

Investigating environmental justice in urban green space development: a spatial and longitudinal
study of Austin, TX

by

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B.L.A., Beijing Forestry University, 2015
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Landscape Architecture and Regional & Community Planning
College of Architecture, Planning and Design

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2025

Abstract

Various greening programs are being adopted worldwide as research shows the benefits of urban green space. In recent years, the quest for a deeper understanding of institutional and structural conditions that have generated and sustained the unequal distribution of urban green space (UGS) has started to develop. This has sparked a research interest that looks at inequity spatially and longitudinally and centers on the obscured forms of racism quantitatively. To address these challenges, this dissertation examines the multi-faceted factors in shaping urban green space (UGS) distribution through spatial and longitudinal analyses, using Austin, TX – a rapidly growing U.S. city experiencing park expansion alongside persistent segregation legacy and potential displacement of minorities, as an example. The dissertation integrates the Environmental Justice framework to investigate how socio-political processes, urbanization and housing pressure, and civic participation collectively influence UGS development spatially and longitudinally.

The first part of the dissertation conducted a cross-sectional spatial analysis to examine the association between UGS distribution and socio-demographic, socio-economic, and housing factors. It uses U.S. Census, housing, and Austin's Park GIS data to construct the 'UGS accessibility score' as the dependent variable and commonly identified vulnerability factors as the independent variables at the census block group level. The initial results highlight the disparities in socioeconomic status and housing factors that impact UGS accessibility, where areas with a higher housing value are consistently associated with better access to UGS, and regions with more old housing units are consistently negatively associated with UGS accessibility. It also contradicts the hypothesis that areas with more White residents will enjoy better access to UGS, offering valuable insight into future urban planning policies.

The second part of the dissertation uses mixed methods to conduct longitudinal analyses to investigate the association between UGS development, housing, and social vulnerability factors, including trends and shifts in proximity and per capita green space over time. In addition, to understand the role of procedural justice in the longitudinal development of UGS, the dissertation uses civic participation data as the key explanatory variable. It performs multiple qualitative comparative analyses (QCAs) with different periods following decadal intervals, where three sets of solution formulas for the three decades were subsequently compared using string analysis. Findings demonstrate that whiter, higher-income neighborhoods with sustained civic engagement consistently enjoy greater UGS access while evolving urban demographics amplify the complexity of socioeconomic factors.

The dissertation bridges gaps between structural critiques of green inequity and institutional practices by showing how Austin's UGS development, framed as city-wide environmental progress, intersects with increased housing pressure and inequitable participatory processes. Results show that procedural justice, represented by civic participation through public meetings, consistently influences the inequitable UGS development. By synthesizing spatial, longitudinal, and qualitative analyses, this dissertation offers a model for evaluating UGS justice that highlights the need to inform equitable urban planning by addressing the complex role of UGS development in mitigating and exacerbating socio-spatial inequality.

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Acknowledgments

I am deeply grateful to the many individuals who supported and guided me throughout my doctoral journey at Kansas State University.

First and foremost, I would like to thank Dr. Hyung Jin Kim, my advisor, for his unwavering mentorship and guidance over the past five years. He has always reserved time to review my work and offered feedback, even when he was away from campus. For his dedication, I am forever indebted. I also wish to thank my committee members - Dr. Audrey Joslin, Dr. Shakil Kashem, and Dr. Matthew Sanderson - for their invaluable insights, critical feedback, and encouragement at every stage of my research. My dissertation research would not have been possible without these amazing scholars.

My doctoral study was made possible through generous funding from the Department of Landscape Architecture and Regional & Community Planning (LARCP) and the College of Architecture, Planning and Design (APDesign). I am also extremely thankful to receive the continuous help and support of the APDesign faculty and staff, Dr. Anne Beamish (Ph.D. Program Director), Dr. Huston Gibson (LARCP Department Head), Jody Hodges (LARCP Project Coordinator), Professor Katie Kingery-Page (Associate Dean), and all the people that I was fortunate to work with before.

Finally, I am deeply grateful to my parents for their unconditional love and support; they have always been the backbone of my achievement.

Dedication

I dedicate this dissertation to my parents for their unconditional love and support.

Chapter 1 - Introduction

1.1 Overview

Research has shown various benefits that urban green spaces (UGS) can provide by altering the physical urban environment. These include improved human health and well-being, better urban development, and many ecosystem services (Anguelovski et al., 2018; Harvey, 2001; Nik Heynen, 2014; Swyngedouw & Heynen, 2003). Local and national governments worldwide are adopting more greening policies because of their commended role as a technological fix and a “win-win” solution to environmental problems, sustainability concerns, and development issues that will benefit all (Garcia-Lamarca et al., 2021; Knuth, 2014).

Recently, however, scholars have argued that potential risks exist in the processes of UGS development. Less advantaged citizens are especially vulnerable to enjoying fewer benefits due to historical residential segregation policies and the refusal of adequate city services in the past (Heck, 2021; Rigolon & Németh, 2018c). In researching this inequity, some studies examined the procedural and recognitional injustice of marginalized communities excluded from decision-making processes, the misrecognition of their perception of green space, and policies that convert environmental externalities into profiting opportunities (Checker, 2011; Curran & Hamilton, 2013; Dooling, 2009; McKendry & Janos, 2015). Other studies emphasizing distributional injustice demonstrated the potential socioeconomic and sociodemographic spatial changes in the affected areas, such as increased adjacent property value and rental prices, increased tax payment, new employment opportunities, and the influx of more affluent residents (Anguelovski et al., 2018; Jo Black & Richards, 2020; Rigolon & Németh, 2019).

The Environmental Justice framework that assesses UGS inequity through distributional, procedural, and recognitional lenses has proved helpful and constructive. The mounting

empirical evidence provided insights into how socio-spatial inequities reproduced through UGS implementation might be overlooked (Anguelovski et al., 2020). However, the cross-sectional focus on analyzing proximity and distance to UGS for distributional injustice might be insufficient to answer how socially constructed categories of inequity were produced geographically. As such, there exists the need to understand the inequitable access to UGS in a broader spatial and longitudinal perspective that comprehends development pressure, the less competitive position of vulnerable neighborhoods, and the financing and investment of projects in and across the city (Garcia-Lamarca et al., 2021; Long, 2016). For procedural justice, it is necessary to identify whether the real needs of marginalized residents are met, as well as their representation during the decision-making processes over time. However, such evidence is also insufficient and scarce.

This dissertation examines the association between various sociodemographic and socioeconomic factors and access to UGS, focusing on cross-sectional and longitudinal aspects.

1.2 Background and Statement of the Problem

Park's creation in the United States has historically been interlinked with the social reproduction of the bourgeois leisure and working classes (Bachin, 2003; Birge-Liberman, 2010). One crucial aspect that many UGS researchers have not made explicit is that urban land is valuable. Therefore, any modification to the built environment needs justification; this often involves political and economic concerns in addition to the social and environmental standpoint. Due to investments from both public and private sectors, UGS has become a commodity that meets the expectations of elite stakeholders, aiming to address shifts in societal values and mitigate urban ecological challenges (Bachin, 2003; Harvey, 2001; Jessop, 2004). As a result,

with normative concepts of Environmental Justice advancing in UGS equity research, the quest for a holistic understanding of the complex but dynamic roles of multi-faceted factors that form such inequity is imperative. Moreover, many existing studies fail to account for the complexity of social, economic, and other factors that evolve and change over time while resolving the UGS equity problem (Anguelovski et al., 2022).

1.2.1 Study Area

Studies focusing on world cities such as New York City and Los Angeles have revealed the complex mechanisms that direct inequitable UGS development (Lang & Rothenberg, 2017; Rigolon & Németh, 2018b; J. Wolch et al., n.d.). Austin, Texas, is one of the fastest-growing cities in the U.S., with its metropolitan area housing over two million people, nearly one million of whom reside within the city limits (Trust for Public Land, 2022). The city has established ambitious economic and ecological goals and has showcased its stunning development in the past few decades. Over the years, it has evolved from a government- and university-centered city in the 1990s to a bustling metropolitan area hosting numerous high-tech companies and industries (Connolly & Lira, 2021). Recently, Austin has gained recognition as a leader in sustainability and equity thanks to its commitment to promoting green and culturally progressive policies while sustaining robust economic growth (Garcia-Lamarca et al., 2021; Long, 2016).

Austin has expanded its park spaces in line with its growing population. Since November 2018, the Austin Parks and Recreation Department (PARC) has developed or expanded 51 parks, covering roughly 200 acres across the city (PARC, 2021). The Parkland Dedication Ordinance, first enacted in 1985, mandates the dedication of parkland to new development projects, promoting an equitable and balanced expansion of the city's park system (PARC, 2021). Despite

the city's well-intentioned policy of allocating municipal bonds to underserved areas such as East Austin to bridge gaps in park access, disparities persist (Tretter, 2012). Although the policy targets communities based on income levels, racial composition, and the proportion of young children, its effectiveness remains questionable. Data from the 2022 Trust for Public Land shows that low-income residents have 59% less access to park space per person than wealthier neighborhoods, despite the city's allocation of \$40 million in municipal bonds for green space acquisition in East Austin between 2000 and 2010 (Connolly & Lira, 2021; Trust for Public Land, 2022). Figure 1.1. shows the spatial distribution of current urban green spaces managed by the Austin Parks and Recreation Department.

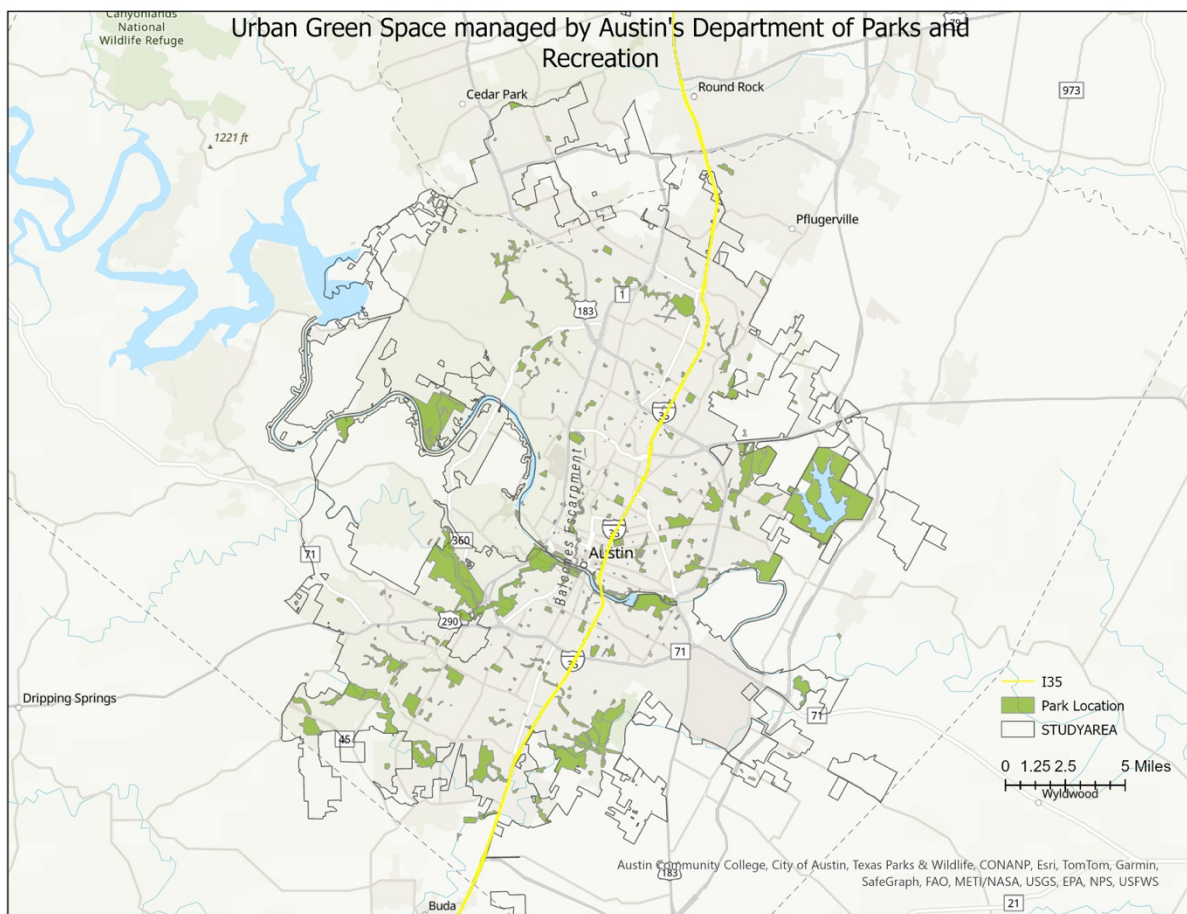


Figure 1.1. Urban Green Spaces managed by the Austin Parks and Recreation Department

1.2.2 A Brief Introduction to the Problematic UGS Development in Austin

Like many other U.S. cities, Austin has been racially segregated throughout the 20th century as the 1928 resolution set out a designated zone, East Austin, that bordered Interstate 35, Airport Boulevard, and Lady Bird Lake for minorities (Long, 2016). At the same time, East Austin was primarily occupied by polluting industries and had limited access to green amenities. The later deed restriction worsened this segregation as it only allowed land use to be locked after the land was developed (Tretter, 2012). In addition, comprehensive plans created before 1979 have no statutory enforcement power but only act as guidelines in directing city and zoning development. Even with the adoption of a comprehensive plan such as the 1979 Austin Tomorrow Comprehensive Plan (ATCP), serious neighborhood enhancement and zoning improvements were lagging until the passing of the late 1990 Neighborhoods Plan, despite the rapid growth in the tech industries that started in the 1980s (Blunt, 2008). As a result, the distribution of green amenities and the demographic pattern in some areas of the city, such as East Austin, has remained primarily unchanged.

On the other hand, the governance structure in Austin was distinct among large cities in the United States as the city council was elected at large rather than being represented by individual districts or based on geographical proximity (Long, 2016; Steverson, 2014). The unique governance structure remained unchanged until 2015. It has repressed the long-time underrepresented neighborhoods, especially in East Austin, to voice their environmental concerns over pollution and the lack of green amenities. Studies have suggested an unfair narrative constructed dominantly by the wealthier white residents regarding environmental

justice concerns in the city (Long, 2016; Mueller & Dooling, 2011). Due to procedural injustice, this has led to the constant negligence of green amenities concerns in the city's east side.

Historical development and conservation efforts have focused on Austin's West side. Therefore, it might cause problems when analyzing the whole city's spatial patterns without considering its existing spatial component effect (Long, 2016; Mets et al., 2017). The grassroots environmental justice group in East Austin started to advocate for a better environment in the early 1990s and successfully removed the Holly Street power plant. Around the same time, Austin branded itself as a green and sustainable development leader. Therefore, the new city council that supported the environmental movements started the neighborhood planning process to allow East Austin residents more say in their land-use decisions. However, the later city-wide proposal of Smart Growth proposed by the same council designated East Austin as a desired development area overpowered the previous rights given to the residents and made the entire area prone to displacement, despite the Parkland Dedication Ordinance (Connolly & Lira, 2021; Garcia-Lamarca et al., 2021; Long, 2016). In comparison, West Austin, designated as a preservation area, was protected under this proposal and has seen fewer demographic changes. The procedural injustice embedded in the city-wide political decisions has made the East Austin residents vulnerable and susceptible to land-use change, especially when big development projects come in with their mandated dedication to parkland.

Therefore, the mixed effect of the historical land-use policies, zoning regulations, city council governance structure, and the adverse rebound effect from environmental justice movements might still influence the current urban planning decisions. Notwithstanding the apparent environmental justice triad embedded in the unjust UGS provision, it is imperative to understand the complicated, multi-faceted factors contributing to this inequity. Some studies

argue that Austin's greening agenda utilizes UGS as a branding tool to achieve economic development. This study focuses on the Environmental Justice perspective manifested through the interrogation of the developmental pattern of UGS. By utilizing mixed methods to analyze data through the Environmental Justice lens, this study provides a holistic understanding of how inequitable UGS development is unveiled in medium-sized cities in the US.

1.3 Structure of the Dissertation

The primary goal of this dissertation is to understand where the UGS inequity is present and how multi-faceted factors contribute to the UGS inequity over time. In addition to examining such association from a spatial perspective, this dissertation investigates the longitudinal impact of multi-faceted factors on urban green space accessibility. Chapter 2 provides a literature review that lays the theoretical foundation of the Environmental Justice Framework in UGS study and how the current UGS development is associated with various factors. Chapter 3 explores the city-wide spatial pattern of UGS distribution in Austin, TX. It utilizes cross-sectional data to examine how identified variables, including race, income, educational attainment, age, and housing factors, impact UGS accessibility at the census block group level. Chapter 4 asks the When and How questions: How did UGS accessibility change in Austin, TX, over time? It builds upon Chapter 3 and further explores the longitudinal effect of how changes in the previously identified variables are associated with changes in UGS accessibility for each area. Chapter 5 considers the longitudinal impact of Procedural Justice, one of the three pillars of the Environmental Justice Framework, on the spatial distributional pattern of UGS accessibility.

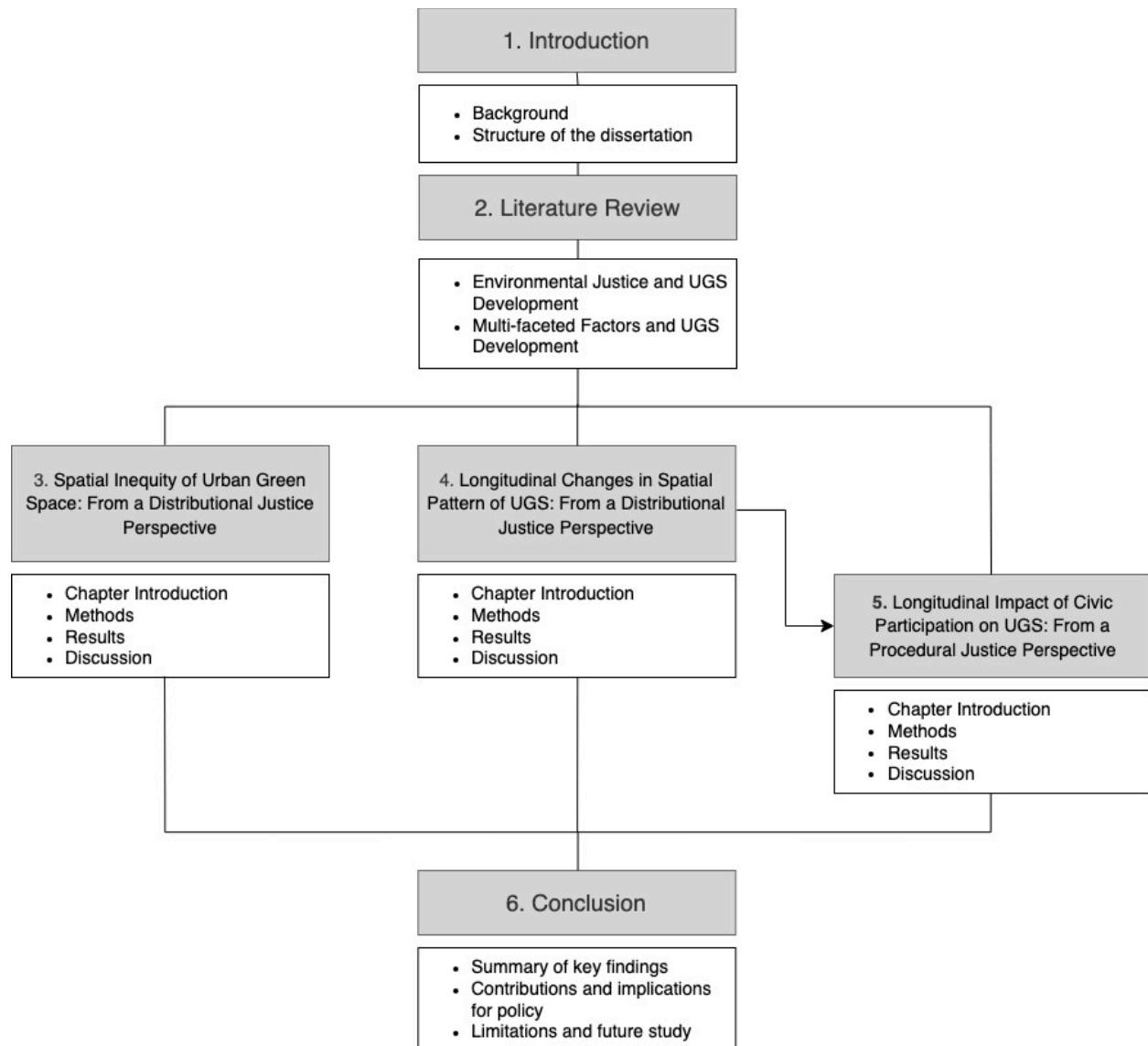


Figure 1.2. Structure of the Dissertation

Chapter 2 - Literature Review

2.1 Environmental Justice Framework and UGS Research

2.1.1 Multiplicity in Environmental Justice Framework

The Environmental Justice (EJ) movement started in the 1970s and 1980s, with grassroots activists in the United States investigating the relationship between the dumping sites of toxic wastes and the groups of people living nearby (Boone et al., 2009; Holifield, 2015). Empirical studies implied an association between the distribution of environmental hazards and racial-ethnic minority neighborhoods (Bullard, 1990; Mohai & Bryant, 1992; Bolin et al., 2002). The original focus of environmental justice was soon enriched and expanded on by scholars from different fields to include ecological goods, such as green space, public transportation, fresh food, and sustainable development (Agyeman & Evans, 2004; Schlosberg, 2013).

Environmental Justice built its theoretical foundation on the broader political theory of Justice; however, the definition of this movement goes beyond the superficial understanding of both the ‘environment’ and ‘justice’ (Schlosberg & Collins, 2014). From early on, environmental justice movement activists have been rejecting the mainstream and mainly white narrative of the definition of ‘environment,’ as it focuses on the wilderness and the absence of people who work, live, and play in it (Schlosberg, 2013; Wright, 2011). This is perhaps an imperative move in distinguishing the movement from then mainstream environmental organizations’ articulations, and this departure from the mainstream might have explained the later success in raising awareness among marginalized people. At the same time, this departure challenges the mainstream thoughts on the separation of humans from the non-human world, and the inclusion of people in the ‘environment’ at the same time expands on the topics and fields to be analyzed for future study (Schlosberg, 2013; Wright, 2011).

It is argued that the ‘Environmental Justice’ concept is both complex and plural. The critiques from the Native American community on the lack of recognition of their culture, spirit, politics, and economy, as well as the struggles of African American and Hispanic communities’ adjacency to environmental hazards, jointly call for the power-related procedural, self-awareness-related recognitional, and self-determining agency related capabilities embedded in the environmental justice movement (Wright, 2011). David Schlosberg synthesizes works by scholars, such as Nancy Fraser, Iris Marion Young, and John Rawls, among others, of the political theory of Justice. He argues that in addition to the commonly accepted distributive principles of justice, the processes of recognition, procedure, and capabilities should also be considered (Schlosberg, 2007). Other studies have proposed to extend the research focus to include scalar parity, globalization, development, and class-based struggle, among others (Cotton, 2018; Mohai et al., 2009; Walker, 2009b). In addition to the multi-layered meanings of ‘Justice,’ it is imperative to acknowledge the multifaceted forces that potentially contribute to environmental injustice. Therefore, making connections between these two dimensions is helpful in fruitfully analyzing the movement theoretically and empirically.

The EJ framework has examined various inequitable issues related to the “environment.” Instead of seeking a universal definition of Environmental Justice, as many researchers have attempted, we should embrace and be explicit about its multiple dimensions and pluralistic interpretations (Holifield, 2001). It might be helpful to step back and understand what “environment” means in our research context. Schlosberg argues that the “environment” should not only be conceived as the wilderness or the “big outside” but rather the environmental conditions with which people interact (Schlosberg, 2007). This notion is especially important for researchers as the environment we interact with daily is not deterministic. In other words, it

encompasses more than just the physical and tangible environmental characteristics; it also encompasses socially constructed ones (Corburn, 2017a; Walker, 2012a). This implies a holistic perspective where a single factor is insufficient in understanding the mechanisms that produce environmental outcomes, and so is the negligence of contending the interrelatedness of spatial characteristics in empirical analysis. This argument also applies to the Environmental Justice framework, where its multiplicity should be acknowledged. For instance, Corburn argues that we should recognize the overlapping nature of one's identity to understand how discrimination and inequity are shaped (Corburn, 2017a). Pellow contends that various forms of social inequality and oppression intersect and lead to the oppression of the non-human world, emphasizing the multiple social categories of difference entangled in the production of environmental injustice (Pellow, 2016).

With the understanding of multiplicity, Radical Environmental Justice was proposed as a framework in contrast with its liberal tradition by John Rawls (Svarstad & Benjaminsen, 2020). Although some researchers distinguish between radical environmental justice frameworks and other types, these various forms depart from their origin with significant expansion in research scopes, adoption of progress in justice theory, and engagement with different frameworks, to be also called "radical." This is because many of the studies that utilized the extended "radical environmental justice framework" inevitably employ research lenses such as decolonization, power relations, globalization and scale, and engagement with the non-human world, among others, that are considered separate frameworks in their respective topics; For example, injustice in climate change and biodiversity conservation (Day, 2010; Lecuyer et al., 2018; Bulkeley et al., 2014; Fisher et al., 2018; Pellow, 2016; Pulido & De Lara, 2018).

2.1.2 Beyond Distributional Justice

The first kind moves beyond the traditional domains of geography on the distributive patterns of location of inequity and calls for understanding deeper institutional and structural conditions (Holifield, 2015; Schlosberg, 2013; Schlosberg, 2007). David Schlosberg, therefore, compiles a more holistic and pluralistic conception of EJ to include Iris Marion Young's procedural notion, Nancy Fraser's misrecognition, and Amartya Sen and Barbara Nussbaum's capabilities approach (Holifield, 2015; Sikor et al., 2014; Walker, 2009a; Schlosberg, 2007). The multiplicity understanding beyond distribution does not mean distancing the framework itself from distributional analysis; on the contrary, studying such focus is inherently a central task for understanding the structural conditions that produce the injustice through empirical evidence (Svarstad & Benjaminsen, 2020).

2.1.2.1 Procedural Justice

Many early studies on EJ issues have focused on the distributive patterns regarding the material aspects of the process using a quantitative method (Svarstad & Benjaminsen, 2020). Iris Marion Young, however, critiqued this paradigm in that the liberal theory should be in search of how dynamics of domination and oppression have generated and sustained the inequitable distribution. Her focus on procedural justice revolves around participation and inclusion during decision-making, especially for marginalized populations. Relating to UGS research, the lack of procedural justice is seen directly through the enclosure of information, access, and power for the local communities. The exhibition of procedural justice in UGS planning means considering the degree of participation in the planning process and the form of governance structure it relies on (Boulton et al., 2021; Derkzen et al., 2017; Walker, 2009a). Injustice might also exist when ideas

and perspectives from, for example, communities cannot freely flow across institutional boundaries, causing constrained networks of interaction or deliberation (Walker, 2009b).

2.1.2.2 Recognitional Justice

Misrecognition is another aspect that scholars have identified as missing from mainstream EJ research. Social subordination is institutionalized through cultural domination, non-recognition, and disrespect, leading to misrecognition, where affected populations lack the necessary channel to voice their sense of justice in the face of more powerful actors. At the same time, they diminish their roles in formulating discourses and narratives that make sense when confronted with environmental injustice (Svarstad & Benjaminsen, 2020; Fraser, 2000). In practice, grassroots EJ activists expanded the sphere of EJ to include marginalized people's spiritual and cultural traditions (Holifield, 2001). Several questions need to be asked: Who receives justice? Recognition by whom? For what purpose? Misrecognition, just like procedural injustice, is inherently related to power relations and the production and distribution of knowledge (Álvarez & Coolsaet, 2020; Holifield, 2015; Svarstad & Benjaminsen, 2020). The perception, narration, and evaluation of injustice are susceptible to subjectivity and the agency, especially for the marginalized population, to voice such concerns (Álvarez & Coolsaet, 2020; Pulido & De Lara, 2018; Svarstad & Benjaminsen, 2020). In UGS research, misrecognition centralizes how local context is manifested, both culturally and spatially. However, the existing UGS scholarship on recognitional justice is still scarce (Calderón-Argelich et al., 2021). The potential directions include how historical and racialized legacies of unequal access to UGS were translated in the first place, whose values are prioritized historically and contemporarily, and

how acknowledging recognitional justice encourages participation and stewardship in promoting equitable access for marginalized populations.

2.1.2.3 Capabilities Approach

The last part engages with Sen's capabilities approach, which centers on enabling people to live based on their values (Svarstad & Benjaminsen, 2020; Schlosberg, 2007). Schlosberg adopted a more radical perspective that focuses on the community's collective benefits. However, limited theoretical and empirical research has been done using the capabilities approach, especially in the UGS scholarship. To a certain extent, it conflicts with recognitional justice because the former tends to project communities as homogenous groups that ignore their inherent diversified nature (Svarstad & Benjaminsen, 2020).

2.1.3 Beyond Localized Scales

The second kind of multiplicity understanding concerns scale. Previously, environmental justice as a framework put much of its emphasis on localized environmental issues, such as toxic and waste disposal. Over the years, it has carried identity beyond political and cultural boundaries and expanded across spatial scales (Pellow, 2016; Schlosberg, 2013; Walker, 2009b, 2012c). Characterized by the different stakeholders' notions of Justice in a specific context, the effectiveness of environmental justice policies varies (Sikor et al., 2014). While equitable distribution remains critical in achieving environmental justice, it must also be understood from a larger social and historical context when traveling across scales (Swyngedouw & Heynen, 2003). Relationships between government agencies, civil society, and nature are significantly reconstructed across geographical scales under neoliberal capitalism. Thus, the governance

structures and decision-making mechanisms affect the delivery of environmental justice policies (Perkins, 2010). David Harvey's classic connotation of 'spatial fix' argues the use of fixed capital in the built environment to relieve the pressure of overaccumulation (Ekers & Prudham, 2017; Harvey, 1996). The sunken capital takes an inert form of fixation in a specific locality, indicating a scalar problem (Ekers & Prudham, 2017). There are two main types to understand how environmental justice moves across scales.

2.1.3.1 Moving Horizontally Across Scales

Horizontally, environmental justice transfers its frame in new places and cultures, emphasizing new issues and constituencies and framing new challenges such as climate justice and sustainable materialist approaches to address environmental conditions (Schlosberg, 2013; Walker, 2012b). Within the United States, UGS research has evolved beyond distributive justice to include historical investigation of institutional practices by the state and corporate actors. Internationally, through deliberate transnational networking between civil environmental justice activist groups, the framework adapts to new cultural and political settings and contextualizes local struggles to avoid generalized conclusions (Walker, 2012a). Though with limited evidence, UGS scholars should scrutinize the transposed concepts such as racism from the US and acknowledge the colonality of knowledge where the possible conceptions of justice, culture, and identity are based on Western ideology rather than the South itself (Álvarez & Coolsaet, 2020; Martinez-Alier et al., 2016). Fraser, in agreeing with Axel Honneth and the reworking of David Scott's writing, argues that the "neoliberal multiculturalism" way of recognition is far from the true emancipation and decolonial justice that positively incorporate "love, rights, and solidarity" into the "practices of techniques of the self" (Fraser, 2018).

2.1.3.2 Moving Vertically Across Scales

Vertically, environmental justice scales up to include indigenous, localized issues and national, international, and global injustice (Walker, 2012a). Nancy Fraser argues that the injustice, including poverty and inner-city and rural area abandonment, is due to the ongoing globalization and neoliberal process. It is done through capitalist market integration, the erosion of nation-state sovereignty in the face of transnational institutions of governance, and the displacement of the working class. The mobilized capital and this process have destroyed local cultures (Fraser, 2009). The upscale of research scope in UGS literature is very much in line with Fraser's previous work that stresses the importance of representation (recognition and procedural justice) of marginalized populations victimized by the actions of state and multinational corporations during the decision-making process (Occhiuto, 2018; Fraser, 2009).

