher 90
Figure 6: GWR results 1990-2000 (distance to parks as independent variable) 91
Figure 7: GWR results 2000-2010 (distance to parks as independent variable) 92
Figure 8: GWR results 2010-2015 (distance to parks as independent variable) 93
Figure 9: GWR results 1990-2000 (distance to parks as dependent variable) 94
Figure 10: GWR results 2000-2010 (distance to parks as dependent variable) 95
Figure 11: GWR results 2010-2015 (distance to parks as dependent variable) 96
Figure 12: Change in Non-Hispanic Black Population 2000-2010 with parks that experienced green gentrification 97

Chapter 1: Introduction

Urban green space is widely regarded as a valuable resource and a key part to a healthy and sustainable city, yet there are large disparities in the distribution of and access to green space, which reflect already existing income and socio-economic disparities. More recently, examples of environmental (or green) gentrification, characterized by environmental or sustainability initiatives that lead to the exclusion, marginalization or displacement of the residents in the surrounding community, have been extensively documented in the literature through qualitative studies (Anguelovski, 2015; O'Connell, 2016; Pearsall, 2012; Wolch, Byrne, & Newell, 2014) (see Chapter 3: Literature Review). From this effect emerges the idea of the green paradox: interventions intended to reduce the disparities in green space access lead to the displacement of the very residents the project was meant to benefit. The impact that the green space has on the surrounding area can be affected by who initiates, designs, develops and funds the project, as well as its intended purpose, use and outcome. Scholars have suggested various solutions, from concrete policy changes, to community participation, to merely forging a counter-narrative to challenge the mainstream discourse around green sustainability.

Substantial research has been conducted demonstrating the disparity in urban green space distribution and gentrification and displacement it triggers. There is also ample discussion in the literature of assessment of historic disparities, although the use of GIS as a tool in green gentrification studies is more recent. Despite the prevalence in the literature of the green paradox and environmental gentrification, there is limited quantitative evidence documenting temporal effects of green space on gentrification. There is also limited empirical and spatial analysis to evaluate green space's effects on gentrification, beyond purely access studies. Anguelovski et al. (2017) conducted the first city-wide longitudinal study on green space in Barcelona and its effects on demographic and real estate changes.

Given these conclusions and gaps in the literature, my original goal was to explore the relationship between green space and neighborhood demographic and real estate change in a US city. I wanted to develop a longitudinal study to identify if when green space is introduced, it is correlated with a change in certain indicators. I chose to do a city-wide green gentrification study of Washington, D.C. because it has an extensive amount of existing green space and has recently attempted to enhance parks with city-wide plans. After doing an extensive literature search and review, I decided to employ methods similar to those used in Anguelovski et al.'s study (2017) of Barcelona to examine the extent to which new and rehabbed green spaces predict green gentrification trends. My study contributes to the literature in several ways. I am working in a United States context where there is different data availability and accessibility, such as race/ethnicity data, and where there are different factors that influence gentrification. Methodologically, I used different methods to assess distance to green space working within the restrictions of census tracts as a spatial unit. I also used a multivariate model in addition to the univariate models because many variables could jointly predict green gentrification. The results of my study point to green gentrification happening in DC, specifically with changes in non-

Hispanic Black population as a major predictor, but also raise important data and methodological questions for GIS-based analysis of this topic in the US context.

Research Questions

In order to narrow the focus of my research to examine green gentrification in Washington, D.C. via GIS methods, I used the following questions to guide my research:

1. Does the introduction of green space predict gentrification? Does green space lead to more spatial segregation in Washington, D.C.?
    a. Are certain indicators of gentrification more highly correlated with distance to parks?
2. How can GIS be used to quantify gentrification potentially induced by green space interventions?
    a. Are the sociodemographic variables (used as gentrification indicators) spatially auto-correlated?
3. Does quantitative GIS analysis contribute to policy discussion around gentrification in any way? If so, are there ways to improve this kind of analysis?

Chapter Breakdown

I will begin by reviewing the context of Washington, D.C. Chapter 2 will provide an overview of the recent boom in economic growth and the role that green space has played in this process, from small community gardens to large municipal projects. The chapter will also explore how the benefits of this economic flourishing have or have not been equitably distributed in relation to the city's history of spatial segregation in DC. The next chapter is a literature review of green gentrification, beginning with understanding the green paradox and how green gentrification has been understood in the literature, and culminating with how other GIS studies have measured both access to parks and gentrification. Chapter 4 will dive into the data and methods. I will describe my data sources and preparation necessary for the analysis. I will then explain my methods and how they compare to Anguelovski et al (2017)'s methods, including the descriptive statistics and the regressions, both ordinary least squares and geographically weighted regression. The following chapter, Chapter 5, reviews the results of the analysis. I compare the results of the different variables as indicators of gentrification, both with distance to parks as the independent variable and as the dependent variable in a multivariate model. The Results chapter also reviews the descriptive statistics and how they relate to determining which areas of the city have experienced green gentrification. Next, Chapter 6 critically discusses the results to evaluate how effective the model was in assessing green gentrification. This chapter also discusses trends of green gentrification in the District, according to this framework and model, and closes with limitations of the data and methods. Chapter 7 concludes with recommendations both for green gentrification research and refining the model's methodology.

Chapter 2: Background

Gentrification in DC began in the 1950s with the urban renewal in Southwest DC ("Urban Renewal," 2013), yet not all neighborhoods have experienced equitable growth. While DC experienced a period of economic depression throughout much of the second half of the century, in 2003, then Mayor Anthony Williams set a goal of adding 100,000 residents over the next 10 years and developing at least 15,000 new homes as a response to DC's economic stagnation (O'Connell, 2012). Now he is widely credited with producing the economic boom the city has experienced in the past couple decades. A major part of DC's recent development has been multiple mega-projects: the MCI Center (now Capital One, a major sports and entertainment venue) in Chinatown in 1997, the new convention center in 2003, Nationals Park by the Navy Yard and a Target-anchored mall in Columbia Heights in 2008, plus a series of large-scale mixed-use projects in Brookland and Shaw in the past few

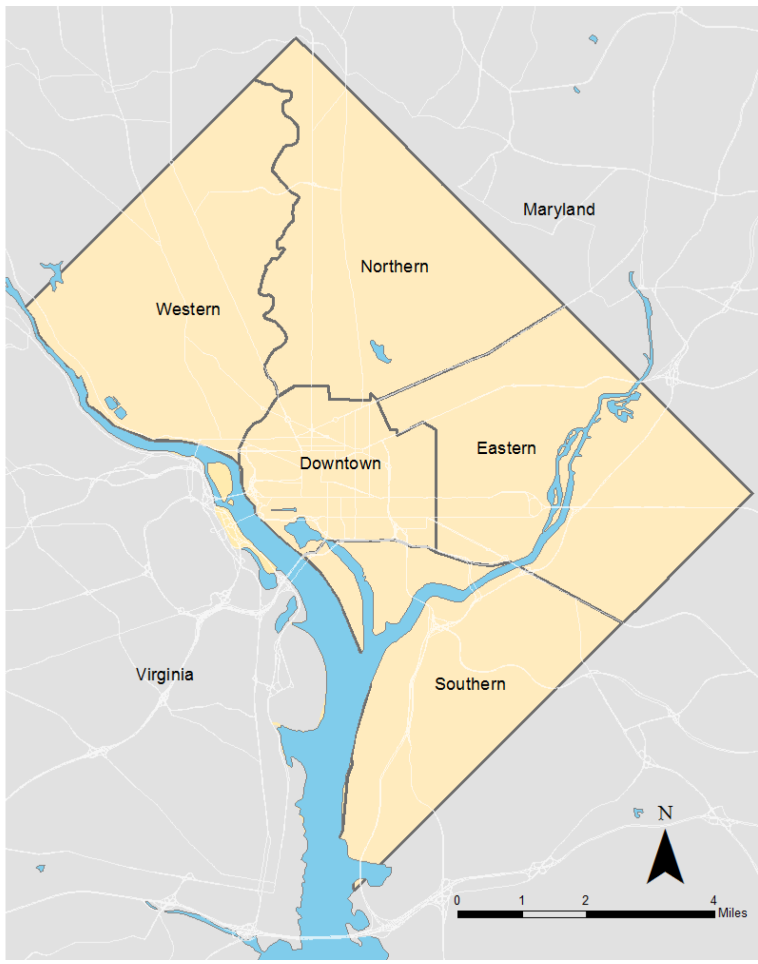


Figure 1: Washington, D.C.

years, with another under construction on the Southwest waterfront (O'Connell, 2016), to be discussed later.

As a result of this targeted development and investment, among other factors, the city is gentrifying, attracting new residents to the city and fueling a dramatic shift in population. The intense economic development of the city has also led to some of the most intense pressure on housing in the country (Gringlas, 2017). According to a report from governing.com, since 2000, Washington D.C. has the second-highest share of eligible census tracts gentrifying (following Portland, OR) (Maciag, 2015).

The economic benefits of this upward trend have not been equitably distributed and have in fact exacerbated already existing inequalities. According to a report from Georgetown University called "The State of African Americans in DC: Trends in Employment & Workforce Development," in the "new" Washington, many black people have been systematically excluded from economic opportunity (Jackson, 2017). Furthermore, a report by the Urban Institute found that White households in DC have a net worth 81 times greater than that of Black households (Kijakazi et al., 2016). Home values are also significantly less for Black-owned homes.

Another major finding from this report is the lack of upward mobility that Black residents experience in the district. The report details the structural barriers that have created the staggering racial disparities, beginning with slavery up through the construction of highways through historically black neighborhoods (Stein, 2016). These factors ultimately influenced the racial makeup in the

District. Similar to many American cities, the proportion of the black population increased during white flight to the suburbs in the 1950s and 60s. As a result, by the 1970s, black residents made up 70 percent of the population. Reflecting the economic boom DC experienced, by 2015, as whites began returning to the city, and incomes began to rise, black residents constituted 48 percent of the population. Hispanics accounted for 10.4 percent.

This demographic shift has been accompanied by gentrification. Between 1999 and 2005, rents for a two-bedroom increased 45 percent (Kijakazi et al., 2016). Furthermore, many owners of Section 8 housing chose to not renew the Section 8 lease, thereby further reducing the supply of affordable housing. In fact, by 2010, the District only had 34,500 low-rent apartments, half the number of units available in 2000 (Kijakazi et al., 2016). The 2008 housing crisis also hit the black population disproportionately harder than White residents. Although it slowed rising rents, Black residents were three times as likely to be targeted for subprime loans during the housing boom, and their home purchases were significantly more likely to result in foreclosure during the late 2000s and early 2010s (Kijakazi et al., 2016).

As aforementioned, not all neighborhoods are experiencing equitable growth at similar rates. Certain neighborhoods exhibit growth more than others, outpacing affordability and equity, resulting in an altering of neighborhood character and ultimately, gentrification. Of course, as a complex and nuanced topic, sources have varying ways of defining gentrification, resulting in inconsistent claims of which neighborhoods are gentrifying or gentrified.

According to Governing magazine's Gentrification Report, all but five of the identified neighborhoods were west of the Anacostia River, although almost all of the tracts east of the river were eligible for gentrification (a tracts median household income and median home value fell within the bottom 40th percentile of tracts in a metro area), highlighting the geographical and racial direction of growth trends (southeast DC is historically black) (Governing, n.d.; Stein, 2015).

Gentrification has been so pervasive in DC that it has been explored extensively in the media. News outlets, including NPR, the Washington Post, the Atlantic, The Guardian, among others, have featured various neighborhoods as a showcase of gentrification, including Columbia Heights, Shaw/U Street, Eckington, NoMa, the H Street and U Street corridors (Franke-Ruta, 2012; Gringlas, 2017; Iweala, 2016; Jan, 2017; McCartney, 2017; Misra, 2017). The stories feature both data of rising house prices as well as anecdotal accounts of changing neighborhoods.

The 11th Street Bridge Park is a prime example of a green space that has gentrifying potential. Often compared to the High Line in New York, the project is a public park located on the piers of the old 11th Street Bridge across the Anacostia River in southeast DC. The campaign has secured $15 million in funding to date and the park is scheduled to open by late 2019 ("About the 11th Street Bridge Park," 2014). The privately operated and publicly owned park is intended to connect neighborhoods across the river, which has been a historically economic and social divisive force in the District (O'Connell, 2016). The four primary goals of the project are to create economic development, improve public health, connect communities on both sides of the river, and re-engage residents with the river itself (“About the 11th Street Bridge Park,” 2014).

Given DC’s gentrifying trends, the project created an Equitable Development Plan, and planners intend to use this process as a model for future development plans. The Equitable Development Task Force drafted a list of recommendations for which they solicited feedback from community representatives. In 2015, they released a set of 19 strategies to support local communities, some of which include setting local hiring goals for construction and operations, forming a network of local businesses, and creating a land trust that can acquire vacant and blighted properties that can be used for housing projects in the future (O’Connell, 2016).

Yet still, concerns exist given the demonstrated effects of such mega-projects in DC. Critics of the project question spending priorities and cite the crumbling infrastructure on the east side of the river and when so many residents east of the Anacostia are homeless and suffer from housing shortages. The DC neighborhoods that saw the largest home price appreciation between 2015 and 2016 ranged from a 17% increase to a 50% increase over just one year (Urban Turf, 2017). The number one spot was Marshall Heights, a neighborhood in Southeast DC, which has traditionally been populated by African-Americans. Congress Heights, a neighborhood adjacent to the new mega green project, experienced a 37% increase in median sales price in 2015 and of the 110 homes sold, 37 percent were all-cash, suggesting that investors were fueling many of the deals (O’Connell, 2012).

Despite claims of green gentrification in DC, park access in the District is actually significantly higher than most other US cities (see Figure 1 for an overview of green space in the District). The city consistently ranks high in the Trust for Public Land's Park Score Index. However, in 2017, it fell to 4th place, following Minneapolis, St. Paul and San Francisco (Trust for Public Land, 2017). The ranking also accounts for access, which my own research does not. Furthermore, Washington, D.C. ranks number 1 of high-density cities for park density, averaging 12.9 acres of parkland per 1000 residents. Plus, 97% of the city population has walkable park access.

Figure 2: Green space in DC (includes national parks, community gardens, and parks and recreation centers)

DC has an extensive history of parks. Beginning in 1791 with Pierre L'Enfant's plan for wide boulevards and grassy open spaces, the philosophy was extended with the McMillan plan (led by Frederick Law Olmsted Jr.), which envisioned and subsequently created an extensive city park system, including Rock Creek Park and some of the waterfront (Play DC, 2015).

Washington, D.C. is unique because as it developed as both a federal city and a national capital, park land also reflected this dual ownership. In fact, 90% of the District's 9,500 acres of park land is owned by the National Parks Service. The disparate management and maintenance has contributed to challenges in use and planning (National Capital Planning Commission, 2010). In response, CapitalSpace, a partnership among NCPC, NPS, DPR, and Office of Planning, emerged as a possible solution. Adopted in 2010 CapitalSpace began by completing the first comprehensive analysis of Washington's parks and open space in nearly 40 years. This analysis found that within Washington's park system, "the wide variety of park types, sizes, and traits, coupled with shared jurisdiction between local and federal authorities, presents challenges in meeting both local and national needs, as well as difficulties in planning, enhancing, and maintaining the parks" (National Capital Planning Commission, 2010).

PlayDC is another plan that developed in the spirit of comprehensive city park planning. Launched in 2013 and adopted in 2015, the plan places an emphasis on the upgrade and maintenance of existing parks (especially DC public schools), as well as acquiring more park space via property transfers, purchases and private development offers. Ultimately, the plan sets a goal that every resident should be within ½ mile walking distance of meaningful green space, defined as a park at least 1/3 of an acre in size. Part of the strategy includes coordinating with the National Park Service to increase access to the waterfront (Play DC, 2015).

Chapter 3: Green Gentrification – a Literature Review

Introduction

This literature review will explore the topic of green gentrification and common methodologies for assessing it spatially. The first section will begin by documenting what green gentrification is and how it has been explored and documented in the literature. The next section will provide a brief overview of how gentrification has been studied, with an emphasis on GIS methods. From there, the following section will explore how GIS has been used to measure different aspects of green space distribution, primarily focused on questions of access and disparities. The chapter concludes by examining the few publications that have studied green gentrification via quantitative spatial methods, highlighting Anguelovski et al. (2017) which will serve as the basis for my methods.

Background

Urban green space is widely regarded as a valuable resource and a key element of a healthy and sustainable city; yet there are large disparities in the distribution of and access to green space which reflect already existing income and socio-economic disparities (Wolch, Byrne, and Newell 2014; Jennings, Johnson Gaither, and Schulterbrandt Gragg 2012; Heynen, Perkins, and Roy 2006). Environmental gentrification, characterized by environmental or sustainability initiatives that lead to the exclusion, marginalization or displacement of the residents in the surrounding community, has been extensively documented in the literature. From this effect emerges the idea of the "green paradox:" interventions intended to reduce the disparities in green space access lead to the displacement of the very residents the project was meant to benefit (Wolch et al. 2014). The impact that the green space has on the surrounding area is influenced by who initiates, designs, develops and funds the project, as well as its intended purpose and outcome. Scholars have suggested various solutions, from concrete policy changes, to community participation, to forging a counter-narrative to challenge the mainstream discourse around green sustainability.

The effects of the green paradox is also known as eco-gentrification, environmental gentrification, or green gentrification. Whatever the origins of park enhancement, because green space improves the desirability of an area, it tends to result in increased property values, ultimately serving as a gentrifying force known as green gentrification or environmental gentrification (Checker 2011). Thus, the the apparently laudable goal of increasing access to green space in low-income communities has the potential to displace the very people it is meant to benefit. As Pearsall and Anguelovski (2016) note, there are a wide variety of interventions that trigger this same effect, such as green space creation, park restoration projects, bike lane infrastructure, smart growth development, and the opening of “healthy” food stores.

The immediate effect of green space interventions is an increase in property values. The High Line in New York City is a relevant example of a large green space intervention that has led to significant property value increases. Property values near the park increased 103 percent between 2003 and 2011. Built on a disused elevated railroad, the park opened in 2009 and has converted the surrounding area from a gritty, mostly working-class area, characterized by auto parts stores, slaughterhouses and meatpacking plants, parking garages, and fashion warehouses, among other small industrial businesses, to a neighborhood of high-rises and trendy hotels and boutiques (Daigneau 2015). Another example of neighborhood changes induced by environmental clean-up is shown by Gamper-Rabindran and Timmins (2011). They tested for residential sorting and changes in neighborhood characteristics in response to hazardous waste site cleanups using restricted access fine-geographical-resolution block data. They found that cleanup is correlated with increases in population and housing unit density, increases in mean household income and shares of college-educated, as well as increases in the shares of minorities.

Another trend explored in the literature of urban greening and infrastructure is the purpose of a park in relation to its target audience. The High Line is extolled as an innovative way to use abandoned space to bring economic development and green space to a dilapidated area (McGeehan 2011). Despite the innovation, the High Line underscores the trend of privileging high profile parks and parks for outside visitors and tourists over the broader provisioning of green space, which many scholars claim to be the contemporary neoliberalization of park space (Loughran 2014; Millington 2015). The New York City planning board rezoned the area of the High Line to favor heightened development possibilities along the line. The purpose of the park is a tourist destination rather than an urban park that provides services for neighborhood residents, an important point to consider given the disproportionate amount of resources designated to its creation. The High Line is the most expensive park per acre in New York City, and covers only 6.7 acres. Upon completion, the construction costs exceeded 250 million dollars. The park was funded through public and private investment, including generous donations from celebrities and socialites, which is suggestive of the privatization of public space, with the ultimate goal of real estate speculation and development (Millington 2015; Loughran 2014).

An underlying assumption of the greening of cities is the universally beneficial and frequently apolitical sustainability agenda, and its promise to deliver economic growth, environmental quality and social justice. Many scholars point to sustainability as another dimension to the problem of green gentrification. Environmental sustainability appears to be a politically-neutral and consensus-based planning initiative, when in reality, it is actually often subordinating equity to profit-minded development (Checker 2011). Typically, many of the actors involved in these large interventions are private developers and individuals. Neighborhood greening and environmental sustainability is officially sponsored by municipal policymakers as a way to incorporate sustainability and nature into the city agenda, creating new visions for sustainable urban forms. Scholars argue that green gentrification is traditionally apolitical; it is a technical agenda which gives it the moral authority that demotes or conceals any equity issues, while engendering normative values. This discourse can then be used as a shield to defend any green urban interventions (Anguelovski 2016, Millington 2015). Ultimately, because this vision prioritizes real estate development and private investors, it leads to capital accumulation, which is linked to the political economy of the neoliberal city. It is this increasing privatization of urban environmental management under the neoliberal political economy that is intensifying inequity of availability of resources (Heynen et al. 2006).

To achieve balance between greening and equity, scholars (Checker 2011; Curran and Hamilton 2012) argue that "greening" needs to be reconceptualized and the discourse needs to be changed. While these scholars advocate altering the discourse and narrative around this problem, Pearsall and Anguelovski (2016) call for more research about how activists concretely oppose the aforementioned technocratic discourse of sustainability and reassert the social and political dimensions of the sustainability concept.

As an alternative, multiple scholars argue that contemporary urban environmental dynamics can be altered to reduce the idealization of immaculate and orderly green spaces to be inclusive of urban waste spaces and other spaces that have been targeted for clean-up (Millington 2015; Wolch et al. 2014; Banzhaf et al. 2006). An alternative to other approaches for addressing the disparity in green space access is the concept of "just green enough," which characterizes the idea of making a neighborhood more livable without triggering gentrification (Wolch et al. 2014; Curran and Hamilton 2012). This strategy promotes the cleanup of industrial spaces and green space aimed at the existing population and industrial land users, not at new development (Curran, and Hamilton 2012). Consequently, these projects that fit the existing character of a neighborhood are less likely to trigger gentrification (Banzhaf et al. 2006). "Green" does not have to be aesthetically pleasing or "natural" but can be understood as a vision that recognizes and even celebrates historical injustices and industrial roots of an area, thereby challenging the narrative of the inevitability of environmental gentrification (Curran and Hamilton 2012).

The Greenpoint neighborhood in Brooklyn, New York provides an illustrative case study of "just green enough". Greenpoint suffered from considerable environmental degradation, including the designation of its bordering body of water, Newtown Creek, as a Superfund site in 2010. The greening of the neighborhood has taken many forms, but ultimately it has both "greened" the neighborhood and maintained its working class character, challenging what "green" looks like. The neighborhood fought to create a vision for the Creek that embraced its industrial past, forging a path for brownfield cleanup and prioritizing public health, although presently this trend is fading slightly as Greenpoint is increasingly gentrifying. This vision contrasted with typical green space projects which are explicitly tied to residential and commercial redevelopment of industrial sites, aiming to attract higher-income residents instead of benefiting the current lower-income residents (Curran and Hamilton 2012).