2.1.4 Framing New Challenges

The third kind of multiplicity concerns environmental justice's engagement with other frameworks in framing new challenges and shifting methodologies. The intersectional and relational notions suggest that environmental justice research on UGS is not a single snapshot at the neighborhood scale but a complex mixture of spatial characteristics and the result of endogenous and exogenous processes in a longitudinal manner across multiple scales (Corburn, 2017a; Hindman et al., 2022; Pellow, 2016; Walker, 2009b, 2012a). Over the years, environmental justice has shifted its research trajectories to include radical political economy, critical social theory, and normative political theory perspectives in analyzing inequity (Holifield, 2001). It is argued that the UGS inequity deals with the spatial distribution and the

unevenness of the socio-spatial distribution of vulnerability and well-being. The previously dominant focus on the quantitative distributive pattern analyses neglects the theoretical insights of social production of geographical scale (Boulton et al., 2021; Holifield, 2001; Walker, 2009b). In addition, the cross-sectional study might miss the opportunity to examine the subjective factors in explaining broader theories of recognitional and procedural justice in comparison to the historical investigations on the institutional and structural aspects that travel across temporal and spatial scales in UGS development (Corburn, 2017a; Hindman et al., 2022; Holifield, 2001; Svarstad & Benjaminsen, 2020). Lastly, the integration of Community-based Participatory Research, community mapping, and Right-based and Need-based strategies are proposed to engage communities in the research process, diffuse power among partners, and incorporate recognition of local cultures to create an equitable way in the knowledge production and sharing within UGS research (Corburn, 2017b; Holifield, 2001; Walker, 2012c).

2.1.5 Criticism of the EJ Framework

Despite the expansion of Environmental Justice from its original form, the new framework has limitations. First, procedural injustice has been criticized for not being explicit about utilizing power theories to discern what form of power dynamic, for instance, economic restructuring or cultural practices, is the main contributor, despite its acknowledgment of power dynamics played in the production of injustice (Svarstad & Benjaminsen, 2020). It is also argued that the lack of power analyses showed the need for an anti-static perspective that posits thinking and acting beyond traditional actors, such as the state, to understand how environmental justice deals with the fundamental ways that political power is distributed and wielded (Pellow, 2016; Pulido & De Lara, 2018). Second, in practice, recognition might get lost or ignored in the context

analysis, and scholarly work might suffer from coloniality that runs the risk of creating new injustice due to concepts not being transposed correctly. Researchers are encouraged to scrutinize their positionality, unpack complex genealogies of social movements, and challenge the actors who govern knowledge production (Álvarez & Coolsaet, 2020; Pulido & De Lara, 2018; Svarstad & Benjaminsen, 2020; Foucault, 1991). Lastly, the welfare approach at the level of communities of capabilities contradicts Fraser's recognition, which demands the actual needs to be represented and the delineation of individual differences. It is suggested that the researcher employs a historical perspective to provide a clear picture of how injustice is enabled in the first place to understand the underlying structural effects (Svarstad & Benjaminsen, 2020; Fraser, 2000).

2.1.6 EJ's Intellectual Cross-fertilization with Other Research Frameworks

Some early starting research foci of Political Ecology include the relationship between producers and market, commodified labor and land, and class struggles (Watts, 2015). The dialectic relationship between society and nature is derived from the Marxist notion that the 'Environment' is constructed and seen differently among different classes (Watts, 2015). According to David Harvey, the environment we see, interpreted differently across the population, is the production of capital's 'ecological' function. The environment has gone through the privatization and commodification processes of the capital, and their dialectic relationship can be understood as being produced and reproduced (Harvey, 1996). Political Ecology, traditionally focusing on rural areas in the Global South, has extended its research to the urban settings in the Global North in recent years, as well as its new foci on the urban

environment in addition to water and urban infrastructure, such as parks and open space (Gandy, 2022).

As we are seeing a fast wave of urbanization globally, Urban Political Ecology's (UPE) role as a theoretical approach and framework to understand the social production of urban nature is both insightful and necessary (Nik Heynen, 2014). UPE's understanding of 'cities' moves beyond the traditional argument that the cities are separable from 'nature' and contends with a metabolic process that involves the commodification of such transformation of the biophysical environment (Gandy, 2022; Nik Heynen, 2014; Tzaninis et al., 2021). UPE's expansion of the notion of metabolism derived from Marxian theory provides a theoretical and empirical ground for understanding the interconnected social-urban processes that result in uneven development (Nik Heynen, 2014; Kitchen, 2013). This metabolic dynamic has been used to explain the circulation of capital within the urban nature. UPE, also seen as a theoretical lens, incorporates ecological processes and interweaving social, political, and economic factors to provide an integrated approach to understanding uneven outcomes, such as the inequitable distribution of UGS (Castree, 2000; Nik Heynen, 2014; Keil & Desfor, 2003; Swyngedouw et al., 2002).

Although at the research core, both Environmental Justice and Urban Political Ecology care deeply about marginalized populations and inequity, in practice, the two research concepts have not formed an organic collaborative relationship (Holifield, 2015; Svarstad & Benjaminsen, 2020). One common critique from political ecology is the heavy focus of environmental justice research on empirical evidence but scarce in theories (Swyngedouw & Heynen, 2003). Early research on EJ was heavily focused on the relationship between human health and environmental conditions, most of which were done quantitatively (Holifield, 2015). The practical inferential analysis based on proximity has left limited space for EJ to move beyond the theoretical arena.

However, as discussed previously, scholars such as Nancy Fraser and David Schlosberg have challenged the long-time focus on distributive patterns and called for recognition and procedural justice in the normative theories of Environmental Justice (Dahl et al., 2004; Schlosberg, 2013). Lately, however, Environmental Justice research has started to emphasize procedural and recognitional justice rather than traditional distributional, which makes it more suitable to see the collaboration between EJ and UPE.

Despite the critique, according to Swyngedouw and Heynen, Marxist Urban Political Ecology still has the potential to connect with Environmental Justice, especially when considering its intertwined social, political, and ecological processes in producing new, often uneven, urban development (Swyngedouw & Heynen, 2003). For example, in Milwaukee, the cross-tabulation of the spatial distribution of tree cover and the socio-demographic and socio-economic data reveals the inequitable capitalist production of the urban forest. This has resulted in unequal access to socio-ecological conditions by privileged and marginalized groups (N. Heynen et al., 2006). What brings the terrain of Urban Political Ecology and Environmental Justice together, in this case, is the argument on how the production of urban forests is understood as commodities produced by human labor power, which is at the root of the tension between capitalist production and consumption (N. Heynen et al., 2006; Kitchen, 2013; Svarstad & Benjaminsen, 2020). Therefore, Marxist Urban Political Ecology is fruitful in expanding the framework of Environmental Justice research and excavating the underlying conflicts of uneven relations under capitalism.

Additionally, the social construction of the city-nature binary was reinforced when Landscape Architecture as an intellectual discipline started transforming the biophysical urban environment to bring nature back into the city (Loughran, 2017). In the United States, this

historical process has its centrality around racial inequalities where both cultural and spatial dimensions were racialized during the development of city-nature relationships (Gandy, 2022; Loughran, 2017). The urban environment has everything to do with human activities intrinsically related to urban ecological processes (Harvey, 1996). From a critical historical perspective, the construction of urban parks can be seen as the capitalization of nature—the deployment of plants in urban settings to combat the inner crisis tendencies of capitalism (Birge-Liberman, 2010). For instance, the Paseo in Kansas City was constructed to divide racial and economic classes spatially. The beautification and reduction of the congested metropolis at the same time solved spatialized social problems or tensions. Similarly, the Chicago South Park transformed the site’s original landscape to appeal to its racialized considerations (Loughran, 2017). The vacant lot in Detroit transformed the economic, social, and political crisis of aesthetic decline into gardens by utilizing ecological solutions.

2.1.7 EJ Framework and UGS Literature

2.1.7.1 Distributional Justice in UGS Literature

Access to greenspace varies, ranging from views of greenery through windows to living adjacent to parks (Ulrich, 1984). Urban green space refers to parks as the main type, but what about waterfronts, agricultural land, and street trees? Different studies have taken different perspectives. For example, a study in Canada involves adjacent waterfront greenways in the overall greenspace to measure the accessibility (Ngom et al., 2016); Others either remain somewhat vague or stick strictly to urban parks. Another potential variable is how to define the boundaries of greenspace or where to stop. A study in Kansas City utilizes a portion of the greenspace because it falls out of the census tract area, which raises the question of whether the

acreage per person would be impacted since people have access to more greenspace in this case (Vaughan et al., 2013). Most articles have utilized a metric that captures the nearest green space to assess accessibility.

In contrast, another metric called “Cumulative Opportunities” provides a framework to include adjacent areas as well (Coutts et al., 2010). In terms of the size of the green space, different studies take different stances. Some argue that parks should only be included that exceed specific acres in size; others tend to include smaller ones as well. The Attention Restoration Theory and the Stress Reduction Theory indicate that even small greenery can help reduce psychological stress; therefore, achieving a certain consensus or having a clearer definition of accessibility in the field seems necessary. Three key categories are identified to assess park accessibility: Park Proximity, Park Acreage, and Park Quality (Rigolon, 2016).

Distance is usually the core determinant when assessing proximity to greenspace. However, there is no consensus in the field regarding the size of green space. Some articles argue a 300-meter threshold (Mears & Brindley, 2019), while others vary (Boone et al., 2009; Rigolon & Flohr, 2014). The methods used to quantify the proximity vary from case to case, which impacts the empirical findings of each study and its potential implications. For example, a study uses Google Maps API to determine the preferred routes based on walking distance as an indicator for the assessment (Zhou & Kim, 2013). Another study, however, identifies driving time instead of walking, claiming that the city sprawl nature and vehicle-dependent characteristics are the determinants for the criteria (Dai, 2011). Considering that vehicles might not be available for those of lower socioeconomic status, some studies using population-weighted distance (PWD) might be questionable in terms of their implications (Wen et al.,

2013). Most studies, on the other hand, utilize a defined threshold as a critical distance to evaluate the proximity of parks (Boone et al., 2009; Rigolon & Flohr, 2014).

There is a mixed result regarding who has closer proximity to parks. For instance, some studies report that people of lower socioeconomic status (SES) or people of color have closer proximity than those who are in higher SES (Boone et al., 2009; Johnson-Gaither, 2011; Mears & Brindley, 2019; Wen et al., 2013; Zhou & Kim, 2013). Some report that people with medium to high SES have closer proximity to parks (Dai, 2011; Ngom et al., 2016; Rigolon & Flohr, 2014). Others either show no significant differences or do not touch on this issue (Comber et al., 2008; Hughey et al., 2016). The numeric result indicates that people of color tend to have closer proximity to parks than whites if they do not consider the size and quality of the parks, and there is no significant difference regarding socioeconomic status. However, some studies show a discrepancy in terms of the location of the parks. A study shows that people of lower SES who are closer to parks tend to live in inner cities or suburban areas, while the reverse result is found in rural areas (Wen et al., 2013). However, recent studies on downtown gentrification might challenge this trend in the future (Checker, 2011; Rigolon & Németh, 2018b).

Park acreage as a determinant of whether greenspace can provide amenities has seen different paths. As SRT and ATR suggest, there is no lower end in terms of size for green space to provide health-related contributions. However, if an organized football game needs to take place, size does matter. For example, a study in Lithuania captures parks larger than 1 hectare, with a buffer threshold of 100, 300, and 500 meters, and concludes a positive relationship between access to green space and health outcomes (Grazuleviciene et al., 2015). In another study, the researcher sets the size threshold to be larger than 0.25 hectares and observes a positive association between greenspace and life satisfaction (Krekel et al., 2016). Similarly, a

study in Germany identified the cut-off size to be larger than 0.5 hectares and found no positive association between proximity to parks and healthy aging (Vogt et al., 2015). However, many of them identify a minimum size of the park. The various studies show inconsistent results. However, the study in Baltimore, Maryland, proposes the importance of calculating park congestion, which helps explain why some of the studies might choose to employ a cut-off size (Boone et al., 2009).

In general, most studies suggest a general positive association between higher SES and more park acreage. Specifically, one study reports that people of lower socioeconomic status have more acreage than those of higher SES (Vaughan et al., 2013). While others have suggested that whites are more likely to enjoy more acres of green space (Boone et al., 2009; Comber et al., 2008; Duncan et al., 2013; Johnson-Gaither, 2011; Kabisch & Haase, 2014; Sister et al., 2010; Wen et al., 2013). Among these studies, some also suggest that medium to high SES people are more likely to enjoy a better acreage of green space in addition to being white (Boone et al., 2009; Sister et al., 2010; Wen et al., 2013).

Though less studied, park quality could be as important as park quantities. Although limited studies have directly linked health outcomes with park qualities, a general thought is that they are positively associated. However, what factors are fundamental in deciding the quality of a park? We might be able to pick up some hints from previously discussed benefits of greenspace. One possible idea is to look at park congestion, which represents the visitor density of the park. To restore stress, it is hard to imagine that a crowded public park would offer such amenities. Similarly, it is hard to support physical activities in a park with heavy traffic. Another idea is to evaluate the potential programs of the park since interpersonal interactions could

increase social cohesion, which will lead to better mental health. One of the core attributes of parks is vegetation; it provides aesthetic value and reduces heat and noise.

Most studies suggest a positive association between park quality and medium-high SES (Bruton & Floyd, 2014; Jenkins et al., 2015; Rigolon & Flohr, 2014; Sister et al., 2010; Vaughan et al., 2013; Zhou & Kim, 2013). The majority of the studies have focused on the quantity of facilities that parks can provide, such as picnic tables, gathering areas, and play courts, among others. One study identified aesthetic value as being associated with mid-high SES (Vaughan et al., 2013). Some studies link higher tree canopy with mid-high SES (Rigolon & Flohr, 2014; Zhou & Kim, 2013). In addition, one study suggested fewer incivilities are found in mid-high SES parks (Bruton & Floyd, 2014).

2.1.7.2 Procedural Justice in UGS Literature

Affluent and middle-class buyers start to pour their investments into a previously undesirable community when the potential value of that community becomes evident and attractive for the middle and higher end of the housing markets. Studies often perceive that an increase in rent price would accompany this process due to the constant influx of wealthier residents in the once undesirable community, which is due to their need for investment and improvement of living conditions. As a result, often, the long-term residents, especially the poor and marginalized ones, will be displaced due to the constant increase in rental and sale prices. Researchers define this whole process of socio-cultural transition as gentrification (Anguelovski et al., 2018). Recent studies that examine how urban sustainable planning and re-naturing strategies are incorporated into the public-private redevelopment processes have brought to the

attention of many scholars. Green gentrification is the name thus given to investigate the extent of green space that acts as a potential driver for the displacement of residents.

In a case study of the restoration of a historically polluted and former industrial community in Greenpoint, Brooklyn, that also lacks parks, the authors conducted semi-structured interviews with core players in the process of countering environmental gentrification due to the site being selected as an EPA Superfund location. The site was able to maintain its majority of working-class residents in the face of zoning changes and the sovereign state mandate from local government. However, it is argued that the result was due to the strong social connection within the neighborhood of old residents and the new gentrifiers with constant input from local activists. This approach of “Just Green Enough,” which advocates for just enough done to improve the quality of life for existing residents but not so much to attract additional capital, was argued to be potentially possible in resisting the process of environmental gentrification (Curran & Hamilton, 2013).

Despite the seemingly positive result of Brooklyn’s study, many others have shown negative results, like what Anguelovski et al. (2018) have found in their study. These studies cover a variety of park types, from big restoration projects to completely new ones. In a city-wide quantitative study done in Barcelona, the researchers found that the historical lack of parks in the 1970s spurred the construction of newer parks and caused displacement of long-term residents. The authors conclude that direct negotiation took place between the government and the developers without input from neighborhood groups in different development stages. Olympic Games, real estate and tourism appeal, and the redevelopment of former industrial land were identified as the policies that facilitated the process of environmental gentrification (Anguelovski et al., 2018). In another study, residents and businesses near High Line Park in

New York City were priced out and replaced by residents of luxury housing and retailers. Public inputs were included in the planning process; however, the mayor's office drowned out their voices and vocal celebrities to attract wealthy tourists (Jo Black & Richards, 2020; Loughran, 2014). In a comparison study between Chicago and Seattle, the researchers found evidence that displacements were happening before the renewal, and the current communities were also afraid of such. Despite residents' active involvement and coherence in all debates to resist the trend of being displaced, it is argued that this effort is constrained by the neoliberal discourses of economic development and greening to benefit the elites (McKendry & Janos, 2015). A study done in Seattle shows an exclusion ordinance initiated by the government, and the park redesign only included housed residents and ignored the sheltered and low-income residents that largely encompassed the parks (Dooling, 2009). Similarly, a study in Montreal, Canada, shows a significant social and physical transformation of the residential areas of a historically derelict industrial neighborhood with limited green spaces and a high poverty rate (Bélanger, 2012). Both the Seattle and Montreal cases show how the governmental policies have ignored the need for affordable housing in the region during the planning processes and the lack of engagement of certain groups of people.

2.1.7.3 Recognitional Justice in UGS Literature

It is argued that recognitional injustice is represented both socially and spatially for certain groups of people. It is realized through the misrecognition of places, affecting the misdistribution of urban amenities (Verheij & Corrêa Nunes, 2021). Therefore, the less-represented groups are often in search of a more inclusive, hybrid, or multi-actor governance

structure to help advocate for their rights. However, this hybrid way of governance is sometimes criticized for its messiness, such as scale differences and difficulty in collaboration.

It is argued that the complexity of scales includes three aspects: spatial, sociopolitical, and temporal (Lemos & Agrawal, 2006). Regarding spatial scales, not considering levels of scales not only mixes the causes and consequences of environmental problems but also adds difficulty to management beyond conventional physical boundaries. Socio-politically, the difficulty lies in the fragmented representations of institutionalized decision-making from different levels of governance. Lastly, temporal scales ignore the potential consequences that current actions might have in the long run. It is argued that the collaborative way of governance might create challenges, including not necessarily presenting a fairer game for unequal power distribution under the old system, potential unfair participation from all stakeholders, the transfer of power to different levels might decrease the effectiveness of governance compared to the old system, and the undesirable consequences, such as increased commodification of nature and more exploitation, in search of efficiency (Lemos & Agrawal, 2006). Similarly, it is argued that the collaboration between different sectors has caused inconsistency regarding boundaries, decision-making processes, and goals, a scalar mismatch due to subjective standards of different actors, and an imbalance of power distribution that gives priority to certain areas over others, thus changing the interaction within, and skepticism regarding the government's role in changing its dynamic relations with other actors (A. Cohen & Bakker, 2014). Lastly, although a decentralized or hybrid governance structure has been in place for a while, some studies argue that it does not necessarily indicate a dispersed power distribution among actors, and some are still underrepresented. This is due to the uncertainty of different social actors and institutions to

respond and adapt to their interaction in both vertical and horizontal directions (Reed & Bruyneel, 2010).

2.2 Multi-faceted Factors in Shaping UGS Development

Despite the equity goals set by many greening policies, the development of UGS in some neighborhoods has resulted in the displacement of long-time residents, furthering the inequity those policies originally targeted (Immergluck & Balan, 2018; Joassart-Marcelli et al., 2011; J. R. Wolch et al., 2014). In researching this inequity, some studies examined procedural injustice, such as the exclusion of marginalized communities from decision-making processes, displacement of residents, and policies that transmute environmental externalities into profit opportunities (Checker, 2011; Curran & Hamilton, 2013; Dooling, 2009; McKendry & Janos, 2015). Other studies that emphasized distributional injustice demonstrated the affected areas' potential economic and demographic spatial changes. This includes increased adjacent property value and rent prices, increased tax payments, new employment opportunities, and the influx of more affluent residents (Anguelovski et al., 2018; Jo Black & Richards, 2020; Rigolon & Németh, 2019).

In addition to environmental justice concerns in UGS research, it appears also important to understand the interrelated political, economic, and cultural social processes that direct the outcomes of urban environmental change (Nik Heynen, 2006). In the meantime, inequitable access to UGS represents the uneven socio-environmental transformations steered by the socio-ecological and political-economic processes within urbanization (Swyngedouw, 2015). Some argue that this uneven transformation is the production of the “commodification of urban nature.” In response, the distribution of UGS is therefore dictated by the political-economic

processes (Nik Heynen, 2006). Together, the dialectic relationship between multi-faceted forces has led to inequitable access to urban amenities. At this point, understanding such interrelated relationships becomes important to direct future policy reforms to achieve better social justice.

The apolitical rhetoric of the benefits that UGS can provide is perpetuated widely and sometimes understated by researchers and policymakers (Angelo, 2019; Anguelovski et al., 2020). As research on the benefits of UGS has expanded exponentially over the years, many studies have tried to explore the relationship between theoretical knowledge and empirical evidence (Hunter et al., 2019; Lachowycz & Jones, 2011; Lovell et al., 2014). Recent studies have shown the potential risks of inequitable green space distribution, especially for its impact on marginalized populations in accessing urban amenities, and people have started to ask how this inequity is formed. UGS literature has put much of its emphasis on spatially distributional equity and has shown fruitful results in revealing the vulnerability of marginalized communities and people of color. This traditional distributional pattern research has gradually expanded into studies that examine procedural and recognition justice related to UGS inequity with the development of normative justice theory (Holifield, 2015). These studies not only enrich the empirical evidence from previous distributive inequity research but also started to explore the enduring effects of reproducing uneven urban development from social, economic, political, and ecological perspectives (Curran & Hamilton, 2013; Dooling, 2009; Jo Black & Richards, 2020; Loughran, 2014).

The normative “green is good” assumption has attracted increasing attention among critical research in examining the consequences of the added values of UGS, which include social, economic, and political ones (Angelo, 2019). Closely related to the Environmental Justice movements, the intellectual work that focuses on the production of uneven social-natural urban

environments revealed its connection with using “greenness” as a monetization tool for growth (Angelo, 2019; Knuth, 2014; Rosol et al., 2017). Concepts such as “sustainability fix” and “spatial fix” have been proposed to explain how UGS is used to target environmental goals set by the neoliberal environmental governance that concerns both urban entrepreneurialism and the pro-growth strategy (Angelo, 2019; Birge-Liberman, 2010; Harvey, 2001; While et al., 2004). At the same time, these governance strategies are historically interlinked with promoting citizenship while retaining middle-class values (Perkins, 2010). For example, the City Beautiful movement showed how commercial interests were in line with civic concerns; the beautification plans also transformed the physical urban environment into a green space that has allegedly retained the connection between the unique and naturalistic features of the social and cultural values of the city to its locale (Bachin, 2003; Perkins, 2010). The connection between economic and social forces influencing UGS development can also be seen in contemporary discourse where “parks-as-social-healers” is seemingly overstated. Similarly, the formal and informal legacy from previous social-environmental relationships were kept, which prevented the mitigation of disparities within the socio-spatial and ecological consequences in the city’s urban environments (Brownlow, 2006; Mullenbach, 2022).

Lastly, UGS development has been intrinsically political, where political and economic processes often contribute to its production. For instance, in Milwaukee, the city’s Urban Forestry Department is responsible for the supervision of urban forests on public land; however, due to the pervasive structural racial segregation and socioeconomic inequalities within the city, the urban forests on private property remained highly unequal (N. Heynen et al., 2006). In Austin, the historical power imbalance, contrasting environmental goals set by different administrations, and developmental asymmetries all contributed to the unequal access to UGS

between racial lines (Connolly & Lira, 2021). Similarly, Barcelona's "strategic urbanism" neglected the negotiation with neighborhood groups. Still, directly with developers, as well as the City Council's later efforts to combine public park design with economic development schemes that focused greatly on "Sustainability" that drew its resources from private funds, all led to the displacement and inequitable access to UGS of residents (Anguelovski et al., 2018; Saurí et al., 2009).

2.2.1 Profiting Urban Greening Agenda?

Some studies argue that growth is the key essence of a given locality's political and economic priority and that it operates as a "growth machine." These land-centered interests are achieved through the promotion by the local government for the growth of the entire city. One indication of success is a city's growing population, which symbolizes the expansion across all sectors of the activities (Cox, 2017; Molotch, 1976). Under the conceptualization of "City as a growth machine," various city elites, including lenders, political elites, and property owners, among others, formed the growth coalition that has fostered and benefited through the creation of nationally visible discourse that leads to economic development. The creation of such discourses is, therefore, to attract capital, investments, and skilled mobile laborers and to compete with other cities similar in size (Malecki, 2007). Due to stratified economic and cultural resources, public spaces have grown more inequitably in contemporary cities (Loughran, 2014). City elites are seeing increasing opportunities and common ground for incorporating municipal policies and ecological and cultural resources to boost economic development, for instance, from artist housing to urban parks (Lang & Rothenberg, 2017; Rigolon & Németh, 2018b; Strom, 2010).

2.3 Conclusion and Moving Forward

In summary, the Environmental Justice framework evolved from addressing distributive inequities at its roots to embracing the procedural, recognitional, and capabilities-based justice that requires a holistic approach to UGS research. Despite the mounting empirical evidence in UGS inequity research that reflects forces like racial disparities, other factors, such as theoretical disconnects, methodological concerns, and the under-researched impact of procedural and recognitional justice, also intersect with UGS development. In addition, complexities such as green gentrification, scalar mismatches, and neoliberal processes further complicate the goal of aligning UGS development with equity goals. Moving forward, researchers should emphasize confronting historical legacies, power asymmetries, urban growth machines, and anti-displacement policies to foster inclusive UGS planning rather than means of exclusion.

Chapter 3 - Spatial Inequity of Urban Green Space: From a Distributional Justice Perspective

3.1 Introduction

Cumulative evidence has shown the potential benefits of Urban Green Space (UGS) on human health and well-being (D. A. Cohen et al., 2007; Hunter et al., 2019). Greenspace accessibility, by definition, refers to the spatial proximity of one's home and commonly includes measuring distance, walkability, and traveling time from the available greenspace or park (Roberts-Gregory & Hawthorne, 2016). Other factors, such as park quality and park acreage, are generally considered to help explain the accessibility to urban green space (Rigolon, 2016). However, due to historical housing discrimination and residential segregation policies, greenspace and parks are not distributed equitably in the cities (Rigolon & Németh, 2018a). At the same time, greater investments in more privileged communities will make people of color and lower socioeconomic status likely to have even less accessibility to quality parks and green spaces, given the limited funding available and the competitive system to secure it (Casey et al., 2017).

The Environmental Justice movement started in the 1980s and focused primarily on the unjust exposure of ethnic minority communities to toxic environments, such as power plants and landfills (Boone et al., 2009). In recent years, a direction has shifted to focus on the distribution of urban amenities. Urban Green Space, as discussed before, provides a range of social, economic, health, and environmental benefits and is seen as an intervention by many studies to act as a “preventative medicine” to shape modern urban health (Corburn, 2015). Therefore, an equitable provision of urban green space falls into the bracket of the current environmental justice category, which can be defined as distributive justice. However, distributive justice is not

entirely enough to achieve environmental justice; there is also a need for procedural justice, which, when applied to urban green space provision, involves decision-making procedures to be fair and just.

3.2 Inequitable Access to UGS

3.2.1 Overview of Factors Influencing UGS Accessibility

Living in cities has multiple advantages, such as being closer to amenities and resources that promote a better lifestyle. On the other hand, densely populated urban environments can create environmental and social stressors. These stressors include air pollution, noise, lack of access to natural environments, and socioeconomic disparities (Lederbogen et al., 2011). The rapid ongoing urbanization and current predictions of climate change have put people who live in the cities, especially those of lower socioeconomic status, under a lot of stress (van den Bosch & Ode Sang, 2017). It is argued that proximity to green space will benefit residents by mitigating some of these negative challenges. However, the differences in variables such as race, ethnicity, and socioeconomic status have shown an unequal distribution of health and well-being status among the population due to unequal urban development, especially regarding income disparities (Jennings & Gaither, 2015).

3.2.2 Research Questions and Hypotheses

This part of the research aims to use novel spatial analysis methods to examine the inequitable UGS spatial distribution in Austin, TX. In this chapter, the following questions are addressed:

1. What are the leading factors contributing to Austin, TX's current UGS spatial pattern?
2. Do census block groups adjacent to each other show similar characteristics (spatial dependence) regarding UGS accessibility?

The following hypotheses were tested:

1. Areas with a higher median household income will have better access to UGS.
2. Areas with a higher percentage of white population will have better access to UGS.
3. Areas with a higher property value or rent price will have better access to UGS.
4. Areas with a higher percentage of the population with bachelor's degrees will have better access to UGS.

3.3 Method

3.3.1 Using Two-Step Floating Catchment Area Method for Spatial Proximity to UGS in Austin

The overall focus of this study is to look at the city-wide distribution pattern of UGS and examine whether it is equitable or not; setting a pre-defined threshold for evaluation is important. Based on several studies and the metric utilized by the Trust for Public Land's methodology, this study chooses a 10-minute walking distance as a desired threshold in analyzing proximity to the UGS (Boone et al., 2009; Dai, 2011; Hu et al., 2020). In this study, the spatial proximity to UGS is measured using the Gaussian-based Two-Step Floating Catchment Area (2SFCA) method that employs a gravity-based function that considers distance decay of accessibility (Dai, 2011). The assumption here is that people do not consider going to parks that are accessible or not. It means

not only the closest parks are used but also parks within the pre-determined travel duration. The employment of a gravity-based function is thought to better capture the scenario of how people use parks in reality (Williams et al., 2020). Including the Gaussian function eliminates the dichotomous fallacy where the residents within the selected threshold are thought to have equal access to resources, and residents outside the range are equally inaccessible (Dai, 2011; Hu et al., 2020). It ensures continuous access differences for individuals to be calculated within the same threshold, which corresponds better to reality.

The first step is to use the predetermined threshold of walking time d_0 , in this case, 10 minutes, and search for all the available population locations (k) for every green space location (j). This step determines the population catchment (P_k) for the green space at location j . Depending on the distance to green space at location j for each population location k , the Gaussian function is introduced to create the weighted service capacity (population) within the threshold. Then, a sum-up of all the potential weighted populations within the catchment for location j is calculated. A supply and demand ratio R_j is then calculated using the size of the green space S (size in acres) at location j divided by all the potential populations (Formula 1).

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} G(d_{kj}, d_0) P_k} \quad (1)$$

Compared to other articles, this study further refines the method of finding the distance between the population location at k and the green space at location j (Dai, 2011; Hu et al., 2020; Liu et al., 2022). The internal road and trails shapefile is used to intercept the park polygon using ArcGIS Pro to determine the trailheads for each park at location j . These trailheads are then considered as the entry points for the respective park instead of the centroid points commonly

used by other studies. For parks that do not have trail shapefiles, the study uses the centroid points as the entrance. Manual selection of the shortest distance between the population location at k and the green space entry at location j is conducted as some parks have multiple entry points if following the trailhead method instead of centroids. In Formula (1), P_k is the population that enjoys access to green space within the threshold through the weighted Gaussian function, d_{kj} is the distance between the centroids of population point k and either the entry point or centroid of the green space at location j . S_j is the size of the green space at location j in acres, and $G(d_{kj}, d_0)$ is the Gaussian function that determines the friction of distance, which is denoted in Formula (2).

$$G(d_{kj}, d_0) = \begin{cases} \frac{e^{-\left(\frac{1}{2}\right) \times \left(\frac{d_{kj}}{d_0}\right)^2} - e^{-\left(\frac{1}{2}\right)}}{1 - e^{-\left(\frac{1}{2}\right)}}, & \text{if } d_{kj} \leq d_0 \\ 0, & \text{if } d_{kj} > d_0 \end{cases} \quad (2)$$

The second step is to search for all available green spaces within the pre-determined threshold d_0 (10 mins) for each population location i . The same procedures are applied to the catchment area to calculate the supply and demand ratio R_i using the Gaussian function (Formula 1). Then, a sum-up of all the weighted ratios produces the UGS accessibility score of A_i . As shown in Formula (3), d_{il} is the distance between the centroids of population point i and either the entry point or centroid of the green space at location l .

$$A_i = \sum_{l \in \{d_{il} \leq d_0\}} G(d_{il}, d_0) R_i \quad (3)$$

The UGS accessibility score A_i indicates the number of green spaces in acres for every 1000 residents for a census area (Dai, 2011). The catchment threshold d_0 is determined based on

previous studies, the preliminary incremental testing of different thresholds on the number of routes, and the unit of analysis for the study (Dai, 2011; Hu et al., 2020; Liu et al., 2022). Because all the data were collected at the census block group level, a catchment larger than 10 minutes will result in too many possible routes, thus creating an over-smooth accessibility score in certain areas. At the same time, it will also become impractical for residents to walk 30 minutes to get to the nearest green space, especially in a car-dependent city like Austin. A catchment smaller than 10 minutes will result in multiple census block groups without access to green spaces. Figure 3.1 shows the spatial accessibility of each census block group to green spaces in Austin within 10 minutes of walking.

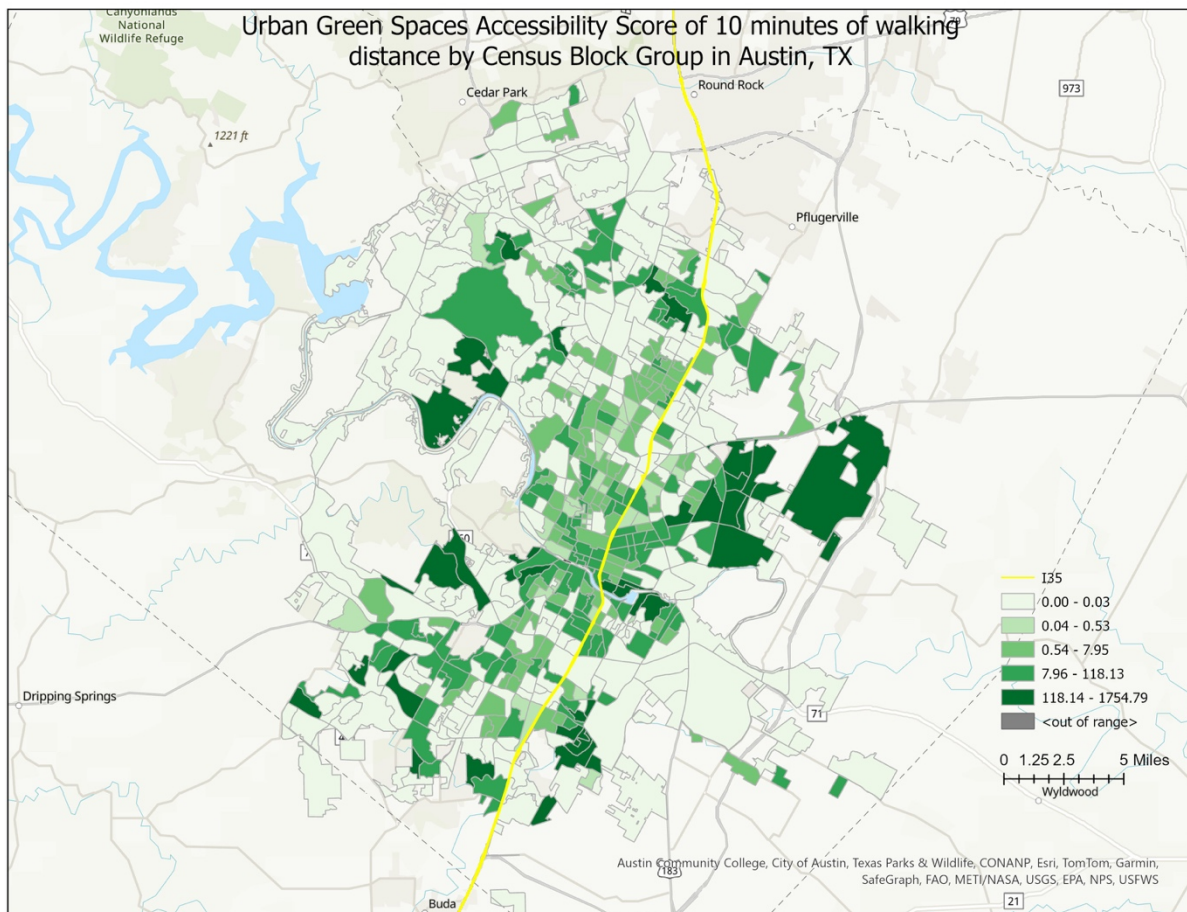


Figure 3.1. Dependent Variable: Urban Green Space Accessibility Score by Census Block Groups with 10 minutes of walking distance in Austin, TX

3.3.2 Independent and Dependent Variables

This chapter focuses on whether the spatial pattern of UGS development and its association with demographic, socio-economic, and housing factors support an equitable city-wide greening agenda. The data focuses on the main components of UGS Accessibility: Park Proximity (Rigolon 2016). Here, the park refers to the green spaces administered by the Austin Parks and Recreation Department, including greenways, neighborhood parks, and urban parks open to the public. Independent Variables (IV) are the block-group-level key housing factors, income, racial and ethnic composition, and educational attainment status. Dependent Variable (DV) is block-group level Accessibility Score (calculated based on the 2SFCA method for proximity to the UGS). Control Variables (CV) include other housing factors, age, poverty status, and population density. The Housing Choice Voucher Program (HUD Section 8) is the federal government's major program for assisting very low-income families, the elderly, and the disabled to afford decent, safe, and sanitary housing in the private market. For the consistency of the data used throughout this study, as the HUD data is not provided at the census-block-group level, it is replaced by the population over 65 years old that lives alone and the Population with income below the poverty line in this part of the dissertation. Table 3.1 shows the variables used in this study and their sources.

Table 3.1. Variables and data sources

Variable name	Description	Source	Type
Accessibility Scores	Sum of A_i scores for each census block-group of Austin	Austin GIS Portal	DV
Income (\$)	Income: Median household income	US Census, LTDB	IV
Home value (\$)	Housing: Median home value for occupied units	US Census, LTDB	IV
Rent (\$)	Housing: Median gross rent	US Census, LTDB	IV

Percent White (%)	Race: Percentage of non-Hispanic white population	US Census, LTDB	IV
Percent Black (%)	Race: Percentage of non-Hispanic African American population	US Census, LTDB	IV
Percent College (%)	Education Level: Percentage of population with at least a bachelor's degree	US Census, LTDB	IV
Population over 65 and lives alone (%)	Housing: Percentage of single-living elders over 65 changes over time	US Census, LTDB	CV
Population (adults) with income below poverty line (%)	Housing: Percentage of population (adults) with income below poverty line	US Census, LTDV	CV
Percentage of old housing units (%)	Housing: Percentage of old housing units	US Census, LTDB	CV
Percentage of vacant housing (%)	Housing: Percentage of vacant housing units	US Census, LTDB	CV
Population density	Population: Population density	US Census	CV
Note: DV (dependent variable), IV (independent variable), and CV (control variable).			

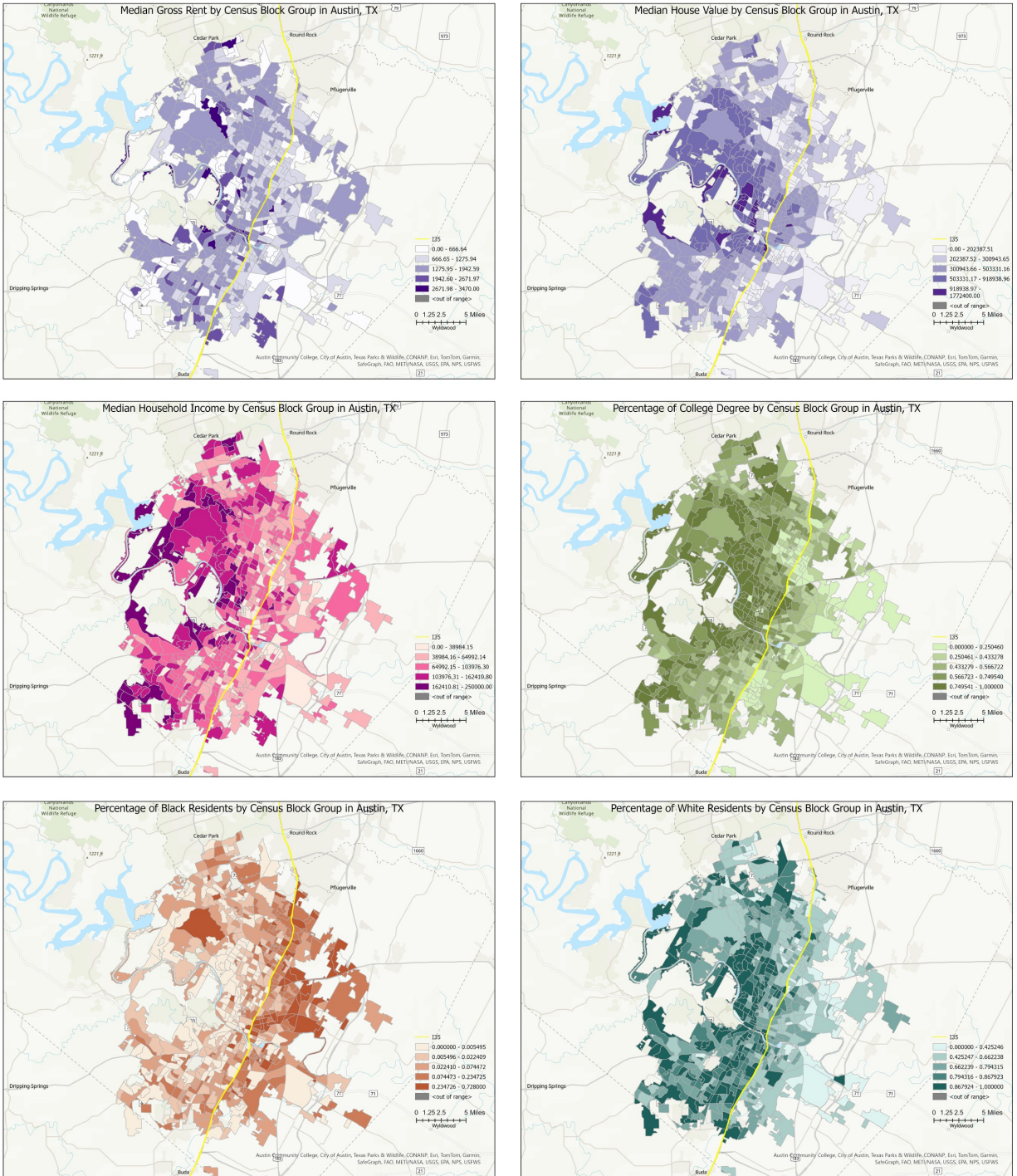


Figure 3.2. Independent Variables: Median Gross Rent, Median House Value, Median Household Income, Percentage of College Degree, Percentage of Black Residents, and Percentage of White Residents by Census Block Groups in Austin, TX

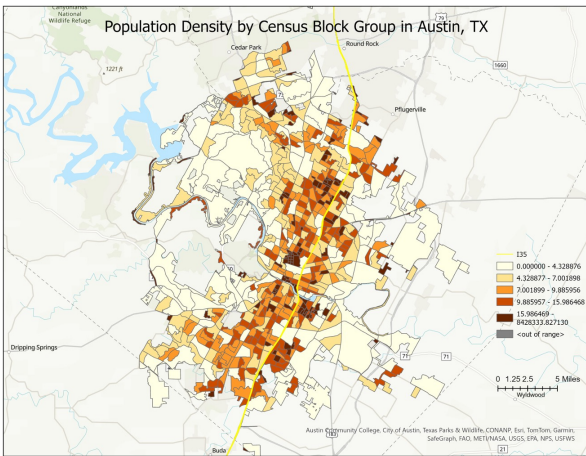
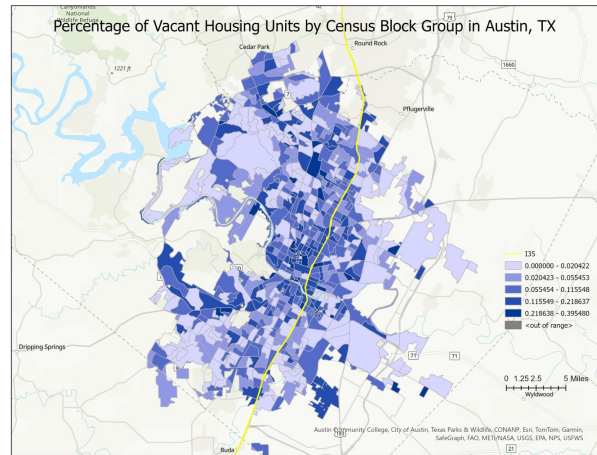
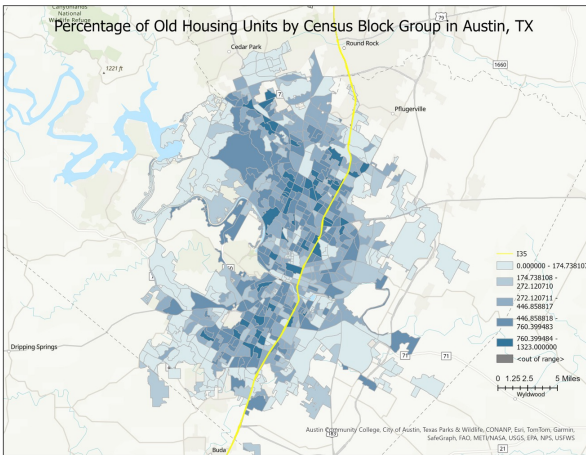
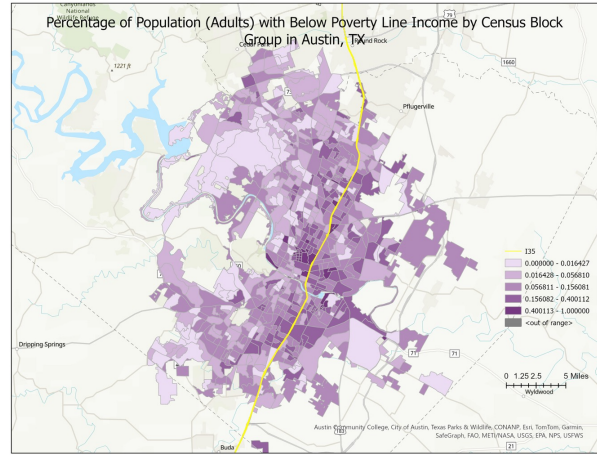
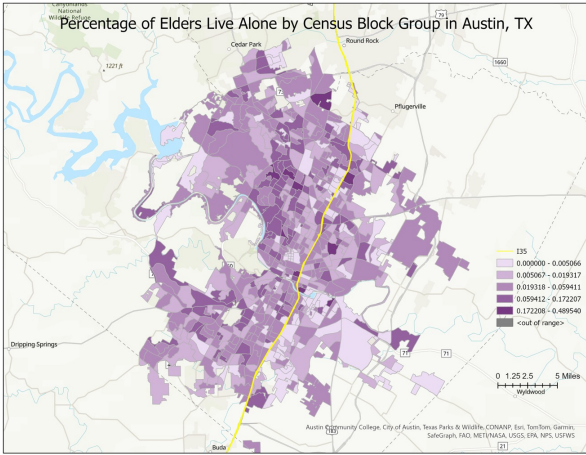


Figure 3.3. Control Variables: Percentages of Elders Live Alone, Population (Adults) with Below Poverty Line Income, Old Housing Units, Vacant Housing Units, and Population Density by Census Block Groups in Austin, TX

3.3.3 Preliminary Diagnostics of Variables

Variance Inflation Factor (VIF) is a common practice used to detect multicollinearity in regression models (Hawes et al., 2022; Rigolon and Gibson, 2021). Multicollinearity occurs when two or more predictive factors are highly correlated, which causes challenges in identifying their individual effect on the dependent variable. VIF is, therefore, a preliminary check on the data to ensure multicollinearity will not affect the model results. In this study, the VIF is calculated using a standard linear model, and the output is listed in the table. Since all VIF values were smaller than 5, the test confirmed that multicollinearity is not a concern for the proceeding models.

Table 3.2. VIF values for predictive variables

Variable	VIF values
Median Household Income (\$)	2.53
Median House Value (\$)	1.93
Median Gross Rent (\$)	1.11
White Population (%)	1.81
Black Population (%)	1.49
Population with at least a bachelor's degree (%)	2.01
Population (adults) with income below poverty line (%)	1.41
Population over 65 years old and lives alone (%)	1.08
Housing Units older than 30 years (%)	1.17
Housing Units that are vacant (%)	1.12
Population Density	1.02

3.4 Results

The analysis of UGS accessibility score disparities includes a bivariate correlation test, an Ordinary Least Square test, and two regression models considering the spatial dependence and their error terms. The unit of analysis for this study is the census block group. Spatial autocorrelation is a factor that needs to be considered for testing the null hypothesis that posits the randomness in spatial attributes (Baller et al., 2001). It is based on Tobler's First Law (TFL) of geography and refers to the similarity of values for the same variable of interest regarding the

proximity of their geographical locations (Baller et al., 2001; Miller, 2004). Global Moran's I test is applied to the Ordinary Least Squares (OLS) linear regression model that consists of the independent variables and the dependent variable to test whether the residuals are significantly clustered. The results from the OLS regression model assume that the relationship between the sociodemographic variable (IV) and DV stays the same (Anguelovski et al., 2018). As the OLS is a global model that contends spatial stationarity across the entire space, it does not take into account the potential changes in variation and processes happening in space (Anguelovski et al., 2018).

Therefore, in addition to the linear regression model, spatial regression models were also performed to test which variable(s) contribute more to the disparities regarding the UGS accessibility score. The first step is to re-examine the potential multicollinearity between covariates to eliminate the confounding effects on the results by calculating the variance inflation factor (Beyer et al., 2014; Williams et al., 2020). This was a step performed in the previous section and acted as a common procedure to prevent the statistical estimation of independent effects from being contaminated by the intercorrelation, where unreliable inferences might be drawn (Baller et al., 2001). The resulting coefficients from the multivariate model will indicate if a higher percentage of a certain demographic variable is linked to poorer access to UGS.

3.4.1 Bivariate Correlation Model

Table 3.2 shows the bivariate correlation between UGS accessibility and 11 variables. The result suggests that areas with a higher percentage of the White population, a higher percentage of old housing units, and a higher percentage of vacant housing units tend to have

poorer access to UGS, and these relationships are statistically significant. None of the other variables show a statistically significant association with UGS accessibility.

Table 3.3. Bivariate correlation (Pearson's correlation coefficient r result) between UGS accessibility and identified independent variables

Variable	Correlation with Access ^a	p-value
Median Household Income (\$)	0.001	0.99
Median House Value (\$)	0.031	0.41
Median Gross Rent (\$)	-0.045	0.24
White Population (%)	-0.082	0.030*
Black Population (%)	0.015	0.70
Population with at least a bachelor's degree (%)	-0.039	0.30
Population (adults) with income below poverty line (%)	-0.048	0.21
Population over 65 years old and lives alone (%)	-0.024	0.53
Housing Units older than 30 years (%)	-0.091	0.015*
Housing Units that are vacant (%)	-0.079	0.038*
Population Density	-0.008	0.82

^a $d_0=10$ min

* Significant at the 0.05 level

3.4.2 Ordinary Least Squares (OLS) Model

Table 3.3 shows the OLS results for the association between UGS accessibility and several variables. The results show that areas with a higher Median Home Value, a lower percentage of White residents, and a lower percentage of Old Housing Units have better access to UGS, and this association is statistically significant. In addition, the estimate for the percentage of vacant units is negative and borderline significant, suggesting that higher vacancy rates might be associated with lower UGS accessibility. However, this association is only statistically significant at the 10% level.

Table 3.4. Ordinal Least Squares (OLS) for UGS accessibility and identified independent variables, N=701

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	-2.42 ^{e-04}	1.70 ^{e-04}	-1.42	0.16
Home Value (\$)	6.89 ^{e-05}	2.90 ^{e-05}	2.38	0.018*
Gross Rent (\$)	-2.48 ^{e-03}	8.25 ^{e-03}	-0.30	0.76
White (%)	-76.57	37.54	-2.04	0.042*
Black (%)	-51.38	66.31	-0.78	0.44

College (%)	-15.34	32.34	-0.47	0.64
Poverty (%)	-50.56	43.96	-1.15	0.25
Elder Alone (%)	-23.79	118.9	-0.20	0.84
Old Unit (%)	-5.81 ^{e-02}	2.33 ^{e-02}	-2.50	0.013*
Vacancy (%)	-136.7	78.65	-1.74	0.083 .
Density	-6.23 ^{e-06}	1.73 ^{e-05}	-0.36	0.72
R ² : 0.031				
Overall p-value: 0.028				
* Significance at 0.05 level.				
. Significance at 0.1 level.				

3.4.3 Spatial Regression Models (Spatial Lag and Spatial Error)

In the spatial lag model, the Median Home Value and the percentage of Old Housing Units are statistically significant, suggesting that areas with a higher housing price and fewer old housing units are associated with better UGS accessibility. The Median Household Income, Percentage of White residents, and Percentage of Vacant Units are marginally significant at the 10% level, indicating these factors might contribute to the UGS accessibility. The spatial autoregressive parameter Rho is significant (p-value = 0.0056), indicating spatial dependence in the data, which justifies using a spatial lag model. In addition, the Akaike Information Criterion (AIC) is a measure of model fit that penalizes for the number of parameters. The spatial lag model has a lower AIC than a linear model (lm), which also suggests a better fit. However, the LM Test that checks for remaining spatial autocorrelation in the residuals yields a significant p-value of 0.00013, indicating that some spatial autocorrelation remains. Therefore, the spatial lag model may not have fully accounted for spatial dependence; an additional model that accounts for spatial dependence in residuals might be needed.

A Spatial error model is performed to test the remaining spatial autocorrelation within the residuals. The spatial error model came back with results similar to those of the spatial lag model. Areas with higher Median House Values and a smaller percentage of Old Housing Units have better access to UGS. The Median Household Income, Percentage of White Residents, and

Percentage of Vacant Units are significant at the 10% level, indicating they might be associated with UGS accessibility. In addition, the Lambda for the spatial error model is significant (p -value = 0.0083) and has a relatively moderate value of 0.11, indicating that spatial autocorrelation is present and was appropriately addressed.

Table 3.5. Spatial lag and spatial error models for UGS accessibility and independent variables, N=701

	Spatial lag model		Spatial error model	
Variables	Estimate	Pr(> z)	Estimate	Pr(> z)
Income (\$)	-13.78	0.11 .	-13.39	0.12 .
Home Value (\$)	16.65	0.026*	16.03	0.036*
Gross Rent (\$)	-1.33	0.81	-1.64	0.77
White (%)	-14.07	0.052 .	-14.37	0.051 .
Black (%)	-5.89	0.37	-5.76	0.39
College (%)	-2.68	0.72	-2.96	0.71
Poverty (%)	-6.97	0.27	-7.43	0.26
Elder Alone (%)	-0.86	0.88	-0.79	0.89
Old Unit (%)	-13.70	0.018*	-13.66	0.023*
Vacancy (%)	-10.46	0.066 .	-10.62	0.063 .
Density	-3.03	0.58	-3.23	0.55
	Rho: 0.11, p-value: 0.0056		Lambda: 0.11, p-value: 0.0083	
Diagnostics	LM Test p-value: 0.00013			
	AIC: 8968 (8974 for OLS)		AIC: 8969 (8974 for OLS)	

‘*’ Significance at 0.05 level, ‘.’ Significance at 0.1 level.

3.5 Discussion

Overall, the statistical results highlight the disparities in socioeconomic status and housing factors that impact the UGS accessibility score. Specifically, census block groups with a higher housing value are consistently associated with closer proximity to urban green space across models, corresponding to the environmental gentrification and displacement of residents’ hypotheses discussed in the literature review. This suggests that the restricted development policies might have contributed to the preservation of green spaces and the prioritization of green space development in the wealthier neighborhoods, which are, therefore, more accessible to

UGS. Contrary to our hypotheses, census block groups with a lower percentage of white residents show closer proximity to UGS across models. Interestingly, this result also contradicted the common findings from the literature review of racial disparities regarding accessibility to UGS. This might suggest that the current spatial distribution pattern could have been affected by site-specific planning and policies to mitigate such inequity.

Census block groups with a higher percentage of old housing units are consistently negatively associated with the UGS accessibility score across models. This might suggest that aging urban infrastructure might hinder urban green space development, as limited vacant land can be used. Similarly, a higher percentage of vacant housing units within a census block group is marginally significant and negatively associated with the UGS accessibility score. This indicates that urban green space development might also be undermined due to affordability issues in the housing market or undesirable urban decay. The results show that interventions in areas with lower home values and aging housing infrastructure are needed to ensure more equitable UGS accessibility.

Lastly, the significant spatial autoregressive parameter (ρ) from the spatial lag model result and the significant λ from the spatial error model indicate the appropriateness of using a spatial model to account for the potential spatial dependence for UGS accessibility. However, the LM test also showed that the spatial lag model did not fully capture the spatial autocorrelation, and the spatial error model was somewhat addressed. Overall, the results emphasize the multi-faceted and spatially dependent nature of urban green space accessibility; a more holistic approach that bridges qualitative perspectives, such as urban planning and policies, and spatial analysis is needed.

Chapter 4 - Longitudinal Changes in Spatial Pattern of UGS: From a Distributional Justice Perspective

4.1 Introduction

Spatial analysis is a blend of inquiries, usually consisting of two parts. One is to map out the spatial patterns of research interest exhibited by the collected data, and the other is the examination and inference of the underlying discrete processes that produce the data (Fotheringham & Sachdeva, 2022). It is generally considered a process with added value that transforms, manipulates, and generates new knowledge using suitable analytical tools for spatial data. It first answers the question of where patterns, clusters, hot spots, and disparities, to name a few, occur within a predefined geographical boundary. Second, it answers the why question of what is special about the location where the previous incidents occurred. Third, it answers the How question central to the research question – the interactions between the environment (or location) and the contents.

This chapter is a continuation of Chapter 3 to investigate the changes over time regarding UGS accessibility in Austin, TX, from 2000 to 2020. The UGS accessibility usually refers to park proximity, park acreage, and park quality (Rigolon, 2016). In this study, Park Proximity refers to the cumulative opportunities toward a desired supply center (Dai, 2011; Hu et al., 2020). It assesses the proximity by setting a catchment area where all population locations within the set travel time will be included. Travel time is used to determine the proximity to parks instead of Euclidean distance, as time is a better intuitive measurement (Williams et al., 2020). The walking time from each parcel to the nearest park is then calculated based on a weighted method. It utilizes a Gaussian-based two-step floating catchment area (2SFCA) approach that differentiates opportunities provided to the residents within a spatial unit of the park (Dai, 2011;

Hu et al., 2020). It does so by integrating a weighted distance decay function that, within the catchment threshold, residents who live further enjoy fewer opportunities than those who live near the park. Park Acreage is calculated by deploying a gravity approach where the metric that population catchment within each park will decay based on its distance to the park. Lastly, Park Quality is usually conducted through on-site audits and comprehensive observation of the amenities, which is beyond the research scope of this study (Rigolon, 2016; Williams et al., 2020).

4.2 Procedures Addressing Longitudinal Spatial Analysis

4.2.1 Modifiable Areal Unit Problem in Spatial Analysis

Despite the ability to show spatial patterns and reveal the underlying mechanisms, spatial analysis is not immune from theoretical challenges. A few points need to be addressed before analyzing the spatial patterns. The first kind concerns the Modifiable Areal Unit Problem (MAUP), a form of Ecological Fallacy that posits that individual behavior cannot be explained at the aggregated level. Therefore, the inferences made about an observed phenomenon might be distorted, and the outcome will be misrepresented (Baller et al., 2001; F. Li et al., 2017). Essentially, MAUP is concerned with the mismatch of scales between collected spatial data and the explanation processes (L. Li et al., 2017). It occurs when data is measured on a different scale, which produces differing analytical results (Duckham et al., 2001). Therefore, one common recommendation for solving the MAUP problem is to find the best possible scales where the underlying processes take place (M. P. Kwan, 2012).

An extended conception of the Uncertain Geographic Context Problem (UGCoP) proposed by Kwan argues that in addition to the problem of mismatch in scales posed by MAUP,

there exists a possible misunderstanding of the contextual background of how individuals within that specific geographic boundary behave (M. P. Kwan, 2012). This extension is not only concerned with spatial scales but also temporal ones in that it contends that the phenomena being observed are not static like spatial data but somewhat fluid. Therefore, the snapshot of spatial analysis at a certain time and space is insufficient for understanding the space-time continuum (M. P. Kwan, 2012; F. Li et al., 2017). In addition, Fisher argues that there is also an inherent fuzziness along the geographical boundary that possesses traits on both sides (Fisher, 2000). This requires a clear conceptualization of how spatial processes are framed and what data at which scale we are using; however, despite the academic efforts toward trying to solve the above issues, vagueness remains regarding the uncertainty of scales. For this chapter, I chose the finest possible scale that agrees with the demographic data available to minimize the effect of geographic unit or scale on the quantification of measurements.

4.2.2 Standardization of Data

After identifying the appropriate scale for research, the next question concerns the standardization of data, especially related to comparing the same categories of data, for example, housing occupancy rate, when the geographical boundary changes over time. Due to population change and the shift in administrative boundaries over time, US census geographies have also evolved to adapt and reflect the changes to meet the needs of various agencies. One way to solve this problem is to adopt the harmonized data edited by projects that have applied complex weighting techniques to transform data from different geographic boundaries from different times into a standardized one. For example, the National Historical Geographic Information System (NHGIS) provides one of the largest databases for summary statistics measured multiple

times at a specific geographic unit. According to NHGIS, the integration includes two types – attribute integration and geographic integration (NHGIS, n.d.). The former ensures that the attributes can be compared across time; the latter ensures that the areas summarized are comparable across time. Currently, it offers standardized data into 2010 census geographic units through interpolation, where estimates are made to assign characteristics to the new units (Schroeder, 2007). This method's primary assumption is that the source zone's characteristics share a proportionate distribution pattern about the target zone based on their spatial relationship (Schroeder, 2007; NHGIS, n.d.). Figure 4.1 shows how the census geographies in the US change over time.

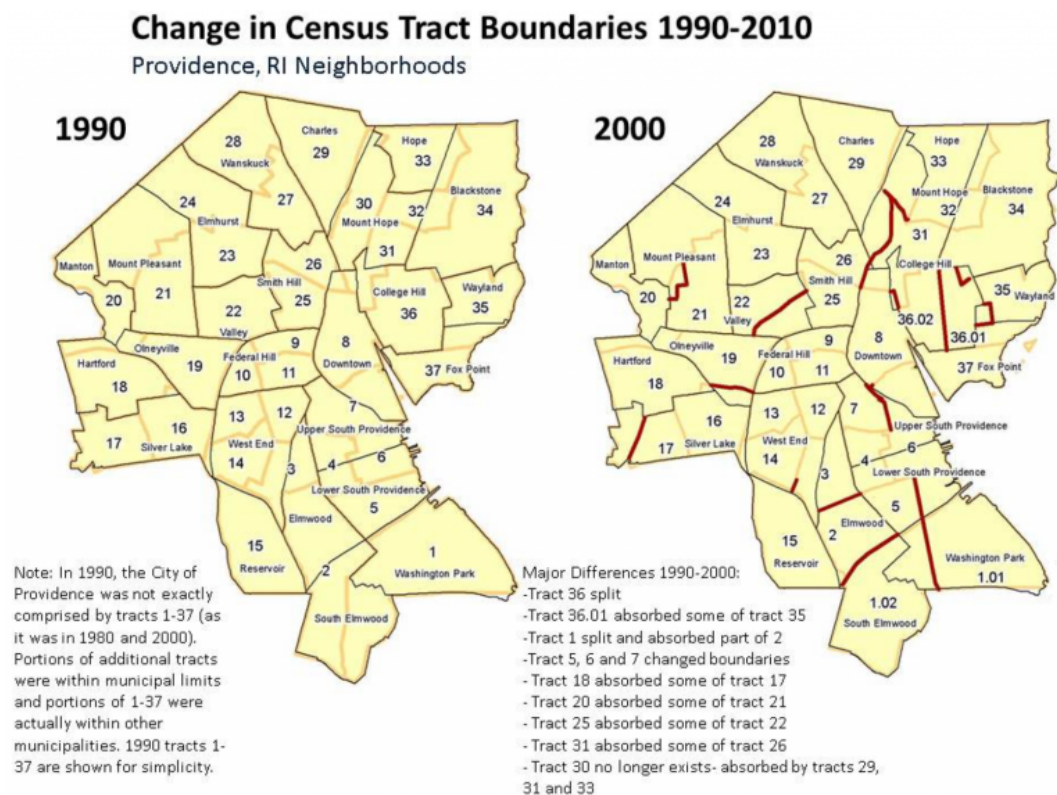


Figure 4.1. Change in Census Tract Boundaries 1990-2010 in Providence, RI Neighborhoods

Source: Duke University Libraries, “Standardizing the U.S. Census,”

<https://blogs.library.duke.edu/data/2021/03/25/standardizing-the-u-s-census/>

The longitudinal dataset utilized in this study encompasses selected socio-demographic and socio-economic indicators, spatial data on green spaces, and housing-related factors from the years 2000, 2010, and 2020. The socio-demographic and socio-economic data were sourced from the U.S. Census and the Longitudinal Tract Database (LTDB), developed by Brown University (Logan et al., 2014). Spatial data on green spaces were obtained from the City of Austin Open Data Portal, while housing data were drawn from the LTDB and the U.S. Department of Housing and Urban Development (HUD). All variables were calculated as decadal changes (10 years) expressed in percentages, covering 20 years from 2000 to 2020. Table 1 provides an overview of the variables used in this study, along with their descriptions, data sources, and types. The unit of analysis in this study is the census tract. Figure 4.2 shows how US census geographical discrepancies were resolved using the NHGIS methods.