The "just green enough" theory is supported by plenty of theoretical and polemical literature, as noted above. There are also case studies around other strategies to prevent green gentrification, as detailed below. However, the lack of empirical evidence on solutions that work and what makes them effective is problematic. Perhaps because displacement is challenging to measure, there are very few studies examining green interventions, such as "just green enough," and the resulting gentrification and displacement.

Considerable research has been conducted demonstrating the disparity in urban green space distribution and gentrification and displacement it triggers. Despite the prevalence in the literature of the green paradox and environmental gentrification, there is limited evidence surrounding a proven intervention to increase green space access while mitigating the resulting displacement. Areas for further research include empirical and spatial studies to test types and methods of intervention in conjunction with various policy and community responses to explore which are most efficient in reducing gentrification as an inevitable byproduct of urban green space.

Measuring Gentrification

While gentrification is a commonly studied phenomenon, there is still no consensus for how best to measure such a complex problem. As far as having policy applicability, many studies have approached it from a vulnerability and/or suitability lens (Torrens and Nara 2007; Kennedy and Leonard 2001; Aka 2010). Torrens and Nara attempt to account for both demand- and supply-side variables to predict future impacts and potential gentrified areas. Similarly, Kennedy and Leonard (2001) detail several factors contributing to gentrification in Atlanta, Cleveland, Washington, D.C., and the San Francisco Bay Area.

Another study (Kolko 2007) evaluated gentrification historically. Using census data from 1990 to 2000, he analyzed changes in tract-level household income as a measure of gentrification. The explanatory variables (location, housing, and demographic characteristics) are derived from the Neighborhood Change Database. The paper concluded that gentrification was more likely in census tracts closer to the city center and with older housing stock, whereas demographic factors have a less significant effect on likelihood of gentrification. The neighborhood spillover effect was also found to significantly contribute to gentrification (Kolko 2007).

Although less extensively explored, evaluating gentrification from a spatial perspective using GIS is another important tool in understanding the causes, effects and nuances of gentrification. For the purposes of this study, I will be focusing on spatial methods for assessing gentrification. There are very few standard approaches for mapping gentrification. Most turn to suitability analyses (Nesbitt 2005; Chapple 2009; Bates 2013), similar to the studies mentioned above. Nesbitt (2005) determined the factors for gentrification based on the literature before conducting the analyses and used a binary system for each factor. Chapple (2009), on the other hand, determined his indicators for gentrification based on factors developed from statistical analysis of Bay area change, adopting a longitudinal approach to see why areas are more or less likely to gentrify.

Taking this a step further, Chang's dissertation (2013) evaluated the advantage of mapping gentrification with GIS, using three New York City neighborhoods as the study site, and emphasized the strength of GIS of being able to document the uneven gentrification process within study neighborhoods. The study mapped gentrification via physical elements (building age and height) and the social environment (total population, ethnic groups, age groups, housing tenure, median household income, median gross rent, and educational attainment). This study used an innovative mapping visualization scheme. Each census tract also contains a bar graph showing growth over each decade (1980-2010). The study does, in fact, suggest expanded research to look at a neighborhood with its adjacent neighborhoods to yield a better understanding of the spatial and temporal patterns of gentrification, which is what I will be doing in my study. The study also suggested investigating the effect of parks on gentrification patterns (Chang 2013).

Delmelle (2016) compared the urban development of Chicago and Los Angeles 1970-2010 by creating longitudinal sequences for each neighborhood. The study used K-means clustering to create socioeconomic typologies at the tract level. From there all variables (selected based on prior literature) were standardized by the z-score each year to control for different measurement in scales and to compare across time. The novelty of this study is that measuring multidimensional neighborhood changes previously used transition matrices to quantify transitions between classes, but Delmelle's study used cluster sequences to match similarities (using a matching algorithm) to identify neighborhoods showing a downgrading process or portraying a renewal process (Delmelle 2016).

Disparities in Access and GIS

When examining green space from an equity lens, most of the literature focuses on historic access to green space and some ultimately connecting it to an environmental justice framework. Very few take the quantitative evidence to the next level of quantitatively investigating the green paradox and the resulting gentrification. There is no consensus in the literature about the best method for assessing access to urban green space (Wolch et al. 2014). Most studies use GIS to measure access and use such metrics as distance to urban green space, presence of park facilities, total green acreage and per capita green acreage. According to

Rigolon's literature review (2016), there is also inconclusive evidence about disparities in park proximity. However, there are inequities in park acreage and park quality; low SES and ethnic minorities have access to fewer acres of park, fewer acres of parks per person and to parks with lower quality, maintenances and safety than more privileged people. These inequities also reflect geographical divides of inner-city versus suburbs (Rigolon 2016).

Some of the benefits of urban green space include critical ecosystem services, such as clean air and stormwater management, as well as health benefits, such as physical activity promotion, psychological well-being and the mitigation of health outcomes disparities experienced in lower income and minority communities (Wolch et al. 2014; Roe, Aspinall, and Thompson 2016; Jennings et al. 2012). Green space and other forms of public places also strengthen social encounters, interactions and community creation (Thompson and Kent 2014). From an economic standpoint, the amount of green space is often used as a proxy to measure a community's socio-economic status; because green space projects often improve economic stability of an area by creating green jobs, increasing property values and improving public health, it is assumed that the amount of green space in an area is positively correlated with its socio-economic status (Jennings, Larson, and Yun 2016).

Despite the extensive and well-known benefits of urban green space, numerous studies have shown that it is inequitably distributed by race, ethnicity, and class, ultimately perpetuating existing inequalities. Inaccessibility to green space is considered an environmental justice issue because many studies prove that access tends to be inequitably distributed in urban areas, ultimately disadvantaging low-income areas and communities of color (Wolch et al. 2014; Heynen et al. 2006). Heynen et al. demonstrate a statistically positive correlation between residential canopy cover and median household income in Milwaukee (2006). Similarly, Wen et al. use census tract-level park and green space data linked with data from the 2010 US Census and the 2006-2010 American Community Surveys to create a linear mixed regression model. They conclude that place-based race-ethnicity and poverty are important correlates of spatial access to parks and green spaces (2014).

One of the primary methods for examining access to green space via quantitative methods is with network analysis. Miyake et al. (2010) look at different spatial techniques to see discrepancies in access to NYC parks because other studies only showed that parks were not distributed evenly. After reviewing previous methodologies employed to assess access, Miyake et al. (2010) conclude that network analysis is a successful and comprehensive way to measure access. Their study uses network analysis and cadastral-based expert dasymetric system (CEDS) to estimate racial/ethnic composition of populations within 400m walking distance of parks in New York City. Specifically, they look at distance to the closest park, number of parks within walking distance, amount of accessible park space and number of physical activity sites - all evaluated across racial/ethnic categories and then compared to city-wide populations using odds ratios. Then using network analysis for each residential tax lot in NYC to find closest park and all parks within walking distance of 400 and 800m, combined with racial/ethnic demographic estimates, they found that 95% of population is within 800m of a park. However because New York City is so dense, these findings are contextual. Although park access in this setting was not found to be issue of distributive injustice, access varies by the type of park and size. The study concludes that all types of parks have different benefits (e.g., public space, physical activity, emotional wellbeing), so the disparities may lie at a more granular level (Miyake et al. 2010).

Another study by Wüstemann, Kalbisch, and Kolbe (2017) investigates access to urban green space on the household and individual level in Germany using network analysis and concludes by identifying strong disparities in green space provision. In the network analysis, they computed the distance to the nearest urban green space based on Euclidean distance between residence and the border of the nearest urban green site. They then calculated the amount of urban green space in hectares/square meters within a walking distance to each residence, using a buffer area of 500 m around the centroid of the grid cell/household. A unique aspect of this study is the use of the Gini coefficient to explain disparities in access.

A method commonly used in the literature to measure access is the use of linear regression. A study by Wen et al. (2013) testing spatial disparities in distributions of parks and green spaces in the US uses linear mixed regression models to examine associations of poverty levels and percentages of blacks and Hispanics with distances to parks and green space coverage. As part of their spatial analysis, they used population-weighted Euclidean distance to the closest seven parks in order to adjust for uneven population distributions within a census tract. They conclude that race/ethnicity and poverty are in fact correlates of spatial access to parks and green spaces, but that these associations vary across the urban-suburban spectrum (Wen et al. 2013). Wustermann et al. (2017) also used multiple regressions using distance to green space and amount of green space as the dependent variables and explanatory variables of income, age, education, employment, migration background, German nationality, and child in household.

Consistent with Rigolon's (2016) literature review conclusions about the inequities in access to urban parks, using methods of GIS network analysis and linear regression indicates disparities in access to green space, but mostly in acreage. This distinction is due to the fact that many low-income and densely populated areas may have ample small, low-quality parks, which reduces the distance to nearest parks, but then occults the disparities in access to quality amount of space, which has implications for usage.

Building off this conclusion, studies have evolved to take a more nuanced approach to park accessibility by classifying the types of parks with varying results. A study showing statistically significant differences in proximity to public space by area-level disadvantage uses four distinct categories of public open space in Melbourne, Australia: natural and semi-natural areas, organized recreation areas, parkland and garden areas, and protected areas (Mavoa et al. 2015). The study's methods used GIS to measure and visualize patterns of access to nearest public open space by category. After conducting one-way analysis of variance (ANOVA) and Scheffe post hoc comparisons, the study concludes that the statistically significant differences in proximity to and size of public open space by area-level disadvantage were not large enough to be meaningful (Mavoa et al. 2015). Even if their findings are inconclusive, the study still contributes a valuable addition for green space methods.

Another case study that introduces a multi-dimensional procedure for empirically classifying urban parks conducts an equity analysis comparing park types to neighborhood social characteristics in Phoenix, AZ (Ibes 2015). The purpose is to discover who has access to what type of park, rather than accessibility at face-value. The variables used in park classification include park size, amenities and facilities, distance from the city center, land cover mix, level of greennesss, and surrounding land uses. The methods used cluster analysis and subsequently ANOVA tests to prove that all clusters were statistically significant. The results of the study show that all but one type of park types are significantly statistically correlated with a particular neighborhood social context, ultimately proving the significance of types of green space in conducting equity analyses.

One study that takes this line of thought to the next level is a study by Zheng and Kahn, which looks at place-based public investments (which can be thought of as a proxy for green space) effects on triggering gentrification around the site (2012). This study measures gentrification by the increase in quality of private-sector economic activity (e.g., home prices, new housing construction and new restaurants). They found that in areas surrounding government investments in public goods, homes sell for higher, developers are building more housing in this area, new restaurant openings have increased, and growth in income and educational attainment (Zheng and Kahn 2013). While the key focus is gentrification, there is no mention of displacement and other unintended consequences until the very end of the article, suggesting that the focus is limited to the effects of investment rather than its effects.

Green Gentrification

Measuring disparities in green space access is useful and contributes to the environmental justice framework, but then fails to take it the next step by examining the effects of inserting a park in an area that is considered to have low access. One approach done by Weems (2016) in her dissertation was to examine the spatial distribution of park access and trajectories of gentrification in Seattle 1990-2010. She began by measuring park access, similarly as above with the number of parks (by type) within 800m buffer of each census block group (or alternatively the amount of park area within buffers of each census block group). From there, she tested the statistical significance of difference in park access by education, home value and income using a two-way ANOVA and then post-hoc Tukey’s multiple comparisons test.

The next section of her dissertation focused on assessing gentrification. As shown via this literature search, Weems acknowledges that there is a wide variation in how gentrification should be mapped. She used trajectories of change based on median household income, median home value and educational attainment and classified all as above or below city median. She complemented this analysis with a semi-structured media content analysis to identify locations of perceived gentrification from news sources, blogs and websites. Finally, she looked at racial changes in the gentrified census block groups.

Ultimately, park investment was used to tie the two analyses together to measure environmental gentrification. She assessed the amount of park investment within 800m of each census block group. The information was processed and filtered to identify which records were associated with park improvements and that was then joined with the park shapefile. She concluded that the number and acreage of parks do not predict gentrification, but information on park investment reveals strong lagged relationships. Increases in park access when combined with high levels of investment in parks appeared to explain spatial patterns of environmental gentrification in Seattle. She also noted, as described above, that the process is sensitive to changes in different park types as well (Weem 2016).

Anguelovski et al. is one of the primary studies that has delved into this topic in depth. A significant study complementing the above conclusions investigates the distributional outcomes of parks added to Barcelona during the 1990s and early 2000s, and how the distribution of these new environmental amenities becomes more or less equitable as the city implements greening agendas (Anguelovski et al. 2017). This study is the first to fill the aforementioned gap of city-wide quantitative studies of green gentrification associated with parks creation. The methods begin by assessing how housing and population trends changed over time near parks, using the average values for tracts that overlap buffers around new parks at three distances. The period of change differed for each park, starting at the year of park creation and ending at the most recent data available.

The next step in the methodology was using local and global regression to see whether distance to parks is a causal driver of the demographic changes. After concluding with an OLS model that residuals were significantly clustered, the study then adjusted to a GWR, using the Euclidean distance proximity to parks as the independent variable, and the sociodemographic indicators as dependent variables. The results then assess each dependent variable's relationship with proximity to parks. These proxies for gentrification were: percentage of residents with a bachelor's degree or higher, percentage of residents over 65 years living alone, percentage of residents from the Global South, household income level, and home sale values. In order to compile these individual results, the study then created a composite score for the five indicators, assigning one point to parks with buffer areas that outpaced their neighboring districts for each of the gentrification indicators selected for the study.

The results indicate statistically significant green gentrification in some of the parks, but not others, suggesting that a park's impacts also depend on other contextual factors including setting, creation source, and the surrounding built environment - a conclusion in line with many of the literature studying park access. This study also illustrates other socio-spatial dynamics and flows to create a new form of polarization and re-segregation. Ultimately, Anguelovski et al. conclude that "parks may fuel, but not primarily drive gentrification processes" in Barcelona (Anguelovski et al. 2017, p. 29).

Conclusion

Green gentrification is clearly a prevalent topic in the current literature; however because it is a relatively newly studied phenomenon, there are many areas left to be explored, including potential solutions and further quantitative studies. The focus up until now has been on the disparities in access, but few studies have connected this topic with the resulting gentrification, especially not at a city-wide level. Given this gap in the literature, I propose developing a city-wide green gentrification study of Washington, D.C., using and modifying the methodology used in Anguelovski et al.'s study (2017) of Barcelona to examine the extent to which new and rehabbed green space sizes, design, access, quality and use predict green gentrification trends.

Chapter 4: Data and Methods

Introduction

In this chapter, I will describe my data and methods. I will begin by detailing my data sources and the preparation and cleaning necessary to complete my analysis, including both portions of the data collection: sociodemographic data as gentrification indicators and green spaces in DC. I will then explain my methods, starting with the descriptive statistics, followed by the spatial analysis with Ordinary Least Squares regression and Geographically Weighted Regression. As described above, I have opted for these methods as an attempt to replicate Anguelovski et al (2017)'s methods. Based on the literature review and contextual factors, however, I have also modified the methods to measure distance to green space and conduct the regressions.

Data Description

The sociodemographic and housing data are from the decennial census (short and long form quetionnaires) from 1990, 2000 and 2010, and 2010 and 2015 5-year estimates from the American Community Survey (ACS). The data came from both Geolytics via researchers at the Barcelona Lab for Urban Environmental Justice and Sustainability and downloaded from Social Explorer. All data are at the census tract level and normalized to 2010 census tract boundaries. These data were then joined to the Tiger Line Shapefile for 2010 census tracts based on GeoID.

Based on the literature of common indicators of gentrification, as well as context-specific factors in Washington, D.C., the general areas of focus were age, race/ethnicity, housing values, poverty, income, and education. Age and race are especially important in the context of DC. Gentrification has been largely associated with an influx of young urban professionals to the District, which is historically a particularly segregated city. The other indicators are commonly accepted variables to investigate as a proxy for gentrification. Specific variables for this study can be seen in the table (Table 1) below. To best measure the temporal aspect, I used the Field Calculator to calculate the change over time for each variable between 1990 and 2000, between 2000 and 2010 and finally between 2010 and 2015, resulting in three distinct time periods.

Table 1: Variables Description

Gentrification Category	Specific Variable	Calculations
Age	Young urban population (ages 18-34)	• Aggregated fields "18-24" and "25-34" and divided by total population • Subtracted earlier year from later year to find change over time in percentage points
Race/Ethnicity	Percent Non-Hispanic Black	• Number of Non-Hispanic Black divided by total population • Subtracted earlier year from later year to find change over time in percentage points
House Values	Median House Value for all Owner-Occupied Housing Units	• Subtracted values and divided by first value to find change over time
Poverty	Population below the poverty line	• Subtracted rates to find change over time in percentage points
Income	Median Family Income	• Subtracted earlier year from later year to find change over time in percentage points
Education	Percent of Population with Bachelor's degree or higher	• Aggregated fields "Bachelor's Degree," "Master's Degree," "Professional Degree," and "Doctorate Degree" and divided by total population

		• Subtracted earlier year from later year to find change over time in percentage points

The data on green spaces in Washington, D.C. come from various sources. The shapefiles were acquired in vector format from the DC government open data portal. Combining the “Community Gardens” and “Parks and Recreation Areas” data sets, one shapefile was created for all green spaces.

Given the temporal aspect of gentrification, the years of acquisition had to be established for each green space. The shapefile for “Parks and Recreation Areas” had some years entered. Others I added from data obtained from the Trust for Public Land. Finally, the dates for the community gardens were obtained by contacting each garden individually to determine their year of acquisition. Ultimately, only the green spaces for which a date was known were included in the analysis. In total, this procedure resulted in 34 total green spaces that were acquired between the years of 1990-2015 (see Figure 3). The analysis was conducted using these green spaces.

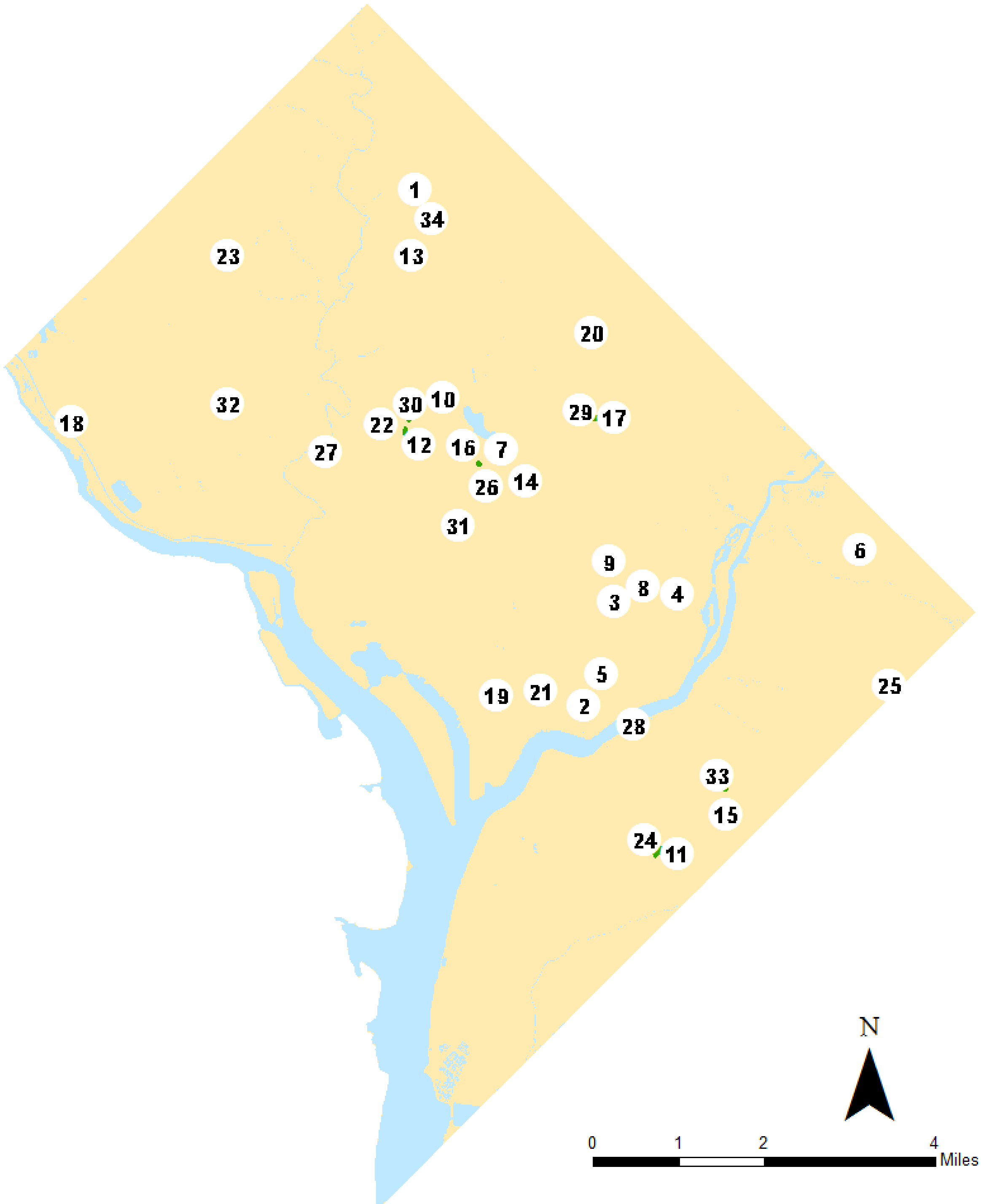


Figure 3: Green spaces acquired post-1990 (legend on following page)

Park ID	Park Name	Year	Acreage
1	Ft. Stevens Garden	2014	33.34
2	Virginia Ave Community Garden	2004	16.76
3	Hill East Community Garden	2004	4.22
4	Kingman Park-Rosdale Community Garden	2007	15.65
5	Pomegranate Alley Community Garden	2002	9.16
6	Deanwood Learning Garden	2011	8.49
7	Common Good City Farm	2007	18.01
8	Green East Community Garden	2008	14.93
9	Wylie Street Community Garden	2005	0.59
10	Bruce Monroe Garden	2007	11.09
11	Douglass Garden	2014	1.56
12	Euclid St. Garden/Justice Park	2012	6.05
13	Hamilton Garden┬á	2015	2.29
14	Harry Thomas Gardens	2015	4.18
15	Hillcrest Garden	2015	2.52
16	Ledroit Gardens	2011	3.17
17	Noyes Gardens	2013	2.27
18	Palisades Garden	1995	3.25
19	Southwest Garden	2013	5.36
20	Turkey Thicket Gardens	2014	5.36
21	Canal Park	2012	21.68
22	Justice Park	2008	11.45
23	Murch Field	2007	24.45
24	Douglass Recreation Center	2012	215.05
25	Benning Park Community Center	1992	361.3
26	Anna J. Cooper Circle	2004	7.84
27	Belmont Park	2014	108.41
28	Anacostia Recreation Center	2001	441.13
29	Noyes Park	2013	36.72
30	14th and Girard Park	2011	10.94
31	7th & N Street Playground	2003	26.05
32	Bishop Lalossu Memorial Park	2010	5.36
33	Alger Park	1999	296.43
34	Emery	2003	361.07

As a result of this compilation of sources, the green spaces represent not just parks, but other classifications as well, such as community gardens, recreation centers, and triangle parks, which merge to form an all-encompassing dataset which for the purpose of this thesis will be called “Green Sites.” Although the literature suggests that gentrification impacts vary by the type and function of green space, this study includes all green spaces in an effort to assess the methodology as applied to the context of Washington, D.C.