Figure 4.2. Electronic Boundary resolved by data harmonization

Source: Duke University Libraries, “Standardizing the U.S. Census,”

<https://blogs.library.duke.edu/data/2021/03/25/standardizing-the-u-s-census/>

4.2.3 Research Question and Hypotheses

This part of the research aims to use novel spatial analysis methods to examine the inequitable UGS spatial distribution in Austin, TX. In this chapter, the following questions are addressed:

1. What are the leading factors contributing to Austin, TX's UGS spatial pattern in a longitudinal manner?
 - a. Specifically, what factors are associated with the proximity to green spaces each decade?
 - b. What factors are associated with per capita green space each decade?
2. Do census tracts adjacent to each other show similar characteristics (spatial dependence) regarding proximity to UGS or per capita green space?

The following hypotheses were tested:

1. Areas with a higher median household income experience improved proximity to UGS and a higher per capita green space over time.
2. Areas with a higher percentage of white population experience improved proximity to UGS and a higher per capita green space over time.
3. Areas with a higher property value or rent price experience improved proximity to UGS and a higher per capita green space over time.
4. Areas with a higher percentage of the population with bachelor's degrees experience improved proximity to UGS and a higher per capita green space over time.

4.3 Method

4.3.1 Spatial Regression Model

A preliminary Moran's I analysis on urban green space distribution showed significant clustering, indicating adequate use of a spatial model. Therefore, to analyze the change in accessibility scores (A_i) in relation to the independent variables over time, a spatial regression model is performed to assess how changes in independent variables are associated with changes in accessibility scores (A_i). The change in A_i is a function of the changes in independent variables using linear regression; the formula below shows how it is done.

$$\Delta A_i = \beta_0 + \beta_1 \Delta X_1 + \beta_2 \Delta X_2 + \dots + \epsilon$$

The change of variables contains observations collected at a regular frequency, and in this study, the frequency is a decadal change. Median Household Income, Median House Value, and Median Gross Rent were calculated in U.S. dollars, and all other variables except for population density were calculated for their respective decadal change (10 years) in percentage.

Changes in accessibility scores (ΔA_i) are computed for each pair of periods, from 2000 to 2010, 2010 to 2020, and 2000 to 2020.

$$\Delta A_{i1 \rightarrow i2} = A_{i2} - A_{i1}$$

Changes in each independent variable (ΔX) are computed for each pair of periods, from 2000 to 2010, 2010 to 2020, and 2000 to 2022.

$$\Delta X_{i1 \rightarrow i2} = X_{i2} - X_{i1}$$

4.3.2 Independent and Dependent Variables

This chapter carries over the spatial analysis method for the city-wide UGS spatial pattern by looking at the longitudinal effect of adjacency to new parks on socio-demographic and

housing factors. Independent Variables (IV) are changes (differences in numeric value or percentage value of each variable between the starting year and the end year of the decadal period) in the census-tract-level key housing factors, income, racial and ethnic composition, and educational attainment status. The dependent Variable (DV) is the census-tract level change in the accessibility score and per capita green space. Control Variables (CV) include other housing factors and population density. Table 4.1 provides an overview of the variables used in this study, as well as descriptions, data sources, and respective types. The unit of analysis used in this study is the census tract.

Table 4.1. Variables and data sources

Variable name	Description	Source	Type
Change of Accessibility Scores	Sum of Ai scores for each census tract of Austin (2000, 2010, and 2020)	Austin GIS Portal	DV
Change of Per Capita Green Space	Per capita green space in square feet for residents of each census tract (2000, 2010, and 2020)	Austin GIS Portal	DV
Change of Income (\$)	Income: Median household income (2000, 2010, and 2020)	US Census, LTDB	IV
Change of Home value (\$)	Housing: Median home value for occupied units (2000, 2010, and 2020)	US Census, LTDB	IV
Change of Rent (\$)	Housing: Median gross rent (2000, 2010, and 2020)	US Census, LTDB	IV
Change of Percent White (%)	Race: Percentage of non-Hispanic white population (2000, 2010, and 2020)	US Census, LTDB	IV
Change of Percent Black (%)	Race: Percentage of non-Hispanic African American population (2000, 2010, and 2020)	US Census, LTDB	IV
Change of Percent College (%)	Education Level: Percentage of population with at least a bachelor's degree (2000, 2010, and 2020)	US Census, LTDB	IV
Change of old housing units (%)	Housing: Percentage of old housing units change over time (2000, 2010, and 2020)	US Census, LTDB	CV
Change of vacant housing (%)	Housing: Percentage of vacant housing change over time (2000, 2010, and 2020)	US Census, LTDB	CV
Change of HUD units (%)	Housing: Percentage of occupied HUD units change over time (2000, 2010, and 2020)	HUD	CV
Change of population density	Population: Percentage of population density change over time (2000, 2010, and 2020)	US Census	CV
Note: DV (dependent variable), IV (independent variable), and CV (control variable).			

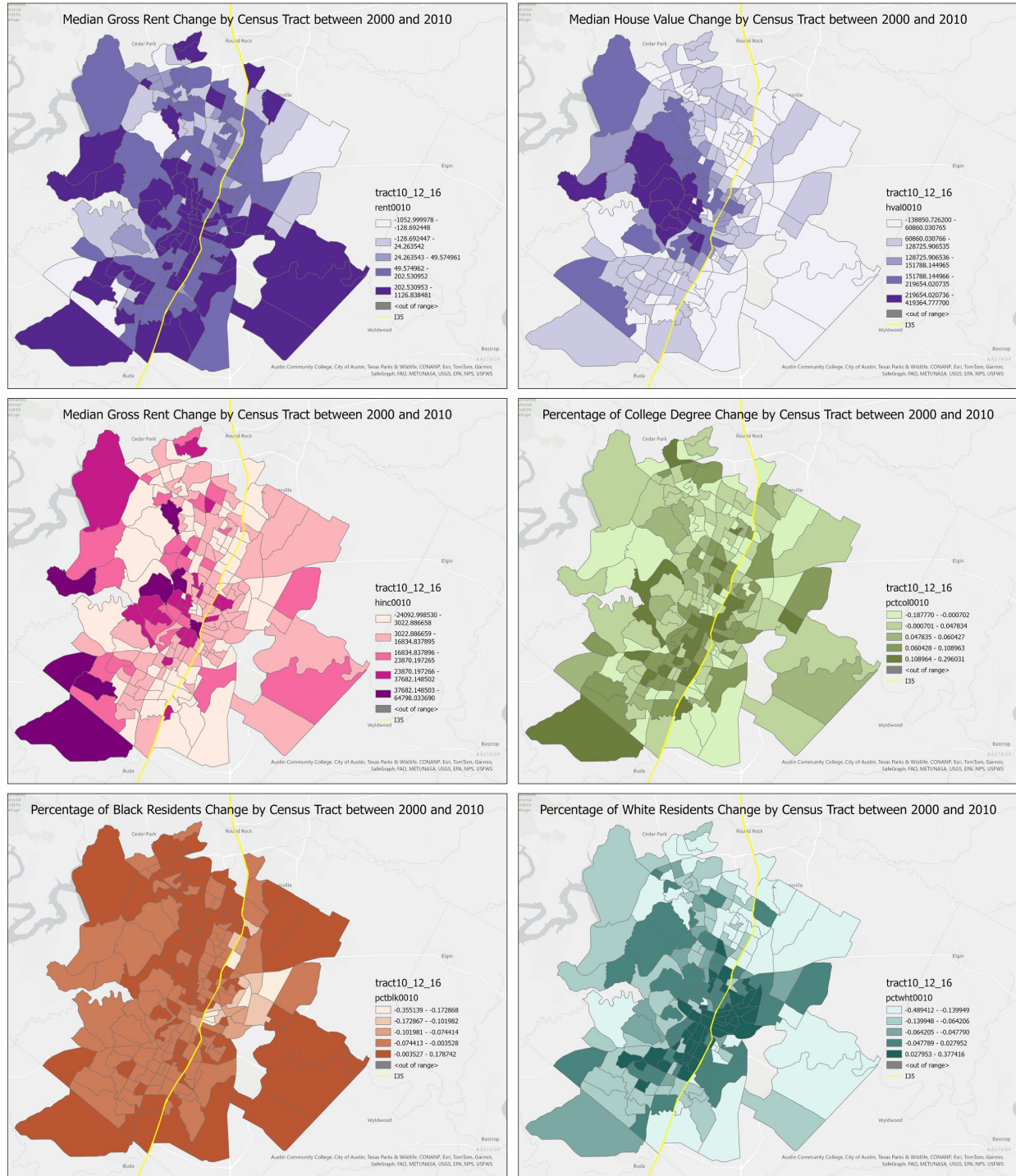


Figure 4.3. Changes in Independent Variables between 2000 and 2010: Median Gross Rent, Median House Value, Median Household Income, Percentage of College Degree, Percentage of Black Residents, and Percentage of White Residents by Census Tracts in Austin, TX

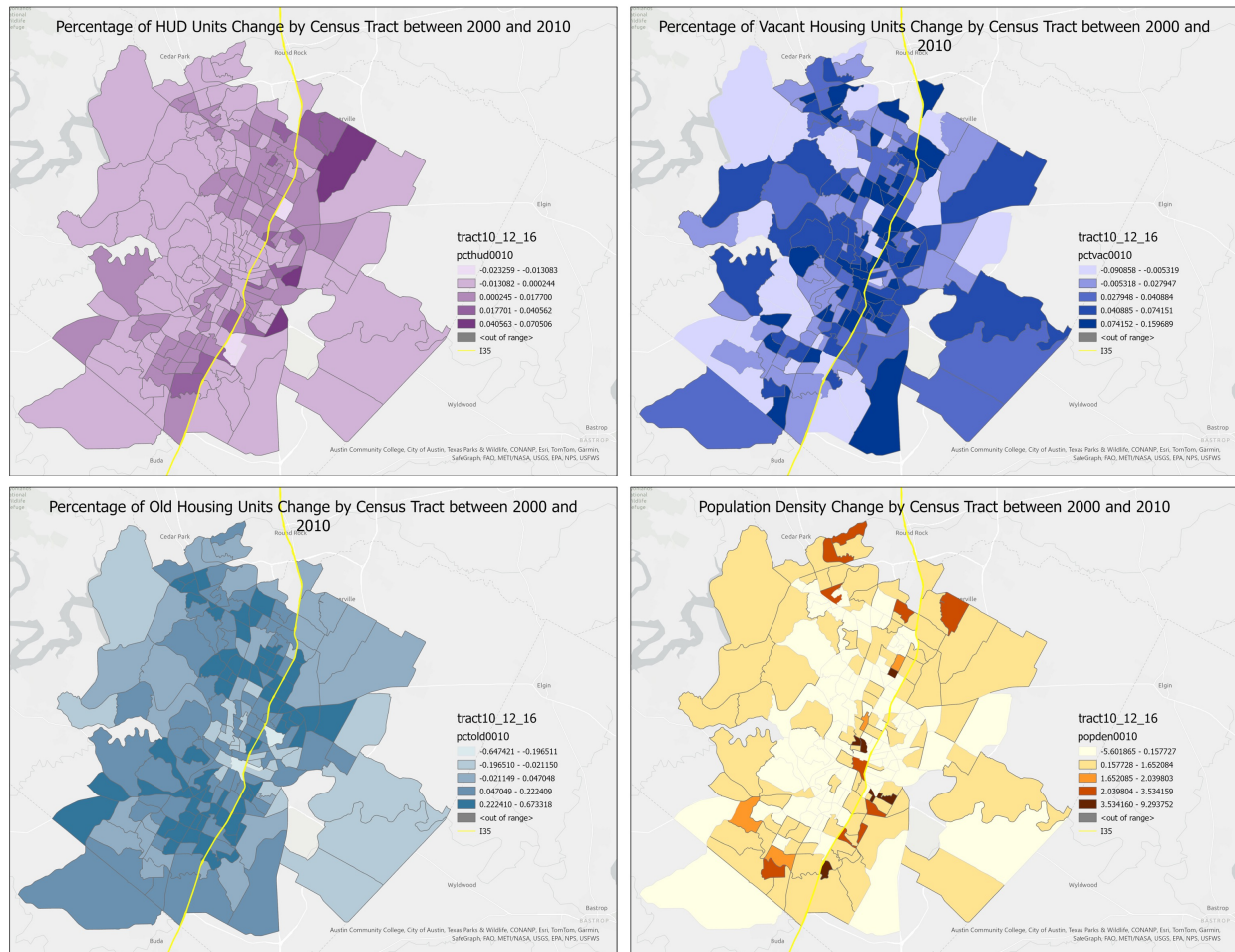


Figure 4.4. Changes in Control Variables between 2000 and 2010: Percentages of HUD Units, Old Housing Units, Vacant Housing Units, and Population Density by Census Tracts in Austin, TX

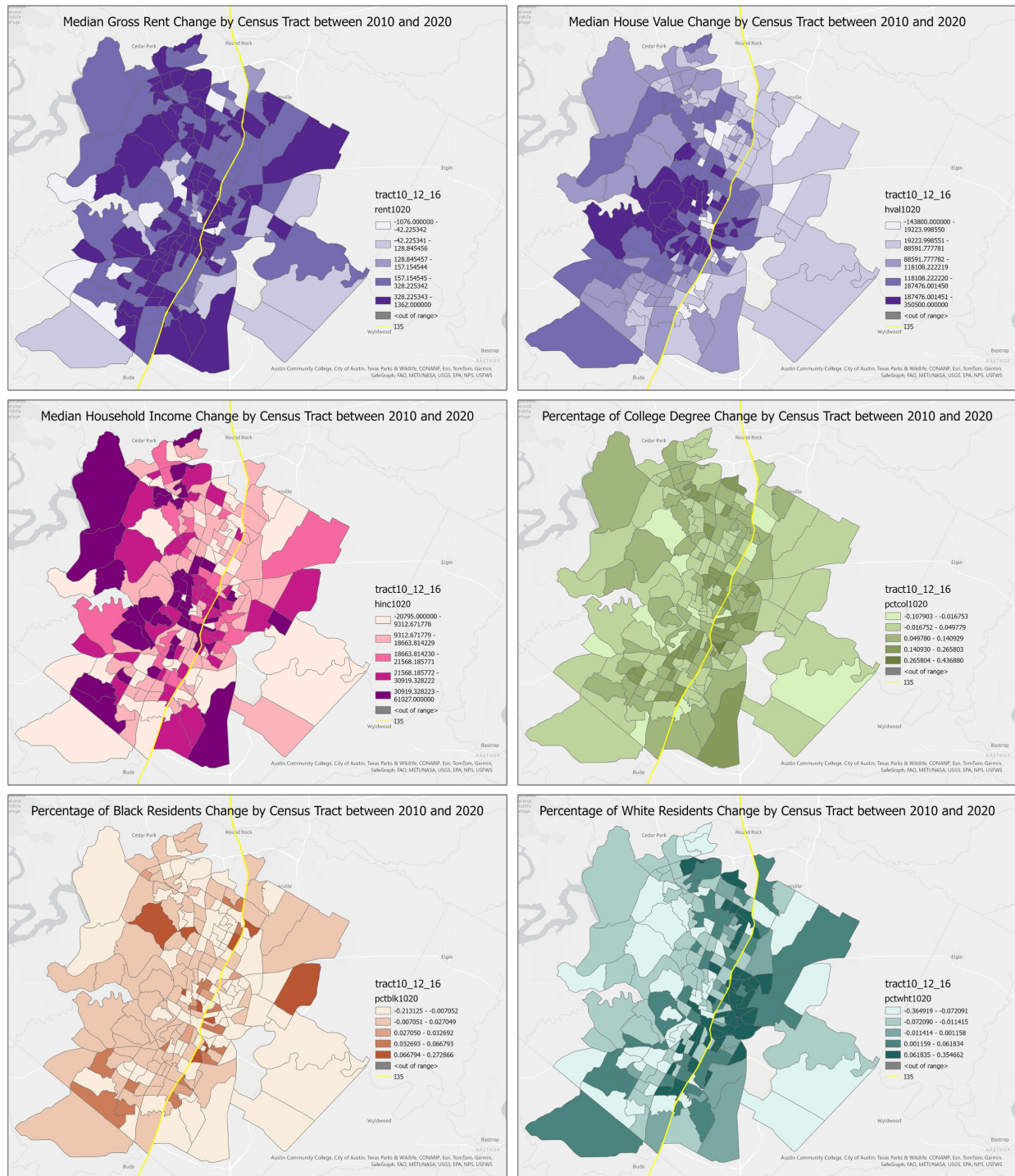


Figure 4.5. Changes in Independent Variables between 2010 and 2020: Median Gross Rent, Median House Value, Median Household Income, Percentage of College Degree, Percentage of Black Residents, and Percentage of White Residents by Census Tracts in Austin, TX

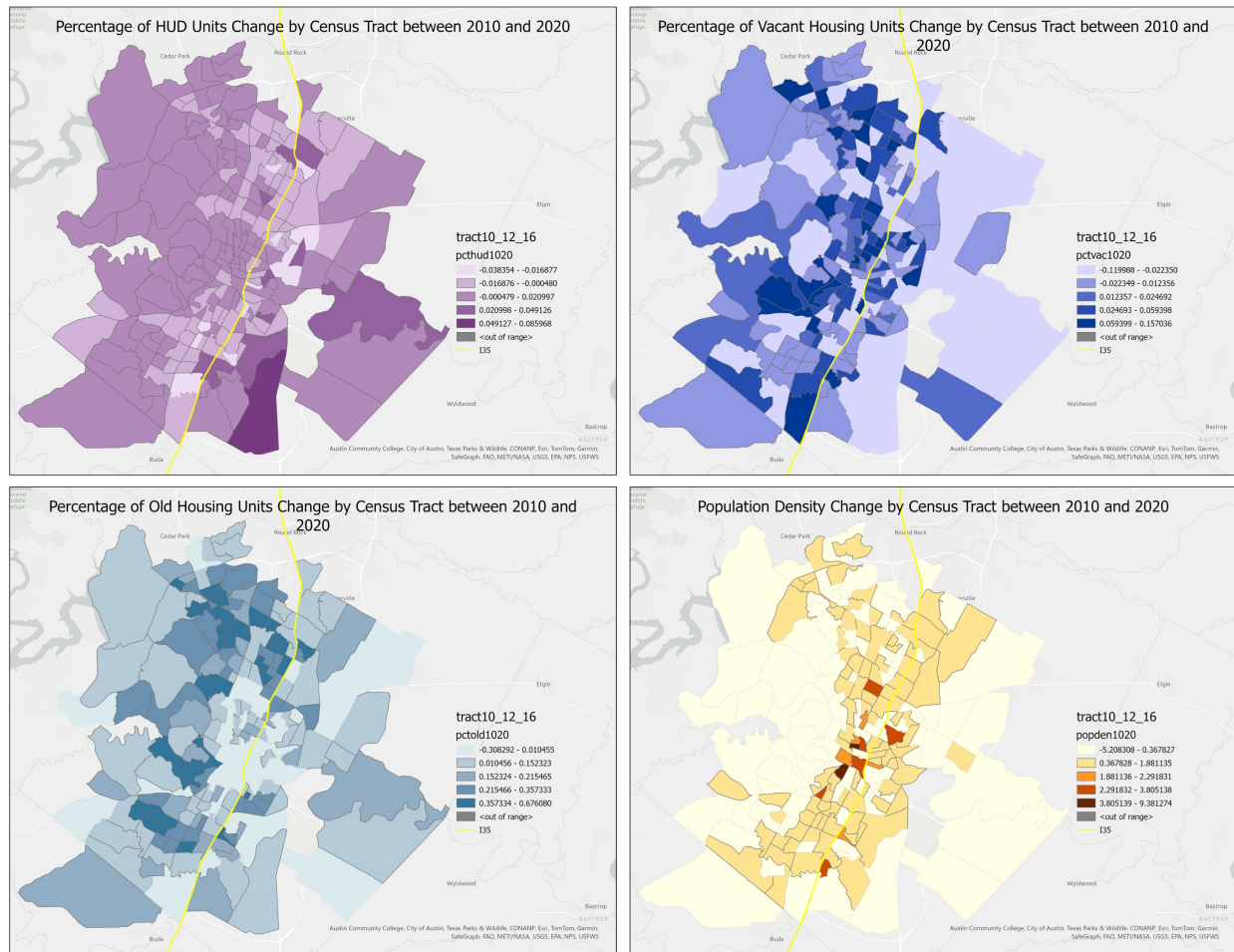


Figure 4.6. Changes in Control Variables between 2010 and 2020: Percentages of HUD Units, Old Housing Units, Vacant Housing Units, and Population Density by Census Tracts in Austin, TX

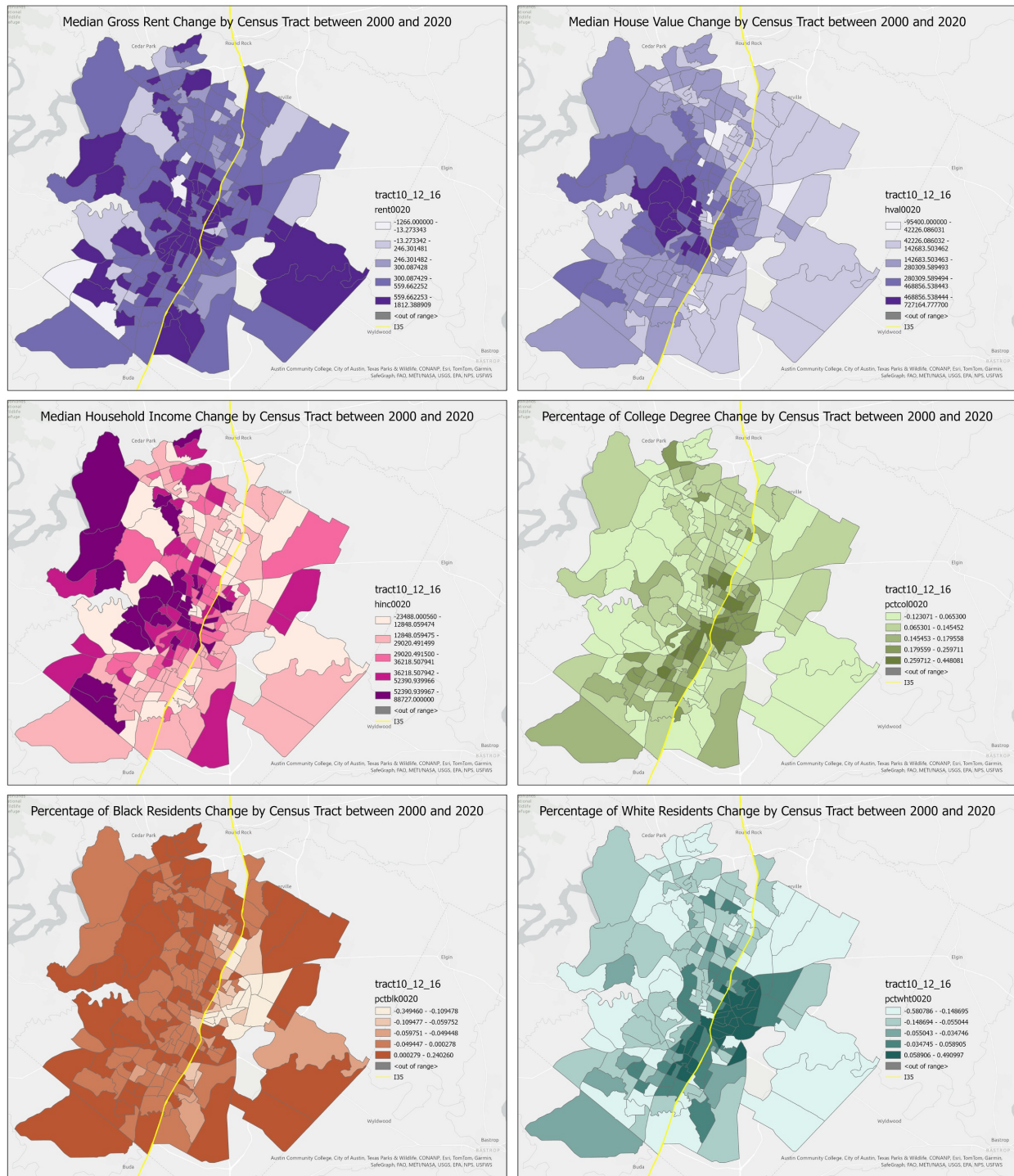


Figure 4.7. Changes in Independent Variables between 2000 and 2020: Median Gross Rent, Median House Value, Median Household Income, Percentage of College Degree, Percentage of Black Residents, and Percentage of White Residents by Census Tracts in Austin, TX

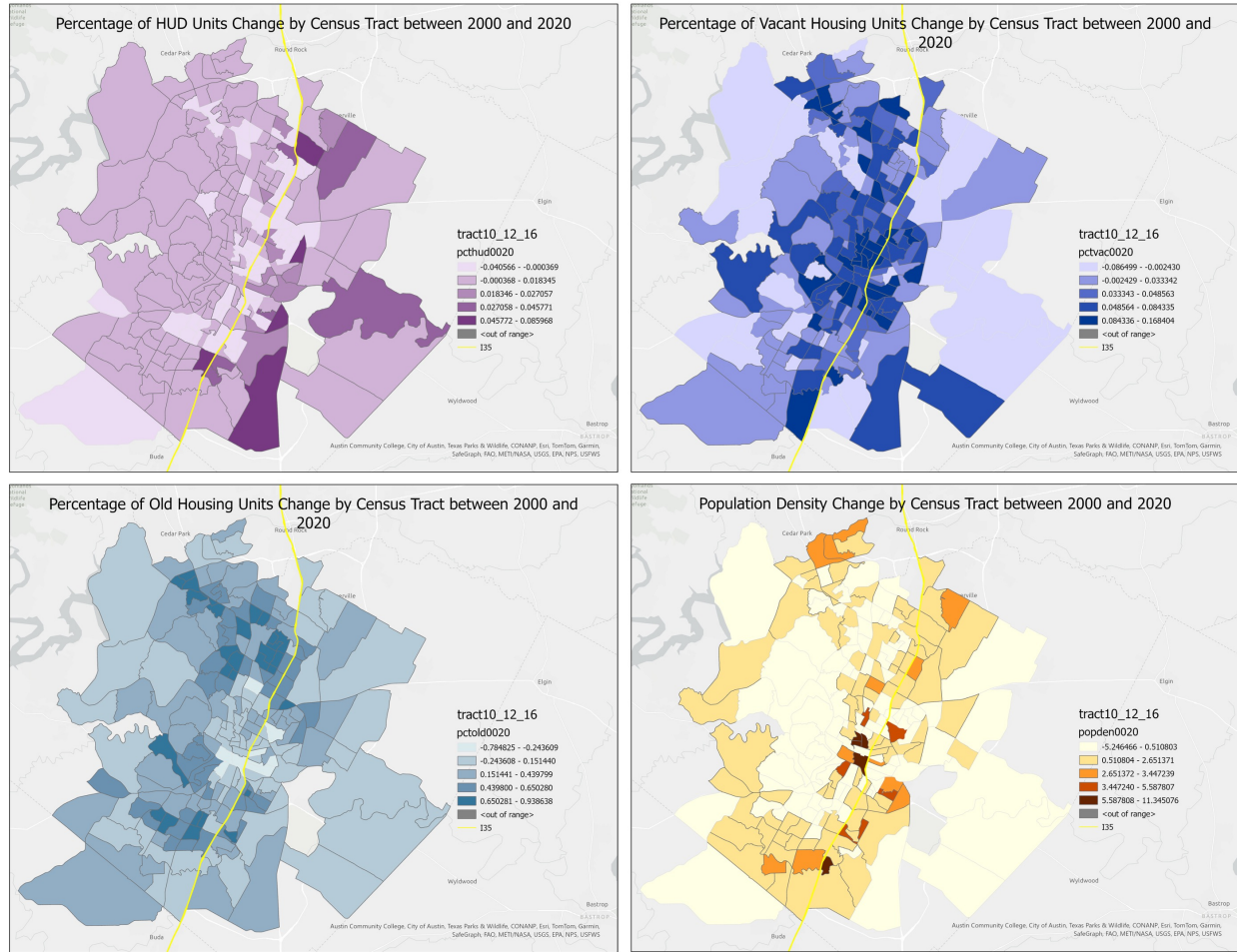


Figure 4.8. Changes in Control Variables between 2000 and 2020: Percentages of HUD Units, Old Housing Units, Vacant Housing Units, and Population Density by Census Tracts in Austin, TX

4.3.3 Preliminary Diagnostics of Variables

Similar to the procedures in Chapter 3, VIF tests were used to detect multicollinearity in regression models (Hawes et al., 2022; Rigolon & Gibson, 2021). Multicollinearity occurs when two or more predictive factors are highly correlated, which causes challenges in identifying their individual effect on the dependent variable. VIF is part of the preliminary checks as multicollinearity is a data issue rather than a model one. In this study, the VIF is calculated using

a standard linear model, and the output is listed in the table. Since all VIF values were smaller than 5, the test confirmed that multicollinearity is not a concern for the proceeding models.

Table 4.2. VIF values for predictive variables from three periods

Variables	VIF (2000-2010)	VIF (2010-2020)	VIF (2000-2020)
Change in Median Household Income (\$)	1.88	1.30	2.01
Change in Median Home Value (\$)	1.76	1.26	1.96
Change in Median Gross Rent (\$)	1.42	1.14	1.23
Change in White Residents (%)	1.87	1.59	2.18
Change in Black Residents (%)	1.42	1.22	1.42
Change in College Residents (%)	1.53	1.46	1.86
Change in Old Unit (%)	1.29	1.20	1.51
Change in Vacant Units (%)	1.06	1.11	1.16
Change in HUD Units (%)	1.04	1.06	1.07
Change in Population Density	1.41	1.14	1.44

4.4 Results

4.4.1 Results for Changes in UGS Accessibility Score

4.4.1.1 Change in UGS Accessibility Score and Socioeconomic Variables between 2000 and 2010

Overall, the parameter measuring spatial dependence is not statistically significant ($\text{Rho} = -0.16$, $p\text{-value} = 0.18$), suggesting the spatial dependence in this model is weak, and neighboring areas' changes do not strongly influence the change in accessibility. In addition, the LM Test that measures the autocorrelation of the residuals ($p\text{-value} = 0.91$) shows non-significance, which suggests the model adequately accounts for spatial dependence in the model. Lastly, the AIC value ($\text{AIC} = 568.5$) is very close to the AIC value for the OLS model ($\text{AIC} = 568.2$), suggesting the spatial lag model does not significantly outperform a standard OLS model. Figure 4.7 shows

the changes in the accessibility score between 2000 and 2010, Figure 4.1 shows the changes in independent variables between 2000 and 2010, and Figure 4.2 shows the changes in control variables between 2000 and 2010. Table 4.3 provides an overview of the outcomes from the spatial regression model, and Table 4.4 provides an overview of outcomes for the OLS model.

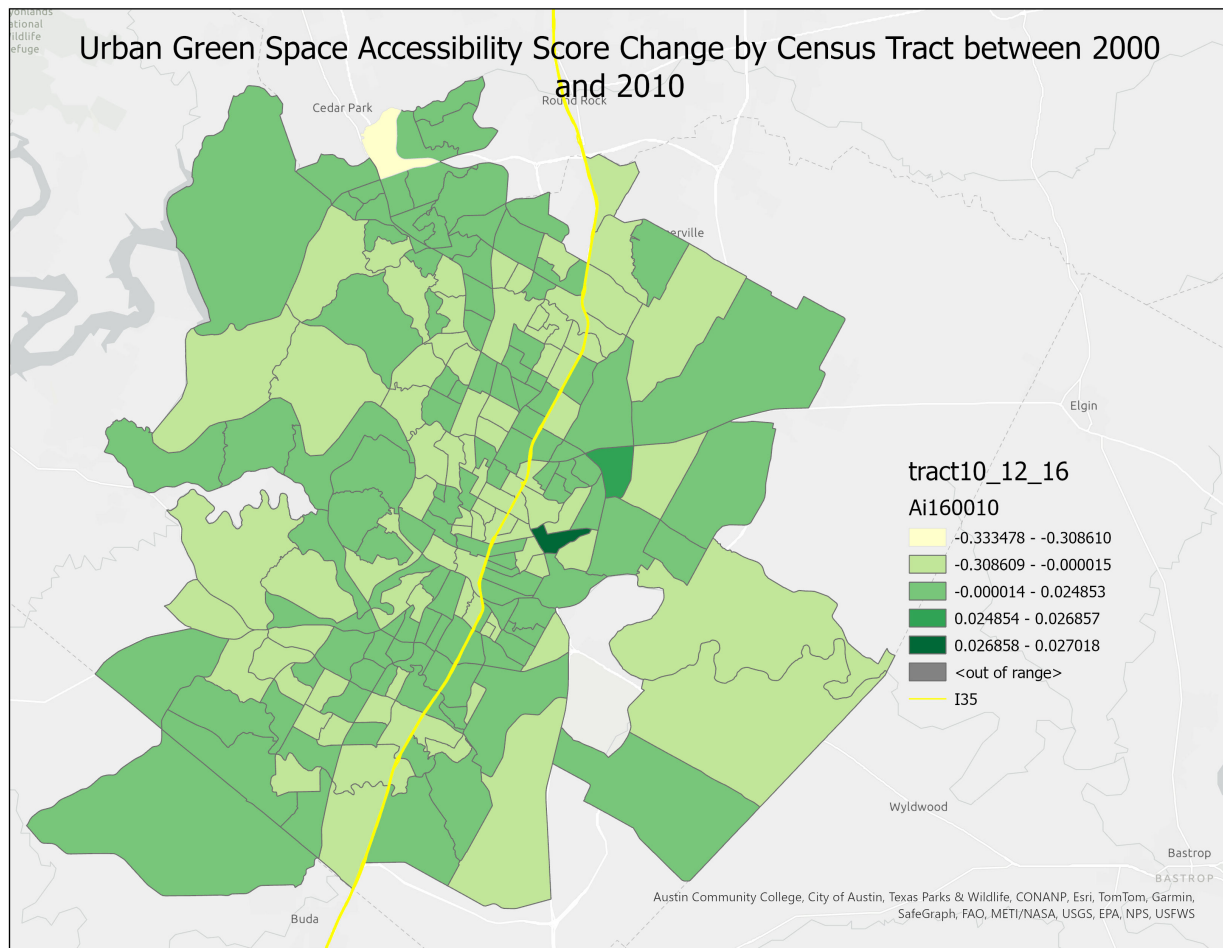


Figure 4.9. Changes in Dependent Variable between 2000 and 2010: Urban Green Space Accessibility Score by Census Tracts in Austin, TX

The dependent variable in this model is the change in accessibility scores for each census tract between 2000 and 2010. Independent variables include various socioeconomic and housing factors. Among all the tested independent variables, the percentage change in White residents is significant and positive, meaning census tracts that experienced an increase in the percentage of

White residents also saw improvements in accessibility to UGS between 2000 and 2010. The percentage change in college education is significant and negative in the spatial lag model, meaning census tracts with a rising percentage of residents who earned at least a bachelor's degree experienced declining accessibility to UGS. However, the change in college degrees is marginally significant in the OLS model, indicating it might not have a substantial impact on the outcome. The percentage change in Housing Units older than 30 years shows a positive and significant association with the dependent variable, meaning areas with more old housing units saw increased accessibility to UGS. Lastly, the change in Median Gross Rent shows a positive and marginally significant relationship with the dependent variable, suggesting census tracts that experienced a rent increase might have seen a slight improvement in accessibility to UGS.

Table 4.3. Change in UGS accessibility score and socioeconomic variables between 2000 and 2010, N=205 (2010 boundary)

Variables	Estimate	Std. Error	z-value	Pr(> z)
Income (\$)	0.034	0.088	0.39	0.70
Home Value (\$)	-0.040	0.085	-0.47	0.64
Gross Rent (\$)	0.13	0.076	1.65	0.099 .
White (%)	0.42	0.088	4.77	1.81 ^{e-06*}
Black (%)	0.080	0.076	1.04	0.30
College (%)	-0.24	0.079	-3.05	0.0023*
Old Unit (%)	0.14	0.073	1.97	0.049*
Vacancy (%)	-0.014	0.066	-0.21	0.83
HUD (%)	0.078	0.065	1.19	0.23
Density	-0.0089	0.076	-0.12	0.91
Rho: -0.16, p-value: 0.18				
LM Test p-value: 0.91				
AIC: 568.5 (568.2 for OLS)				

*, Significance at 0.05 level, . Significance at 0.1 level.

Table 4.4. Ordinal Least Squares (OLS) for Change in UGS accessibility score and socioeconomic variables between 2000 and 2010, N=205 (2010 boundary)

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	0.023	0.091	0.25	0.80
Home Value (\$)	-0.043	0.088	-0.48	0.63
Gross Rent (\$)	0.12	0.079	1.57	0.12 .
White (%)	0.41	0.091	4.54	9.88 ^{e-06***}
Black (%)	0.093	0.079	1.17	0.24

College (%)	-0.23	0.082	-2.82	0.0054**
Old Unit (%)	0.14	0.075	1.90	0.060 .
Vacancy (%)	-0.012	0.068	-0.17	0.86
HUD (%)	0.070	0.068	1.04	0.30
Density	-0.0068	0.079	-0.086	0.93
R ² : 0.15				
Overall p-value: 0.00033				
‘***’, Significance at 0 level, ‘**’, Significance at 0.01 level, ‘.’ Significance at 0.1 level.				

4.4.1.2 Change in UGS Accessibility Score and Socioeconomic Variables between 2010 and 2020

The non-statistically significant spatial dependence parameter (Rho = 0.014, p-value = 0.90) suggests that the spatial dependence in this model is weak, and neighboring areas’ changes do not strongly influence the change in accessibility. The LM Test that measures the autocorrelation of the residuals (p-value = 0.71) is not statistically significant, which suggests the model adequately accounts for spatial dependence. Lastly, the AIC value (AIC = 559.3) is slightly larger than the AIC value for the OLS model (AIC = 557.3), suggesting the spatial lag model does not significantly outperform a standard OLS model. Figure 4.8 shows the changes in the accessibility score between 2010 and 2020, Figure 4.3 shows the changes in independent variables between 2010 and 2020, and Figure 4.4 shows the changes in control variables between 2010 and 2020. Table 4.5 provides an overview of the outcomes from the spatial regression model, and Table 4.6 provides an overview of outcomes for the OLS model.

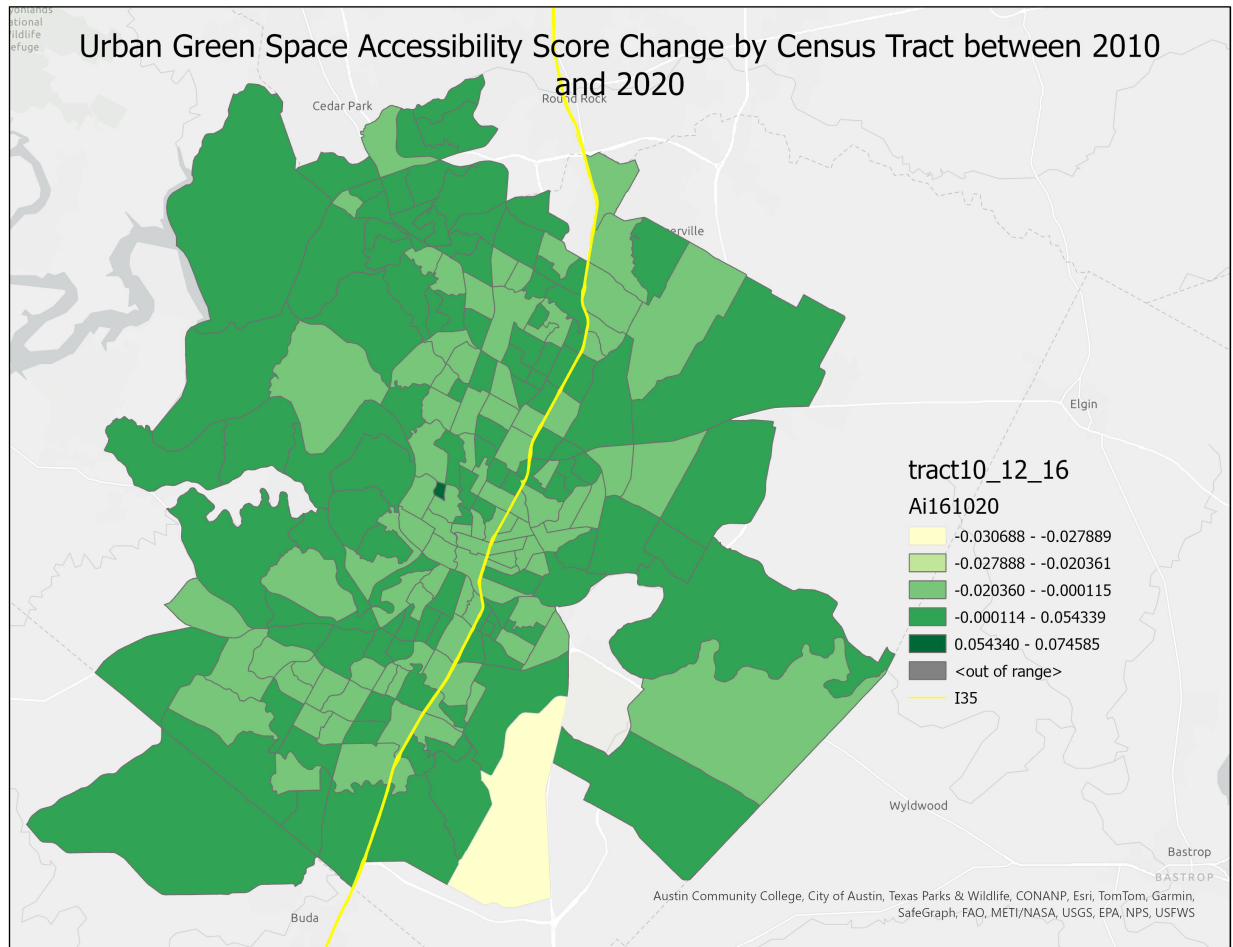


Figure 4.10. Changes in Dependent Variable between 2010 and 2020: Urban Green Space Accessibility Score by Census Tracts in Austin, TX

The dependent variable in this model is the change in accessibility scores for each census tract between 2010 and 2020. Independent variables include various socioeconomic and housing factors. The census-tract level percentage change of White residents is significant and negative, indicating that areas with decreasing white populations experienced improved accessibility to UGS. The percentage change of Housing Units older than 30 years is significant and negative, suggesting that the census tracts with increased older housing units experienced a decline in accessibility to UGS. The percentage change of housing units receiving the federal assistance program (HUD Section 8) is significant and negative, indicating that the census tracts with more

housing assistance programs experienced a decline in accessibility to UGS. Lastly, the population density change is significant and negative, suggesting that densely populated neighborhoods saw a decrease in accessibility to UGS.

Table 4.5. Change in UGS accessibility score and socioeconomic variables between 2010 and 2020, N=205 (2010 boundary)

Variables	Estimate	Std. Error	z-value	Pr(> z)
Income (\$)	-0.10	0.071	-1.41	0.16
Home Value (\$)	-0.065	0.070	-0.93	0.35
Gross Rent (\$)	-0.045	0.067	-0.67	0.51
White (%)	-0.27	0.079	-3.36	0.00078*
Black (%)	0.088	0.069	1.26	0.21
College (%)	0.052	0.076	0.69	0.49
Old Unit (%)	-0.17	0.069	-2.49	0.013*
Vacancy (%)	-0.0041	0.066	-0.062	0.95
HUD (%)	-0.23	0.065	-3.58	0.00034*
Density	-0.31	0.067	-4.62	3.90 ^{e-06*}
Rho: 0.014, p-value: 0.90				
LM Test p-value: 0.71				
AIC: 559.3 (557.3 for OLS)				

*, Significance at 0.05 level, ., Significance at 0.1 level.

Table 4.6. Ordinal Least Squares (OLS) for Change in UGS accessibility score and socioeconomic variables between 2010 and 2020, N=205 (2010 boundary)

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	-0.10	0.073	-1.36	0.18
Home Value (\$)	-0.065	0.072	-0.89	0.37
Gross Rent (\$)	-0.045	0.069	-0.66	0.51
White (%)	-0.27	0.081	-3.27	0.0013**
Black (%)	0.088	0.071	1.23	0.22
College (%)	0.052	0.078	0.67	0.51
Old Unit (%)	-0.17	0.071	-2.42	0.016*
Vacancy (%)	-0.0043	0.068	-0.063	0.95
HUD (%)	-0.23	0.067	-3.49	0.00059***
Density	-0.31	0.069	-4.49	1.21 ^{e-05***}
R ² : 0.20				
Overall p-value: 4.93 ^{e-06}				

***, Significance at 0 level, **, Significance at 0.01 level, *, Significance at 0.05 level.

4.4.1.3 Change in UGS Accessibility Score and Socioeconomic Variables between 2000 and 2020

The spatial dependence parameter ($\text{Rho} = -0.11$, $\text{p-value} = 0.33$) is negative and not statistically significant, suggesting that the spatial dependence is weak and not a critical factor for neighboring tracts to impact the accessibility scores. The LM Test that measures the autocorrelation of the residuals ($\text{p-value} = 0.68$) is not statistically significant and suggests that the model adequately accounts for spatial dependence. Lastly, the AIC value ($\text{AIC} = 580.0$) is slightly larger than the AIC value for the OLS model ($\text{AIC} = 579.0$), suggesting the spatial lag model does not significantly outperform the standard OLS model. Figure 4.9 shows the changes in the accessibility score between 2000 and 2020, Figure 4.5 shows the changes in independent variables between 2000 and 2020, and Figure 4.6 shows the changes in control variables between 2000 and 2020. Table 4.7 provides an overview of the outcomes from the spatial regression model, and Table 4.8 provides an overview of outcomes for the OLS model.

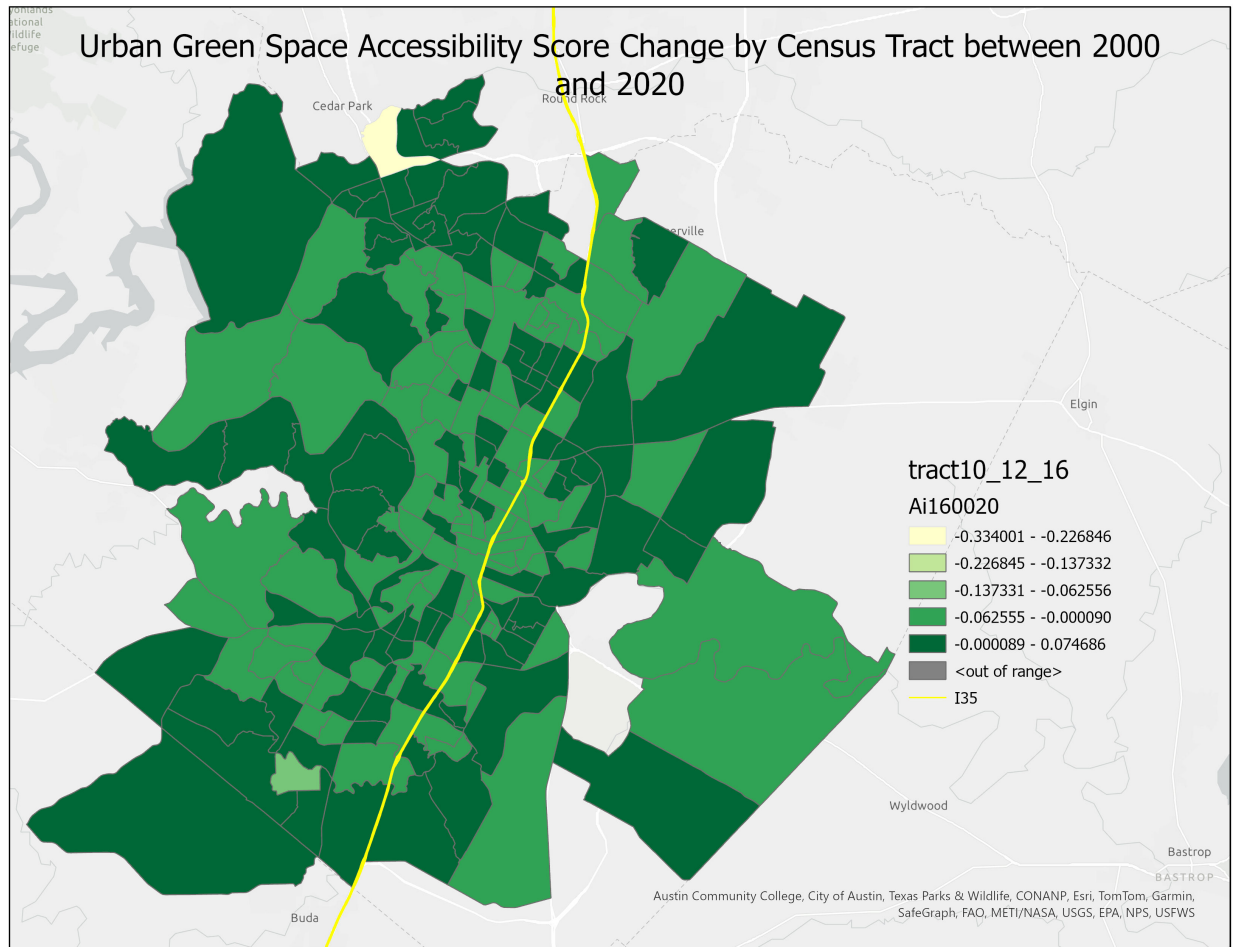


Figure 4.11. Changes in Dependent Variable between 2000 and 2020: Urban Green Space Accessibility Score by Census Tracts in Austin, TX

The dependent variable in this model is the change in accessibility scores for each census tract between 2000 and 2020. Independent variables include various socioeconomic and housing factors differences calculated for the same period. The percentage change of White residents is positive and statistically significant, indicating census tracts with an increase in white population experienced better accessibility to UGS. The percentage change in college degrees is negative and significant, suggesting census tracts with a decreased college population saw improvements in accessibility to UGS. Lastly, the change in population density is negative and marginally

significant, indicating that the more populated census tracts might have decreased accessibility to UGS.

Table 4.7. Change in UGS accessibility score and socioeconomic variables between 2000 and 2020, N=205 (2010 boundary)

Variables	Estimate	Std. Error	z-value	Pr(> z)
Income (\$)	0.0022	0.093	0.024	0.98
Home Value (\$)	-0.046	0.092	-0.50	0.62
Gross Rent (\$)	0.072	0.073	0.99	0.32
White (%)	0.38	0.098	3.87	0.00011*
Black (%)	0.069	0.079	0.88	0.38
College (%)	-0.28	0.090	-3.14	0.0017*
Old Unit (%)	0.041	0.081	0.50	0.62
Vacancy (%)	0.028	0.071	0.39	0.70
HUD (%)	-0.030	0.068	-0.43	0.67
Density	-0.13	0.079	-1.66	0.097 .
Rho: -0.11, p-value: 0.33				
LM Test p-value: 0.68				
AIC: 580.0 (579.0 for OLS)				

*, Significance at 0.05 level, . Significance at 0.1 level.

Table 4.8. Ordinal Least Squares (OLS) for Change in UGS accessibility score and socioeconomic variables between 2000 and 2020, N=205 (2010 boundary)

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	-0.0033	0.096	-0.035	0.97
Home Value (\$)	-0.050	0.095	-0.52	0.60
Gross Rent (\$)	0.073	0.075	0.97	0.33
White (%)	0.36	0.10	3.6	0.00039***
Black (%)	0.067	0.081	0.83	0.41
College (%)	-0.28	0.093	-3.00	0.0031**
Old Unit (%)	0.036	0.083	0.43	0.67
Vacancy (%)	0.029	0.073	0.40	0.69
HUD (%)	-0.033	0.070	-0.47	0.64
Density	-0.13	0.081	-1.64	0.10 .
R ² : 0.11				
Overall p-value: 0.014				

***, Significance at 0 level, **, Significance at 0.01 level, . Significance at 0.1 level.

4.4.2 Results for Changes in Per Capita Green Spaces

4.4.2.1 Change in Per Capita Green Spaces and Socioeconomic Variables between 2000 and 2010

This model's spatial dependence parameter ($\text{Rho} = -0.020$, $\text{p-value} = 0.86$) is not statistically significant, meaning a weak spatial dependence and neighboring areas do not substantially impact the changes in Per Capita Green Space in one location. The residual autocorrelation also did not show significance, suggesting the model adequately accounts for spatial dependence. Lastly, the AIC value (593.8) is slightly higher compared to an OLS model (591.9); despite reasonable, the lack of significant spatial effects might indicate other factors that were not accounted for are more important to understanding Per Capita Green Space change over time. Figure 4.10 shows the changes in per capita green space between 2000 and 2010, Figure 4.1 shows the changes in independent variables between 2000 and 2010, and Figure 4.2 shows the changes in control variables between 2000 and 2010. Table 4.9 provides an overview of the outcomes from the spatial regression model, and Table 4.10 provides an overview of outcomes for the OLS model.

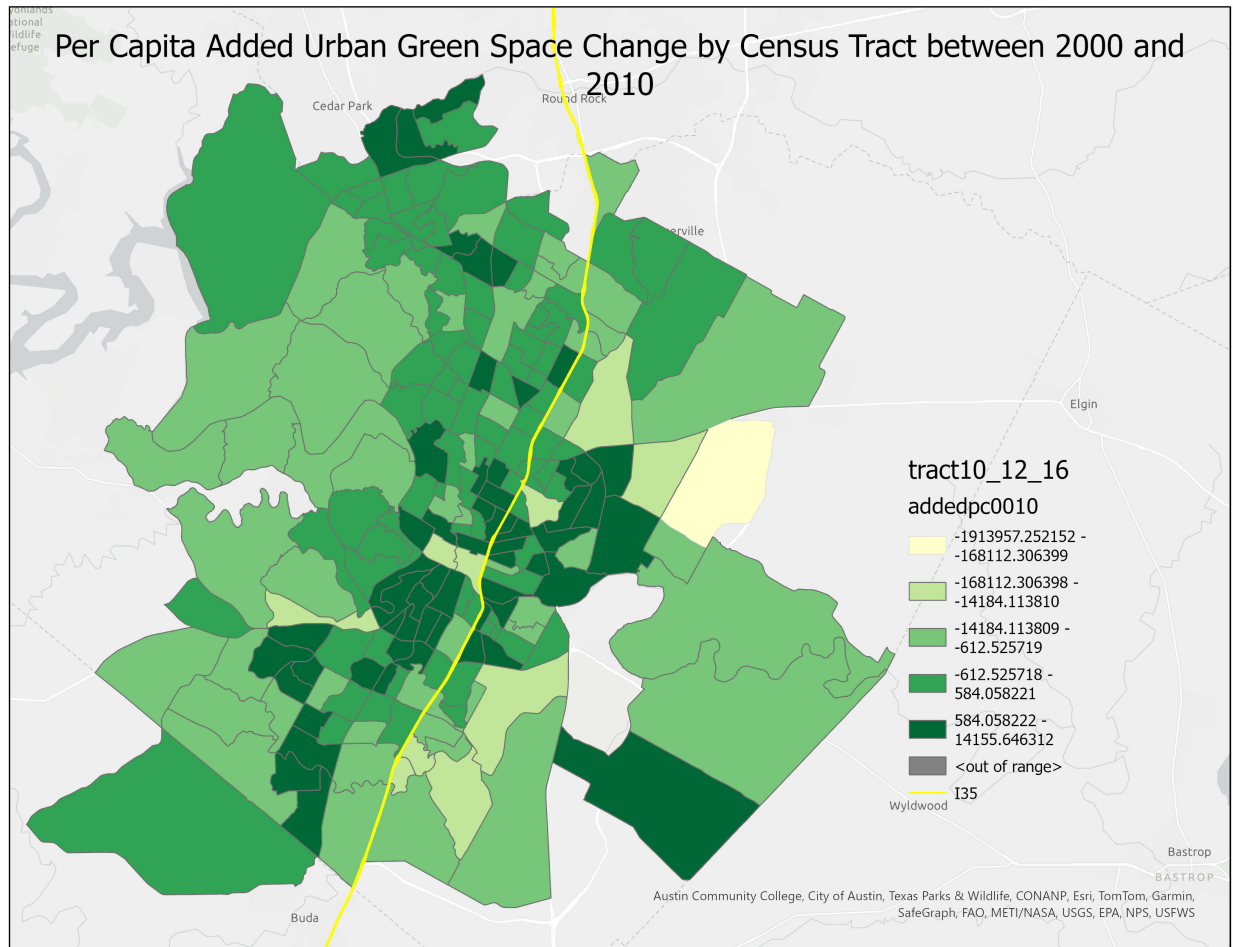


Figure 4.12. Changes in Dependent Variable between 2000 and 2010: Per Capita Added Urban Green Space by Census Tracts in Austin, TX

The dependent variable in this model is the change in Per Capita Green Spaces for each census tract between 2000 and 2010. Independent variables include various socioeconomic and housing factors differences calculated for the same period. Only the percentage change in vacant units is positive and statistically significant, indicating census tracts with higher vacancy rates between 2000 and 2010 tend to have an increase in Per Capita Green Space.

Table 4.9. Change in Per Capita Green Spaces and socioeconomic variables between 2000 and 2010, N=205 (2010 boundary)

Variables	Spatial lag model		Spatial error model	
	Estimate	Pr(> z)	Estimate	Pr(> z)

Income (\$)	-0.10	0.29	-0.099	0.29
Home Value (\$)	0.10	0.27	0.099	0.27
Gross Rent (\$)	0.0088	0.28	0.087	0.28
White (%)	-0.02	0.85	-0.017	0.85
Black (%)	0.0086	0.92	0.0090	0.91
College (%)	-0.033	0.084	-0.032	0.70
Old Unit (%)	0.11	0.16	0.11	0.17
Vacancy (%)	0.15	0.037*	0.15	0.037*
HUD (%)	0.043	0.54	0.042	0.54
Density	0.019	0.82	0.019	0.82
Diagnostics		Rho: -0.020, p-value: 0.86	Lambda: -0.013, p-value: 0.92	
		LM Test p-value: 0.67	Sigma Squared: 0.95	
		AIC: 593.8 (591.9 for OLS)	AIC: 593.9 (591.9 for OLS)	

‘*’ Significance at 0.05 level, ‘.’ Significance at 0.1 level.

Table 4.10. Ordinal Least Squares (OLS) for Change in Per Capita Green Spaces and socioeconomic variables between 2000 and 2010, N=205 (2010 boundary)

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	-0.099	0.096	-1.03	0.30
Home Value (\$)	0.099	0.093	1.06	0.29
Gross Rent (\$)	0.088	0.084	1.05	0.29
White (%)	-0.019	0.096	-0.20	0.84
Black (%)	0.0082	0.084	0.098	0.92
College (%)	-0.032	0.087	-0.37	0.71
Old Unit (%)	0.11	0.080	1.34	0.18
Vacancy (%)	0.15	0.072	2.03	0.044*
HUD (%)	0.042	0.072	0.59	0.56
Density	0.018	0.083	0.21	0.83
R ² : 0.048				
Overall p-value: 0.47				

‘*’ Significance at 0.05 level.

4.4.2.2 Change in Per Capita Green Spaces and Socioeconomic Variables between 2010 and 2020

The spatial dependence parameter (Rho = 0.049, p-value = 0.65) shows a weak spatial dependence in which Per Capita Green Space in one area does not substantially impact its neighboring tracts. The LM Test is significant, indicating spatial autocorrelation in the model’s residuals. A spatial error model was also tested and interpreted in this case. Lastly, the AIC values in spatial lag and spatial error are slightly higher than the OLS model, indicating a decent

model fit, while the spatial dependence might not play a crucial part in the model. Figure 4.11 shows the changes in per capita green space between 2010 and 2020, Figure 4.3 shows the changes in independent variables between 2010 and 2020, and Figure 4.4 shows the changes in control variables between 2010 and 2020. Table 4.11 provides an overview of the outcomes from the spatial regression model, and Table 4.12 provides an overview of the outcomes for the OLS model.

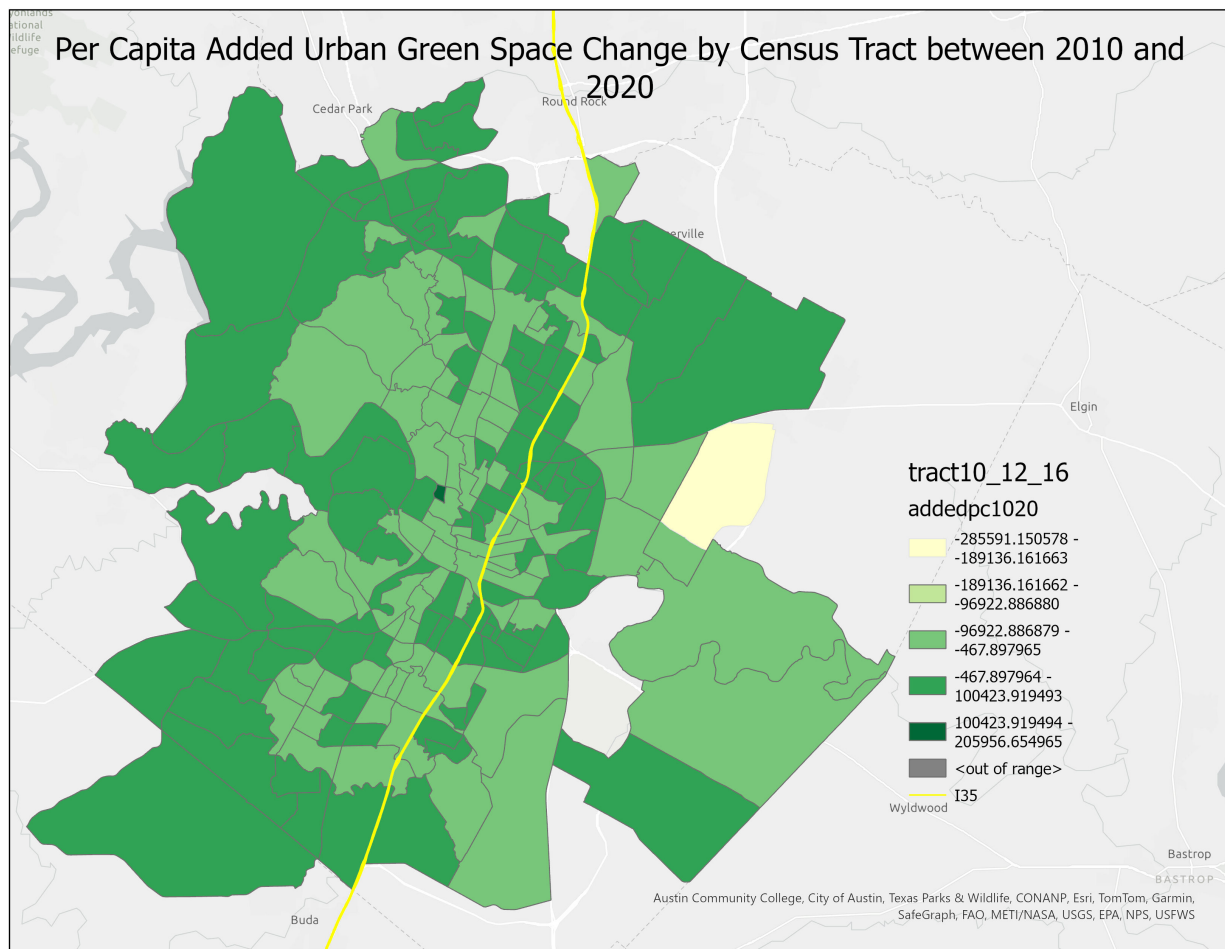


Figure 4.13. Changes in Dependent Variable between 2010 and 2020: Per Capita Added Urban Green Space by Census Tracts in Austin, TX

The dependent variable in this model is the change in Per Capita Green Spaces for each census tract between 2010 and 2020. Independent variables include various socioeconomic and

housing factors differences calculated for the same period. The change in the percentage of White residents shows a significant negative association, indicating census tracts experienced more white population influx and less Per Capita Green Space. The change in the percentage of Black residents, similar to the Whites, also shows a significant negative association. The change in population density is significant and shows a negative association with Per Capita Green Space. The change in median household income shows a marginal negative effect, suggesting that areas with higher median household income might have less Per Capita Green Space. Lastly, the change in the percentage of college degrees is positive and marginally significant in both spatial lag and the OLS model but not in the spatial error model, indicating the change in college degrees might have a weak impact on increased Per Capita Green Space.