Distance to Green Space

As described in the literature review, there is not a clear consensus on the best way to measure access and distance to green space. Due to the lack of consistency in methodology, I opted to experiment with a few methods to determine which is best fit for my desired outcome. The first technique I used was the “Euclidean Distance” tool to calculate, for each cell, the Euclidean distance to the closest park. The resolution of the raster was set to 10 meters for sufficient granularity to consider the smallest community gardens. From there, I used the tool “Zonal Statistics as Table” with inputs of the Euclidean distance raster result, and the census tracts layer, calculating the mean distance to the closest park for each census tracts. Finally, I joined the table of the sociodemographic information to the results based on GeoID so that each census tract had its sociodemographic data as well as its mean distance to the closest park. The second method I tried was the Near tool, which produced a distance for each tract for the closest park. This output allowed me to sort the tracts by NearFID and use the Summarize function of the attribute table to determine the average sociodemographic values for each park. Finally, I used the Buffer tool to have a more accurate radius around each park, but ultimately opted against this method since it did not easily accommodate my spatial unit of census tracts. The results are summarized in Table 2 below.

Table 2: Methods for Calculating Distance to Green Space

	Euclidean Distance	**Near Tool**	**Buffer**
Tool	EucDist, Zonal Statistics, Select	Near	Buffer
Layer Names	DistParks_EucDistContain_400m DistParks_EucDistContain_800m	DistParks_Near	DistParks_Buffer_400m DistParks_Buffer_800m
Method Description	I used the “Euclidean Distance” tool to calculate, for each cell, the Euclidean distance to the closest park. The resolution of the raster was set to 10 meters for sufficient granularity to consider the smallest community gardens. From there, I used the tool “Zonal Statistics as Table” with inputs of the Euclidean distance raster result, and the tracts layer, calculating the mean distance to the closest park for each tract. I selected tracts that had a mean distance of 400m or less and merged that with a layer of all the tracts that contain a park within them.	Using the “Near” tool, for each tract I calculated the distance to the nearest park, and also tagged the tract with that park’s ID.	The “Buffer” tool creates polygons around the input features of parks to a specified distance of both 400 and 800 meters. I did not use dissolve so that each park would have its own buffer regardless of overlap.
Resulting Tracts	49 101	80 137	
Advantages	This method fits easily into census tracts and facilitates analysis at this level of spatial unit.	This method facilitates analysis for each park by producing a set of tracts associated with each park.	This method is the most precise.
Disadvantages	This method does not account for all tracts that contain a park if the tract is large and has an average higher than 400m. To account for this, I added tracts that contained parks directly within them.	This tool selects more tracts than is conducive for the analysis.	Buffers overlap tracts, and therefore make it difficult to aggregate variables of split tracts.1[1]

[1] This is typically done using areal allocation method, which is very problematic and imprecise.

Descriptive Statistics

I have based my methods on the literature surrounding both gentrification and access to green space, as well as Anguelovski et al (2017)'s methods. I've begun with descriptive statistics to gain a better understanding of the changes over time and the visual patterns. This is followed by a more in-depth spatial analysis to determine if there are any statistically significant patterns.

To conduct the descriptive analyses, I began by joining all sociodemographic variables and park distances into one shapefile so that each census tract is associated with a corresponding value for each variable. Because of the District's unique context as the U.S. capital, there are census tracts that primarily encompass federal buildings such as museums and monuments. In order to avoid skewing the data, census tracts were removed with total population of less than 50 people because this removed the census tract that encompasses the Mall, memorials and museums. I mapped each sociodemographic and housing variable individually to visually examine the patterns for each one (see Figures 4-9).

To review the change over time in specified distances around parks, I created a new field with a classification for each distance (based on the Euclidean distance described above). Each census tract was classified based on the following qualifications:

1. 1 for tracts that have average distance of 400 or less OR contain a park
2. 2 for tracts that have average distance of 400-800 m
3. 3 for more than 800 m

Using the "statistics" function in the attribute table, I found the mean for each distance classification in each respective time period and compared that to the

District average. The overall District was used as the comparison group because the census data did not fit into any other geographic options. While there are other possible options, such as city planning areas, neighborhoods, or quadrants, these boundaries did not have the same data as the census to be able to accurately compare. Likewise, the census zip code tabulation areas represent approximations of postal zip codes, follow postal rather than statistical dictates, and do not nest with tracts (i.e. they overlap tracts), which makes them difficult to use as valid comparison areas. The results can be seen in Table 3 (in appendix).

The second component to the descriptive statistics was to explore the change surrounding each park. For each park, I calculated the mean change in sociodemographic variable for those tracts ID's as the closest tract, again using the "statistics" function of the attribute table. The parks that experienced a higher change toward gentrification as compared to the overall change in the District are bolded in Table 3. The limitation of using this method to compare individual parks is that it does not result in a uniform area for each park, but given the restriction of using census tracts, it is the most effective way to show change by park.

Exploratory Spatial Data Analysis

Using a first-order Queen's Contiguity Matrix, I conducted a Univariate Moran's I for each dependent variable (education, race/ethnicity, age, median family income, median house value, and poverty) to explore significant clustering in the changes over time and the spatial lag of the variables, using distance to parks as the independent variable in each model. A Moran's I is a statistical test that assesses if the attribute values of features are clustered or dispersed. The results range from -1 to 1, with a result of -1 signifying a checkered pattern, 0 as a completely random pattern, and 1 as a clustered pattern. I then did Bivariate Local Moran's I with the same weights file to generate scatterplots showing the spatial lag of the dependent variable on the vertical axis and the distance to parks on the horizontal axis (see results in the GeoDa output in Tables 4-9).

Regression

The framework used by Anguelovski et al (2017) was to test distance to parks as a predictor of gentrification, using the distance as the independent variable and the sociodemographic and real estate variables as the dependent variables for individual models. In accordance with these methods, I first ran Ordinary Least Squares (OLS) for each of the gentrification indicators (change over time) as the outcome variables, recording the R^2, coefficient and p-value for each.

To supplement the OLS results, Geographically Weighted Regression (GWR) was also utilized to explore the spatial patterns. GWR accounts for spatial autocorrelation and makes estimates of local variation in spatial relationships rather than a uniform equation for the whole study area. Each target features is assigned a unique regression equation based on contextual spatial patterns (Pearsall & Christman, 2012). Thus, because of the spatial autocorrelation seen in the GeoDa results, Geographically Weighted Regression (GWR) was run for each variable during each time period to determine the R^2 and Adjusted R^2 value for each model. Results from both the OLS and GWR models can be seen in Table 10.

Because gentrification is a complex and nuanced process, the direction of cause and effect is not always clear. Hence, I have chosen to reverse the independent and dependent variables to further explore the relationship between green space and gentrification. In this model, like many other models in the literature, the gentrification indicators serve as predictors of distance to green space in a multivariate model. The benefit of this model is that it controls for other sociodemographic variables. Again, given the spatial autocorrelation of the outcome variable, I performed both OLS and GWR models with distance to green space as the outcome variable. Results can be seen in Table 11.

Chapter 5: Results

Introduction

In this chapter, I will discuss the results of the descriptive statistics and the spatial analysis, highlighting the differing results of each method. I will begin by reviewing each variable used as an indicator for gentrification, including their respective clustering and spatial autocorrelation. I will then describe two methods for evaluating the change around parks. I will conclude by examining the regression results, both from OLS and GWR. Non-Hispanic Black emerges as the most significant gentrification indicator in relation to distance to green spaces, a foreseeable result given the spatial segregation traditionally seen in DC.

Descriptive Statistics

Overall context

As can be seen in Figure 3, there are 34 new green sites in the District between 1990 and 2015 and they appear to be generally uniformly dispersed throughout the city, with perhaps a slight cluster in the center. The EPA designated brownfields are also generally clustered around the center of the District.

Sociodemographic and Housing Variables

Upon visual inspection of the rates of change in the sociodemographic and housing variables, there appear to be geographical patterns gentrification generally moving from NW eastward. Looking first at the young urban population, in line with the general directional pattern of the gentrification indicators, it appears that the positive increases in the percentage of population between the ages of 18 to 34 is on the border of NW between 1990 and 2000. It then expands to most of the eastern part of the city between 2000 and 2010, with the highest increases in the center (maximum increase of 43%), specifically around Chinatown, Penn Quarters and Union Station. Finally by 2015, the increases are more dispersed throughout the District but still with the most dramatic increases in the center.

In the 1990-2000 period, most tracts that experienced an increase in non-Hispanic black population were located in the northwest section of the city, with another cluster in the southeast. The greatest losses were seen in the center of the city. Between 2000 and 2010, the most heightened period of gentrification, the majority of the tracts experienced a decrease in the non-Hispanic black population. The largest decreases were seen in the center, running along the north-south line, dividing east and west parts of the city; a similar pattern to the previous time period but with higher rates of decreases and slightly further east. A similar pattern in 2010-2015 was seen as that of 1990-2000. The cluster of high population decreases is located slightly east of center.

The areas of increase in educational attainment is generally dispersed throughout the District between 1990 and 2000, although census tracts with a decrease in high educational attainment were slightly clustered in the SE. In the period of 2000-2010, the highest areas of increases in educational attainment were clustered around the center of the District, but the majority of census tracts experienced growth in this variable. Finally, between 2010 and 2015, the highest increases were slightly east of center and the decreases were again clustered in the east and southeast.

The median house value displays similar patterns as the other variables. The largest increases were seen between 2000 and 2010, which aligns with the housing boom the US experienced at the time, and the increases were clustered in the eastern side of the city. Again, the highest rates followed the boundary between east and west. By 2010-2015, the increases were more dispersed throughout the city.

Examining the variable of median family income, most of the district experienced an increase in between 1990 and 2000, aside from a small cluster of decreases in SE DC. The same pattern was exhibited in 2000 to 2010, except that the highest increases were in the center of the city, where incomes more than doubled, rather than in the NW corner. In the period of 2010-2015, there were more decreases in median family income, generally spread around the city. The most dramatic increases were again concentrated in the center.

In the period of 1990-2000, increases and decreases of poverty rates followed a clear east-west divide; increases in poverty on the east side of the city and decreases on the west side. In the time periods of 2000-2010 and 2010-2015 there were not any clear patterns or clusters.

GeoDa and Spatial Autocorrelation

The results from the exploratory spatial data analysis in GeoDa reveal a high level of spatial autocorrelation. Examining the Moran's I results, almost all variables are significant for all three time periods. As seen in Table 12 (as well as Tables 4-9), clearly some are more clustered than others. Percent of non-Hispanic Black shows the highest level of spatial autocorrelation, which makes sense given how racially segregated DC is. The next highest level of spatial autocorrelation is displayed in levels of high education, followed by young urban population. Because the variables of interest are demographic variables which are typically influenced by geographic context, it makes sense that most of these would have a positive Moran's I. The methodological implications of these results are that OLS regression may not adequately account for models where these variables are used as the dependent variable. On a contextual level, these relatively high levels of spatial autocorrelation suggest that areas of gentrification and neighborhood change are also most likely clustered; gentrification follows along lines of neighborhood change.

Table 12: Moran's I values for all variables

	1990-2000	2000-2010	2010-2015
Ages 18-34	0.2618*	0.3312*	0.1025*
Percent Non-Hispanic Black	0.4478*	0.5247*	0.3810*
Median House Value	0.0306	0.1751*	-0.0073
Median Family Income	0.1823*	0.1329*	0.1866*
Poverty Rate	0.1038*	0.0829*	0.0919*
Bachelor's Degree or Higher	0.2470*	0.3881*	0.2903*

*Significant at the .05 level

Individual Park Buffers

Tables 13-18 show the summarized results for each green space using the Near function in Arc. As described in more detail in the Methods section, each census tract was associated with the nearest park, and then the variables were summarized for all the tracts assigned to each park and compared to the district average. The purpose of these calculations was to observe changes over time around each park and be able to calculate them as either having contributing to gentrification in an area or not. Because the parks are not organized by their year of acquisition, these statistics are less helpful than they were for Anguelovski et al (2017)'s analysis; but I still opted to include them in order to demonstrate general patterns of parks that displayed more trends towards gentrification than the District average. I did, however, single out the parks that were indicative of green gentrification based on their year. Using the results from change in non-Hispanic Black population, I looked at the year of creation for the park and determined larger changes than the district average following the insertion of the park. The results can be seen in Figure 12. The names of these parks are Virginia Ave Community Garden, Hill East Community Garden, Pomegranate Alley Community Garden, Wylie Street Community Garden, Green East Community Garden, Bruce Monroe Garden, Noyes Gardens, Southwest Gardens, Anna J. Cooper Circle, Noyes Park, 7th & N Street Playground, and Emery, all located in areas of gentrification. An important trend to note is that the majority of the green spaces are correlated with green gentrification are community gardens. These parks generally correspond to the following neighborhoods: Brightwood, Columbia Heights, LeDroit Park, Brookland, Mt. Vernon Square, Logan Circle/Shaw, Kingman Park, Stanton Park, Southwest/Waterfront, Navy Yard, and Near Southeast.

Summarized Park Buffers

Table 3 below shows the compiled results of each variable and its average change in each distance range. Most of the variables do demonstrate changes in the closest proximity to parks which are characteristic of green gentrification. For the young urban population (ages 18-34), given the gentrification trends in the District, we would expect that areas closest to parks would have a higher rate of change than the average in the city. The change was in fact lower than average for 1990-2000, but rose to higher than average for 2000-2010, and then leveled out to match the city rate for 2010-2015. This timeline matches the general growth timeline for the District.

Unlike the age variable, we expect that tracts closer to parks would experience a larger decrease in the non-Hispanic Black population than compared to the city average. This trend held true for every time block during the study period, but the decrease for the years 2000-2010 was especially pronounced with a decrease of 15.27% closest to parks compared to a city average of 9.56% decrease.

Median house value is expected to increase in the tracts closest to parks. This trend was displayed in the 2010-2015 time period. However, in the period of 2000-2010, the period for which we see the most heightened signs of gentrification for other variables, the average around parks is lower than the District average. Besides the housing boom during this time, there is also discrepancy in the data for one tract that skews the averages, ultimately rendering this analysis unreliable.

For the median family income, we would expect that the change closest to parks would increase at a rate higher than the District average. On average, tracts closest to parks increased at a slower rate for 1990-2000, and at about the same pace as the rest of the District for 2000-2010. The rate of change only surpassed the city average for the period of 2010-2015, in which the rates were 38.22% and 24.84% respectively.

Similar to non-Hispanic Blacks, with traditional trends of green gentrification, we would expect that closer to parks, poverty rates would decrease more than the District average for the same period. In 1990-2000, poverty increased throughout the District but the rate of increase closer to parks was lower than the full District. Then for the periods of 2000-2010 and 2010-2015, as expected, the areas closer to parks saw a larger decrease in poverty rate than the District's average for the same times.

For education, we would expect that the rate of increase for those with a Bachelor's degree or higher would be higher than that of the District average. Interestingly, the increase between 1990 and 2000 was actually lower than the full District's average, but then rose considerably above the average for 2000-2010, and again for 2010-2015.

Regression Results

Distance to Parks as Independent Variable

As described in the Methods section, I opted to use distance to parks as both the independent and dependent variable in order to examine to the complexities of gentrification. I first explored the results of using distance to green space as the independent variable, as Anguelovski et al (2017) did in their methods.

I first review the results from the OLS models. The results from the OLS models with distance to parks as the independent variable were largely insignificant. Between 1990 and 2000, the only significant model (with a p-value for the coefficient of .08), was poverty rate. As distance to parks increases by 1 km, change in poverty rate increases by 1%, a small change with a low R^2 value of .048 for the model.

Moving to the 2000-2010 models, as expected (due to the time period of most intense gentrification) there are additional significant variables. Not surprisingly, the model measuring the change in non-Hispanic Black as the outcome variable had a significant coefficient with a p-value of .01 and an R^2 value of .493; for each increase in 1 km, percent change of non-Hispanic Black increased by 2.2%. Median house value experienced a decrease of 87.5% for each additional kilometer of distance (with an R^2 value of .12). Finally, with an R^2 of .321 and a significant p-value of .01, for each additional kilometer of distance from a park, the change in percent of population with a Bachelor's degree or higher decreases by 2.3%. In this interpretation, I switch to kilometers to facilitate a more lucid interpretation since the numbers are so small.

The models for the 2010-2015 time period displayed similar results, with the caveat that this is only half the amount of time of the two comparison groups. With a p-value of .01, for each additional kilometer of distance, percent non-Hispanic Black increased by 1.3% (with an R^2 for the model of .288). Median house value also increased by 1,926% for each additional kilometer of distance (with a p-value of 0 and R^2 of .272). Finally, poverty rate had significant results, even if just a small R^2 of .045. For each kilometer of distance, poverty rate increased by 1.4%.

Proceeding to the GWR results using distance to parks as the independent variable, only a few variables show significant results (see Figures 6-8). Once again, non-Hispanic Black showed the most distinct patterns associated with green gentrification. There was a large positive, significant cluster in 1990-2000 running from north to south in the northern half of the city. In 2000-2010, this cluster clearly expanded and moved southeast to encompass the center and areas south and east of center. Finally, in 2010-2015, the cluster moved even further east. These areas represent areas of green gentrification, according to the indicators; as distance to parks increases, so does the percent of non-Hispanic Blacks.

For ages 18-34, in 1990-2000, there is a large area of significant positive tracts surrounding and north of the Mall, signifying that as distance to parks increases in this area, so does the rate of increase of the younger population. Interestingly, in the period of 2000-2010, the largest cluster was northeast of center and with negative coefficients, meaning that as distance to parks increase, the rate of younger population decreases, which is what we would expect for a gentrifying area.

Another variable that showed interesting results was education (percent of population with Bachelor's degree or higher). In 1990-2000, there was a small significant negative cluster in NW DC and a significant positive cluster just north of the Mall in the center of the District. In this case, we expect areas of gentrification to have negative coefficients; as distance to green spaces increases, the percent of high-education population decreases. Then in 2000-2010, the majority of the middle of the District displays significant, negative coefficients. 2010-2015 shows the same pattern but with a smaller cluster and farther east, continuing with the east-moving pattern of gentrification.

Distance to Parks as Dependent Variable

Reversing the direction of causation and using distance as the dependent variable with the sociodemographic variables as the independent variables in multi-variate models reveals comparable results. The results from the OLS models with distance to parks as the dependent variable were also largely insignificant, despite the high R^2 values. There were no significant coefficients in the 1990-2000 model. In the 2000-2010 model, the two significant coefficients were for non-Hispanic Black and median house value. With a p-value of .09, for each 1% increase in non-Hispanic Black population, distance to parks increases by 677 meters. With a p-value of .01, all else equal, for each 1% increase in median house value, average distance to parks decreases by 362 meters. Similarly, in the 2010-2015 model, the same variables had significant coefficients. With a p-value of .03, for each 1% increase in non-Hispanic Black population, distance to parks increases by 1087 meters. Contrary to expected results, all else equal, with a p-value of 0, for each 1% increase in median house value, average distance to parks increases by 7.01 meters.

Looking at the GWR results for distance to parks as the dependent variable, there are three resulting models, just as with the OLS models (see Figures 9-11). The GWR models have slightly higher R^2 values than the OLS models, but lower if looking at the adjusted R^2. First looking at the GWR model for 1990-2000, there are a couple variables that have very clear patterns of where the coefficients are significantly positive and/or negative. As has been seen consistently throughout the various forms of analysis, non-Hispanic Black showed the most distinct patterns, with all the positive, significant t-statistics on the western side of the District, and all the negative significant t-statistics in the Southeast. In this model, these results mean that in the positive areas, as the percent of non-Hispanic Black population increases, the average distance to green space also increases, and vice versa in the negative areas. Poverty also shows a large significant, positive cluster slightly NW of center, meaning that as change in poverty increases, distance to green space also increases, as we would expect with the patterns of green gentrification.

As expected (from the increased R^2 value), there are more significant patterns in the time period of 2000 to 2010. Again, the coefficient for non-Hispanic Blacks resulted in the most pronounced patterns, with a large cluster of positive coefficients in SE DC and another smaller cluster slightly northwest of center. These clusters indicate tracts with a positive significant coefficient; as the percentage of non-Hispanic Blacks increase, so does average distance to parks, all else equal. This would be an indicator of green gentrification, according to traditional definitions. Interestingly, change in poverty rate and median family income also both displayed a small significant positive cluster just north of center. In this area, which aligns with areas highlighted via other methods, as poverty rates increase, the distance to parks also increases, all else equal. This same area (just north of center) displays positive, significant coefficients for age; as the rate of change for younger populations increases, the distance to parks also increases, which actually runs counter to what we would expect for an area of green gentrification.

There are fewer patterns from the GWR model for 2010-2015, perhaps due to the reduced time period. Again, we see that non-Hispanic Black showed clear patterns. There are three distinct clusters in which as the rate of change of non-Hispanic Black population increased, so did distance to parks. Median house value also distinct patterns. A large swath of the center of the city, running from the northernmost tip south to the center showed significant negative coefficients, meaning that as changes in house values decrease, distance to parks decreased. The area of significant positive coefficients is in the south of the District. This conclusion is contrary to what we would expect for green gentrification for 2010-2015, and it does in fact encompass much of the area that had been identified for green gentrification with other methods.

Chapter 6: Discussion Section

Introduction

This section discusses the results enumerated in the previous section and highlights major trends in green gentrification. I begin by investigating the content-related conclusions of my analysis, primarily the results of the non-Hispanic Black variable as the major predictive factor of green gentrification. Based on the regression results, neighborhoods that are experiencing green gentrification are those immediately northeast, east, and southeast of the Mall; the temporal direction of the process is eastward over time. I then proceed to discuss the various research challenges of conducting this study, including both data and methodology. Primarily, green gentrification is a complex issue to study, and given the data and methods limitations, it is possible that there is not sufficient data at this point in time to adequately study this process in the US or at least in certain cities.