Table 4.11. Change in Per Capita Green Spaces and socioeconomic variables between 2010 and 2020, N=205 (2010 boundary)

Variables	Spatial lag model		Spatial error model	
	Estimate	Pr(> z)	Estimate	Pr(> z)
Income (\$)	-0.13	0.068 .	-0.14	0.055 .
Home Value (\$)	0.031	0.67	0.0076	0.92
Gross Rent (\$)	0.0047	0.95	0.025	0.71
White (%)	-0.29	0.00034*	-0.28	0.00059*
Black (%)	-0.34	2.30 ^{e-06} *	-0.36	5.28 ^{e-07} *
College (%)	0.12	0.12 .	0.11	0.18
Old Unit (%)	-0.052	0.46	-0.045	0.55
Vacancy (%)	0.024	0.73	0.019	0.78
HUD (%)	-0.025	0.70	-0.011	0.87
Density	-0.19	0.0069*	-0.19	0.0054*
Diagnostics	Rho: 0.049, p-value: 0.65		Lambda: 0.15, p-value: 0.16	
	LM Test p-value: 0.042		Sigma Squared: 0.84	
	AIC: 571.2 (569.3 for OLS)		AIC: 570.0 (569.3 for OLS)	

‘*’ Significance at 0.05 level, ‘.’ Significance at 0.1 level.

Table 4.12. Ordinal Least Squares (OLS) for Change in Per Capita Green Spaces and socioeconomic variables between 2010 and 2020, N=205 (2010 boundary)

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	-0.13	0.076	-1.77	0.079 .
Home Value (\$)	0.035	0.075	0.47	0.64
Gross Rent (\$)	0.0016	0.071	0.023	0.98
White (%)	-0.29	0.084	-3.50	0.00057***

Black (%)	-0.33	0.073	-4.55	9.32 ^{e-06***}
College (%)	0.12	0.080	1.54	0.12 .
Old Unit (%)	-0.050	0.073	-0.69	0.49
Vacancy (%)	0.024	0.070	0.35	0.73
HUD (%)	-0.028	0.069	-0.41	0.68
Density	-0.19	0.071	-2.61	0.0097**
R ² : 0.15				
Overall p-value: 0.00049				
***, Significance at 0 level, **, Significance at 0.01 level, . Significance at 0.1 level.				

4.4.2.3 Change in Per Capita Green Spaces and Socioeconomic Variables between 2000 and 2020

The spatial dependence parameter (Rho = 0.049, p-value = 0.65) shows a weak spatial dependence in which Per Capita Green Space in one area does not substantially impact its neighboring tracts. The LM Test is significant, indicating spatial autocorrelation exists in the model's residuals. A spatial error model was also tested and interpreted in this case. Lastly, the AIC values in spatial lag and spatial error are slightly higher than the OLS model, indicating a decent model fit, while the spatial dependence might not play a crucial part in the model. Figure 4.12 shows the changes in per capita green space between 2000 and 2020, Figure 4.5 shows the changes in independent variables between 2000 and 2020, and Figure 4.6 shows the changes in control variables between 2000 and 2020. Table 4.13 provides an overview of the outcomes from the spatial regression model, and Table 4.14 provides an overview of outcomes for the OLS model.

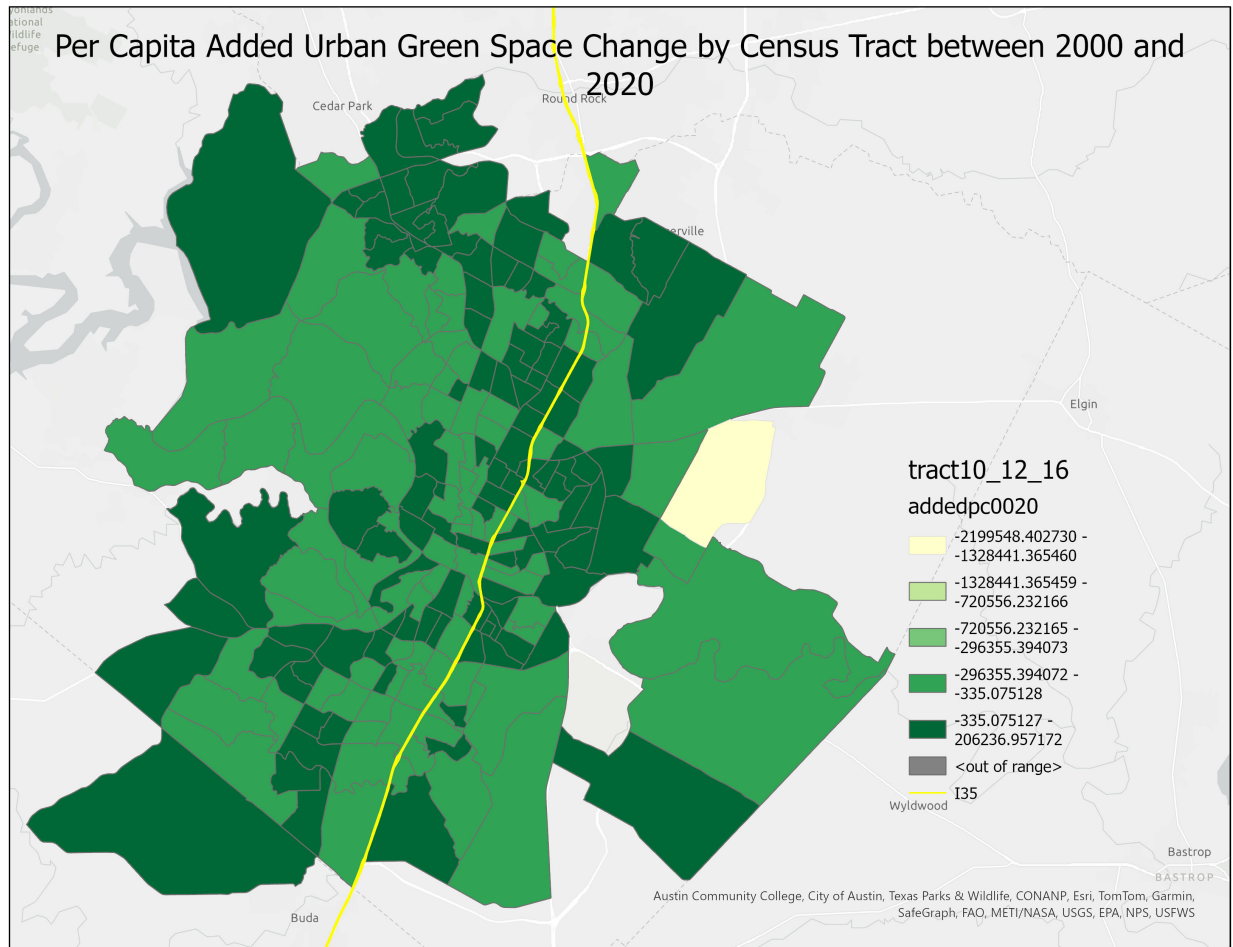


Figure 4.14. Changes in Dependent Variable between 2000 and 2020: Per Capita Added Urban Green Space by Census Tracts in Austin, TX

The dependent variable in this model is the change in Per Capita Green Spaces for each census tract between 2000 and 2020. Independent variables include various socioeconomic and housing factors differences calculated for the same period. The change in the percentage of White residents shows a negative and significant association with the outcome, indicating census tracts with an increase in the percentage of White residents experienced a declined Per Capita Green Space. Similarly, the negative and significant association between the percentage change in Black residents and the outcome indicates that neighborhoods with an increase in Black residents saw a decrease in Per Capita Green Space. The change in vacant housing units is

positive and significant, suggesting areas with more vacant units experienced improved Per Capita Green Space. Lastly, Median Household Income and Median Home Value show a marginally significant association with the outcome, indicating these two variables might have impacted the Per Capita Green Space change.

Table 4.13. Change in Per Capita Green Spaces and socioeconomic variables between 2000 and 2020, N=205 (2010 boundary)

Variables	Spatial lag model		Spatial error model	
	Estimate	Pr(> z)	Estimate	Pr(> z)
Income (\$)	-0.15	0.10 .	-0.15	0.096 .
Home Value (\$)	0.17	0.059 .	0.16	0.088 .
Gross Rent (\$)	0.098	0.17	0.11	0.13
White (%)	-0.27	0.0043*	-0.29	0.0034*
Black (%)	-0.36	3.54 ^{e-06*}	-0.40	4.37 ^{e-07*}
College (%)	0.080	0.36	0.071	0.43
Old Unit (%)	0.11	0.16	0.095	0.25
Vacancy (%)	0.18	0.0087*	0.18	0.012*
HUD (%)	0.021	0.75	0.030	0.65
Density	-0.012	0.88	-0.025	0.75
Diagnostics	Rho: -0.0045, p-value: 0.97		Lambda: 0.13, p-value: 0.26	
	LM Test p-value: 0.0022		Sigma Squared: 0.84	
	AIC: 570.8 (568.8 for OLS)		AIC: 569.8 (568.8 for OLS)	

*,** Significance at 0.05 level, ‘.’ Significance at 0.1 level.

Table 4.14. Ordinal Least Squares (OLS) for Change in Per Capita Green Spaces and socioeconomic variables between 2000 and 2020, N=205 (2010 boundary)

Variables	Estimate	Std. Error	t-value	Pr(> t)
Income (\$)	-0.15	0.094	-1.60	0.11 .
Home Value (\$)	0.17	0.093	1.84	0.068 .
Gross Rent (\$)	0.099	0.074	1.34	0.18
White (%)	-0.27	0.098	-2.78	0.00069**
Black (%)	-0.36	0.079	-4.54	9.71 ^{e-06***}
College (%)	0.080	0.091	0.89	0.38
Old Unit (%)	0.11	0.081	1.36	0.18
Vacancy (%)	0.18	0.071	0.31	0.011*
HUD (%)	0.021	0.069	0.31	0.76
Density	-0.012	0.080	-0.15	0.88
R ² : 0.15				
Overall p-value: 0.00041				

***, Significance at 0 level, **, Significance at 0.01 level, *, Significance at 0.05 level, ‘.’ Significance at 0.1 level.

4.5 Discussion

The first part of Chapter 4 examined the evolution and shift of key predictors associated with proximity to UGS (denoted as accessibility score A_i) in each period. Several key patterns are listed below.

1. Racial and Ethnic Background: 1) between 2000 and 2010, urban green space development favored tracts with a higher percentage of white residents; 2) between 2010 and 2020, tracts with a higher percentage of white residents saw a decline in UGS development; and 3) between 2000 and 2020, areas with a higher percentage of white residents showed a cumulative gain of UGS development, suggesting the advantage persisted despite later shifts of trends.
2. Housing and Urbanization: Population Density and Percentage of HUD Units became significant and negatively impacted access to UGS after 2010. This finding aligns with the housing and displacement pressure discussed in the literature review section.
3. Education: The Percentage of College Degrees negatively impacted access to UGS in all periods, contradicting the literature. This suggests that more educated areas might prioritize other forms of development over green space.
4. Economic Factors: Median Household Income, Median Home Value, and Median Gross Rent were not significant in all periods, suggesting that green space changes were driven more by other factors. This finding was inconsistent with the findings from Chapter 3.

Overall, low R-squared values were found in all models, suggesting that other variables, such as policy changes, grassroots activism, and environmental factors, might have unexplained

variance that was not captured by the identified predictive variables. In addition, decadal intervals may mitigate or hide the shorter-term social dynamics, like rapid gentrification. Lastly, political forces at a larger scale could impact the UGS accessibility analyses done at the local scale.

The second part of Chapter 4 investigates the other aspect of accessibility, urban green space size, in relation to the evolution and shift of identified predictive variables. Several key patterns are listed below.

1. Racial and Ethnic Background: Areas with a higher Percentage of White and Black Residents experienced loss of per capita green space in both the 2010-2020 and 2000-2020 periods. However, Black-majority tracts suffered the steepest long-term losses compared to their White counterparts. This finding suggests the systemic underinvestment in Black-majority neighborhoods and the incompatible UGS development that is scaled with population growth.
2. Housing and Urbanization: The Percentage of Vacant Units was consistently associated with increased per capita green space in 2000-2020, suggesting areas with higher housing pressure or aging infrastructure might have experienced UGS development gains. In addition, Population Density became a significant negative predictor after 2010, suggesting that population growth in dense tracts outpaced UGS development.
3. Economic Factors: Median Household Income, Median Home Value, and Median Gross Rent were not significant across all periods, suggesting per capita green space changes might be driven by race and land use variables rather than economic status.

Overall, per capita green space changes during 2000-2010 were weakly structured and not strongly tied to any identified predictive variables. The rest of the models contrasted with the proximity analysis. More specifically, in the proximity analyses, tracts with a higher percentage of White residents experienced improved proximity to UGS but failed to keep pace with population growth between 2000 and 2010. On the other hand, Black neighborhoods consistently lost in both metrics, indicating persistent systemic inequity. Furthermore, population density showed a completely different role in both analyses, suggesting the importance of metric choice in urban planning. Lastly, low explanatory power was found in the 2000-2010 model, suggesting there might exist omitted variables, such as local policies and environmental factors, that might play a major role in UGS development.

Chapter 5 - Longitudinal Impact of Civic Participation on UGS:

From a Procedural Justice Perspective

5.1 Introduction

In design and planning, spatial analysis is a vital tool for researchers studying environmental justice, particularly in assessing spatial disparities in UGS access. Its popularity stems from the availability of diverse datasets and its ability to present findings quantitatively. While conventional spatial analysis can provide insight into the severity of inequities, it often fails to explain the forces behind these injustices. An important aspect of UGS research is understanding how spatial patterns are tied to socially constructed contexts and shaped by local governance and institutional practices (Silva et al., 2014). This has led to increased interest in combining both qualitative and quantitative methods despite longstanding debates (Cairns et al., 2017; Elman et al., 2016; M. Kwan, 2004). One way to achieve this is by crossing geographical boundaries using spatial technologies and linking them to qualitative approaches that reflect local conditions (M. Kwan, 2004). As spatial and temporal factors evolve, traditional approaches may not fully capture the non-linear relationships between variables, highlighting the need for mixed-method research to uncover the complex interactions shaping UGS distribution (Cairns et al., 2017).

5.2 Complexity in Spatial-Temporal Research

5.2.1 Spatial and Temporal Scale Issues

Scale is not a neutral construction but a discursive frame that goes through negotiations between competing stakeholders for the ideal location of political power and geographic

boundaries for policies and regulations (Delaney & Leitner, 1997). Ontologically, it is not given but related to the historical material constitution of society while maintaining its fluidity (Marston, 2000; McCann, 2003). This fluidity, or the process of rescaling, refers to how policies are shifted from a formerly identified scale to a redefined one to suit the problem-solving (Brenner, 1998, 2000). As environmental justice concerns in UGS emerged in recent years, the previous set of urban policies related to the provision of green spaces has become untenable in catching up with communities' needs. As the situation worsens, potential rescaling policies are developed to overcome the uneven geographical UGS development (McCann, 2003). The adoption of rescaling for problem-solving also relates to the "scalar fix," where the social and political processes facilitate the redistribution of social and political resources for effective urban governance (Brenner, 1998). For instance, the attempts from the state-level policy implementation to solve the historical legacy of institutionalized racism that has directed contemporary urban green space development in Austin can be seen as a scalar fix. Creating new scalar fixes can be scaled up or down, depending on the specific urban problems (McCann, 2003). The study recognizes that the level of UGS inequity is also impacted by the actions undertaken at larger or smaller geographic scales. In addition, as spatiality and temporality are connected in a complex way, researchers may not discard the consideration of the temporal scale, especially when examining the material effects of the policies (McCann, 2003). As introduced in Chapter 1's introduction part, Austin has seen rapid growth since the 1990s, with the influx of population and high-tech industries (Connolly & Lira, 2021). The land use and planning-related policies introduced during that period, Smart Growth Initiative, has set out a desired developmental zone that deepened the environmental injustice regarding urban green space accessibility for marginalized communities (Connolly & Lira, 2021; Garcia-Lamarca et al., 2021;

Long, 2016). The connections across temporal scales and the politics of spatial scales in Austin can be found during this period as the adoption of the late-1990 Neighborhood Plan succeeding the Smart Growth Initiative to scale down to the neighborhood level development in which urban green space was also part of it (Blunt, 2008). As a result, the examination of the spatial-temporal scale following the 1990 demarcation makes sense.

One possible way to understand whether city planning decision-making contributes to a better UGS distribution in vulnerable neighborhoods over time is to use Qualitative Comparative Analysis (QCA). This technique combines the rich contextual information from qualitative research with the large number of cases for testing statistical significance that are considered more generalizable from quantitative research (Cairns et al., 2017; Pappas & Woodside, 2021). It contends the possibility of how different combinations of conditions may lead to the same outcome. This approach is suitable for answering complex spatial planning questions while paying close attention to the local context using small- and medium-sized cases (Verweij & Trell, 2019; Rihoux et al., 2013). In addition, unlike quantitative research that focuses on how different variables produce effects on the outcome, it tries to explain how a specific outcome is produced, a way of understanding the relationship between conditions and outcome, which echoes well with the purpose of the study (Verweij & Trell, 2019; Schneider & Wagemann, 2010).

However, few studies have used QCA in the planning field, especially concerning its complex nature and scale problems. The first notion that needs to be addressed before proceeding with the technique concerns the spatial scale. One systematic research that summarizes the cases and conditions from various QCA studies argues that it can be used for comparing cases at any scale if the cases themselves are at the same level (Verweij & Trell,

2019). For instance, the direct and meaningful assessments of approving or engaging with park project planning gathered from public documents are appropriate to be analyzed at the community scale. This is because the projects are fixed in that specific locality and cannot be extrapolated across space or time (Singh-Peterson & Underhill, 2017). On the other hand, the assessment of the city-wide planning strategy needs to utilize a regional or even larger scale as it is heavily influenced by the institutional and political will, which, reversely, greatly impacts the UGS equity locally. As a result, two levels of indicators are extracted or modified to examine the qualitative aspect of UGS equity both at the community and city scales. On the other hand, for the quantitative aspect of this dissertation, it decided to use the finest scale of data at the census tract level for research to be conducted at a reasonable scale. For a park within a reasonable walking distance for any resident in that community to enjoy its perks, researchers must find the best possible scales where the underlying processes take place (M. P. Kwan, 2012). The use of the census tract scale coincides well with the qualitative data identified at the community level.

The second notion concerns the temporal scale. Tracking configuration over time with QCA requires data on multiple time points for the same socio-spatial units, thus making sense of the first step of data harmonization to regulate the spatial data into the same geographic units (Verweij & Vis, 2021). One way to solve the problem is to adopt the harmonized data that have applied complex weighting techniques to transform data from different geographic boundaries from different times into a standardized one. For example, the Longitudinal Tract Data Base developed by Brown University provides summary statistics measured multiple times at a specific geographic unit (Logan et al., 2014). The integration includes two types – attribute integration and geographic integration, with the primary assumption that characteristics of the source zone share a proportionate distribution pattern about the target zone based on their spatial

relationship (Schroeder, 2007). The former ensures that the attributes can be compared across time; the latter ensures that the areas summarized are comparable across time. Currently, it offers standardized data for 2010 census geographic units through interpolation, where estimates are made to assign characteristics to the new units (Schroeder, 2007). The strategy to utilize a reasonable temporal scale to track changes over time is similar to the census data that follows a decadal interval. As a result, the qualitative data concerning the 1990s adoption of scaled-down policy will work well by following the decadal interval, in which the approved cases will be categorized into the years 1990-2000, 2000-2010, and 2010-2020.

5.2.2 Integrating Spatial and Temporal Scales in Research

Multiple fsQCAs with different periods following decadal intervals are conducted to understand the mechanisms that lead to the current UGS distribution over time (Verweij & Vis, 2021). Subsequently, three solution formulas for the different periods are compared with each other. The outcome of interest would be the census tract level UGS accessibility score, coded as either one (1) equal to being equitable or zero (0) equal to inequitable. Five conditions of interest are identified, representing differences in kind rather than degree, and they are calculated in comparison with the city-wide mean values.

In the result section, truth tables for each decade show the different configurations. The contradictory cases might show, for instance, that higher UGS accessibility scores might overpower the existence of approved park cases regarding pathways to UGS equity in those areas. Boolean minimization is performed to simplify complex configurations into ones that are easier to interpret (Rihoux & De Meur, 2009). At the same time, the table produces consistent numbers indicating how strong the solution is (Cairns et al., 2017). The parameter of fit of consistency is used to determine whether empirical set relations exist, either necessary or sufficient. It provides

knowledge on what conditions can be considered sufficient for UGS inequity to occur. The coverage parameters are used to tell how many cases can be explained by the conditions. To compare configurations over time, first examine the first-decade formula with the third-decade formula to take a longer-term perspective. Then, the in-between period formula is compared to the first and third, respectively, to examine which conditions are stable over time and which are changing.

5.2.3 Research Questions and Hypotheses

Austin has grown rapidly since the 1990s with the population influx and new high-tech industries (Connolly & Lira, 2021). Some scholars argued that the land use and planning-related policies introduced during that period, like the Smart Growth Initiative, have set out a desired developmental zone that deepened the environmental injustice regarding urban green space accessibility for marginalized communities (Connolly & Lira, 2021; Garcia-Lamarca et al., 2021; Long, 2016). The demographic data is related to powerful, wealthier, and whiter communities, so they tend to have more say in procedural justice. As the focus travels across time and space, the traditional approach might not be sufficient to understand the potential non-linear relationship. The notions of spatial and temporal scales are crucial to analyzing their relationship, as historical decisions made regarding UGS development were deeply embedded in the contextual background, which makes identifying the right variables even more complex (Cairns et al., 2017). In this chapter, the following questions are addressed:

1. How do we explain the current spatial pattern of UGS distribution in Austin, TX, longitudinally from a procedural justice perspective?
2. Do other identified factors, coupled with civic participation, impact UGS development in Austin, TX, longitudinally?

The following hypotheses were tested:

1. Civic participation is important in impacting urban green space distribution over time.
2. Areas with more White residents are more embedded in the decision-making process during public meetings.
3. Areas with higher median household income are more embedded in the decision-making process during public meetings.

5.3 Method

5.3.1 Data Treatment

Based on publicly available documents, the summary of the analysis on citizen participation in Austin's Department of Park and Recreation (PARC) board meetings involved a review of meeting minutes from 1991 to 2020, focusing on three decadal periods (1991-2000, 2001-2010, and 2011-2020). This analysis excluded canceled meetings and cross-checked the Agenda and Backup files to ensure no citizen participation information was missed. It specifically gathered data from the "Citizen Communication" sections of meeting minutes, considering only issues directly related to Austin parks (Figure 5.1). Irrelevant topics, such as those concerning Planned Unit Development (PUD), business opportunities, structures not managed by PARC, or parks outside the research boundary, were excluded. Each instance of citizen participation related to a specific park was coded as "1" for the corresponding month in an Excel file; broader issues affecting all city parks, like dog restrictions or long-term park plans, were coded as "1" for every park. The data was then summarized monthly, yearly, and by decade for further analysis.

Minutes
Parks and Recreation Board
January 22, 1991

The regular meeting of the Parks and Recreation Board was held at the Parks and Recreation Department Board Room, 1500 W. Riverside Drive with Mrs. Beverly Griffith, Chair, presiding. Board Members present: Terry Colgan, Neil Iscoe, ErmaLinda Cruz-Torres, Beverly Griffith, Louise Nivison, Ron Cartlidge, and Agnes Edwards. Staff present: Manuel Mollinedo, Jody Hamilton, Stuart Strong, Peter Marsh, Carolyn Kelley, Valleri Edelbrock and Donna Bohls.

CALL TO ORDER

The meeting was called to order at 6:30 p.m.

CITIZEN COMMUNICATIONS

Mr. Robert Simmons addressed the Board with a proposal for the installation of a carousel in Zilker Park. Mr. Simmons requested that the concessions RFP currently being prepared include a carousel concession. He provided Board Members with pictures of his proposed carousel which would have a Texas history theme.

SPECIAL PRESENTATIONS

Slide Show from Flag Football Programs

Robert Sopronyi, Acting Division Manager for Programs, made a presentation to the Board. He showed slides of the Department's At-Risk Youth flag football program including the cheerleaders. Mr. Sopronyi outlined the participation in both the flag football and basketball programs, funding for the programs and upcoming programs such as "Dare to Dance" and "High Adventure." He informed Board Members about the sponsorship of Pizza Hut, Pepsi and the Optimists Clubs in providing food for the sports banquets.

COMMITTEE REPORTS

None

CHAIR'S REPORT

Mrs. Griffith made a report on the RUDAT (Regional Urban Design Assistance Team) visit to Austin and their favorable report in regard to our downtown parks. She indicated that the Team stressed programming our resources.

ITEMS FROM PREVIOUS AGENDA

Approval of Conceptual Design of Gazebo at Lou Neff Point

David Santos, Project Manager, and Valleri Edelbrock, Horticulturalist, answered questions for Board Members regarding the gazebo project and the wisteria located on the site. Terry Colgan made a motion to approve the conceptual design of the project. ErmaLinda Cruz-Torres seconded the

Figure 5.1. Sample "Citizen Communication" concerning park development from Austin Department of Parks and Recreation board meetings

The next step is to geocode citizen participation data for later QCA analysis. First, if the citizen communication content concerns one specific park, that park is coded as “1” during that month; if the content concerns overall green space planning, then all 313 parks are coded as “1” for that month. Second, the total number for each park is then summed up for the whole decade. Third, to summarize the total cases for each census tract. The assumption was that each park has a service area, with a 1600-meter threshold representing an easy walking distance for most citizens, as supported by other studies (Anguelovski et al., 2022). The same threshold was applied to issues affecting specific parks, assuming these would draw neighboring citizens to the park. Maps depicting citizen participation in Austin over the three decades were included for reference. The data was further analyzed using fsQCA to examine the mechanisms influencing the current distribution of urban green spaces over time, considering citizen participation in the three decades (1991-2000, 2001-2010, and 2011-2020). The analysis included variables such as the percentage of the White and Black populations, median household income, population density, and civic participation (measured by the number of cases per census tract for each decadal period). The outcome variable was the census-tract-level green space accessibility score. The data was calibrated on a scale from 0 to 1, using the 95th, 50th, and 5th percentiles as benchmarks. Data calibration is an essential step as it transforms the raw data into meaningful set memberships, including full membership, partial membership, and non-membership in a set (Pappas & Woodside, 2021). For example, a calibrated data of 0.8 means “mostly in,” and a calibrated data of 0.2 means “mostly out.” This step captures the complex social phenomena that are not binary. In addition, the calibrated data is standardized into the same metric, enabling the comparison of cases with different measurement scales, which was discussed before regarding the advantage of using QCA to deal with complex spatial and temporal scales (Pappas &

Woodside, 2021). The truth table and sufficiency analysis are core tools to help identify causal conditions or combinations of conditions that lead to an outcome (Verweij & Trell, 2019; Rihoux et al., 2013; Cairns et al., 2017; Pappas & Woodside, 2021). In the QCA software, these two steps were performed automatically to formalize the assumption that the outcomes result from the combination of conditions and ensure the possibility of multiple combinations can lead to the same outcome, therefore making the reasoning explicit and replicable (Verweij & Trell, 2019; Rihoux et al., 2013; Cairns et al., 2017). The truth table and sufficiency analyses in this research indicated no necessary conditions (all values were smaller than 0.9). The final step involved generating solution formulas for different decadal periods to facilitate longitudinal comparisons. Figure 5.2 shows the steps to perform fsQCA, and Figure 5.3 shows the Per Capita Civic Participation by Census Tract from 2000 to 2020.

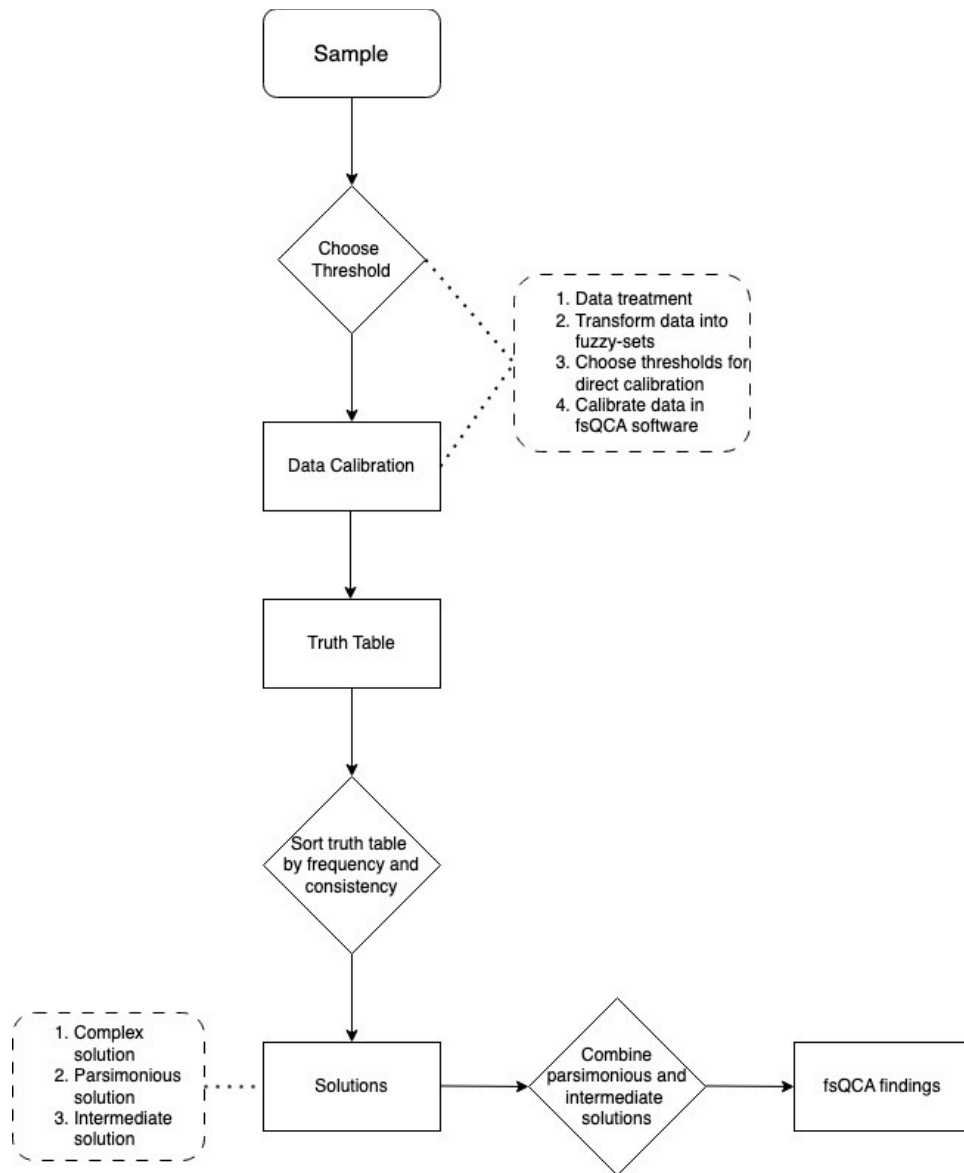


Figure 5.2. Steps to perform fsQCA

Source: Adapted from Pappas and Woodside, “Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing,” *International Journal of Information Management* 58 (2021): 102310

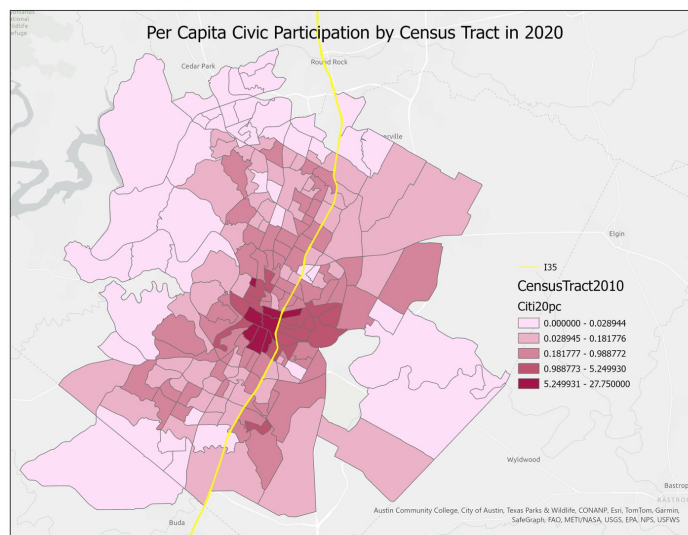
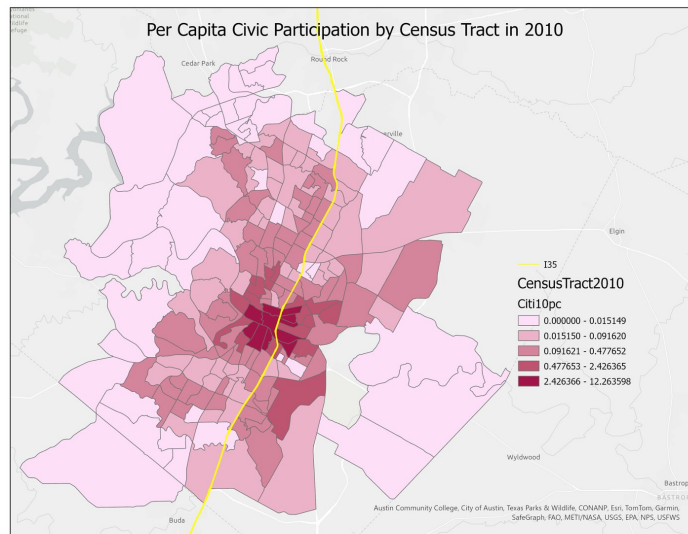
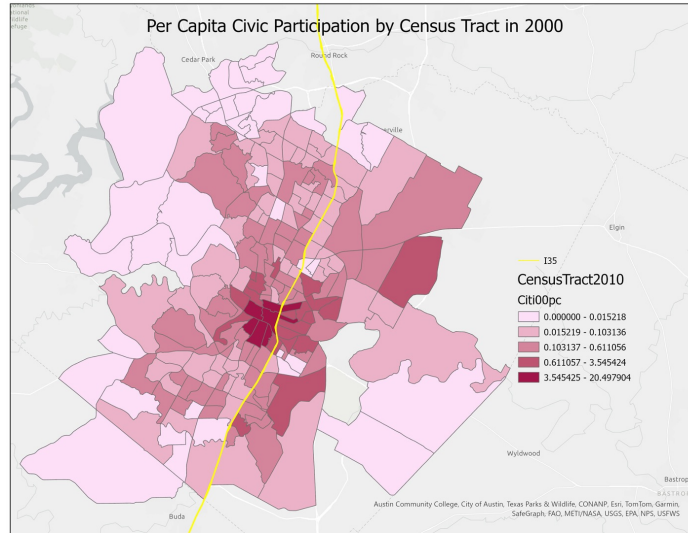


Figure 5.3. Per Capita Civic Participation by Census Tract from 2000 to 2020

5.3.2 Data Calibration

The commonly used thresholds are 0.95, 0.5, and 0.05. The data is transformed into corresponding log-odds metric values ranging from 0 to 1. The data that corresponds to each threshold is calculated using percentiles. Due to the multicollinearity of the data, especially between the Percentage of the White Population and the Percentage of College Degrees, only the former was included in the final analysis.