Green Gentrification Discussion

There is considerable evidence that green gentrification is occurring in DC. After examining all the results of the various methodologies, the variable of non-Hispanic Blacks emerges as the most significant predictor of green gentrification. This is partly due to DC's history as a spatially segregated city. Focusing on change in non-Hispanic Black population around parks, I examined the parks that have the largest decreases in non-Hispanic Black population after the year of their creation. Ultimately focusing on twelve of the parks, all except one are located in the ring around the Mall, north, east and slightly south. In line with the GWR results, this area encompasses the neighborhoods of Brightwood, Columbia Heights, LeDroit Park, Brookland, Mt. Vernon Square, Logan Circle/Shaw, Kingman Park, Stanton Park, Union Station, Southwest/Waterfront, Navy Yard, and Near Southeast. All of these neighborhoods are ones encompassed in areas identified as significant green gentrification with the GWR models (with distance as independent variable). The majority of the parks identified as leading to green gentrification were actually community gardens, suggesting that these green spaces, which are often highlighted as a means to locally-led economic development, could actually be contributing to gentrification.

However, using distance to parks as the outcome variables proves to be the most revealing of all the regression analyses. Because this model allows for the controlling of other variables, it is easier to see the direct effect of each variable on distance to green space. Looking specifically at the results from the non-Hispanic Black variable reiterates the same conclusion of the eastward movement of green gentrification across the District. The spaces gentrifying in 2010-2015 fill in the tracts that had yet to be gentrified previously.

This conclusion is supported by the regression results. While admittedly there were few statistically significant coefficients, in the OLS models with non-Hispanic Black as the outcome variable had significant coefficients for both the period of 2000-2010 and the period of 2010-2015. Similarly, the R^2 values for the GWR results were considerably higher than for other variables, signifying that more of the variation is explained by this model.

Another variable that may be predictive of green gentrification is education, specifically the percentage of the population with a Bachelor's degree or higher. The OLS results showed significant coefficients for 2000-2010 and

2010-2015 (with a slightly higher p-value). In other words, distance to parks proved to be a predictive factor for increases in education level as an indicator of gentrification post-2000, a likely result since the economic boom intensified in the early 2000s. The GWR model also exhibited relatively high R^2 values compared to the other variables. These results are reflected visually in the GWR maps (see Figures 6-11). The area in 2000-2010 that shows green gentrification essentially mirrors the significant tracts for non-Hispanic Blacks, as described above. Again, the significant tracts move eastward in the period of 2010-2015. As to be expected, looking at the change around parks and considering the year of each park's creation, almost identical parks were identified as the ones experiencing green gentrification. Finally, changes in poverty rates and median family income in the period 2000-2010 also seem to be important variables for an understanding of green gentrification during this period of time.

Political and Economic Context

There are larger political and economic factors to consider during the study period, which have most likely impacted the results, but may be challenging to quantify. These factors further complicate the results interpretation. Following the nation-wide housing boom, the Great Recession hit and reduced economic prosperity for the majority of the population. Washington, D.C., however, as the nation's capital, may have been slightly insulated from the recession's impacts. Because much of the economic activity in the District is fueled by federal funding and administration rather than private production, stability for employed people was likely greater than in many other places. This economic insulation was most likely not experienced equitably, so the actual impacts on the results of this analysis are ambiguous.

Another large event that impacted DC and may further confound the results was the 2001 attacks. Following these attacks, funding for intelligence and military grew dramatically, leading to a wealth of both direct increases for military and intelligence employees, as well as contractors. While this may have added to the boom DC experienced in the early 2000s, it also may have helped to shelter the city from the Recession (Priest & Arkin, 2010).

Research Challenges

Beyond contextual conclusions about how green gentrification is occurring in the District, there are also extensive conclusions to draw surrounding the efficacy of this model and how it can be applied in other settings. Beyond the challenges of quantitatively measuring and predicting gentrification, there were also challenges in the data availability and quality, and the methods.

Difficulties of Measuring Green Gentrification

As described in the literature review, gentrification is a complex topic. It is not easily measurable or quantifiable, and while there is general consensus around neighborhood changes that are associated with it, there is no determination over the direction of causation. Thus, many of the methods enumerated in this study (and others) are replicable due to the generalizable trends in green gentrification, but others are irrelevant due to context-specific factors. DC, for example, has a relatively high level of green space per population, much of which is part of national parks and green space associated with federal buildings, monuments and the Mall. A possible conclusion here is that there are other factors or confounding variables fueling the gentrification for which this framework does not accommodate. For example, Hamilton Garden was installed in 2015, yet it saw a larger rate of decrease of non-Hispanic Black for every time period, indicating that the gentrification began before the park was installed. On the other hand, there are also parks, such as the 14th and Girard Park that show signs of gentrification until the park is installed (2011), and the rate of loss of non-Hispanic Blacks stabilizes to above the District average.

The regression results support this conclusion as well; based on p-values and R^2 values, the results were largely insignificant. Aside from the variables explanation, it is also possible that there are other contextual factors influencing gentrification, or certain characteristics about the parks that are having a larger effect, such as the amount of green space investment.

As described above, the variable for non-Hispanic Black did show mostly significant results, suggesting that this could be a factor for predicting green gentrification. This is an especially important conclusion given how coarse the level of analysis was. With an even finer unit of analysis, the processes of gentrification would likely be even more pronounced. However, even with significant results, the direction of causation is still not clear. It is possible that a gentrifying area spurred increased investment in green space, or that investment in a green space encouraged other forms of investment in the surrounding area, resulting in gentrification, or a hybrid of the two. As further evidence, reversing the direction of causation and using distance to parks as the outcome variable in a multivariate model produces slightly different results than the other way around, indicating that green gentrification can be understood and measured with different frameworks.

Data Discussion

This study has a number of limitations, particularly around data reliability and completeness. The US census is the most widespread source of national demographic data, but it is intrinsically problematic. Some of the variables from 2010 and all of the data from 2015 come from the ACS survey. Because this survey is based on samples, the sampling error is larger, which results in poorer precision, especially for smaller areas like tracts. To attempt to compensate for the smaller sample at the tract level, ACS data is released only as 5-year averages. Beyond just the sampling error, the ACS data is a five year average rather than a specific point in time, which makes it more difficult for comparison purposes. Furthermore, it means that the 2010 data actually covers 2006-2010, a time period that covers both the final stages of a national boom in housing prices as well as the recession. Then 2011-2015 includes the recovery period. Consequently, there are multiple political and economic factors occurring within one time period (as detailed above), and the nature of the census data makes it hard to distinguish among their effects.

Furthermore, gentrification is a process that can occur on a small a level as a block-by-block case. Using census tracts conceals much of the fine details. Census tracts are large enough to encompass a high level of heterogeneity within them. However, going down to the block group level would introduce a higher level of sampling error and key variables are not available at the block level.

The green space data also was challenging to acquire and consequently presented other limitations to the study. As described in Chapter 4, many of the parks were missing a year of acquisition, meaning that if they had been built post-1990 but did not have a year, they were excluded from the study. Pocket parks are also particularly prominent in DC, yet I was unable to find a spatial dataset that incorporated them. The community gardens data were compiled from multiple sources and presented problems of inconsistency. First of all, land ownership and acreage are varying, which present challenges in determining if the community gardens should be counted as part of an adjacent park or as its own entity. Secondly, gardens tend to operate on a boom and bust cycle, so it was often unclear if the year provided was of the year the garden was originally introduced or was the year it was revamped. In the same vein, some gardens no longer exist, so they were excluded from the analysis even if their year of acquisition was post-1990. Ultimately, the variation in community gardens and other green spaces introduced variability and inconsistency to the analysis.

Methods Discussion

In addition to data limitations in the nature and availability of data, there were also limitations in the methodology, most of which could ideally be improved upon in future research. In an effort to replicate Anguelovski et al (2017)'s methods, I used census tracts as my spatial unit. However, this methodological decision limited what analyses I was able to conduct. Additionally, there is Inconsistency in studies about DC as to which areal unit to use for neighborhood analysis. Possibilities include zip codes, census tracts, block groups, neighborhoods, wards, and DC Planning Areas. In line with the Modifiable Areal

Unit Problem (MAUP), using census tracts likely produced certain results that would have been different had I used different scales or zones. Furthermore, due to the structure of the decennial census (conducted every 10 years) and the American Community Survey (continuous monthly sampling released every year for five year periods), I was only able to conduct the analysis up until 2015. While being more current is advantageous, having a time period of only five years (2010-2015) is inconsistent with the other time periods used and adds volatility to the results.

Also the time period considered (1990-2015) has a unique data issue: the US Census Bureau changed the way it collects certain data, including income, poverty, house value and educational attainment. From 1940 to 2000, the Bureau collected this data once every 10 years via a sample survey of households that went out at the same time as the decennial census. The sample survey is generally referred to as the "long form" or SF3 data, while the 100% census was called the "short form" or SF1 data. Starting in 2004, the American Community Survey replaced the once every 10 years "long form." Thus the present study straddles the period in which this change took place, making comparisons between the 1990 to 2000 period and the later 2010 to 2015 period very difficult.

Finally, there are contextual limitations. Washington, D.C. is the nation's capital so large swaths of land are occupied by federal buildings. As a result, many census tracts have a low population and skew the results. Furthermore, because the data is spatially dependent and the study focuses specifically on DC, the analysis fails to account for edge effects of bordering states.

This study was also done in a short period of time, which limited the extent of data collection, methodology and analysis. With additional time and funding, the study could be improved in ways described in the concluding chapter.

Chapter 7: Conclusion

Ultimately, this model offers considerable potential in terms of its ability to quantitatively evaluate and compare the predictors of green gentrification in varying cities. Nonetheless, there are many limitations in applying this same model to different contexts, and it is possible that at this time, there is not sufficient data to be able to draw reliable conclusions. The results clearly indicate some level of green gentrification in DC; the change non-Hispanic Black population was a significant predictor for distance to green space, controlling for other variables. The analysis, however, also raises important data and methods issues. Due to the lack of comprehensive green space data and sociodemographic data as gentrification indicators, as well as a lack of alternatives for measuring gentrification, the applications of these conclusions are narrow.

Policy Implications of the DC Study

The study has confirmed to an extent that green gentrification is real at least in the DC context. In Washington, D.C., we can see that non-Hispanic Black is by far the most significant predictor of green gentrification. The results also reveal that certain neighborhoods just northeast, east, and southeast of the Mall have consistently experienced the most intense green gentrification, a conclusion that aligns with the anecdotal evidence reviewed in the Background chapter. These neighborhoods include Union Station, Navy Yard, Shaw, Howard University, near Southeast and Capitol Hill, among others.

Within this framework then, it does appear that distance to green space is a predictor of some indicators of green gentrification. Given this conclusion and the recent trends of growth in the District, it is critical that planners take extra precaution in planning green spaces that provide equitable development. Acknowledging that green space can be leveraged as a tool for economic growth, a city hoping to harness this potential should be careful to ensure that initiatives are locally led and carefully structured so as to not disempower local stakeholders or further depress surrounding areas. Rather, green spaces in low income neighborhoods should be planned and driven by community groups in a way that simultaneously enhances local neighborhood character and uplifts communities without displacement.

Data Recommendations

Due to the limitations discussed in the previous chapter, there are important ways in which the spatial analysis of green gentrification could be improved, and implications as to the extent we can rely on spatial quantitative methods.

There are very important limitations for analysis due to the nature of the American Community Survey: geographic unit of analysis (Tract), sampling error, and multi-year aggregation of data. This was especially problematic in this study because it is examining a time period where the survey methods changed dramatically, and made comparisons tenuous. In the future, a study using ACS data could be more effective if looking at several non-overlapping time periods (e.g., 2006-2010, 2011-2015, 2016-2020). The politics of US Federal budgets is such that we cannot expect major changes in a positive direction for ACS data collection.

Secondly, there are important improvements that could be made to developing and documenting greenspace data, including documenting year of creation and recent investments in terms of dollar value. To facilitate more comprehensive studies in the future, it is advisable that cities invest further efforts into data collection processes. This data would help to parse out exactly which factors are contributing to its impacts on gentrification.

Third, there is considerable scope for including other types of data to estimate changes in and around parks. Parcel assessor data with assessor and sale prices data would be invaluable. If sales data is not available from the assessor, then including a budget for the purchase of privately-developed real estate data would be important. Building permits are another data source that could be analyzed to understand private investments at the parcel, block and neighborhood level. Building permits could serve as a more accurate and granular proxy for gentrification, especially condos, which have been particularly emphasized in the context as DC of a product of the rapid pace of gentrification. Examining the density of the proliferation of condos would highlight areas of rapid growth and bypass having to use census tracts. Similarly, other factors to explore could be distance to highways or a density of map of the EPA brownfields and perhaps other LULUs (locally unwanted land uses), as well as state-identified environmental justice areas. These results would be representative of areas that are particularly at risk of gentrification, according to the green paradox framework. These areas could then be related back to high areas of growth to look for correlations.

Methods Recommendations

Beyond additional data, there are also modifications to this study's methods that have implications for future research. As Anguelovski and her team did, creating a composite score could help to more clearly illuminate which parks particularly contributed to green gentrification and facilitate the prioritization of certain areas for planning and policy interventions. It would be a method of summarizing all relevant factors. As long as they are well-described individually, this method would not necessarily occult nuances occurring around each individual park.

Furthermore, because so much of the literature cited park usage and acreage as major factors that impact the kind of impact it has on the surrounding area, park classification could be an important next step. Via ground-truthing or in-depth exploration on Google maps, it would be useful to classify each park by characteristics such as access, type of facilities, usage, pocket parks, etc. Then a regression could be run to determine if park usage affects the magnitude of gentrification effects.

To further refine green space research, it would be useful to map each park and its associated variable average (results from Tables 13-18). Exploring these results visually would be conducive to pinning down which parks are potentially contributing most to green gentrification (although when it was done for non-Hispanic Blacks, the parks lined up with gentrifying tracts). Another helpful step to enhance level of detail would be to also map the parks by year of creation. In my research, I used the year of acquisition in order to narrow down which parks would be the focus of my analysis. However, this data could also be used to cluster parks by year of insertion in order to achieve a higher level of granularity in the analysis of change over time. In this way, each park would be associated with a “before” and “after” value.

Finally, qualitative analysis is indispensable and should always accompany quantitative analysis. One of the purposes of this study was to study the possibilities and methods for studying green gentrification quantitatively, specifically via spatial analysis in GIS. As a result, there are clear benefits as well as limitations to studying gentrification in this way. Qualitative research, on the other hand, can also be especially fruitful in understanding this process of green gentrification. While I did not have sufficient time to perform this kind of investigation, qualitative research would help to answer my other research question of how the introduction of green space predicts gentrification and would help to illuminate some of the nuances of such a complex process.

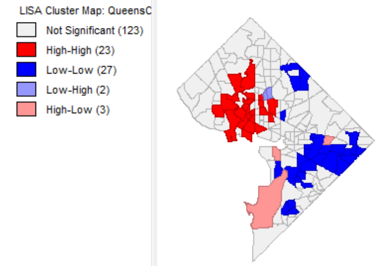
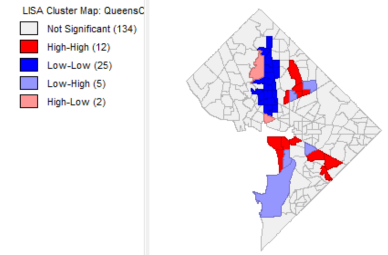
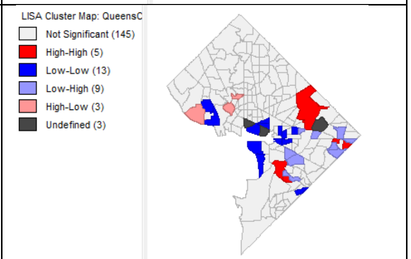
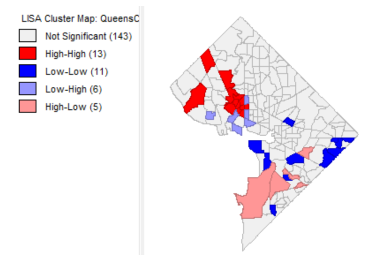
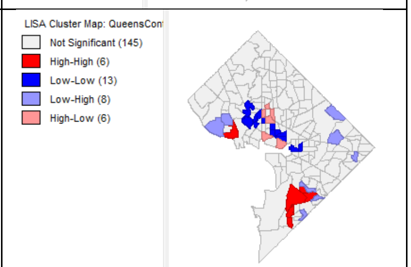
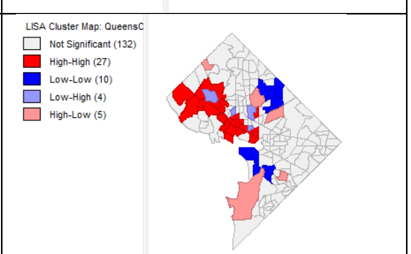
Appendices

Table 3: Average change around parks by distance (Bold denotes a change higher than the District average, indicating green gentrification)
*percentage point change

	1990-2000			2000-2010			2010-2015		
	Avg Change Within 400 m	Avg Change 400-800m	Full District	Avg Change Within 400 m	Avg Change 400-800m	Full District	Avg Change Within 400 m	Avg Change 400-800m	Full District
Ages 18-34	-5.11%	-3.20%	-3.69%	**6.58%**	5.41%	4.42%	0.22%	-0.19%	0.22%
Percent Non-Hispanic Black*	-2.53%	-4.10%	-2.32%	**-15.27%**	-12.43	-9.56%	**-7.73%**	-4.86%	-5.02%
Median House Value**	26.95%	28.69%	26.97%	180.84%	188.40%	359.29%	**9.54%**	1.87%	2.12%
Median Family Income**	25.42%	33.62%	29.80%	60.78%	29.18%	60.20%	**38.22%**	21.53%	24.84%
Poverty Rate*	3.19%	3.87%	4.02%	**-3.56%**	-3.43%	-1.55%	**-2.57%**	-1.02%	-0.58%
Bachelor’s Degree or Higher*	1.83%	2.59%	3.25%	**15.39%**	12.71%	10.41%	**7.99%**	6.53%	5.89%

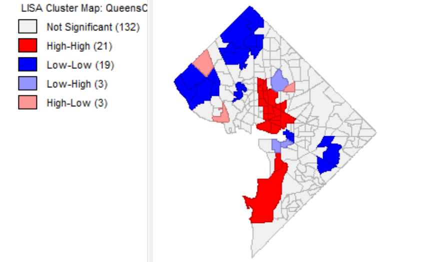
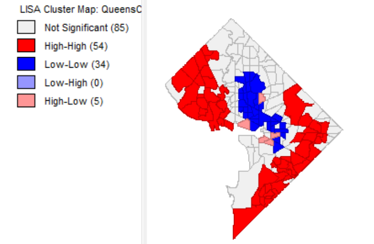
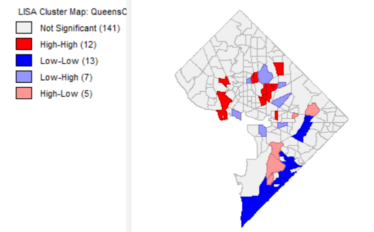
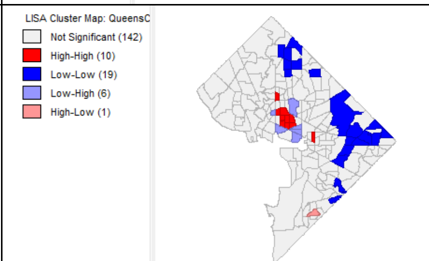
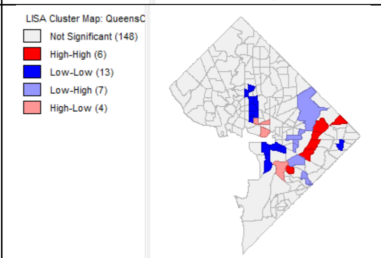
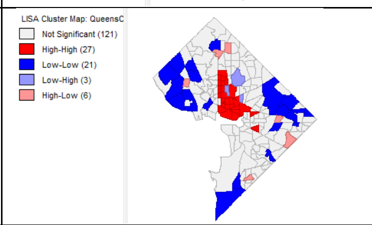
**percent change

Table 4: Local Univariate Moran's I: 1990-2000

	Moran's I	P-Value with 999 Permutations	Cluster Map
Young Urban Population	.2618*	.001	
Percent Non-Hispanic Black	.4478*	.001	
Median House Value	.0306	.185	
Median Family Income	.1823*	.001	
Poverty Rate	.1038*	.004	
Bachelor's Degree or Higher	.2470*	.001	

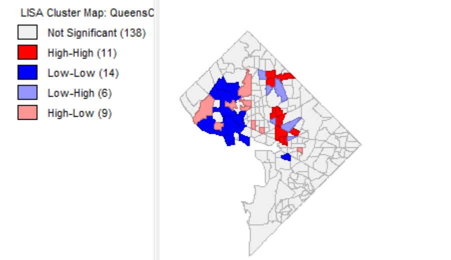
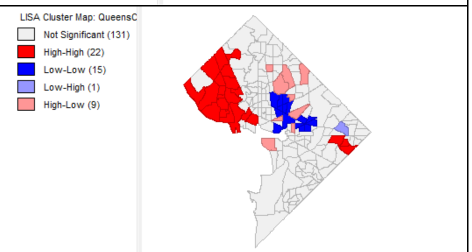
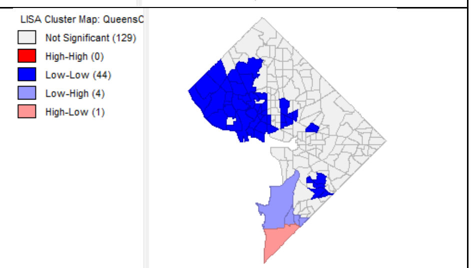
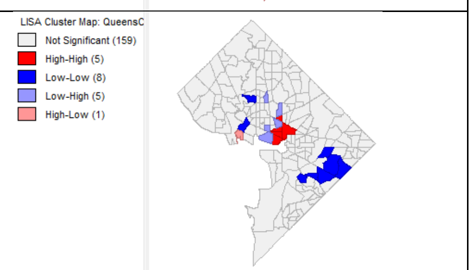
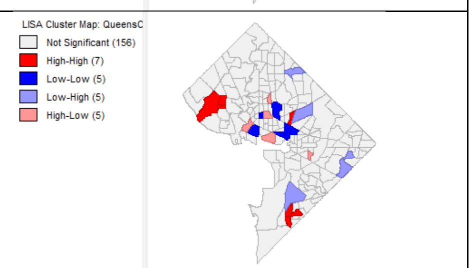
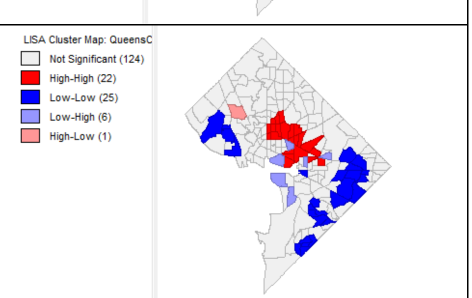
*significant at the .05 level

Table 5: Local Univariate Moran’s I: 2000-2010

	Moran’s I	P-Value with 999 Permutations	Cluster Map
Young Urban Population	.3312*	.001	
Percent Non-Hispanic Black	.5247*	.001	
Median House Value	.1751*	.002	
Median Family Income	.1329*	.007	
Poverty Rate	.0829*	.020	
Bachelor’s Degree or Higher	.3881*	.001	

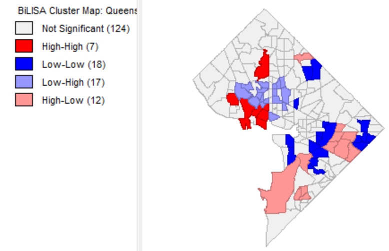
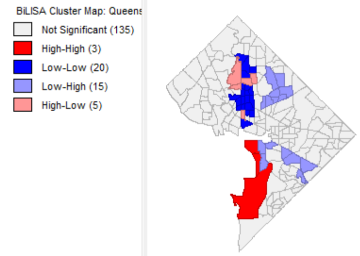
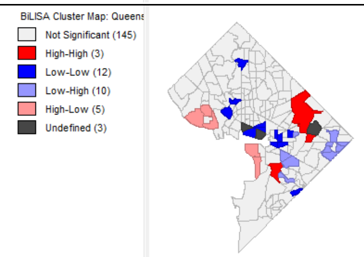
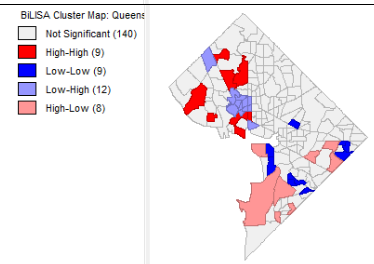
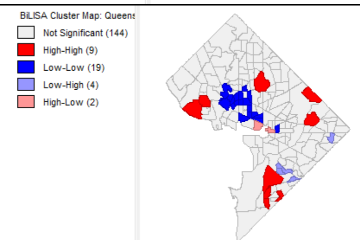
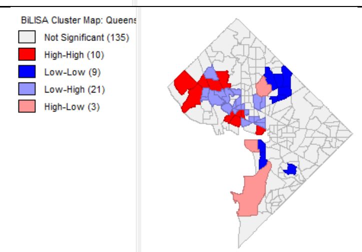
*significant at the .05 level

Table 6: Local Univariate Moran's I: 2010-2015

	Moran's I	P-Value with 999 Permutations	Cluster Map
Young Urban Population	.1025*	.009	
Percent Non-Hispanic Black	.3810*	.001	
Median House Value	-.0073	.249	
Median Family Income	.1866*	.001	
Poverty Rate	.0919*	.021	
Bachelor's Degree or Higher	.2903*	.001	

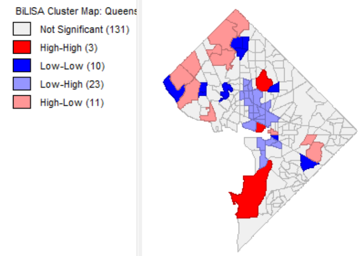
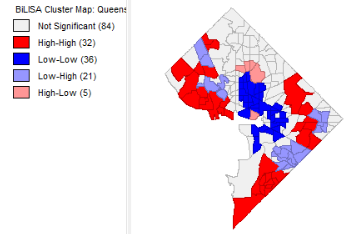
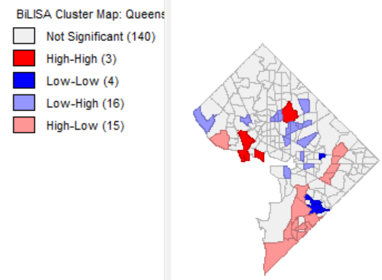
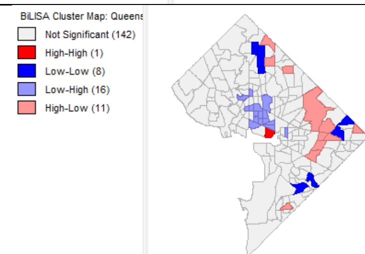
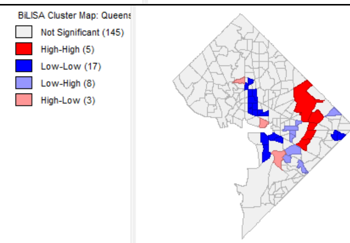
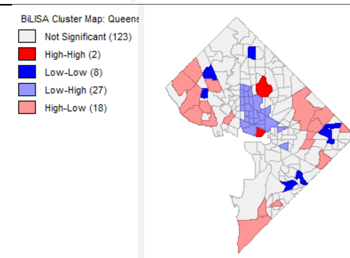
*Significant at the .05 level

Table 7: Local Bivariate Moran's I: 1990-2000 (with distance to parks as independent variable and Queen's Contiguity)

<table>
<tr><th></th><th>Moran's I</th><th>P-Value with 999 Permutations</th><th>Cluster Map</th></tr>
<tr><td>Young Urban Population</td><td>-.0606*</td><td>.041</td><td>
</td></tr>
<tr><td>Percent Non-Hispanic Black</td><td>.1152*</td><td>.001</td><td>
</td></tr>
<tr><td>Median House Value</td><td>-.0307</td><td>.169</td><td>
</td></tr>
<tr><td>Median Family Income</td><td>-.0541*</td><td>.048</td><td>
</td></tr>
<tr><td>Poverty Rate</td><td>.1132*</td><td>.001</td><td>
</td></tr>
<tr><td>Bachelor's Degree or Higher</td><td>-.0576*</td><td>.041</td><td>
</td></tr>
</table>

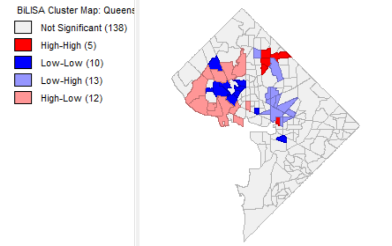
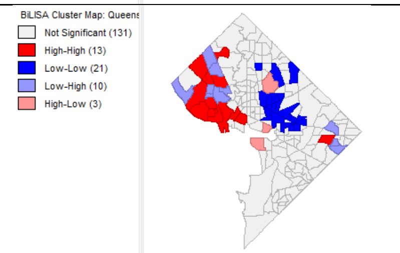
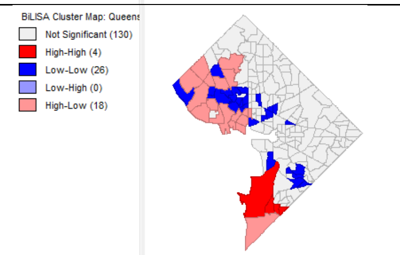
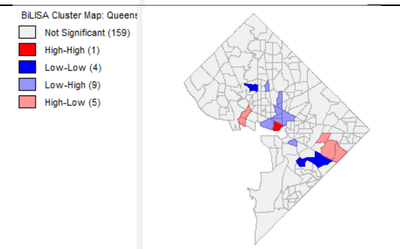
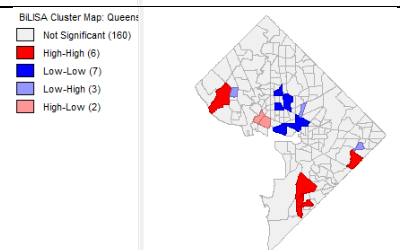
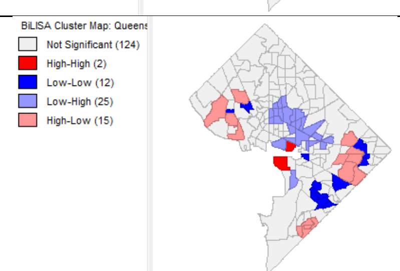
*Significant at the .05 level

Table 8: Local Bivariate Moran's I: 2000-2010 (with distance to parks as independent variable and Queen's Contiguity)

	Moran's I	P-Value with 999 Permutations	Cluster Map
Young Urban Population	-.1582*	.001	
Percent Non-Hispanic Black	.2902*	.001	
Median House Value	-.2402*	.001	
Median Family Income	-.1346*	.001	
Poverty Rate	.0783*	.016	
Bachelor's Degree or Higher	-.2519*	.001	

*Significant at the .05 level

Table 9: Local Bivariate Moran's I: 2010-2015 (with distance to parks as independent variable and Queen's Contiguity)

	Moran's I	P-Value with 999 Permutations	Cluster Map
Young Urban Population	-.0336	.140	
Percent Non-Hispanic Black	.1954*	.001	
Median House Value	.1751*	.001	
Median Family Income	-.0893*	.001	
Poverty Rate	.1331*	.001	
Bachelor's Degree or Higher	-.1701*	.001	

*Significant at the .05 level

Table 10: Results of OLS and GWR Models for core gentrification indicators (with Distance to Parks as independent variable)

		OLS Results*			GWR Results		
		1990-2000	2000-2010	2010-2015	1990-2000	2000-2010	2010-2015
Ages 18-34	R^2	0.166899	0.255278	0.03455	0.319165	0.344632	0.11196
	Adj R^2				0.249073	0.217652	0.052971
	Coefficient	0.00000387	-0.000008208	-0.000004447			
	P-Value of Coefficient	0.47029	0.14315	0.33354			
Percent Non-Hispanic Black	R^2	0.395448	0.492725	0.287926	0.363939	0.501381	0.385772
	Adj R^2				0.240699	0.404772	0.300415
	Coefficient	0.00000479	0.00002197**	0.00001327**			
	P-Value of Coefficient	0.39043	0.00981	0.01389			
Median House Value	R^2	0.003641	0.141261	0.272428	0.000481	0.267618	0.949424
	Adj R^2				-0.005335	0.20709	0.939625
	Coefficient	-0.00000651	-0.000875**	0.0192611**			
	P-Value of Coefficient	0.80194	0.00012	0			
Median Family Income	R^2	0.086754	0.053231	0.115544	0.138862	0.177003	0.014864
	Adj R^2				0.092578	0.09919	0.00923
	Coefficient	-0.0000176	-0.0000937	-0.0000656			
	P-Value of Coefficient	0.59729	0.15848	0.22495			
Poverty Rate	R^2	0.048104	0.034101	0.045433	0.158509	0.016032	0.024463
	Adj R^2				0.101198	0.010404	0.018884
	Coefficient	0.0000117**	0.0000152	0.000014169**			
	P-Value of Coefficient	0.07738	0.12835	0.07899			
Bachelor's Degree or Higher	R^2	0.149845	0.321185	0.189994	0.323888	0.374693	0.253355
	Adj R^2				0.206773	0.278835	0.167416
	Coefficient	0.00000221	-0.0000231**	-0.0000108			
	P-Value of Coefficient	0.728	0.0107	0.1369			

*with spatial lag using Queen's contiguity

**Significant at the .10 level

Table 11: Results of OLS and GWR Models for core gentrification indicators (with Distance to Parks as dependent variable)

		OLS Results*			GWR Results		
		1990-2000	2000-2010	2010-2015	1990-2000	2000-2010	2010-2015
Overall Model Goodness of Fit	R^2	0.7463	0.75511	0.7985	0.78249	0.829499	0.793767
	Adj R^2				0.6685	0.715011	0.673696
Ages 18-34	Coefficient	497.51	700.729	58.45			
	P-Value of Coefficient	0.38025	0.30473	0.92216			
Percent Non-Hispanic Black	Coefficient	252.851	676.52**	1086.82**			
	P-Value of Coefficient	0.54111	0.08935	0.02774			
Median House Value	Coefficient	-19.92	-361.82**	7.01**			
	P-Value of Coefficient	0.86061	0.00566	0			
Median Family Income	Coefficient	-49.57	61.37	-37.48			
	P-Value of Coefficient	0.65697	0.22749	0.47121			
Poverty Rate	Coefficient	401.82	90.35	315.07			
	P-Value of Coefficient	0.48181	0.79633	0.3795			
Bachelor's Degree or Higher	Coefficient	900.77	-319.95	291.979			
	P-Value of Coefficient	0.08852	0.47376	0.46033			

*with spatial lag using Queen's contiguity

**Significant at the .10 level

Table 13: Changes for ages 18-34 around individual parks (bold denotes changes towards green gentrification)

			1990-2000		2000-2010		2010-2015	
Park ID	Park Name	Year	Average with Near Function	Average District Change	Average with Near Function	Average District Change	Average with Near Function	Average District Change
1	Ft. Stevens Garden	2014	-4.48%	-3.69%	-0.23%	4.42%	**0.45%**	0.22%
2	Virginia Ave Community Garden	2004	-14.03%	-3.69%	**43.02%**	4.42%	-3.34%	0.22%
3	Hill East Community Garden	2004	-5.10%	-3.69%	3.55%	4.42%	0.11%	0.22%
4	Kingman Park-Rosdale Community Garden	2007	-6.34%	-3.69%	1.11%	4.42%	**1.27%**	0.22%
5	Pomegranate Alley Community Garden	2002	-4.97%	-3.69%	**4.71%**	4.42%	-5.00%	0.22%
6	Deanwood Learning Garden	2011	-5.56%	-3.69%	2.89%	4.42%	0.11%	0.22%
7	Common Good City Farm	2007	**-0.37%**	-3.69%	**9.90%**	4.42%	-3.32%	0.22%
8	Green East Community Garden	2008	-6.49%	-3.69%	**6.13%**	4.42%	**1.97%**	0.22%
9	Wylie Street Community Garden	2005	-3.63%	-3.69%	**4.76%**	4.42%	**2.41%**	0.22%
10	Bruce Monroe Garden	2007	**5.75%**	-3.69%	**6.56%**	4.42%	**1.35%**	0.22%
11	Douglass Garden	2014	-7.24%	-3.69%	2.99%	4.42%	-2.62%	0.22%
12	Euclid St. Garden/Justice Park	2012	**0.65%**	-3.69%	**6.82%**	4.42%	-2.15%	0.22%
13	Hamilton Garden┬á	2015	-5.71%	-3.69%	3.37%	4.42%	**2.97%**	0.22%
14	Harry Thomas Gardens	2015	-7.04%	-3.69%	**11.28%**	4.42%	**8.80%**	0.22%
15	Hillcrest Garden	2015	-3.81%	-3.69%	0.79%	4.42%	-2.65%	0.22%
16	Ledroit Gardens	2011		-3.69%		4.42%		0.22%
17	Noyes Gardens	2013	-5.40%	-3.69%	**6.51%**	4.42%	**5.25%**	0.22%
18	Palisades Garden	1995	**-2.28%**	-3.69%	-5.18%	4.42%	-1.14%	0.22%
19	Southwest Garden	2013	-7.18%	-3.69%	**6.34%**	4.42%	**5.07%**	0.22%
20	Turkey Thicket Gardens	2014	-7.88%	-3.69%	4.00%	4.42%	**3.01%**	0.22%
21	Canal Park	2012	**-2.45%**	-3.69%	2.44%	4.42%	**1.77%**	0.22%
22	Justice Park	2008	**-1.51%**	-3.69%	**4.83%**	4.42%	**2.97%**	0.22%

23	Murch Field	2007	**-2.94%**	-3.69%	2.56%	4.42%	-2.38%	0.22%
24	Douglass Recreation Center	2012	-6.12%	-3.69%	1.31%	4.42%	**0.87%**	0.22%
25	Benning Park Community Center	1992	-7.38%	-3.69%	2.97%	4.42%	0.24%	0.22%
26	Anna J. Cooper Circle	2004	-7.81%	-3.69%	**17.39%**	4.42%	**1.41%**	0.22%
27	Belmont Park	2014	**5.71%**	-3.69%	3.21%	4.42%	-3.95%	0.22%
28	Anacostia Recreation Center	2001	-7.84%	-3.69%	2.59%	4.42%	**0.65%**	0.22%
29	Noyes Park	2013	-5.44%	-3.69%	**5.75%**	4.42%	-0.79%	0.22%
30	14th and Girard Park	2011	**-1.64%**	-3.69%	**7.96%**	4.42%	-0.11%	0.22%
31	7th & N Street Playground	2003	**-1.97%**	-3.69%	**11.92%**	4.42%	-0.46%	0.22%
32	Bishop Lalossu Memorial Park	2010	**-0.26%**	-3.69%	2.10%	4.42%	-3.29%	0.22%
33	Alger Park	1999	-7.12%	-3.69%	-0.54%	4.42%	**3.16%**	0.22%
34	Emery	2003	-5.36%	-3.69%	2.21%	4.42%	**1.74%**	0.22%

Table 14: Changes for Bachelor's degree or higher around individual parks (bold denotes changes towards green gentrification)

			1990-2000		2000-2010		2010-2015	
Park ID	Park Name	Year	Average with Near Function	Average District Change	Average with Near Function	Average District Change	Average with Near Function	Average District Change
1	Ft. Stevens Garden	2014	2.13%	3.25%	3.24%	10.41%	5.17%	5.89%
2	Virginia Ave Community Garden*	2004	-9.83%	3.25%	**49.46%**	10.41%	**23.34%**	5.89%
3	Hill East Community Garden*	2004	**5.49%**	3.25%	**16.31%**	10.41%	**7.53%**	5.89%
4	Kingman Park-Rosdale Community Garden	2007	1.76%	3.25%	3.36%	10.41%	**6.44%**	5.89%
5	Pomegranate Alley Community Garden*	2002	**5.13%**	3.25%	**12.42%**	10.41%	3.67%	5.89%
6	Deanwood Learning Garden	2011	0.61%	3.25%	2.71%	10.41%	2.03%	5.89%
7	Common Good City Farm*	2007	2.52%	3.25%	**30.04%**	10.41%	**9.36%**	5.89%
8	Green East Community Garden*	2008	-2.30%	3.25%	**17.08%**	10.41%	**7.04%**	5.89%
9	Wylie Street Community Garden*	2005	**4.84%**	3.25%	**12.95%**	10.41%	**11.13%**	5.89%
10	Bruce Monroe Garden*	2007	**5.89%**	3.25%	**11.75%**	10.41%	**16.28%**	5.89%
11	Douglass Garden	2014	0.00%	3.25%	**17.81%**	10.41%	-2.26%	5.89%
12	Euclid St. Garden/Justice Park	2012	**11.88%**	3.25%	**20.45%**	10.41%	**11.23%**	5.89%
13	Hamilton Garden	2015	3.14%	3.25%	**11.25%**	10.41%	**7.33%**	5.89%
14	Harry Thomas Gardens	2015	2.69%	3.25%	**16.26%**	10.41%	**23.37%**	5.89%
15	Hillcrest Garden	2015	0.51%	3.25%	2.76%	10.41%	1.68%	5.89%
16	Ledroit Gardens	2011		3.25%		10.41%		5.89%
17	Noyes Gardens*	2013	-5.97%	3.25%	**22.90%**	10.41%	-2.74%	5.89%
18	Palisades Garden	1995	**8.56%**	3.25%	2.19%	10.41%	-0.12%	5.89%
19	Southwest Garden	2013	-4.26%	3.25%	8.70%	10.41%	**8.53%**	5.89%
20	Turkey Thicket Gardens	2014	-0.61%	3.25%	5.05%	10.41%	**6.22%**	5.89%
21	Canal Park	2012	**7.38%**	3.25%	6.12%	10.41%	4.02%	5.89%
22	Justice Park*	2008	-3.89%	3.25%	**29.71%**	10.41%	-2.38%	5.89%

23	Murch Field	2007	**6.98%**	3.25%	8.34%	10.41%	2.17%	5.89%
24	Douglass Recreation Center	2012	-0.32%	3.25%	4.08%	10.41%	0.72%	5.89%
25	Benning Park Commuity Center	1992	0.45%	3.25%	6.24%	10.41%	0.63%	5.89%
26	Anna J. Cooper Circle*	2004	**7.01%**	3.25%	**28.41%**	10.41%	**12.23%**	5.89%
27	Belmont Park	2014	**10.24%**	3.25%	5.76%	10.41%	4.22%	5.89%
28	Anacostia Recreation Center	2001	-1.60%	3.25%	10.40%	10.41%	2.11%	5.89%
29	Noyes Park	2013	-5.16%	3.25%	9.87%	10.41%	**7.35%**	5.89%
30	14th and Girard Park	2011	3.03%	3.25%	**22.59%**	10.41%	**9.26%**	5.89%
31	7th & N Street Playground*	2003	**8.40%**	3.25%	**24.60%**	10.41%	**10.45%**	5.89%
32	Bishop Lalossu Memorial Park	2010	**4.51%**	3.25%	2.23%	10.41%	1.76%	5.89%
33	Alger Park	1999	0.20%	3.25%	5.74%	10.41%	0.16%	5.89%
34	Emery	2003	2.83%	3.25%	8.69%	10.41%	5.77%	5.89%

*Parks that exhibit characteristics of green gentrification based on year of acquisition

Table 15: Changes in median house value around individual parks (bold denotes changes towards green gentrification)

			1990-2000		2000-2010		2010-2015	
Park ID	Park Name	Year	Average with Near Function	Average District Change	Average with Near Function	Average District Change	Average with Near Function	Average District Change
1	Ft. Stevens Garden	2014	17.07%	26.97%	126.06%	361.28%	6.02%	8.52%
2	Virginia Ave Community Garden	2004	**115.65%**	26.97%	184.54%	361.28%	**28.63%**	8.52%
3	Hill East Community Garden	2004	11.48%	26.97%	210.47%	361.28%	**11.68%**	8.52%
4	Kingman Park-Rosdale Community Garden	2007	**57.71%**	26.97%	115.80%	361.28%	-28.73%	8.52%
5	Pomegranate Alley Community Garden	2002	11.49%	26.97%	196.26%	361.28%	**16.71%**	8.52%
6	Deanwood Learning Garden	2011	25.82%	26.97%	144.78%	361.28%	-3.13%	8.52%
7	Common Good City Farm	2007	19.40%	26.97%	233.39%	361.28%	**42.83%**	8.52%
8	Green East Community Garden	2008	21.42%	26.97%	261.28%	361.28%	**18.43%**	8.52%
9	Wylie Street Community Garden	2005	25.47%	26.97%	221.78%	361.28%	**10.53%**	8.52%
10	Bruce Monroe Garden	2007	**36.17%**	26.97%	226.60%	361.28%	**9.63%**	8.52%
11	Douglass Garden	2014	**55.78%**	26.97%	249.70%	361.28%	-20.68%	8.52%
12	Euclid St. Garden/Justice Park	2012	**50.49%**	26.97%	130.09%	361.28%	7.81%	8.52%
13	Hamilton Garden	2015	20.78%	26.97%	216.24%	361.28%	2.16%	8.52%
14	Harry Thomas Gardens	2015	24.13%	26.97%	235.95%	361.28%	**20.93%**	8.52%
15	Hillcrest Garden	2015	**32.04%**	26.97%	92.97%	361.28%	-11.39%	8.52%
16	Ledroit Gardens	2011		26.97%		361.28%		8.52%
17	Noyes Gardens	2013	19.09%	26.97%	205.98%	361.28%	-0.05%	8.52%
18	Palisades Garden	1995	26.92%	26.97%	65.58%	361.28%	**22.19%**	8.52%
19	Southwest Garden	2013	-1.03%	26.97%	131.89%	361.28%	**14.05%**	8.52%
20	Turkey Thicket Gardens	2014	25.73%	26.97%	149.56%	361.28%	5.41%	8.52%