5.4 Results

5.4.1 Civic Participation in the 2000s

The year 2000s fsQCA results analyze the UGS accessibility score outcome AiCal as a function of five calibrated conditions: income (HincCal), racial composition (WhtCal, BlkCal), population density (DenCal), and civic participation (CitiCal). The Quine-McCluskey algorithm processes the truth tables following the logic of elimination and has identified three primary combinations of conditions that lead to the outcome (Schneider & Rohlfing, 2016).

5.4.1.1 Individual Combination of Conditions

$\sim\text{HincCal} * \text{WhtCal} * \text{CitiCal}$

The Raw Coverage score of 0.405 indicates the combination of a low level of income ($\sim\text{HincCal}$), a high percentage of White residents (WhtCal), and a high level of Civic Participation (CitiCal) explains about 40.5% of the instances where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.048 shows that this path uniquely explained around 4.8% of the total cases. The Consistency score of 0.778 indicates that the path is a reasonably reliable predictor, and the combination leads to the outcome with a consistency of approximately 77.8%.

WhtCal*BlkCal*CitiCal

The Raw Coverage score of 0.313 indicates the combination of a high percentage of White residents (WhtCal), a high percentage of Black residents (BlkCal), and a high level of Civic Participation (CitiCal) explains about 31.3% of the cases where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.002 accounts for a very small portion (0.2%) of the outcome, suggesting that it mostly overlaps with other paths in explaining the outcome. The Consistency score of 0.778 indicates that the path is a reliable predictor, and the combination leads to the outcome with a consistency of approximately 79.1%.

HincCal*DenCal*CitiCal

The Raw Coverage score of 0.376 indicates the combination of a high level of income (HincCal), high population density (DenCal), and a high level of Civic Participation (CitiCal) explains about 37.6% of the cases where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.068 shows that this path uniquely explained around 6.8% of the total cases, making it a more distinct pathway than others. The Consistency score of 0.835 indicates this path is the most consistent, with a score of 83.5%, the most reliable of the three combinations in predicting the outcome.

5.4.1.2 Overall Solution Metrics and Interpretation

The overall coverage is approximately 49.1%, meaning that these combinations together explain nearly half of the instances where the outcome of AiCal occurs. The overall consistency of the solution is about 76.3%, indicating that, on the whole, the identified paths are fairly reliable in leading to the outcome (see Table 5.1).

Civic Participation (CitiCal) is a common factor across all three combinations, suggesting it plays a crucial role in achieving the outcome of access to the UGS (AiCal). For income and

racial composition, the results indicate that different levels of income and racial composition interact with civic participation and population density to lead to the outcome. Both high and low income can contribute to the outcome, depending on how they interact with other factors. Lastly, high population density combined with high income and civic participation appears to be a strong predictor of the outcome, as indicated by the high consistency in the third path.

The result suggests that multiple pathways exist to achieving access to the UGS (AiCal), each involving different combinations of income, racial composition, population density, and civic participation. Civic Participation emerges as a key factor across all pathways. The overall coverage of about 49.1% implies that while these combinations explain a significant portion of the outcome, other unexplored factors might also contribute to access to the UGS.

Table 5.1. Intermediate Solutions for the 2000s

Year	Solution Formula	Unique Coverage	Raw Coverage	Consistency
2000s	~HincCal*WhtCal*CitiCal	0.048	0.405	0.778
	WhtCal*BlkCal*CitiCal	0.002	0.313	0.791
	HincCal*DenCal*CitiCal	0.068	0.376	0.835
				<i>Solution Coverage: 0.491</i>
				<i>Solution Consistency: 0.763</i>

5.4.2 Civic Participation in the 2010s

The year 2010s fsQCA results analyze the UGS accessibility score outcome AiCal as a function of five calibrated conditions: income (HincCal), racial composition (WhtCal, BlkCal), population density (DenCal), and civic participation (CitiCal). Below is a breakdown of each solution formula.

5.4.2.1 Individual Combination of Conditions

*WhtCal*CitiCal*

The Raw Coverage score of 0.494 indicates the combination of a high percentage of White residents (WhtCal) and a high level of Civic Participation (CitiCal) explains about 49.4%

of the instances where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.187 shows that this path uniquely explained around 18.7% of the total cases. The consistency score of 0.741 indicates that the path is a fairly reliable predictor, and the combination leads to the outcome in about three-quarters of the cases.

$$BlkCal * \sim DenCal * CitiCal$$

The Raw Coverage score of 0.401 indicates the combination of a high percentage of Black residents (BlkCal), low population density ($\sim$ DenCal), and a high level of Civic Participation (CitiCal) explains about 40.1% of the instances where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.085 shows that this path uniquely explained around 8.5% of the total cases. The Consistency score of 0.808 indicates that the path is a reliable predictor and predicts the outcome in just over 80% of cases.

$$HincCal * BlkCal * CitiCal$$

The Raw Coverage score of 0.295 indicates the combination of the high level of income (HincCal), a high percentage of Black residents (BlkCal), and a high level of Civic Participation (CitiCal) explains about 29.5% of the instances where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.003 shows that this path uniquely explained a very small portion (about 0.3%) of the outcome. The consistency score of 0.804 indicates that the path is a reasonably reliable predictor, and the combination leads to an outcome with a consistency of approximately 80.4%.

5.4.2.2 Overall Solution Metrics and Interpretation

Together, the three combinations of conditions explain about 60.2% of the cases where the outcome of access to the UGS (AiCal) occurs, indicating a relatively strong explanatory

power. The overall solution consistency of 0.728 means that when these combinations occur, the outcome will likely occur in nearly three-quarters of the cases (see Table 5.2).

During the 2010s, Civic Participation (CitiCal) remained a common factor, as it is present in all three combinations of conditions. A high income and a high percentage of any racial composition, combined with a high level of Civic Participation, will lead to access to the UGS (AiCal).

The result suggests that the combination of racial composition, income, population density, and Civic Participation influences access to the UGS (AiCal). Specifically, white residents' presence combined with Civic Participation, black residents combined with low density and Civic Participation, and income combined with black residents and Civic Participation are important in determining the outcome. However, the model also suggests that other factors not included might contribute to the outcome, given the coverage and consistency scores.

Table 5.2. Intermediate Solutions for the 2010s

Year	Solution Formula	Unique Coverage	Raw Coverage	Consistency
2010s	WhtCal*CitiCal	0.187	0.494	0.741
	BlkCal*~DenCal*CitiCal	0.085	0.401	0.808
	HincCal*BlkCal*CitiCal	0.003	0.295	0.804
				<i>Solution Coverage: 0.602</i>
				<i>Solution Consistency: 0.728</i>

5.4.3 Civic Participation in the 2020s

The year 2020s fsQCA results analyze the UGS accessibility score outcome AiCal as a function of five calibrated conditions: income (HincCal), racial composition (WhtCal, BlkCal), population density (DenCal), and civic participation (CitiCal). Below is a breakdown of each solution formula.

5.4.3.1 Individual Combination of Conditions

WhtCal*~DenCal*CitiCal

The Raw Coverage score of 0.423 indicates the combination of a high percentage of White residents (WhtCal), low population density, and a high level of Civic Participation (CitiCal) explains about 42.3% of the cases where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.016 shows that this path uniquely explained around 1.6% of the total cases. The consistency score of 0.811 indicates that the path is a reliable predictor, and the combination leads to an outcome slightly above 80 percent of the cases.

HincCal*WhtCal*CitiCal

The Raw Coverage score of 0.446 suggests that high income (HincCal), high percentage of White residents (WhtCal), and high level of Civic Participation (CitiCal) explain about 44.6% of the cases where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.034 shows that this combination uniquely explained around 3.4% of the total cases. The Consistency score of 0.778 indicates that the combination is fairly reliable and predicts the outcome in about 80% of cases.

WhtCal*BlkCal*CitiCal

The Raw Coverage score of 0.318 suggests that a high percentage of the White population (WhtCal), a high percentage of the Black population (BlkCal), and high Civic Participation (CitiCal) explain about 31.8% of the cases where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.017 shows that this path uniquely explained a very small portion (about 1.7%) of the outcome. The Consistency score of 0.799 indicates that the path is fairly reliable.

HincCal*BlkCal*DenCal*CitiCal

The Raw Coverage score of 0.283 suggests that high income (HincCal), a high percentage of the Black population (BlkCal), high population density (DenCal), and a high level of Civic Participation (CitiCal) explain about 28.3% of the cases where access to the UGS (AiCal) occurs. The Unique Coverage score of 0.010 shows that this path uniquely explained a very small portion (about 1.0%) of the outcome. The Consistency score of 0.844 indicates that this is a very consistent predictor of access to the UGS (AiCal).

5.4.3.2 Overall Solution Metrics and Interpretation

Together, the three combinations of conditions explain about 50.8% of the cases where the outcome of access to the UGS (AiCal) occurs, indicating a relatively strong explanatory power. The overall solution consistency of 0.757 means that, on average, the identified configurations are reasonably consistent predictors for the outcome of access to the UGS (AiCal) (see Table 5.3).

During the 2020s, Civic Participation (CitiCal) was present in all four combinations of conditions, similar to the previous two decades (2000s and 2010s). A high percentage of White residents (3 out of 4) and high income (2 out of 4), combined with a high level of Civic Participation, will lead to access to the UGS (AiCal).

The results suggest that high civic participation (CitiCal) plays a crucial role among the four configurations. Different combinations of racial composition (white and black populations), income levels, and population density contribute to the presence of access to the UGS (AiCal). The configurations show moderate to high consistency, indicating that these combinations are reliable predictors of the outcome variable.

Table 5.3. Intermediate Solutions for the 2020s

Year	Solution Formula	Unique Coverage	Raw Coverage	Consistency
2020s	WhtCal*~DenCal*CitiCal	0.016	0.423	0.811
	HincCal*WhtCal*CitiCal	0.034	0.446	0.778
	WhtCal*BlkCal*CitiCal	0.017	0.318	0.799
	HincCal*BlkCal*DenCal*CitiCal	0.010	0.283	0.844
				<i>Solution Coverage: 0.508</i>
				<i>Solution Consistency: 0.757</i>

5.4.4 Identifying the Core and Periphery Solutions

The fsQCA software provides complex solutions, parsimonious solutions, and intermediate solutions that consist of combinations of configurations (Pappas and Woodside, 2021). The complex solutions consist of all the possible combinations that can be very large and complex for interpretation. As a result, a simplified set of solutions, such as parsimonious and intermediate, are also provided for the researchers. Parsimonious solutions are a simplified subset of complex solutions, including counterfactual combinations that lead to logical solutions. Identified by the software, this simplified set is the most important one that cannot be excluded and, therefore, often referred to as core conditions (Park et al., 2020; Pappas & Woodside, 2021). Intermediate solutions are the middle ground between complex and parsimonious solutions. This set computes theoretically plausible counterfactuals of the other two. In fsQCA analyses, necessary or sufficient conditions explain the outcome and are present as either core or peripheral elements in the solution formula (Pappas & Woodside, 2021). Intermediate solutions are such a set that contain both core and peripheral conditions, where core elements suggest the combination of conditions indicates a strong causal relationship with the outcome and a weaker causal relationship with the outcome for the periphery (Park et al., 2020). Understanding the core and peripheral conditions is important for interpreting the fsQCA results and discerning whether one combination of conditions predicts the outcome.

The first step is to examine the parsimonious and intermediate solutions provided by the fsQCA software for each period. Core solutions are present in both the parsimonious and intermediate solutions. The periphery solutions are present only in the intermediate solution and are excluded from the parsimonious solution. Below are the results of core and periphery conditions for each period (2000s, 2010s, and 2020s).

5.4.4.1 Core and Periphery Solutions for the Year 2000

As shown in Table 5.4, the fsQCA software provided the same results for both the parsimonious and intermediate solutions. Therefore, there are no periphery elements for this period, and all the solutions are considered core.

$$\sim HincCal * WhtCal * CitiCal$$

This solution indicates that lower-income tracts with a higher percentage of White residents and a high level of Civic Participation were critical to accessing urban green space.

$$WhtCal * BlkCal * CitiCal$$

This solution indicates that census tracts with high percentages of White and Black residents and a high level of Civic Participation were also key to the UGS accessibility.

$$HincCal * DenCal * CitiCal$$

This solution indicates that access to the UGS was facilitated by high-income, high-density census tracts with a high level of Civic Participation.

Table 5.4. Parsimonious and intermediate solutions for the year 2000

Type	Solution Formula	Unique Coverage	Raw Coverage	Consistency
Parsimonious	$\sim HincCal * WhtCal * CitiCal$	0.048	0.405	0.778
	$WhtCal * BlkCal * CitiCal$	0.002	0.313	0.791
	$HincCal * DenCal * CitiCal$	0.068	0.376	0.835
				<i>Solution Coverage: 0.491</i>
				<i>Solution Consistency: 0.763</i>

Intermediate	~HincCal*WhtCal*CitiCal	0.048	0.405	0.778
	WhtCal*BlkCal*CitiCal	0.002	0.313	0.791
	HincCal*DenCal*CitiCal	0.068	0.376	0.835
<i>Solution Coverage: 0.491</i>				
<i>Solution Consistency: 0.763</i>				

5.4.4.2 Core and Periphery Solutions for the Year 2010

As shown in Table 5.5, core and periphery elements are identified based on the results for parsimonious and intermediate solutions.

Core:

*WhtCal * CitiCal*

This solution is present in both solutions, and it indicates that tracts with a higher percentage of White residents and a high level of Civic Participation were key in predicting UGS accessibility.

Periphery:

*~DenCal * CitiCal*

This solution is present only in the parsimonious solution, and it indicates that census tracts with lower density and a high level of Civic Participation are important to predict UGS accessibility.

*HincCal * CitiCal*

This solution is present only in the parsimonious solution, and it indicates that high-income with a high level of Civic Participation census tracts led to access to the UGS.

*BlkCal * ~DenCal * CitiCal*

This solution is present only in the intermediate solution, and a high percentage of Black residents, low density, and a high level of Civic Participation census tracts led to access to the UGS but are less important than other combinations.

$$HincCal * BlkCal * CitiCal$$

This solution is present only in the intermediate solution. It indicates that high-income census tracts with a high percentage of black residents and a high level of Civic Participation led to access to the UGS, though not as important as other combinations.

Table 5.5. Parsimonious and intermediate solutions for the year 2010

Type	Solution Formula	Unique Coverage	Raw Coverage	Consistency
Parsimonious	~DenCal*CitiCal	0.088	0.543	0.761
	HincCal*CitiCal	0.003	0.439	0.758
	WhtCal*CitiCal	0.026	0.494	0.741
				<i>Solution Coverage: 0.605</i>
				<i>Solution Consistency: 0.722</i>
Intermediate	WhtCal*CitiCal	0.187	0.494	0.741
	BlkCal*~DenCal*CitiCal	0.085	0.401	0.808
	HincCal*BlkCal*CitiCal	0.003	0.295	0.804
				<i>Solution Coverage: 0.602</i>
				<i>Solution Consistency: 0.728</i>

5.4.4.3 Core and Periphery Solutions for the Year 2020

As shown in Table 5.6, core and periphery elements are identified based on the results for parsimonious and intermediate solutions.

Core:

$$WhtCal * \sim DenCal * CitiCal$$

This solution is present in both solutions, and it indicates that tracts with a higher percentage of White residents, low density, and high Civic Participation were important for predicting UGS accessibility.

$$WhtCal * BlkCal * CitiCal$$

This solution is present in both solutions, and it indicates that tracts with high percentages of White and Black residents and a high level of Civic Participation were important to predict UGS accessibility.

Periphery:

*HincCal * DenCal * CitiCal*

This solution is present only in the parsimonious solution, and it indicates that high-income census tracts with high density and a high level of Civic Participation are important to predict UGS accessibility, though not as important as other combinations.

*HincCal * WhtCal * CitiCal*

This solution is present only in the intermediate solution, and it indicates that high-income census tracts with a high percentage of White residents and a high level of Civic Participation led to access to the UGS, but it is not as important.

*HincCal * BlkCal * DenCal * CitiCal*

This solution is present only in the intermediate solution, high-income census tracts with a high percentage of Black residents, high density, and a high level of Civic Participation predicted access to the UGS. However, it is less important than other combinations.

Table 5.6. Parsimonious and intermediate solutions for the year 2020

Type	Solution Formula	Unique Coverage	Raw Coverage	Consistency
Parsimonious	WhtCal*~DenCal*CitiCal	0.062	0.423	0.811
	HincCal*DenCal*CitiCal	0.045	0.402	0.815
	WhtCal*BlkCal*CitiCal	0.017	0.318	0.799
				<i>Solution Coverage: 0.509</i>
				<i>Solution Consistency: 0.763</i>
Intermediate	WhtCal*~DenCal*CitiCal	0.016	0.423	0.811
	HincCal*WhtCal*CitiCal	0.034	0.446	0.778
	WhtCal*BlkCal*CitiCal	0.017	0.318	0.799

5.4.5 Comparison of Core and Periphery Elements Over Time

5.4.5.1 Stable Core Solutions

Civic Participation (CitiCal) has been consistently seen in all core solutions across three periods, indicating its stable presence and importance in predicting UGS accessibility. A high percentage of White residents was seen in most core configurations, which shows its persistent influence on access to the UGS. Lastly, both high percentages of White and Black residents (WhtCal*BlkCal) were seen in the years 2000 and 2020, making it a recurring pattern coupled with a high level of Civic Participation to predict access to the UGS.

5.4.5.2 Evolving Solution Patterns

Income (HincCal) was part of the core configurations in the year 2000 but became peripheral by 2020, suggesting that income was less significant in explaining UGS accessibility over time. Over time, low density has replaced high density as one of the core elements in predicting access to the UGS, reflecting the changing dynamics of how density level (DenCal) impacts the outcome.

Its influence on the outcome fluctuates in census tracts with a higher percentage of Black residents. The absence of the solution, HincCal * BlkCal * DenCal * CitiCal, indicates changes in the impact of Black residents on the outcome, especially between 2010 and 2020.

Overall, the core elements, such as a high level of Civic Participation and a high percentage of White residents, remain stable and consistently influence accessibility to green spaces. However, factors like income, density, and the role of the black population have shifted between the core and periphery, reflecting the evolving socio-economic and demographic

landscape. This change indicates a trend towards more complex and nuanced influences on UGS accessibility, with density becoming increasingly important and income becoming more peripheral.

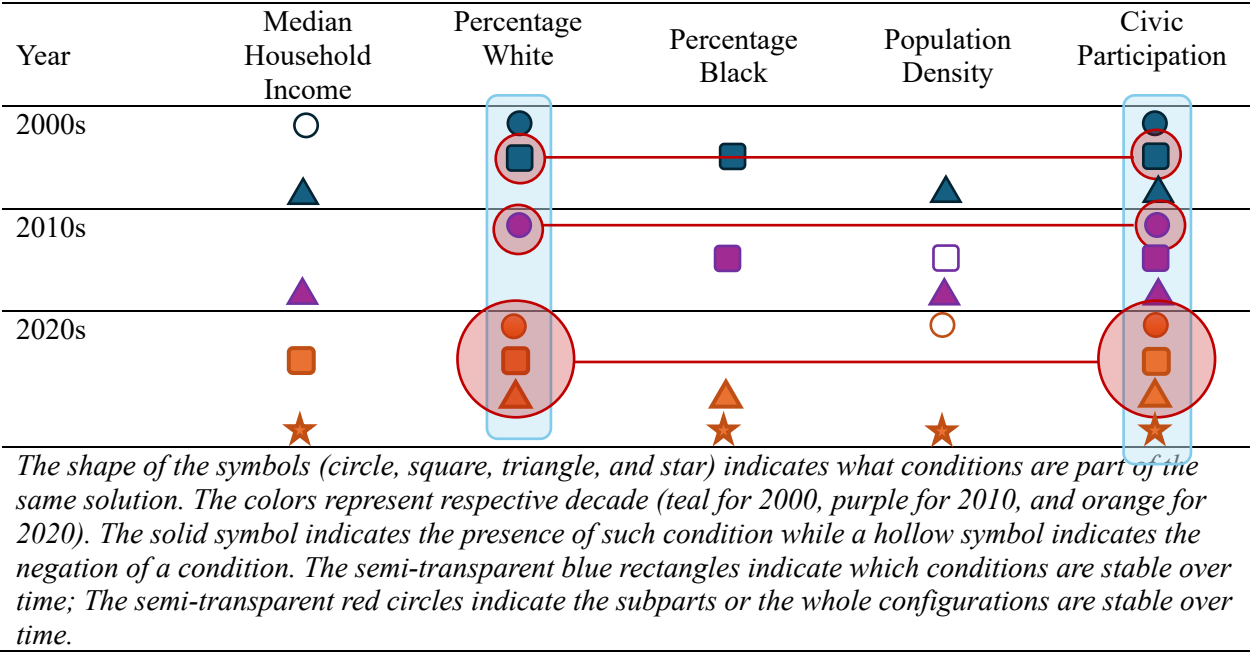
5.4.6 String Analysis for Solution Formulas of Three Periods

As shown in Table 5.7, solution coverage, which reflects how much of the outcome is explained by the solutions, increased significantly from 2000 to 2010, indicating that the explanatory power of the models improved during that period. However, it slightly decreased in 2020. Solution consistency, which measures how well the data support the solutions, decreased from 2000 to 2010 but improved slightly by 2020, suggesting a fluctuating but generally stable relationship between the conditions and the outcome. Table 5.8 shows the visualization of the time series of minimized configurations for 2000, 2010, and 2020.

Table 5.7. Multiple QCAs, different time periods, Intermediate Solutions

Year	Solution Formula	Unique Coverage	Raw Coverage	Consistency
2000s	~HincCal*WhtCal*CitiCal	0.048	0.405	0.778
	WhtCal*BlkCal*CitiCal	0.002	0.313	0.791
	HincCal*DenCal*CitiCal	0.068	0.376	0.835
				<i>Solution Coverage: 0.491</i>
				<i>Solution Consistency: 0.763</i>
2010s	WhtCal*CitiCal	0.187	0.494	0.741
	BlkCal*~DenCal*CitiCal	0.085	0.401	0.808
	HincCal*BlkCal*CitiCal	0.003	0.295	0.804
				<i>Solution Coverage: 0.602</i>
				<i>Solution Consistency: 0.728</i>
2020s	WhtCal*~DenCal*CitiCal	0.016	0.423	0.811
	HincCal*WhtCal*CitiCal	0.034	0.446	0.778
	WhtCal*BlkCal*CitiCal	0.017	0.318	0.799
	HincCal*BlkCal*DenCal*CitiCal	0.010	0.283	0.844
				<i>Solution Coverage: 0.508</i>
				<i>Solution Consistency: 0.757</i>

Table 5.8. Visualization of the time series of minimized configurations for 2000, 2010, and 2020



The overall coverage and consistency of the solutions generally improved from 2000 to 2020, suggesting a better fit of the models over time. This suggests that the identified configurations have become more effective in explaining the outcome variable as urban conditions evolved. The changes over time indicate a shift towards more complex combinations of factors influencing accessibility to green spaces. The role of population density, in particular, has become more important, and the influence of socioeconomic factors reflects broader urban and demographic changes.

5.5 Discussion

The purpose of Chapter 5 was to understand how civic participation, a form of procedural justice, impacts proximity to UGS development longitudinally. Overall, civic participation (CitiCal) remains constant and has been present in all solution formulas across three decades. This indicates its role as a necessary condition for enhancing access to UGS.

Additionally, the percentage of White residents (WhtCal) was present in all decades and appears together with civic participation in the same solution formula. Some cross-decade key trends are listed below. Comparing the Three Periods (2000, 2010, 2020), the solutions show increasing complexity over time, especially in the intermediate solutions. The number of conditions combined in the solutions has increased, reflecting a more complex interplay between factors influencing UGS accessibility. The role of Density (DenCal) has become more important. In 2000, density was less prominent, but by 2020, it had become a significant factor in both its presence and absence. The shift from focusing on low-density areas to considering high-density areas (HincCal * DenCal * CitiCal) in the parsimonious solution highlights changing urban dynamics. Throughout the solutions across the three periods, civic participation remains a key factor, indicating its consistent role in influencing accessibility to green spaces. Socioeconomic factors (HincCal, WhtCal), like the tracts with higher Median Household Income and predominantly White tracts, are present across all periods. However, the specific combinations with other factors, for example, density and percentage of Black residents, were unstable, suggesting changing city-wide socioeconomic patterns.

Chapter 6 - Conclusion

6.1 Summary of Key Findings

This dissertation research examined the Urban Green Space inequity spatially and longitudinally. Chapter 3 used the Two-Step Floating Catchment Area (2SFCA) method to conduct a cross-sectional spatial analysis to examine the association between key demographic and housing factors and access to green space. The study proposed four main research hypotheses: 1) Areas with a higher median household income will have better access to UGS; 2) Areas with a higher percentage of white population will have better access to UGS; 3) Areas with a higher property value will have better access to UGS; and 4) Areas with a higher percentage of the population with bachelor's degrees will have better access to UGS.

The findings of Chapter 3 suggested that multifaceted factors impact proximity to UGS. However, commonly identified factors, such as educational attainment, median household income, and racial and ethnic backgrounds, showed weak or no significant impact on spatial proximity to UGS. Instead, housing factors played a more important role. More specifically, areas with a higher property value are positively associated with closer proximity to UGS at the 0.05 level, which aligns with the original hypothesis. Areas with a lower percentage of white residents are positively associated with closer proximity to UGS at the 0.1 level, which is contrary to the original hypothesis and the findings from the literature, where racial disparities usually favor white-dominant areas. In addition, areas with a lower percentage of old housing units or vacant housing units are positively associated with proximity to UGS, which aligns with the environmental gentrification theory discussed in the literature review part and shows there exists a potential negative impact from housing pressure. Lastly, other variables show no association with proximity to UGS.

In Chapter 4, proximity and per capita green space, two components of UGS accessibility, were tested longitudinally. Compared to the cross-sectional spatial analysis used in Chapter 3, Chapter 4 examined how the changes in independent variables impact dependent variables over time. The four proposed hypotheses were tested for how racial and ethnic backgrounds, housing factors, educational attainment, and socioeconomic factors impact the outcome.

The findings from Chapter 4 showed persistent racial inequities and a shift in the socio-spatial relationships. Between 2000 and 2020, predominantly White areas saw a cumulative gain regarding proximity to UGS despite experiencing a decline between 2010 and 2020, which generally aligns with the original hypothesis. During the same period, predominantly Black areas saw a greater loss in terms of per capita green space compared to their White counterparts, suggesting the continuation of systemic inequity and underinvestment within those areas and aligning with the original hypothesis. In addition to the predictive variables commonly examined in UGS equity literature, the results showed a rising impact of urbanization and housing pressures. Specifically, the rising population density negatively impacted both proximity to the UGS and per capita green space, which was especially apparent after 2010. The percentage of public housing units (HUD) was negatively associated with proximity to the UGS post-2010. The housing pressure findings align with the environmental gentrification theory and correspond to a previous study examining the city-wide displacement risks, showing that greening efforts started to negatively affect housing factors around the same period (Anguelovski et al., 2022). Contradicting previous studies and contrary to the original hypothesis, higher educational attainment was found to negatively impact proximity to the UGS between 2000 and 2020, suggesting the potential for competing development priorities during this period. Similar to

Chapter 3, socioeconomic factors (median household income, median home value, and median gross rent) showed weak to no association with proximity to the UGS or per capita green space over time. Even when they showed borderline association, the effect was divergent. Overall, predominantly White areas experienced cumulative gain in proximity to the UGS while failing to keep up with population growth; predominantly Black areas experienced loss in proximity to the UGS and per capita green space at a greater scale.

As Chapter 4 findings suggested, the potential of unmeasured variables' impact on UGS accessibility, such as policy shifts, decision-making dynamics, and other obscured short-term factors. Chapter 5 explored how civic participation, a form of procedural justice embedded in the decision-making processes, impacts access to UGS longitudinally. Based on Chapter 3 and Chapter 4's findings, Chapter 5 hypothesized that 1) civic participation has a longitudinal impact on the spatial distribution of UGS, 2) predominantly White neighborhoods are more likely to get involved in the decision-making processes regarding UGS development, and 3) wealthier neighborhoods are also more involved in the decision-making processes.

Using Qualitative Comparative Analysis, Chapter 5 geocoded qualitative data into spatial one and conducted a string analysis to compare the shift and trends of key predictive variables over time. The findings confirmed the hypotheses that civic participation remained constant and contributed to better access to the UGS. In addition, predominantly White neighborhoods had a higher involvement with public meetings. Furthermore, the solutions showed increasing complexity over time, aligning with the findings in Chapter 4, where factors like population density became more prominent in determining access to the UGS, suggesting a changing city-wide socioeconomic pattern.

Table 6.1 shows the summary of the key findings of this dissertation.

Table 6.1. Summary of key findings

Study	Hypothesis	Results
Chapter 3 - Cross-sectional spatial study	Hypothesis 1: Areas with a higher median household income will have better access to UGS.	Not significant
	Hypothesis 2: Areas with a higher percentage of white population will have better access to UGS.	Borderline significant (0.05) and negative
	Hypothesis 3: Areas with a higher property value or rent price will have better access to UGS.	Significant and positive (house value only, not significant for rent price)
	Hypothesis 4: Areas with a higher percentage of the population with at least a bachelor's degrees will have better access to UGS.	Not significant
Chapter 4 - Longitudinal spatial study	Hypothesis 1: Areas with a higher median household income experience improved proximity to UGS and a higher per capita green space over time.	Not significant
	Hypothesis 2: Areas with a higher percentage of white population experience improved proximity to UGS and a higher per capita green space over time.	Significant for White (cumulatively positive)
	Hypothesis 3: Areas with a higher property value or rent price experience improved proximity to UGS and a higher per capita green space over time.	Not significant
	Hypothesis 4: Areas with a higher percentage of the population with at least a bachelor's degrees experience improved proximity to UGS and a higher per capita green space over time.	Significant and negative for proximity (between 2000 and 2020)
Chapter 5 - Qualitative Comparative Analysis study	Hypothesis 1: Civic participation is important in impacting urban green space distribution over time.	Constant
	Hypothesis 2: Areas with more White residents are more embedded in the decision-making process during public meetings.	Constant
	Hypothesis 3: Areas with higher median household income are more embedded in the	Not constant

6.2 Contributions and Implications for Policy

This dissertation provides contributions and implications that fill the knowledge gap in the existing UGS inequity literature. Focusing on both spatial and temporal scales, it offers a comprehensive understanding of how the current distribution of UGS was generated and sustained. By including the qualitative data in spatial analysis, this dissertation explored the use of qualitative comparative analysis methods to examine the less researched procedural justice aspect, one of the commonly recognized pillars of the Environmental Justice framework. The findings provide valuable insights for landscape architects and urban planners to target systemically underserved areas.