21	Canal Park	2012	19.90%	26.97%	26.46%	361.28%	-39.40%	8.52%
22	Justice Park	2008	18.23%	26.97%	169.20%	361.28%	-4.77%	8.52%
23	Murch Field	2007	23.54%	26.97%	76.59%	361.28%	**10.67%**	8.52%
24	Douglass Recreation Center	2012	**27.37%**	26.97%	**2390.16%**	361.28%	-24.56%	8.52%
25	Benning Park Commuity Center	1992	**42.29%**	26.97%	139.21%	361.28%	-2.90%	8.52%
26	Anna J. Cooper Circle	2004	**39.28%**	26.97%	259.34%	361.28%	**11.41%**	8.52%
27	Belmont Park	2014	24.43%	26.97%	21.20%	361.28%	**12.43%**	8.52%
28	Anacostia Recreation Center	2001	**39.20%**	26.97%	150.25%	361.28%	-0.23%	8.52%
29	Noyes Park	2013	23.88%	26.97%	163.71%	361.28%	**20.81%**	8.52%
30	14th and Girard Park	2011	21.73%	26.97%	186.89%	361.28%	**8.55%**	8.52%
31	7th & N Street Playground	2003	26.46%	26.97%	149.36%	361.28%	3.44%	8.52%
32	Bishop Lalossu Memorial Park	2010	14.02%	26.97%	29.71%	361.28%	-4.18%	8.52%
33	Alger Park	1999	16.50%	26.97%	148.46%	361.28%	-10.51%	8.52%
34	Emery	2003	26.76%	26.97%	171.86%	361.28%	3.93%	8.52%

Table 16: Changes in median family income around individual parks (bold denotes changes towards green gentrification)

			1990-2000		2000-2010		2010-2015	
Park ID	Park Name	Year	Average with Near Function	Average District Change	Average with Near Function	Average District Change	Average with Near Function	Average District Change
1	Ft. Stevens Garden	2014	**30.84%**	29.80%	32.48%	60.20%	5.88%	24.84%
2	Virginia Ave Community Garden	2004	6.70%	29.80%	**196.43%**	60.20%	**189.51%**	24.84%
3	Hill East Community Garden	2004	**39.48%**	29.80%	**105.07%**	60.20%	9.62%	24.84%
4	Kingman Park-Rosdale Community Garden	2007	22.61%	29.80%	7.35%	60.20%	14.95%	24.84%
5	Pomegranate Alley Community Garden	2002	**41.56%**	29.80%	**67.17%**	60.20%	**51.94%**	24.84%
6	Deanwood Learning Garden	2011	25.17%	29.80%	9.73%	60.20%	**30.15%**	24.84%
7	Common Good City Farm	2007	-4.96%	29.80%	10.25%	60.20%	**250.63%**	24.84%
8	Green East Community Garden	2008	12.05%	29.80%	**79.42%**	60.20%	4.81%	24.84%
9	Wylie Street Community Garden	2005	15.04%	29.80%	**77.14%**	60.20%	**28.51%**	24.84%
10	Bruce Monroe Garden	2007	25.51%	29.80%	**66.73%**	60.20%	**39.61%**	24.84%
11	Douglass Garden	2014	-48.83%	29.80%	**191.29%**	60.20%	18.60%	24.84%
12	Euclid St. Garden/Justice Park	2012	**63.15%**	29.80%	**80.75%**	60.20%	**49.26%**	24.84%
13	Hamilton Garden	2015	**36.86%**	29.80%	42.08%	60.20%	17.05%	24.84%
14	Harry Thomas Gardens	2015	25.17%	29.80%	54.19%	60.20%	**72.12%**	24.84%
15	Hillcrest Garden	2015	0.12%	29.80%	40.56%	60.20%	-6.82%	24.84%
16	Ledroit Gardens	2011		29.80%		60.20%		24.84%
17	Noyes Gardens	2013	**47.25%**	29.80%	**109.17%**	60.20%	-33.16%	24.84%
18	Palisades Garden	1995	**67.81%**	29.80%	22.08%	60.20%	14.66%	24.84%
19	Southwest Garden	2013	-2.61%	29.80%	**87.47%**	60.20%	**26.87%**	24.84%
20	Turkey Thicket Gardens	2014	11.40%	29.80%	27.51%	60.20%	11.71%	24.84%
21	Canal Park	2012	**34.18%**	29.80%	40.40%	60.20%	**33.11%**	24.84%
22	Justice Park	2008	**68.20%**	29.80%	**186.33%**	60.20%	**36.38%**	24.84%

23	Murch Field	2007	**61.70%**	29.80%	38.71%	60.20%	11.11%	24.84%
24	Douglass Recreation Center	2012	15.64%	29.80%	27.80%	60.20%	11.98%	24.84%
25	Benning Park Commuity Center	1992	5.53%	29.80%	47.55%	60.20%	2.03%	24.84%
26	Anna J. Cooper Circle	2004	18.73%	29.80%	**143.97%**	60.20%	23.33%	24.84%
27	Belmont Park	2014	**87.17%**	29.80%	58.80%	60.20%	8.76%	24.84%
28	Anacostia Recreation Center	2001	10.88%	29.80%	53.35%	60.20%	1.60%	24.84%
29	Noyes Park	2013	17.61%	29.80%	45.71%	60.20%	6.46%	24.84%
30	14th and Girard Park	2011	**39.02%**	29.80%	**115.28%**	60.20%	-2.96%	24.84%
31	7th & N Street Playground	2003	27.78%	29.80%	**155.36%**	60.20%	**86.58%**	24.84%
32	Bishop Lalossu Memorial Park	2010	27.03%	29.80%	45.54%	60.20%	12.96%	24.84%
33	Alger Park	1999	19.68%	29.80%	30.71%	60.20%	-2.40%	24.84%
34	Emery	2003	**35.58%**	29.80%	16.19%	60.20%	**31.21%**	24.84%

Table 17: Changes in non-Hispanic Black around individual parks (bold denotes changes towards green gentrification)

			1990-2000		2000-2010		2010-2015	
Park ID	Park Name	Year	Average with Near Function	Average District Change	Average with Near Function	Average District Change	Average with Near Function	Average District Change
1	Ft. Stevens Garden	2014	**-4.35%**	-2.32%	-7.77%	-9.56%	**-5.40%**	-5.02%
2	Virginia Ave Community Garden*	2004	14.82%	-2.32%	**-65.73%**	-9.56%	-4.49%	-5.02%
3	Hill East Community Garden*	2004	**-4.04%**	-2.32%	**-21.20%**	-9.56%	**-7.11%**	-5.02%
4	Kingman Park-Rosdale Community Garden	2007	-0.45%	-2.32%	-4.92%	-9.56%	**-6.93%**	-5.02%
5	Pomegranate Alley Community Garden*	2002	-0.62%	-2.32%	**-15.27%**	-9.56%	-4.33%	-5.02%
6	Deanwood Learning Garden	2011	-0.01%	-2.32%	-2.43%	-9.56%	-1.77%	-5.02%
7	Common Good City Farm	2007	-0.14%	-2.32%	**-15.12%**	-9.56%	**-18.87%**	-5.02%
8	Green East Community Garden*	2008	1.63%	-2.32%	**-10.71%**	-9.56%	**-14.29%**	-5.02%
9	Wylie Street Community Garden*	2005	**-4.55%**	-2.32%	**-14.48%**	-9.56%	**-10.80%**	-5.02%
10	Bruce Monroe Garden*	2007	**-9.60%**	-2.32%	**-21.73%**	-9.56%	**-6.09%**	-5.02%
11	Douglass Garden	2014	-0.24%	-2.32%	-2.75%	-9.56%	-3.83%	-5.02%
12	Euclid St. Garden/Justice Park	2012	**-14.86%**	-2.32%	**-16.96%**	-9.56%	-4.50%	-5.02%
13	Hamilton Garden	2015	**-8.83%**	-2.32%	**-14.65%**	-9.56%	**-9.31%**	-5.02%
14	Harry Thomas Gardens	2015	-1.04%	-2.32%	**-20.55%**	-9.56%	**-19.89%**	-5.02%
15	Hillcrest Garden	2015	8.70%	-2.32%	-0.45%	-9.56%	-2.55%	-5.02%
16	Ledroit Gardens	2011		-2.32%		-9.56%		-5.02%
17	Noyes Gardens*	2013	5.51%	-2.32%	**-26.79%**	-9.56%	**-14.10%**	-5.02%
18	Palisades Garden	1995	-0.11%	-2.32%	0.02%	-9.56%	1.75%	-5.02%
19	Southwest Garden*	2013	7.89%	-2.32%	**-10.97%**	-9.56%	**-11.80%**	-5.02%
20	Turkey Thicket Gardens	2014	0.61%	-2.32%	-6.76%	-9.56%	**-8.24%**	-5.02%
21	Canal Park	2012	-1.74%	-2.32%	-2.39%	-9.56%	-0.44%	-5.02%
22	Justice Park	2008	**-15.10%**	-2.32%	**-15.66%**	-9.56%	-4.64%	-5.02%

23	Murch Field	2007	1.53%	-2.32%	0.07%	-9.56%	0.75%	-5.02%
24	Douglass Recreation Center	2012	-0.32%	-2.32%	-0.17%	-9.56%	-2.50%	-5.02%
25	Benning Park Commuity Center	1992	-0.32%	-2.32%	-1.99%	-9.56%	-0.81%	-5.02%
26	Anna J. Cooper Circle*	2004	-0.39%	-2.32%	**-28.37%**	-9.56%	**-16.66%**	-5.02%
27	Belmont Park	2014	**-2.88%**	-2.32%	-1.32%	-9.56%	-1.63%	-5.02%
28	Anacostia Recreation Center	2001	0.46%	-2.32%	-6.24%	-9.56%	-4.10%	-5.02%
29	Noyes Park*	2013	2.34%	-2.32%	**-11.65%**	-9.56%	**-6.42%**	-5.02%
30	14th and Girard Park	2011	**-12.94%**	-2.32%	**-13.51%**	-9.56%	-2.29%	-5.02%
31	7th & N Street Playground*	2003	**-6.81%**	-2.32%	**-22.47%**	-9.56%	**-5.67%**	-5.02%
32	Bishop Lalossu Memorial Park	2010	0.51%	-2.32%	-0.83%	-9.56%	1.22%	-5.02%
33	Alger Park	1999	0.89%	-2.32%	-0.53%	-9.56%	**-6.30%**	-5.02%
34	Emery*	2003	**-3.95%**	-2.32%	**-14.83%**	-9.56%	**-8.16%**	-5.02%

*Parks that exhibit characteristics of green gentrification based on year of acquisition

Table 18: Changes in poverty rate around individual parks (bold denotes changes towards green gentrification)

			1990-2000		2000-2010		2010-2015	
Park ID	Park Name	Year	Average with Near Function	Average District Change	Average with Near Function	Average District Change	Average with Near Function	Average District Change
1	Ft. Stevens Garden	2014	2.57%	4.02%	**1.68%**	-1.55%	**0.45%**	-0.58%
2	Virginia Ave Community Garden	2004	**8.49%**	4.02%	-50.34%	-1.55%	**0.42%**	-0.58%
3	Hill East Community Garden	2004	1.88%	4.02%	-1.37%	-1.55%	-4.04%	-0.58%
4	Kingman Park-Rosdale Community Garden	2007	**7.68%**	4.02%	**13.63%**	-1.55%	**1.64%**	-0.58%
5	Pomegranate Alley Community Garden	2002	3.04%	4.02%	-1.55%	-1.55%	-9.27%	-0.58%
6	Deanwood Learning Garden	2011	3.77%	4.02%	**5.31%**	-1.55%	-4.12%	-0.58%
7	Common Good City Farm	2007	**10.49%**	4.02%	-6.20%	-1.55%	-15.17%	-0.58%
8	Green East Community Garden	2008	**8.99%**	4.02%	**5.73%**	-1.55%	-14.58%	-0.58%
9	Wylie Street Community Garden	2005	3.71%	4.02%	**-1.08%**	-1.55%	-0.58%	-0.58%
10	Bruce Monroe Garden	2007	**4.38%**	4.02%	-3.48%	-1.55%	-3.99%	-0.58%
11	Douglass Garden	2014	**22.62%**	4.02%	-14.60%	-1.55%	-8.40%	-0.58%
12	Euclid St. Garden/Justice Park	2012	2.27%	4.02%	-1.44%	-1.55%	-7.47%	-0.58%
13	Hamilton Garden	2015	3.92%	4.02%	**0.48%**	-1.55%	-1.02%	-0.58%
14	Harry Thomas Gardens	2015	**7.25%**	4.02%	-10.14%	-1.55%	**4.09%**	-0.58%
15	Hillcrest Garden	2015	**8.24%**	4.02%	-5.35%	-1.55%	**11.34%**	-0.58%
16	Ledroit Gardens	2011		4.02%		-1.55%		-0.58%
17	Noyes Gardens	2013	-5.38%	4.02%	-7.71%	-1.55%	**2.67%**	-0.58%
18	Palisades Garden	1995	0.26%	4.02%	-0.70%	-1.55%	**3.76%**	-0.58%
19	Southwest Garden	2013	3.12%	4.02%	-3.69%	-1.55%	-2.86%	-0.58%
20	Turkey Thicket Gardens	2014	**4.57%**	4.02%	**-0.03%**	-1.55%	**1.22%**	-0.58%
21	Canal Park	2012	-1.61%	4.02%	-2.57%	-1.55%	**4.09%**	-0.58%
22	Justice Park	2008	2.90%	4.02%	-15.45%	-1.55%	**5.20%**	-0.58%

23	Murch Field	2007	0.94%	4.02%	**1.66%**	-1.55%	-0.88%	-0.58%
24	Douglass Recreation Center	2012	**7.83%**	4.02%	**0.49%**	-1.55%	**1.67%**	-0.58%
25	Benning Park Commuity Center	1992	**9.14%**	4.02%	-7.33%	-1.55%	**5.14%**	-0.58%
26	Anna J. Cooper Circle	2004	3.72%	4.02%	**-0.71%**	-1.55%	-8.93%	-0.58%
27	Belmont Park	2014	-0.78%	4.02%	**2.55%**	-1.55%	-1.76%	-0.58%
28	Anacostia Recreation Center	2001	6.17%	4.02%	-2.18%	-1.55%	**6.28%**	-0.58%
29	Noyes Park	2013	5.14%	4.02%	**0.97%**	-1.55%	**0.28%**	-0.58%
30	14th and Girard Park	2011	0.37%	4.02%	-9.74%	-1.55%	-0.67%	-0.58%
31	7th & N Street Playground	2003	-0.66%	4.02%	-5.99%	-1.55%	-7.43%	-0.58%
32	Bishop Lalossu Memorial Park	2010	7.74%	4.02%	-2.80%	-1.55%	**4.41%**	-0.58%
33	Alger Park	1999	3.52%	4.02%	**5.87%**	-1.55%	**0.23%**	-0.58%
34	Emery	2003	3.16%	4.02%	-2.35%	-1.55%	**3.32%**	-0.58%

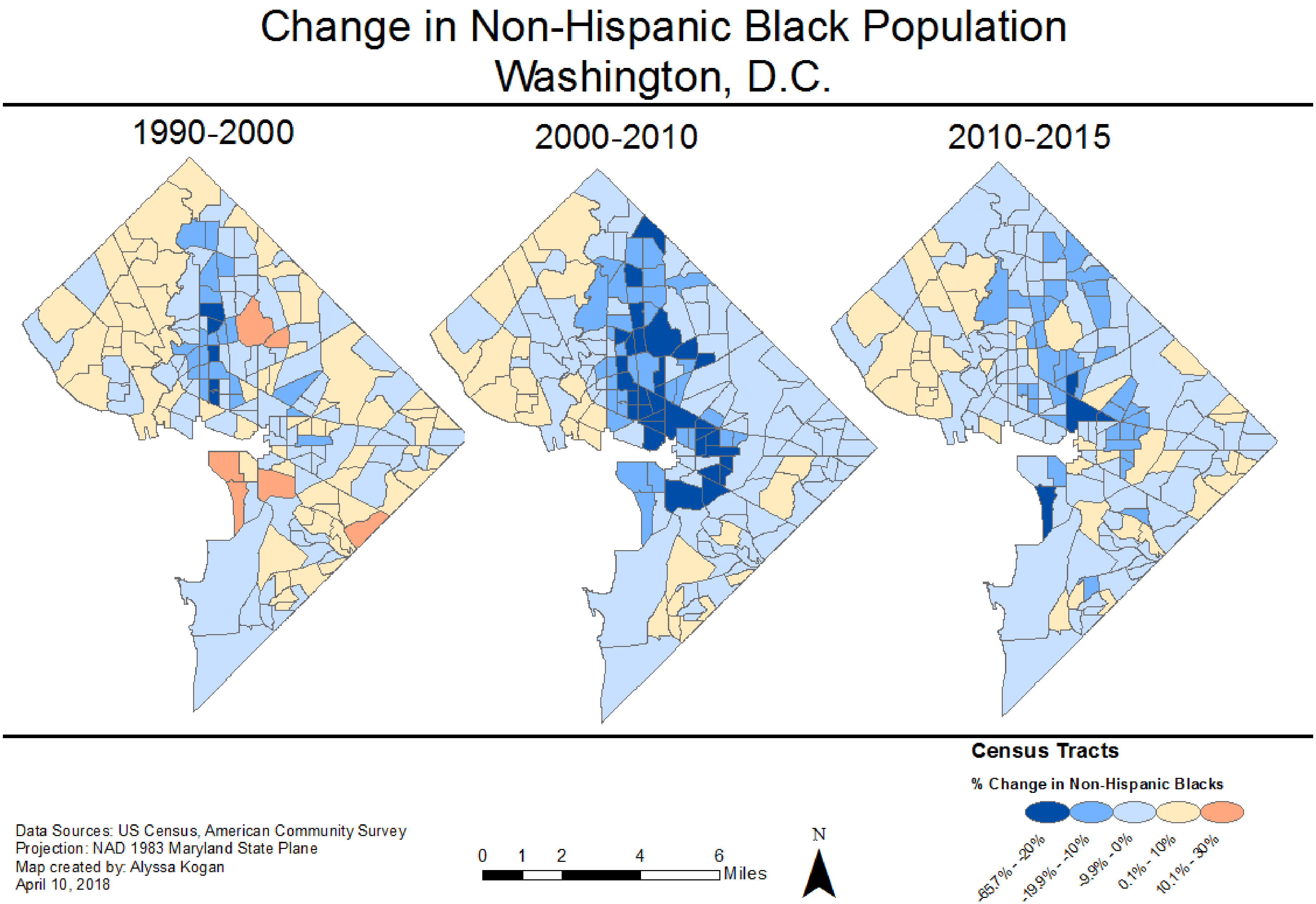


Figure 4: Change in Non-Hispanic Black Population

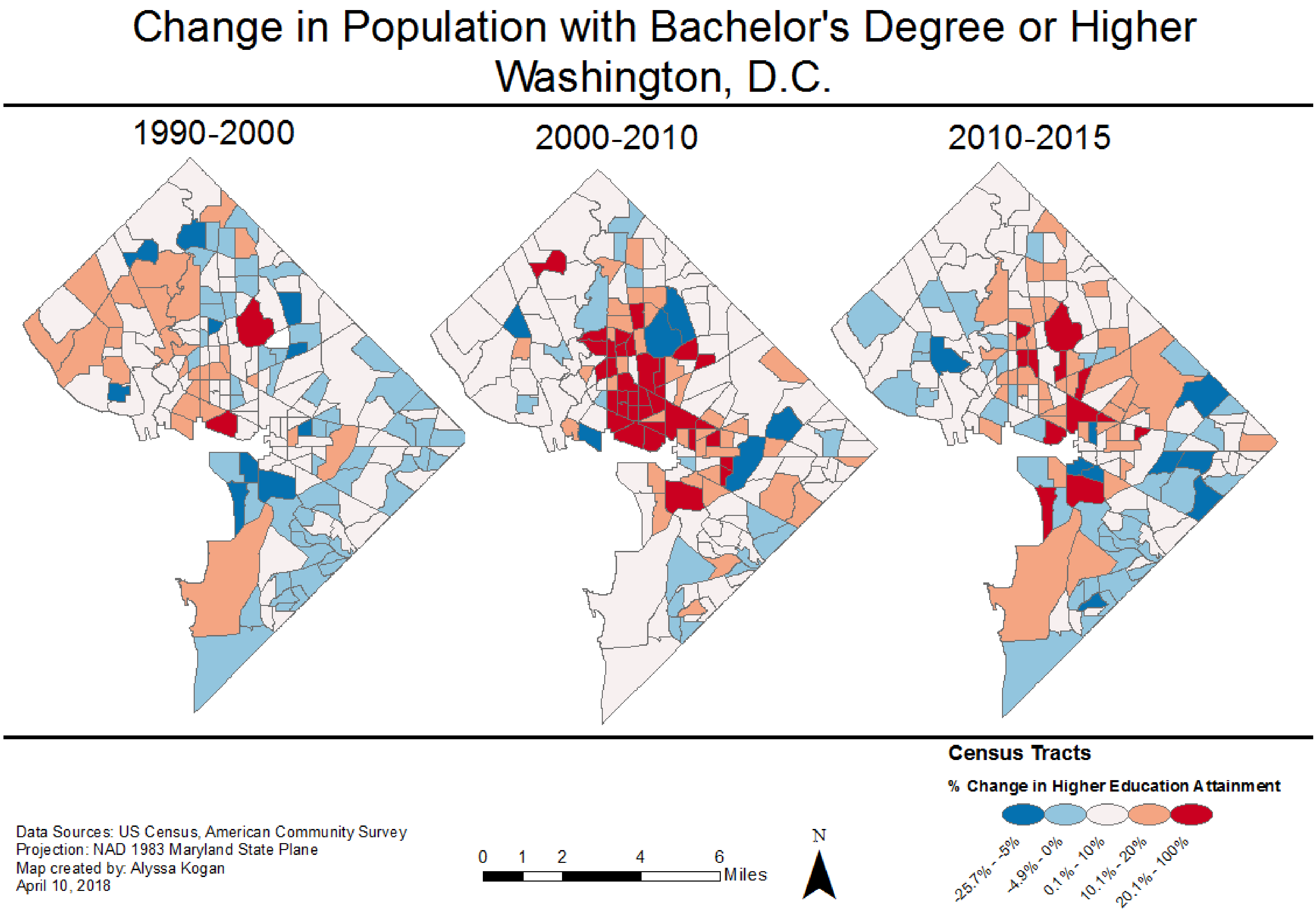
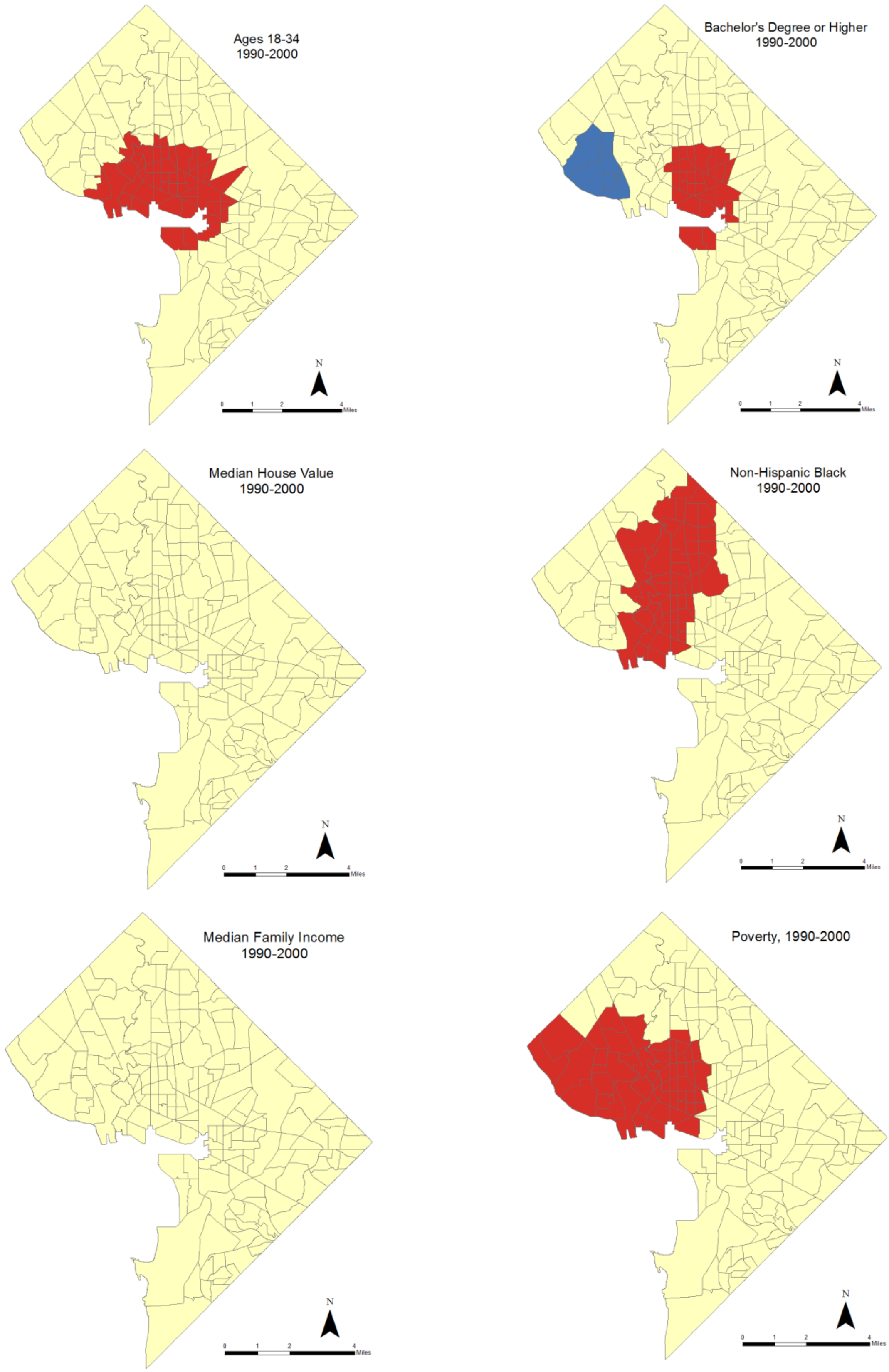


Figure 5: Change in Population with Bachelor's Degree or Higher



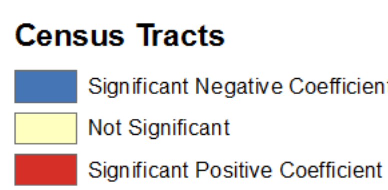


Figure 6: GWR results 1990-2000 (distance to parks as independent variable)

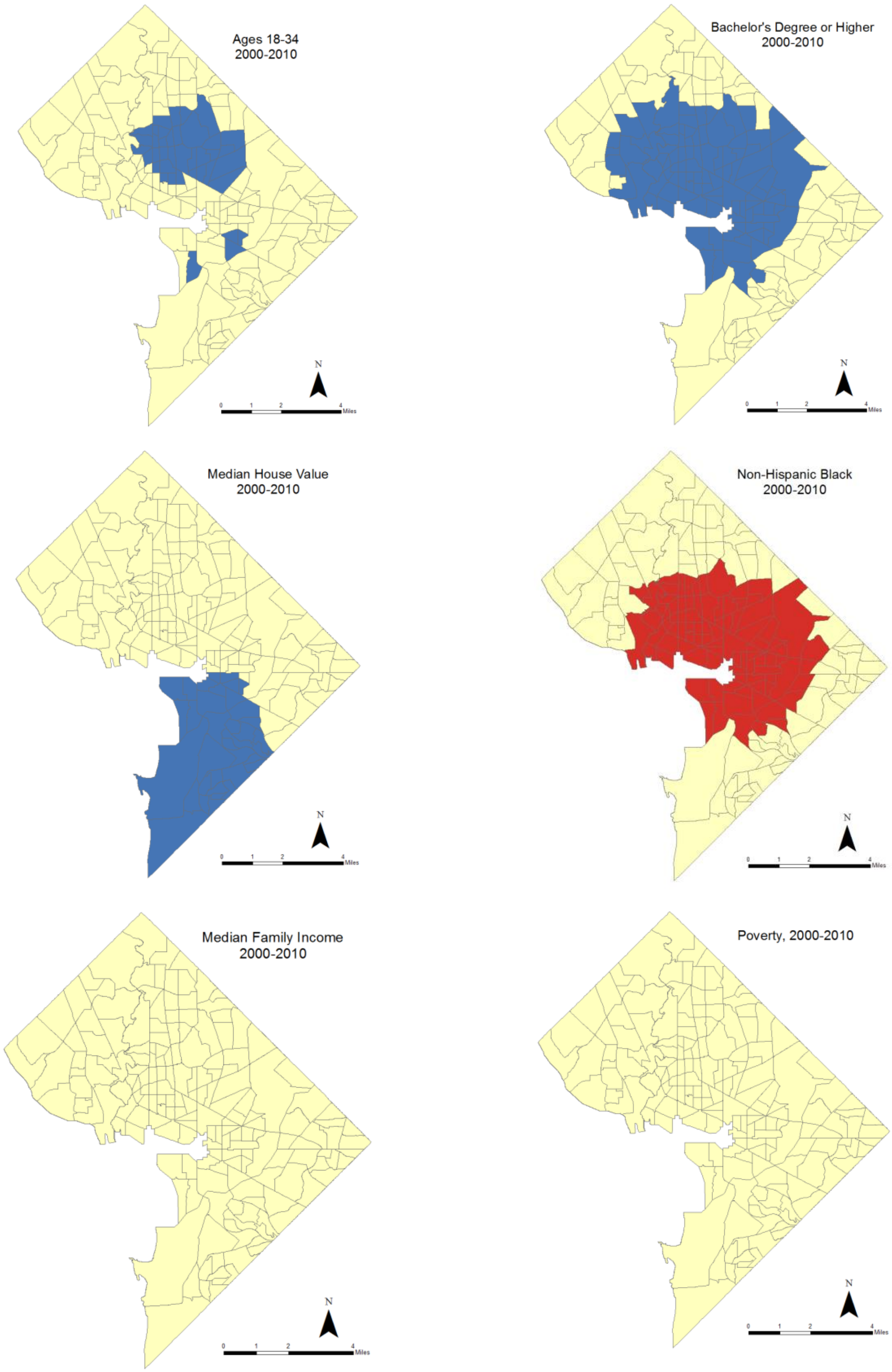


Figure 7: GWR results 2000-2010 (distance to parks as independent variable)

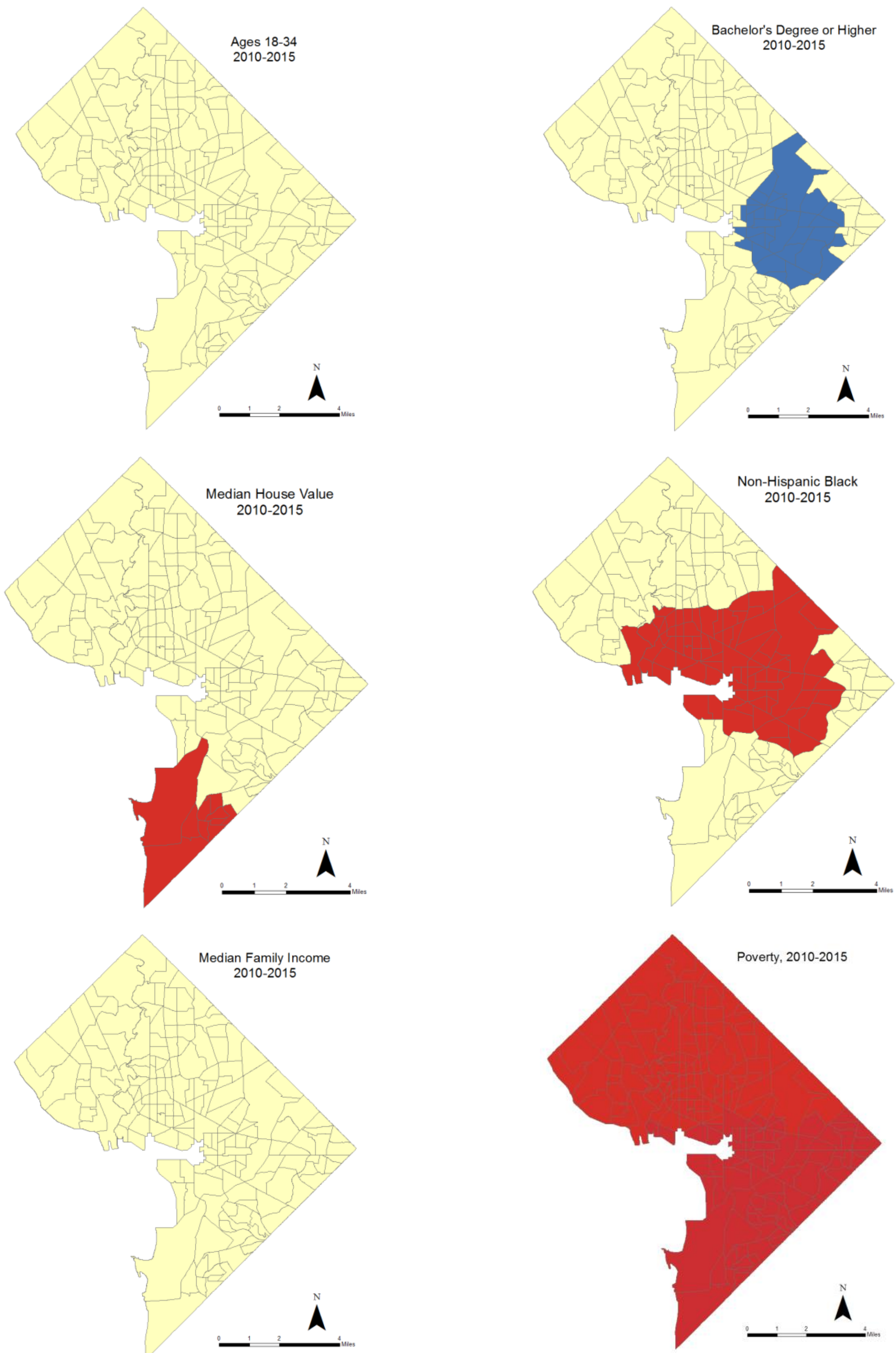
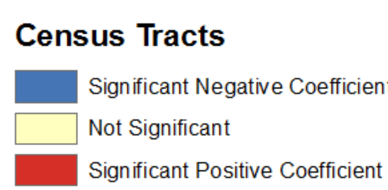
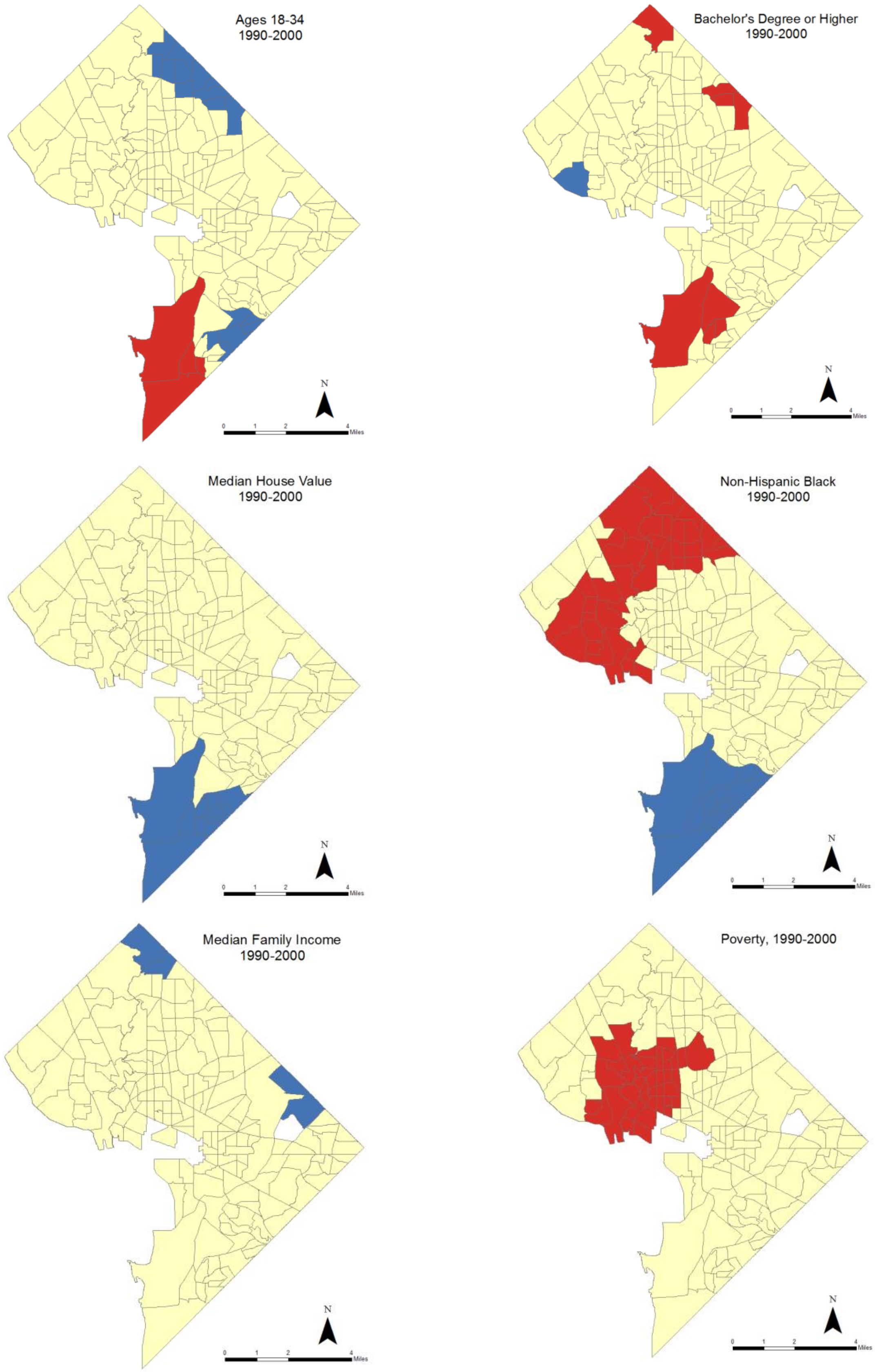


Figure 8: GWR results 2010-2015 (distance to parks as independent variable)





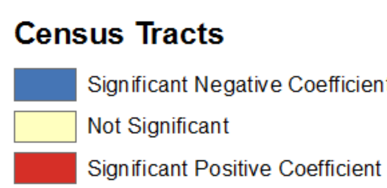


Figure 9: GWR results 1990-2000 (distance to parks as dependent variable)

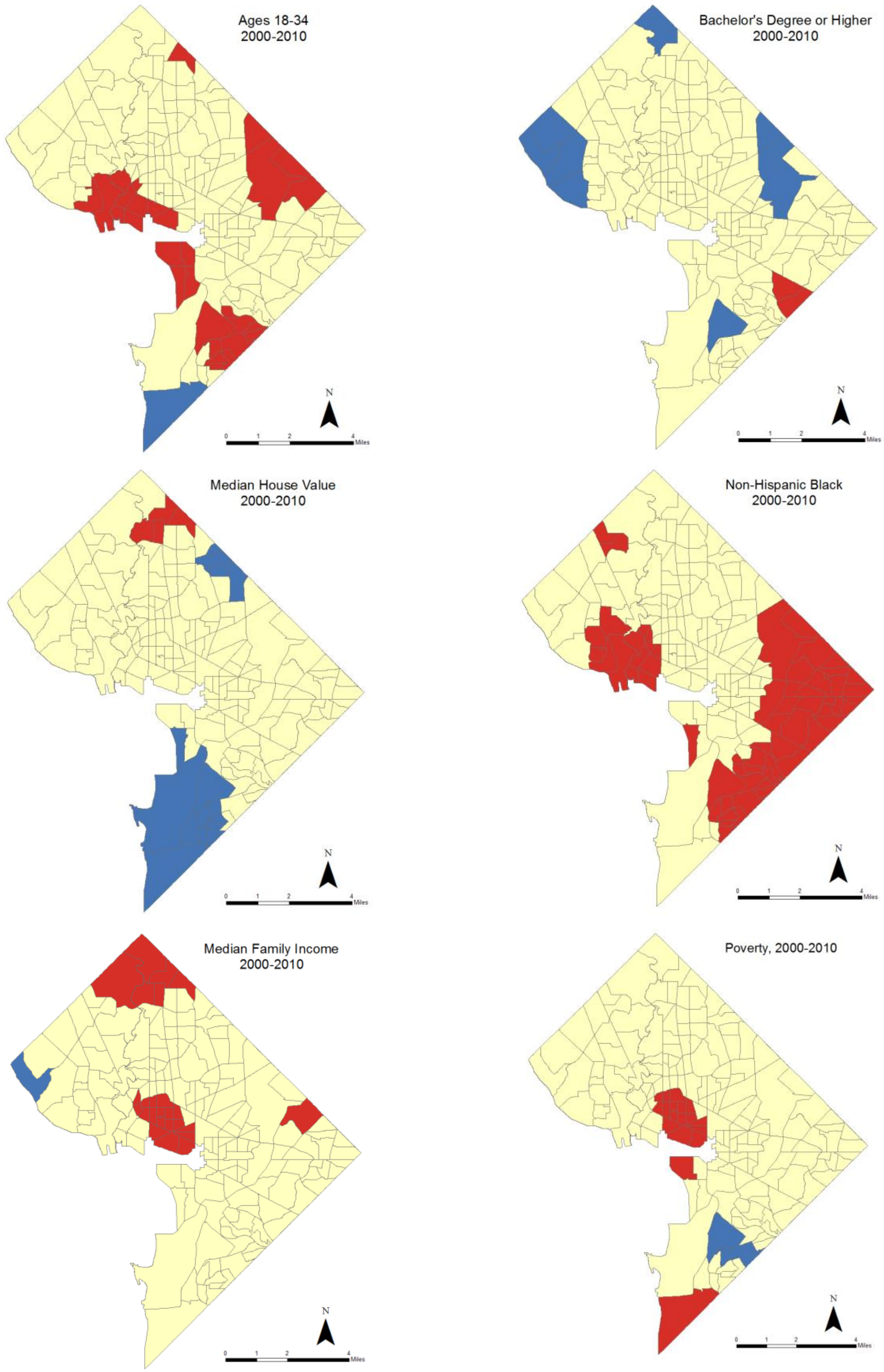
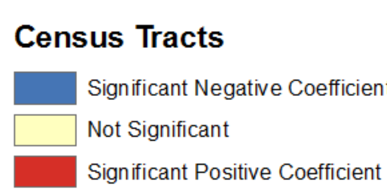


Figure 10: GWR results 2000-2010 (distance to parks as dependent variable)



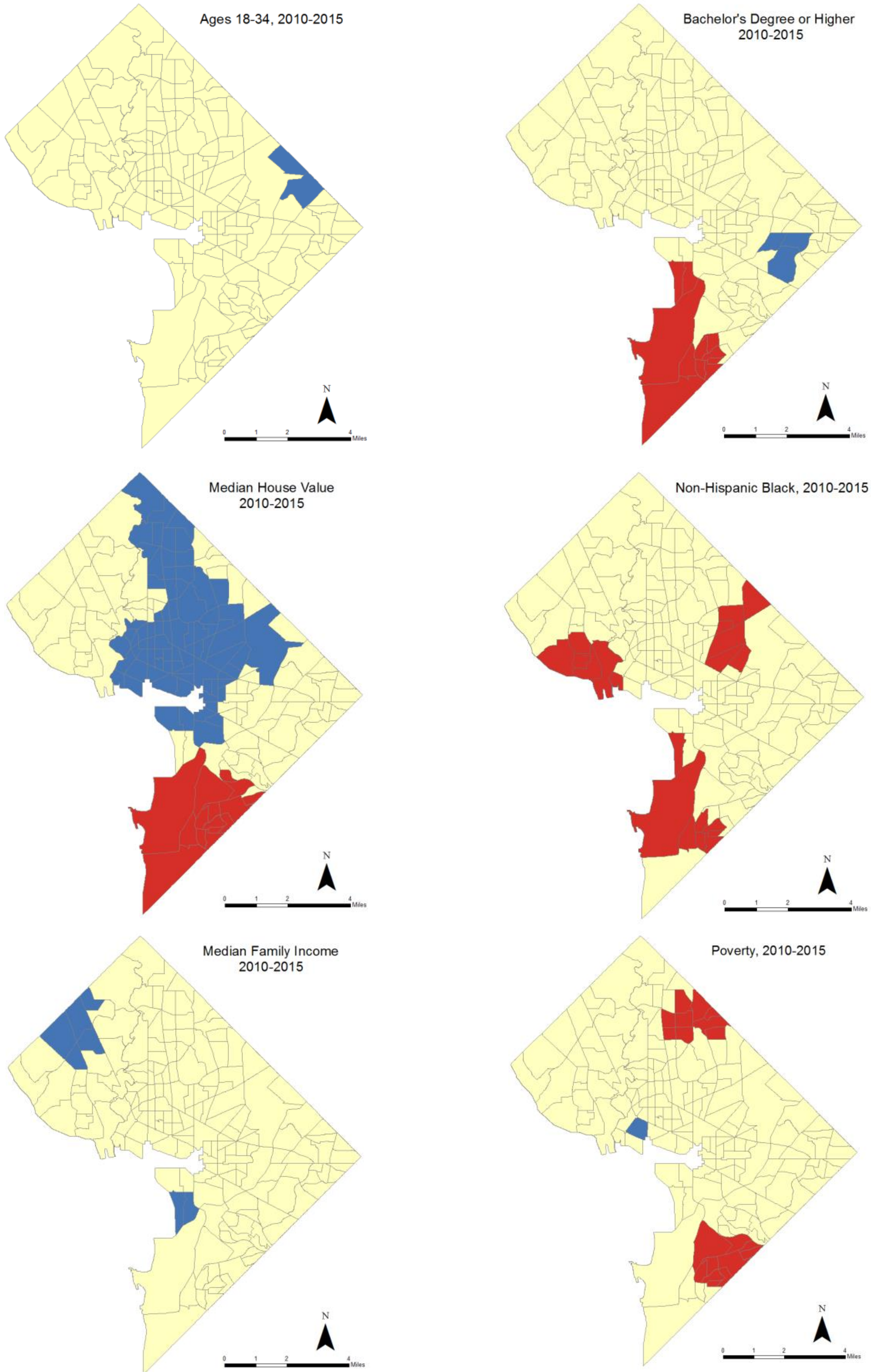


Figure 11: GWR results 2010-2015 (distance to parks as dependent variable)

:

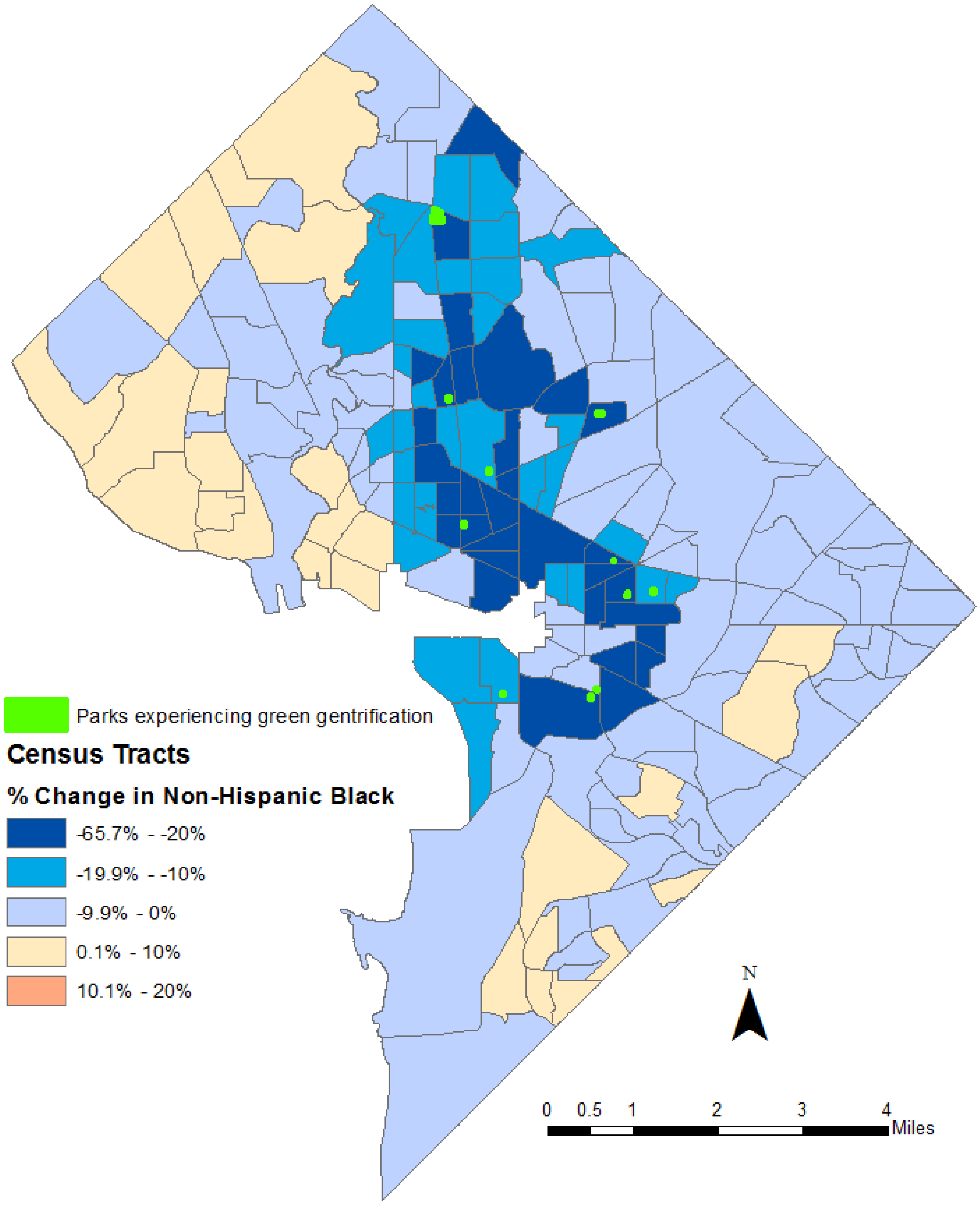


Figure 12: Change in Non-Hispanic Black Population 2000-2010 with parks that experienced green gentrification

References

About the 11th Street Bridge Park. (2014, January 13). Retrieved April 14, 2018, from https://www.bridgepark.org/about-11th-st-bridge-park

Abel, Troy D., Jonah White, and Stacy Clauson. 2015. "Risky Business: Sustainability and Industrial Land Use across Seattle's Gentrifying Riskscape." *Sustainability* 7 (11):15718–53. https://doi.org/10.3390/su71115718.

Aka, Ebenezer. 2010. "Gentrification and Socioeconomic Impacts of Neighborhood Integration and Diversification in Atlanta, GA." National Social Science Association. 2010. http://nssa.us/journals/2010-35-1/2010-35-1-01.htm.

Anguelovski, I. (2015). From Toxic Sites to Parks as (Green) LULUs? New Challenges of Inequity, Privilege, Gentrification, and Exclusion for Urban Environmental Justice. *Journal of Planning Literature*, 885412215610491. https://doi.org/10.1177/0885412215610491

Anguelovski, Isabelle, James J. T. Connolly, Laia Masip, and Hamil Pearsall. 2017. "Assessing Green Gentrification in Historically Disenfranchised Neighborhoods: A Longitudinal and Spatial Analysis of Barcelona." *Urban Geography* 0 (0):1–34. https://doi.org/10.1080/02723638.2017.1349987.

Banzhaf, H. Spencer, and Eleanor McCormick. 2006. "Moving Beyond Cleanup: Identifying the Crucibles of Environmental Gentrification." SSRN Scholarly Paper ID 990074. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=990074.

Bates, Lisa. 2013. "Gentrification and Displacement Study: Implementing an Equitable Inclusive Development Strategy in the Context of Gentrification." Commissioned by City of Portland Bureau of Planning and Sustainability. https://www.portlandoregon.gov/bps/article/454027.

Chang, Chung. 2013. "The Advantage of Mapping Gentrification with Geographic Information Systems: Comparisons of Three New York City Neighborhoods, 1980 - Present." *All Graduate Works by Year: Dissertations, Theses, and Capstone Projects*, January. https://academicworks.cuny.edu/gc_etds/2248.

Chapple, Karen. 2009. "Mapping Susceptibility to Gentrification: The Early Warning Toolkit." Institute of Urban and Regional Development. http://communityinnovation.berkeley.edu/reports/Gentrification-Report.pdf.

Checker, Melissa. 2011. "Wiped Out by the 'Greenwave': Environmental Gentrification and the Paradoxical Politics of Urban Sustainability." *City & Society* 23 (2):210–29. https://doi.org/10.1111/j.1548-744X.2011.01063.x.

Curran, Winifred, and Trina Hamilton. 2012. "Just Green Enough: Contesting Environmental Gentrification in Greenpoint, Brooklyn." *Local Environment* 17 (9):1027–42. https://doi.org/10.1080/13549839.2012.729569.

Delmelle, Elizabeth C. 2016. "Mapping the DNA of Urban Neighborhoods: Clustering Longitudinal Sequences of Neighborhood Socioeconomic Change." *Annals of the American Association of Geographers* 106 (1):36–56.

Dooling, Sarah. 2009. "Ecological Gentrification: A Research Agenda Exploring Justice in the City." *International Journal of Urban and Regional Research* 33 (3):621–39. https://doi.org/10.1111/j.1468-2427.2009.00860.x.

Franke-Ruta, G. (2012, August 10). The Politics of the Urban Comeback: Gentrification and Culture in D.C. *The Atlantic*. Retrieved from https://www.theatlantic.com/politics/archive/2012/08/the-politics-of-the-urban-comeback-gentrification-and-culture-in-dc/260741/

Gamper-Rabindran, Shanti, and Christopher Timmins. 2011. "Hazardous Waste Cleanup, Neighborhood Gentrification, and Environmental Justice: Evidence from Restricted Access Census Block Data." *American Economic Review* 101 (3):620–24. https://doi.org/10.1257/aer.101.3.620.

Governing. (n.d.). Washington, D.C., Gentrification Maps and Data. Retrieved April 14, 2018, from http://www.governing.com/gov-data/washington-dc-gentrification-maps-demographic-data.html

Gringlas, S. (2017, January 16). Old Confronts New In A Gentrifying D.C. Neighborhood. Retrieved April 14, 2018, from https://www.npr.org/2017/01/16/505606317/d-c-s-gentrifying-neighborhoods-a-careful-mix-of-newcomers-and-old-timers

Heynen, Nik, Harold A. Perkins, and Parama Roy. 2006. "The Political Ecology of Uneven Urban Green Space: The Impact of Political Economy on Race and Ethnicity in Producing Environmental Inequality in Milwaukee." *Urban Affairs Review* 42 (1):3–25. https://doi.org/10.1177/1078087406290729.

Ibes, Dorothy C. 2015. "A Multi-Dimensional Classification and Equity Analysis of an Urban Park System: A Novel Methodology and Case Study Application." *Landscape and Urban Planning* 137 (Supplement C):122–37. https://doi.org/10.1016/j.landurbplan.2014.12.014.

Irvine, Katherine N., Sara L. Warber, Patrick Devine-Wright, and Kevin J. Gaston. 2013. "Understanding Urban Green Space as a Health Resource: A Qualitative Comparison of Visit Motivation and Derived Effects among Park Users in Sheffield, UK." *International Journal of Environmental Research and Public Health* 10 (1):417–42. https://doi.org/10.3390/ijerph10010417.

Iweala, U. (2016, September 12). The gentrification of Washington DC: how my city changed its colours. Retrieved April 14, 2018, from http://www.theguardian.com/cities/2016/sep/12/gentrification-washington-dc-how-my-city-changed-colours

Jackson, M. (2017). *The State of African Americans in DC: Trends in Employment & Workforce Development*. Georgetown University. Retrieved from https://georgetown.app.box.com/s/769rvofp6ow18vqi7hbvh83778g8z9xd

Jan, T. (2017, November 22). How foreign investors are transforming a long-forgotten D.C. neighborhood. *Washington Post*. Retrieved from https://www.washingtonpost.com/business/economy/how-foreign-investors-are-transforming-a-long-forgotten-dc-neighborhood/2017/11/22/aed34a58-cbb7-11e7-aa96-54417592cf72_story.html

Jennings, Viniece, Cassandra Johnson Gaither, and Richard Schulterbrandt Gragg. 2012. "Promoting Environmental Justice Through Urban Green Space Access: A Synopsis." *Environmental Justice 5(1):1-7* 5 (1):1–7. https://doi.org/10.1089/env.2011.0007.

Jennings, Viniece, Lincoln Larson, and Jessica Yun. 2016. "Advancing Sustainability through Urban Green Space: Cultural Ecosystem Services, Equity, and Social

Determinants of Health." *International Journal of Environmental Research and Public Health* 13 (2):196. https://doi.org/10.3390/ijerph13020196.

Kennedy, Maureen, and Paul Leonard. 2001. "Dealing with Neighborhood Change: A Primer on Gentrification and Policy Choices." Washington, United States: Brookings Institution Press. https://search-proquest-com.ezproxy.library.tufts.edu/docview/1794522946/abstract/A64DCCC5FF8141CAPQ/1.

Kijakazi, K., Atkins, R. M. B., Paul, M., Price, A., Hamilton, D., & Jr, W. A. D. (2016, October 31). The Color of Wealth in the Nation's Capital. Retrieved April 14, 2018, from https://www.urban.org/research/publication/color-wealth-nations-capital

Kolko, Jed. 2007. "The Determinants of Gentrification." SSRN Scholarly Paper ID 985714. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=985714.

Landscape and Urban Planning. n.d. Accessed November 13, 2017. https://www.journals.elsevier.com/landscape-and-urban-planning/editors-choice/access-to-urban-green-space-and-environmental-inequalities-i.

Loughran, Kevin. 2014. "Parks for Profit: The High Line, Growth Machines, and the Uneven Development of Urban Public Spaces." *City & Community* 13 (1):49–68. https://doi.org/10.1111/cico.12050.

Maciag, M. (2015, February). Gentrification in America Report. Retrieved April 14, 2018, from http://www.governing.com/gov-data/census/gentrification-in-cities-governing-report.html

Mavoa, Suzanne, Mohammad Javad Koohsari, Hannah M. Badland, Melanie Davern, Xiaoqi Feng, Thomas Astell-Burt, and Billie Giles-Corti. 2015. "Area-Level Disparities of Public Open Space: A Geographic Information Systems Analysis in Metropolitan Melbourne." *Urban Policy and Research* 33 (3):306–23. https://doi.org/10.1080/08111146.2014.974747.

McCartney, R. (2017, May 3). Perspective | "Black branding" — how a D.C. neighborhood was marketed to white millennials. *Washington Post*. Retrieved from https://www.washingtonpost.com/local/black-branding--how-a-dc-neighborhood-was-marketed-to-white-millenials/2017/05/02/68b0ae06-2f47-11e7-9534-00e4656c22aa_story.html

Mcgeehan, Patrick. 2011. "With Next Phase Ready, Area Around High Line Is Flourishing." *The New York Times*, June 5, 2011. http://www.nytimes.com/2011/06/06/nyregion/with-next-phase-ready-area-around-high-line-is-flourishing.html.

Millington, Nate. 2015. "From Urban Scar to 'park in the Sky': Terrain Vague, Urban Design, and the Remaking of New York City's High Line Park." *Environment and Planning A* 47 (11):2324–38. https://doi.org/10.1177/0308518X15599294.

Misra, T. (2017, May 15). Don't Confuse Gentrifying Neighborhoods for Diverse Neighborhoods. Retrieved April 14, 2018, from https://www.citylab.com/housing/2017/05/gentrifying-neighborhoods-arent-really-diverse/526092/

Miyake, Keith K., Andrew R. Maroko, Kristen L. Grady, Juliana A. Maantay, and Peter S. Arno. 2010. “Not Just a Walk in the Park: Methodological Improvements for Determining Environmental Justice Implications of Park Access in New York City for the Promotion of Physical Activity.” *Cities and the Environment* 3 (1):1–17.

National Capital Planning Commission. (2010). CapitalSpace. Retrieved April 14, 2018, from https://www.ncpc.gov/plans/capitalspace/

Nesbitt, Ashon. 2005. “A Model of Gentrification: Monitoring Community Change in Selected Neighborhoods of St. Petersburg, Florida Using the Analytic Hierarchy Process.” http://ufdc.ufl.edu.ezproxy.library.tufts.edu/UFE0010582/00001.

Ngom, Roland, Pierre Gosselin, and Claudia Blais. 2016. “Reduction of Disparities in Access to Green Spaces: Their Geographic Insertion and Recreational Functions Matter.” *Applied Geography* 66 (January):35–51. https://doi.org/10.1016/j.apgeog.2015.11.008.

O’Connell, J. (2012, May 25). D.C.’s growth is fueled by 20-somethings. Can the city grow up with them? *Washington Post*. Retrieved from https://www.washingtonpost.com/opinions/dcs-growth-is-fueled-by-20-somethings-can-the-citygrow-up-with-them/2012/05/25/gJQAYBS3pU_story.html

O’Connell, J. (2016, January 21). Can D.C. build a $45 million park for Anacostia without pushing people out?; Proponents of 11th Street Bridge project want to try to mitigate effects even before construction starts. Retrieved April 14, 2018, from https://advance-lexis-com.ezproxy.library.tufts.edu/document/?pdmfid=1516831&crid=3e587552-cdae-49f6-8ace-38aeaf0e7c3d&pddocfullpath=%2Fshared%2Fdocument%2Fnews%2Furn%3AcontentItem%3A5HX1-6SB1-DXKP-J47W-00000-00&pddocid=urn%3AcontentItem%3A5HX1-6SB1-DXKP-J47W-00000-00&pdcontentcomponentid=409005&pdteaserkey=sr0&pditab=allpods&ecomp=dy_k&earg=sr0&prid=c096447c-5d91-4b1b-91e3-cc1ebf3ec424

Pearsall, H. (2012). Moving out or moving in? Resilience to environmental gentrification in New York City. *Local Environment*, *17*(9), 1013–1026. https://doi.org/10.1080/13549839.2012.714762

Pearsall, H., & Christman, Z. (2012). Tree-lined lanes or vacant lots? Evaluating non-stationarity between urban greenness and socio-economic conditions in Philadelphia, Pennsylvania, USA at multiple scales. *Applied Geography*, *35*(1), 257–264. https://doi.org/10.1016/j.apgeog.2012.07.006

Pearsall, Hamil, and Isabelle Anguelovski. 2016. “Contesting and Resisting Environmental Gentrification: Responses to New Paradoxes and Challenges for Urban Environmental Justice.” *Sociological Research Online* 21 (3):6.

Play DC. (2015, January). District of Columbia Parks and Recreation Master Plan: Vision and Implementation Framework. Retrieved from https://dpr.dc.gov/sites/default/files/dc/sites/dpr/publication/attachments/DCPRMP_Vision%2BImplementation%20Final%20Document_123014_sm.pdf

Priest, D., & Arkin, W. (2010, July 19). A hidden world, growing beyond control | washingtonpost.com. *Washington Post*. Retrieved from http://projects.washingtonpost.com/top-secret-america/articles/a-hidden-world-growing-beyond-control/

Rigolon, Alessandro. 2016. "A Complex Landscape of Inequity in Access to Urban Parks: A Literature Review." *Landscape and Urban Planning* 153 (Supplement C):160–69. https://doi.org/10.1016/j.landurbplan.2016.05.017.

Roe, Jenny, Peter A. Aspinall, and Catharine Ward Thompson. 2016. "Understanding Relationships between Health, Ethnicity, Place and the Role of Urban Green Space in Deprived Urban Communities." *International Journal of Environmental Research and Public Health* 13 (7):681. https://doi.org/10.3390/ijerph13070681.

Stein, P. (2015, February 5). Portland is the only city gentrifying faster than D.C., report says. *Washington Post*. Retrieved from https://www.washingtonpost.com/news/local/wp/2015/02/05/portland-is-the-only-city-gentrifying-faster-than-d-c-report-says/

Stein, P. (2016, November 2). Net worth of white households in D.C. region is 81 times that of black households. *Washington Post*. Retrieved from https://www.washingtonpost.com/news/local/wp/2016/11/02/net-worth-of-white-households-in-d-c-region-is-81-times-greater-than-black-households/

Thompson, Susan, and Jennifer Kent. 2014. "Healthy Built Environments Supporting Everyday Occupations: Current Thinking in Urban Planning." *Journal of Occupational Science* 21 (1):25–41. https://doi.org/10.1080/14427591.2013.867562.

Torrens, Paul M., and Atsushi Nara. 2007a. "Modeling Gentrification Dynamics: A Hybrid Approach." *Computers, Environment and Urban Systems*, GeoComputation 2005, 31 (3):337–61. https://doi.org/10.1016/j.compenvurbsys.2006.07.004.

———. 2007b. "Modeling Gentrification Dynamics: A Hybrid Approach." *Computers, Environment and Urban Systems*, GeoComputation 2005, 31 (3):337–61. https://doi.org/10.1016/j.compenvurbsys.2006.07.004.

Trust for Public Land. (2017, May 24). The Trust for Public Land Releases 2017 ParkScore® Index, Rating Park Systems in the 100 Largest U.S. Cities. Retrieved April 14, 2018, from https://www.tpl.org/media-room/trust-public-land-2017-parkscore%C2%AE-index-rating

Urban Renewal: The Story of Southwest D.C. (2013, May 17). Retrieved April 14, 2018, from https://whosedowntown.wordpress.com/urban-renewal-the-story-of-southwest-d-c/

Urban Turf. (2017, November 7). The DC Neighborhoods with the Greatest Price Appreciation in 2017. Retrieved April 14, 2018, from https://dc.urbanturf.com/articles/blog/the_dc_neighborhoods_with_the_greatest_price_appreciation_in_2017/13228

Weems, Candice. 2016. "Examining the Spatial Distribution of Park Access and Trajectories of Gentrification in Seattle, Washington 1990-2010." http://ir.library.oregonstate.edu/xmlui/bitstream/handle/1957/58802/WeemsCandiceM2016.pdf?sequence=4.

Wen, Ming, Xingyou Zhang, Carmen D. Harris, James B. Holt, and Janet B. Croft. 2013. "Spatial Disparities in the Distribution of Parks and Green Spaces in the USA."

Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine 45 (Suppl 1):18–27. https://doi.org/10.1007/s12160-012-9426-x.

Wolch, Jennifer R., Jason Byrne, and Joshua P. Newell. 2014. "Urban Green Space, Public Health, and Environmental Justice: The Challenge of Making Cities 'just Green Enough.'" *Landscape and Urban Planning* 125 (May):234–44. https://doi.org/10.1016/j.landurbplan.2014.01.017.

Wüstemann, Henry, Dennis Kalisch, and Jens Kolbe. 2017. "Access to Urban Green Space and Environmental Inequalities in Germany." *Landscape and Urban Planning* 164 (Supplement C):124–31. https://doi.org/10.1016/j.landurbplan.2017.04.002.

Zheng, Siqi, and Matthew E. Kahn. 2013. "Does Government Investment in Local Public Goods Spur Gentrification? Evidence from Beijing." *Real Estate Economics* 41 (1):1–28. https://doi.org/10.1111/j.1540-6229.2012.00339.x.