The racial disparities regarding access to the UGS still persist; predominantly Black neighborhoods experience heavier losses in terms of per capita green space compared to their White counterparts. This highlights the legacy of historical segregation and that institutional practices continue to influence environmental outcomes despite city-wide policy interventions. In addition, educated areas tend to prioritize non-green development, challenging the common assumptions that more socio-economically privileged areas inherently prioritize environmental good, urging planners and city officials to emphasize engagement with communities and their real needs in addition to relying on demographic data. Furthermore, socio-economic factors like median household income and median house value were not significant in the statistical analyses, suggesting that a potential trend in the market-driven UGS agendas will potentially exacerbate inequity unless redistributive interventions are introduced.

The seemingly divergent outcomes between proximity to the UGS and per capita green space stress the importance of multi-scalar multi-dimensional assessment in UGS planning, as relying on single indicators methodologically could obscure systemic disadvantages. In addition, the weak explanatory power of models also suggests the urgency of querying hidden factors, such as grassroots activism, zoning policies, or social networks, in shaping UGS outcomes. These advocates use mixed-method approaches to target complex spatial-temporal UGS development issues on multiple scales. Overall, the findings call for city-wide planning policies to prioritize community agency during decision-making processes and focus on obscured factors, such as market-driven housing pressures, to prevent the circumvention of public interests.

In addition, the findings also provide several implications for engaging communities. First, various forms of civic engagement should be implemented and subsidized to ensure inclusive participation in marginalized neighborhoods. In the most recent Austin Department of Parks and Recreation's long-range plan, surveys and community-led workshops were included as a key step to achieve better planning efficacy. In the future, specific budget plans and potential incentivized community-led design workshops could be an equitable way to enhance community involvement, as civic participation was found to be a constant contributing factor to better UGS accessibility. Second, adaptation policies addressing temporal shifts in pressing factors such as density and housing pressures should be implemented to overcome obsolescence through static planning. Third, longitudinal studies proved to be an effective way to track existing and emerging complex factors that impact UGS development, and urban planners and city officials should take advantage of the findings to better monitor and address future shifts and trends. Lastly, UGS inequity is a complex problem that requires cross-sector collaborations. Better

integration of research and administrative forces should be stressed to align equitable UGS development across actors, horizontally and vertically.

6.3 Limitations and Future Study

Although the dissertation's findings explain several questions, future research needs to address limitations. The results of Chapter 3 revealed a mismatch with some existing literature where wealthier and predominantly White neighborhoods tend to enjoy closer proximity to the UGS. This suggests that other forces, in addition to the commonly identified ones, might impact proximity to the UGS, such as the policy at the local scale and the short-term prioritization shift in UGS development. Future studies could explore other factors with theoretical support. In addition, this part of the research used proximity as an indicator to evaluate whether the spatial distribution of UGS in Austin is equitable. The spatial models showed better performance compared to the use of an Ordinary Least Square model, justifying the existence of clustered areas with closer proximity to UGS compared to the rest of the city. The significant Lambda value in the spatial error model only addressed the spatial autocorrelation to some extent; a more comprehensive spatial model, such as focusing on the local interactions, should be explored. As introduced in the previous chapters, UGS accessibility also includes park quality, which was not examined in this dissertation (Rigolon, 2016). An important reason for not including park quality as an indicator was due to the fact that it usually concerns park amenities, which require on-site audits and comprehensive documentation. In addition, during the preliminary analysis phase, external funding for maintaining park maintenance levels, another important aspect of park quality, was used to examine whether the distribution of funds is equitable across the city and found clustering evidence. However, the data was not comprehensive as the city fund data was

not acquired, and only external funds data was available. As a result, park quality was not used as an indicator for evaluating UGS accessibility in the dissertation. Future studies can explore further in this realm and examine other factors, such as crime rate or perceived safety, as proxies for park quality analyses (Williams et al., 2020).

Compared to Chapter 3's cross-sectional spatial analysis of the UGS distributive pattern, Chapter 4 examined the longitudinal association between UGS accessibility and identified sociodemographic and socioeconomic factors. However, the unit of analysis changed from census block groups in Chapter 3 to census tracts in Chapter 4, which might introduce analytical constraints. As discussed in Chapter 4's introduction part, census geographic boundaries, for example, block groups, frequently change over decennial censuses to reflect population shifts, urban development or expansion, and political-administrative adjustments. It is a common practice for longitudinal spatial study to use harmonized data that is standardized to fixed boundaries, in this study, the 2010 shapefile, to ensure comparability over time. However, the conundrum here is that block groups are highly dynamic and are hard to harmonize across decades, while the tract-level data stays relatively stable and is often prioritized for harmonization by third-party sources due to the slower changing nature, thus making a practical compromise for studying long-term trends, for example, the Longitudinal Tract Database used in this dissertation. The biggest impact of changing the unit of analysis could be the Modifiable Areal Unit Problem (MAUP), also discussed in Chapter 4, which might cause several problems. The first is the loss of granularity that the tract-level data might obscure localized disparities in UGS accessibility or sociodemographic variation within tracts. For example, a tract might appear "average" in terms of proximity to UGS, masking the deprived block groups' proximity within such tract. The second problem is that the association observed at the tract level may be different

from the block-group level, which could potentially inflate or suppress the real correlations due to the smoothing of data when conducting statistical analysis. Therefore, to address these concerns associated with the change of unit of analysis, the first step is to acknowledge the limitations that tract-level results in Chapter 4 are not directly comparable to block-group findings from Chapter 3 due to MAUP. If possible, future studies should compare tract-level and block-group-level associations for overlapping years to quantify scale effect differences. The second notion is to acknowledge that the tract-level analysis prioritizes temporal validity over spatial precision, and the longitudinal results should be interpreted as trends rather than making claims about smaller geographies. Overall, despite the unit of analysis change that might cause analytical constraints, Chapter 4's longitudinal spatial analyses still provided practical implications. By addressing MAUP and contextualizing results within the limitations of tract-level data, Chapter 4 maintained rigor while balancing spatial and temporal resolution which aligns with empirical studies in the field where harmonized tract-level data are widely accepted for comparisons.

Chapter 4 uses the differencing of dependent and independent variables between the three periods to analyze the changes in relationships over time. That is, the cross-sectional model used in Chapter 3 transformed into a new model that emphasizes how changes in independent variables are associated with changes in the dependent variable. Differencing both the dependent and independent variables is a valid and statistically meaningful approach, particularly when the goal is to study how changes in independent variables are associated with changes in the dependent variable over time. When coupled with a spatial lag model, it can reveal insights into the spatial dynamics of these changes, and it is useful for understanding how their relationships evolve. However, non-significant Moran's I test results were found in models, indicating the

spatial autocorrelation is not statistically detectable in the dependent variable's differences over time, even after accounting for predictive variables. This suggests that the spatial lag model and the spatial error model used in addition to the OLS model might not be necessary for the analysis. Despite the hypotheses that certain areas, especially those with a higher percentage of white residents and college degrees, the results suggest otherwise. To break it down, a few reasons contribute to the insignificant spatial autocorrelation. First, the differencing of dependent and independent variables eliminates time-invariant unobserved heterogeneity. If certain factors are constant across the periods, their influence is removed, allowing the model to focus on factors that changed, reflecting temporal dynamics. For example, if access to UGS changed uniformly across census tracts, the differences would show little spatial clustering rather than persistent spatial patterns, opposite from the original hypothesis that wealthy areas consistently have more green space. Second, differencing also avoids spurious relationships that might arise due to trends in the data. The risk of confounding due to common trends in the dependent and independent variables is mitigated by analyzing changes. For example, the independent variables, such as median household income, explained most of the spatial variation in green space changes; there might be little residual spatial autocorrelation left in the model. Third, potential non-stationary spatial processes exist. Differencing assumes that the relationship between the variables is stable over time. If the underlying processes are non-stationary or the changes are inconsistent across space, for example, the main drivers of urban green space changes in 2000-2020 could differ from those in 2000-2010, leading to spatially unstructured residuals. Fourth, differencing can sometimes amplify noise in the data, especially if the original variables have small changes. Changes in urban green space access may be random or driven by non-spatial factors, such as Austin's city-wide equity campaign that equally affects all tracts.

Lastly, this spatial model used the queen contiguity weights matrix, which assumes spatial dependence only exists between adjacent tracts. However, Moran's I might fail to detect the spatial autocorrelation if the actual spatial process happens at a larger scale or is better captured by a distance-based spatial weights matrix. As a result, future studies could emphasize a few aspects to capture the spatial autocorrelation better: 1) use an alternative spatial weights matrix method in the spatial model. For example, the k-nearest neighbors' distance-based weights matrix can be tested to see if the spatial dependence operates at a different scale than the census tract level; 2) investigate how strong predictive variables, such as median household income, are spatially correlated with the space and the impact of them leaving the residuals unstructured; 3) include factors, such as policy interventions or environmental factors, that would have a spatially structured impact; and 4) re-examine the data source. This study used the LTDB dataset; however, a major revision of the alternative estimates of the 2000 longitudinal dataset in 2010 tract boundaries was released lately. According to the author, the new longitudinal dataset "estimates far better than the original LTDB, where estimates for every decade were based on interpolation methods." Future studies should be mindful and look for the most updated data source for an optimized outcome.

Lastly, the low R-squared values were found in most regression models from Chapter 4, which could be explained from several aspects. First, from a bigger picture and specifically related to this research, fields like landscape architecture, human behavior, socio-ecological systems, and policies could have unobserved factors related to cultural norms or measurement errors. A low R-squared value of 0.15 indicates that 15% of the variance in proximity to UGS is explained by the predictors between 2000 and 2010, reflecting the inherent complexity of the phenomena, not necessarily a flawed model (Lewis-Beck & Lewis-Beck, 2015). Second, as

discussed in the previous paragraphs, the models prioritized identifying the longitudinal trends rather than maximizing the spatial precision or the predictive power. Even with a low R-squared, the coefficients have provided insightful explanations about the directional associations that answer the research questions that concern the evolving relationships over time (Moksony & Heged, 1990). Third, the low R-squared could also be caused by the nonlinear or interactive effects not captured by the OLS model (Moksony & Heged, 1990; Lewis-Beck & Lewis-Beck, 2015). Future studies could identify models that improve such explanatory power, utilize qualitative insights, including interviews and case studies, to provide deeper explanations for the patterns observed in the regression model, or explore the Qualitative Comparative Analysis method used further in Chapter 5.

In Chapter 5, the attention given to both spatial and temporal scales offers sensitivity to the local context while attempting to answer complex questions using qualitative and quantitative methods (Cairns et al., 2017; Verweij & Trell, 2019). As Kwan has argued to move beyond geographic boundaries and incorporate local context, it links geocoded physical context with broader socio- and economic-political processes (Kwan, 2004). The outcome has deeply embedded policy implications regarding the effectiveness of decisions made toward UGS development in vulnerable communities, thus informing the potential site-specific institutional change. Furthermore, the comparison across time opens the opportunity to examine which combinations of conditions lead to the same outcome and which ones contradict others (Cragun et al., 2016).

However, this study is not without challenges and limitations. For instance, if my research utilizes a different scale, there exists the potential risk of small changes in the calibration that can cause a shift in the truth table, which in turn changes the minimization

process (Verweij & Trell, 2019). The temporal scale used in this study coincides well with the decadal interval for the spatial data. However, this might not work in other cases. Lastly, since it deals with spatial data, there could also be potential clustering of profiles. Future studies could use a one-way Chi-square goodness of fit to test if the observed frequencies are significantly different from a uniform distribution (Summers & Caballero, 2017).

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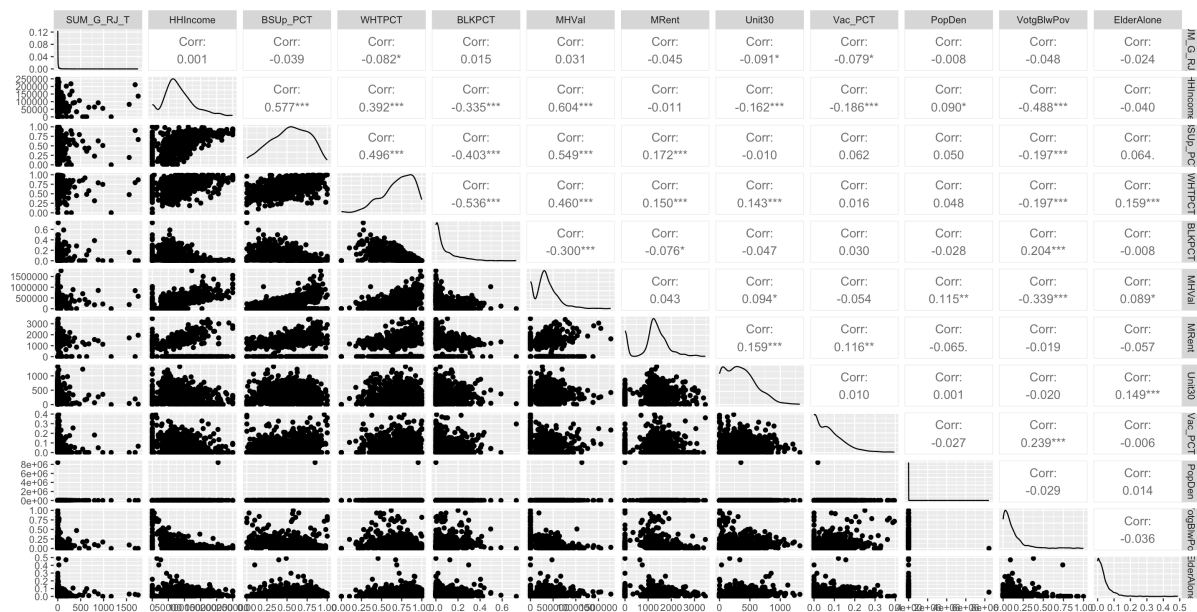
Appendix A - R Output for the 2SFCA Spatial Model

Bivariate R output

Bivariate R correlation test results

	SUM_G_RJ_T	HHIncome	BSUp_PCT	WHTPCT	BLKPCT	MHVal	MRent	Unit30	Vac_PCT
SUM_G_RJ_T	1.000000000	0.0005287462	-0.039273507	-0.08196416	0.014606497	0.03095963	-0.04453343	-0.091443973	-0.078545255
HHIncome	0.0005287462	1.000000000	0.576909365	0.39246668	-0.334781603	0.60396116	-0.01064506	-0.161936505	-0.186346428
BSUp_PCT	-0.0392735075	0.5769093649	1.000000000	0.49599857	-0.403452481	0.54865499	0.17225216	-0.009700027	0.061609344
WHTPCT	-0.0819641626	0.3924666803	0.495998571	1.00000000	-0.535956149	0.45953370	0.15006327	0.142782794	0.016200787
BLKPCT	0.0146064967	-0.3347816030	-0.403452481	-0.53595615	1.000000000	-0.30040753	-0.07581864	-0.046869526	0.029708361
MHVal	0.0309596277	0.6039611551	0.548654993	0.45953370	-0.300407534	1.00000000	0.04315837	0.094051345	-0.053931601
MRent	-0.0445334301	-0.0106450570	0.172252163	0.15006327	-0.075818644	0.04315837	1.00000000	0.158536193	0.116196570
Unit30	-0.0914439733	-0.1619365051	-0.009700027	0.14278279	-0.046869526	0.09405134	0.15853619	1.000000000	0.010186440
Vac_PCT	-0.0785452553	-0.1863464279	0.061609344	0.01620079	0.029708361	-0.05393160	0.11619657	0.010186440	1.000000000
PopDen	-0.0084519800	0.0904728576	0.050338451	0.04827983	-0.027635014	0.11514685	-0.06510890	0.001423696	-0.026709365
VotgBlwPov	-0.0475122245	-0.4882284494	-0.197466609	-0.19674881	0.204251987	-0.33875595	-0.01875254	-0.019734681	0.239437357
ElderAlone	-0.0235031628	-0.0399433094	0.064289290	0.15945462	-0.007901883	0.08922881	-0.05677080	0.149455503	-0.006408466
	PopDen	VotgBlwPov	ElderAlone						
SUM_G_RJ_T	-0.008451980	-0.04751222	-0.023503163						
HHIncome	0.090472858	-0.48822845	-0.039943309						
BSUp_PCT	0.050338451	-0.19746661	0.064289290						
WHTPCT	0.048279833	-0.19674881	0.159454625						
BLKPCT	-0.027635014	0.20425199	-0.007901883						
MHVal	0.115146847	-0.33875595	0.089228811						
MRent	-0.065108904	-0.01875254	-0.056770804						
Unit30	0.001423696	-0.01973468	0.149455503						
Vac_PCT	-0.026709365	0.23943736	-0.006408466						
PopDen	1.000000000	-0.02913911	0.014474460						
VotgBlwPov	-0.029139110	1.000000000	-0.036061283						
ElderAlone	0.014474460	-0.03606128	1.000000000						

Bivariate R ggplot results



Bivariate R summary

	Variable	Correlation	P_value
HHIncome	HHIncome	0.0005287462	0.98885047
BSUp_PCT	BSUp_PCT	-0.0392735075	0.29909960
WHTPCT	WHTPCT	-0.0819641626	0.03001476
BLKPCT	BLKPCT	0.0146064967	0.69945376
MHVal	MHVal	0.0309596277	0.41311001
MRent	MRent	-0.0445334301	0.23897002
Unit30	Unit30	-0.0914439733	0.01544118
Vac_PCT	Vac_PCT	-0.0785452553	0.03760839
PopDen	PopDen	-0.0084519800	0.82323769
VotgBlwPov	VotgBlwPov	-0.0475122245	0.20896464
ElderAlone	ElderAlone	-0.0235031628	0.53443217

OLS R Output

OLS R results

```
lm(formula = SUM_G_RJ_T ~ HHIncome + MHVal + MRent + WHTPCT +  
    BLKPCT + BSUp_PCT + VotgBlwPov + ElderAlone + Unit30 + Vac_PCT +  
    PopDen, data = my_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-134.34	-41.06	-23.28	-3.84	1705.22

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.343e+02	3.044e+01	4.413	1.18e-05 ***
HHIncome	-2.419e-04	1.704e-04	-1.420	0.1562
MHVal	6.889e-05	2.901e-05	2.375	0.0178 *
MRent	-2.483e-03	8.249e-03	-0.301	0.7635
WHTPCT	-7.657e+01	3.754e+01	-2.040	0.0417 *
BLKPCT	-5.138e+01	6.631e+01	-0.775	0.4387
BSUp_PCT	-1.534e+01	3.234e+01	-0.474	0.6355
VotgBlwPov	-5.056e+01	4.396e+01	-1.150	0.2504
ElderAlone	-2.379e+01	1.189e+02	-0.200	0.8414
Unit30	-5.813e-02	2.328e-02	-2.497	0.0128 *
Vac_PCT	-1.367e+02	7.865e+01	-1.738	0.0826 .
PopDen	-6.231e-06	1.730e-05	-0.360	0.7188

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 144.3 on 689 degrees of freedom
Multiple R-squared: 0.03065, Adjusted R-squared: 0.01517
F-statistic: 1.98 on 11 and 689 DF, p-value: 0.02779

Spatial Models R Output

Spatial Lag R results

```
Call:lagsarlm(formula = SUM_G_RJ_T ~ HHIncome + BSup_PCT + WHTPCT +  
BLKPCT + MHVal + MRent + Unit30 + Vac_PCT + PopDen + VotgBlwPov + ElderAlone, data = test_data, listw = W)
```

Residuals:

Min	1Q	Median	3Q	Max
-211.5547	-38.9858	-21.3723	-1.5753	1688.2406

Type: lag

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	27.58174	5.66167	4.8717	1.107e-06
HHIncome	-13.77807	8.54039	-1.6133	0.10668
BSUp_PCT	-2.67967	7.61431	-0.3519	0.72489
WHTPCT	-14.06857	7.23182	-1.9454	0.05173
BLKPCT	-5.89258	6.55222	-0.8993	0.36848
MHVal	16.65049	7.46405	2.2308	0.02570
MRent	-1.33093	5.65634	-0.2353	0.81398
Unit30	-13.69922	5.81169	-2.3572	0.01841
Vac_PCT	-10.45542	5.69209	-1.8368	0.06623
PopDen	-3.03320	5.42445	-0.5592	0.57604
VotgBlwPov	-6.97316	6.38735	-1.0917	0.27496
ElderAlone	-0.85886	5.59065	-0.1536	0.87791

Rho: 0.11345, LR test value: 7.6687, p-value: 0.0056187

Asymptotic standard error: 0.058016

z-value: 1.9556, p-value: 0.050517

Wald statistic: 3.8242, p-value: 0.050517

Log likelihood: -4470.022 for lag model

ML residual variance (sigma squared): 20193, (sigma: 142.1)

Number of observations: 701

Number of parameters estimated: 14

AIC: 8968, (AIC for lm: 8973.7)

LM test for residual autocorrelation

test value: 14.607, p-value: 0.00013243

Spatial Error R results

```
Call:errorsarlm(formula = SUM_G_RJ_T ~ HHIncome + BSup_PCT + WHTPCT +  
BLKPCT + MHVal + MRent + Unit30 + Vac_PCT + PopDen + VotgBlwPov + ElderAlone, data = test_data, listw = W)
```

Residuals:

Min	1Q	Median	3Q	Max
-204.9021	-39.5484	-22.2253	-2.5149	1690.6728

Type: error

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	31.14297	6.03621	5.1594	2.478e-07
HHIncome	-13.38795	8.69354	-1.5400	0.12356
BSUp_PCT	-2.95732	7.88552	-0.3750	0.70764
WHTPCT	-14.37055	7.37773	-1.9478	0.05144
BLKPCT	-5.76016	6.67093	-0.8635	0.38788
MHVal	16.02849	7.64674	2.0961	0.03607
MRent	-1.63931	5.70138	-0.2875	0.77371
Unit30	-13.66125	5.99282	-2.2796	0.02263
Vac_PCT	-10.61974	5.70962	-1.8600	0.06289
PopDen	-3.23494	5.42650	-0.5961	0.55108
VotgBlwPov	-7.43416	6.64315	-1.1191	0.26311
ElderAlone	-0.79472	5.60454	-0.1418	0.88724

Lambda: 0.11033, LR test value: 6.974, p-value: 0.00827

Asymptotic standard error: 0.05864

z-value: 1.8815, p-value: 0.059904

Wald statistic: 3.54, p-value: 0.059904

Log likelihood: -4470.369 for error model

ML residual variance (sigma squared): 20215, (sigma: 142.18)

Number of observations: 701

Number of parameters estimated: 14

AIC: 8968.7, (AIC for lm: 8973.7)

Appendix B - R Output for the Longitudinal Spatial Models

Accessibility Score 2000-2010

Spatial Lag R results

```
Call:lagsarlm(formula = Ail60010 ~ hinc0010 + hval0010 + rent0010 +  
  pctwht0010 + pctblk0010 + pctcol0010 + pctold0010 + pctvac0010 +  
  pcthud0010 + popden0010, data = test_data, listw = W)
```

```
Residuals:  
      Min       1Q   Median       3Q      Max  
-11.328177  -0.203378   0.028472   0.262400   1.816841
```

Type: lag

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.001148	0.063922	0.0180	0.985672
hinc0010	0.034255	0.087814	0.3901	0.696470
hval0010	-0.040203	0.085049	-0.4727	0.636428
rent0010	0.125980	0.076310	1.6509	0.098761
pctwht0010	0.421984	0.088398	4.7737	1.809e-06
pctblk0010	0.079649	0.076467	1.0416	0.297594
pctcol0010	-0.241241	0.079121	-3.0490	0.002296
pctold0010	0.143638	0.072805	1.9729	0.048505
pctvac0010	-0.013926	0.065861	-0.2114	0.832538
pcthud0010	0.077903	0.065277	1.1934	0.232704
popden0010	-0.008913	0.076049	-0.1172	0.906701

Rho: -0.15587, LR test value: 1.7312, p-value: 0.18825

Asymptotic standard error: 0.11524

z-value: -1.3525, p-value: 0.1762

Wald statistic: 1.8294, p-value: 0.1762

Log likelihood: -271.2602 for lag model

ML residual variance (sigma squared): 0.83325, (sigma: 0.91282)

Number of observations: 204

Number of parameters estimated: 13

AIC: 568.52, (AIC for lm: 568.25)

LM test for residual autocorrelation

test value: 0.011498, p-value: 0.91461

OLS R results

Call:

```
lm(formula = Ail60010 ~ hinc0010 + hval0010 + rent0010 + pctwht0010 +  
  pctblk0010 + pctcol0010 + pctold0010 + pctvac0010 + pcthud0010 +  
  popden0010, data = test_data)
```

```
Residuals:  
      Min       1Q   Median       3Q      Max  
-11.4137  -0.1967   0.0284   0.2670   1.7831
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.305e-17	6.612e-02	0.000	1.00000
hinc0010	2.308e-02	9.085e-02	0.254	0.79971
hval0010	-4.259e-02	8.793e-02	-0.484	0.62871
rent0010	1.240e-01	7.894e-02	1.570	0.11797
pctwht0010	4.111e-01	9.055e-02	4.540	9.88e-06 ***
pctblk0010	9.265e-02	7.911e-02	1.171	0.24297
pctcol0010	-2.306e-01	8.185e-02	-2.817	0.00535 **
pctold0010	1.425e-01	7.521e-02	1.895	0.05962 .
pctvac0010	-1.160e-02	6.811e-02	-0.170	0.86488
pcthud0010	6.992e-02	6.753e-02	1.035	0.30179
popden0010	-6.782e-03	7.867e-02	-0.086	0.93139

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9443 on 193 degrees of freedom

Multiple R-squared: 0.1522, Adjusted R-squared: 0.1082

F-statistic: 3.464 on 10 and 193 DF, p-value: 0.0003298

Accessibility Score 2010-2020

Spatial Lag R results

```
Call: lagsarlm(formula = Ai161020 ~ hinc1020 + hval1020 + rent1020 +  
  pctwht1020 + pctblk1020 + pctcol1020 + pctold1020 + pctvac1020 +  
  pcthud1020 + popden1020, data = test_data, listw = W)
```

Residuals:

Min	1Q	Median	3Q	Max
-3.658252	-0.233708	-0.023062	0.208047	10.245703

Type: lag

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.00047534	0.06261796	0.0076	0.9939432
hinc1020	-0.10053936	0.07148835	-1.4064	0.1596130
hval1020	-0.06537962	0.07048958	-0.9275	0.3536631
rent1020	-0.04461534	0.06700001	-0.6659	0.5054747
pctwht1020	-0.26629170	0.07921943	-3.3614	0.0007754
pctblk1020	0.08762177	0.06927744	1.2648	0.2059448
pctcol1020	0.05238280	0.07602207	0.6890	0.4907935
pctold1020	-0.17111635	0.06866389	-2.4921	0.0126995
pctvac1020	-0.00413552	0.06633738	-0.0623	0.9502915
pcthud1020	-0.23176206	0.06475584	-3.5790	0.0003449
popden1020	-0.30989504	0.06712778	-4.6165	3.903e-06

Rho: 0.014274, LR test value: 0.015008, p-value: 0.9025

Asymptotic standard error: 0.11005

z-value: 0.1297, p-value: 0.8968

Wald statistic: 0.016823, p-value: 0.8968

Log likelihood: -266.6685 for lag model

ML residual variance (sigma squared): 0.7997, (sigma: 0.89426)

Number of observations: 204

Number of parameters estimated: 13

AIC: 559.34, (AIC for lm: 557.35)

LM test for residual autocorrelation

test value: 0.14083, p-value: 0.70746

OLS R results

Call:

```
lm(formula = Ai161020 ~ hinc1020 + hval1020 + rent1020 + pctwht1020 +  
  pctblk1020 + pctcol1020 + pctold1020 + pctvac1020 + pcthud1020 +  
  popden1020, data = test_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-3.6530	-0.2327	-0.0223	0.2078	10.2487

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-1.375e-16	6.437e-02	0.000	1.000000
hinc1020	-9.971e-02	7.345e-02	-1.358	0.176196
hval1020	-6.460e-02	7.243e-02	-0.892	0.373505
rent1020	-4.527e-02	6.888e-02	-0.657	0.511804
pctwht1020	-2.665e-01	8.142e-02	-3.273	0.001262 **
pctblk1020	8.789e-02	7.120e-02	1.234	0.218583
pctcol1020	5.212e-02	7.806e-02	0.668	0.505103
pctold1020	-1.710e-01	7.055e-02	-2.424	0.016278 *
pctvac1020	-4.258e-03	6.812e-02	-0.063	0.950218
pcthud1020	-2.324e-01	6.655e-02	-3.492	0.000594 ***
popden1020	-3.100e-01	6.899e-02	-4.493	1.21e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9194 on 193 degrees of freedom

Multiple R-squared: 0.1963, Adjusted R-squared: 0.1546

F-statistic: 4.713 on 10 and 193 DF, p-value: 4.927e-06

Accessibility Score 2000-2020

Spatial Lag R results

```
Call:lagsarlm(formula = Ai160020 ~ hinc0020 + hval0020 + rent0020 +  
  pctwht0020 + pctblk0020 + pctcol0020 + pctold0020 + pctvac0020 +  
  pcthud0020 + popden0020, data = test_data, listw = W)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-11.515978	-0.162342	0.036072	0.262817	3.216679

Type: lag

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-7.9942e-05	6.5792e-02	-0.0012	0.9990305
hinc0020	2.2298e-03	9.3497e-02	0.0238	0.9809730
hval0020	-4.6217e-02	9.2345e-02	-0.5005	0.6167363
rent0020	7.2071e-02	7.3092e-02	0.9860	0.3241176
pctwht0020	3.7824e-01	9.7770e-02	3.8687	0.0001094
pctblk0020	6.9109e-02	7.8578e-02	0.8795	0.3791337
pctcol0020	-2.8274e-01	9.0003e-02	-3.1414	0.0016815
pctold0020	4.0631e-02	8.0984e-02	0.5017	0.6158684
pctvac0020	2.7634e-02	7.1045e-02	0.3890	0.6973034
pcthud0020	-2.9510e-02	6.8245e-02	-0.4324	0.6654366
popden0020	-1.3106e-01	7.9051e-02	-1.6579	0.0973361

Rho: -0.11437, LR test value: 0.94786, p-value: 0.33027

Asymptotic standard error: 0.11674

z-value: -0.97969, p-value: 0.32724

Wald statistic: 0.95979, p-value: 0.32724

Log likelihood: -276.977 for lag model

ML residual variance (sigma squared): 0.88288, (sigma: 0.93962)

Number of observations: 204

Number of parameters estimated: 13

AIC: 579.95, (AIC for lm: 578.9)

LM test for residual autocorrelation

test value: 0.16759, p-value: 0.68226

OLS R results

Call:

```
lm(formula = Ai160020 ~ hinc0020 + hval0020 + rent0020 + pctwht0020 +  
  pctblk0020 + pctcol0020 + pctold0020 + pctvac0020 + pcthud0020 +  
  popden0020, data = test_data)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-11.5741	-0.1515	0.0463	0.2647	3.1610

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-8.868e-17	6.787e-02	0.000	1.000000
hinc0020	-3.348e-03	9.645e-02	-0.035	0.972343
hval0020	-4.990e-02	9.526e-02	-0.524	0.601007
rent0020	7.326e-02	7.537e-02	0.972	0.332266
pctwht0020	3.631e-01	1.005e-01	3.612	0.000387 ***
pctblk0020	6.697e-02	8.105e-02	0.826	0.409654
pctcol0020	-2.782e-01	9.285e-02	-2.997	0.003087 **
pctold0020	3.590e-02	8.348e-02	0.430	0.667653
pctvac0020	2.918e-02	7.325e-02	0.398	0.690811
pcthud0020	-3.287e-02	7.040e-02	-0.467	0.641105
popden0020	-1.341e-01	8.154e-02	-1.644	0.101770

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9693 on 193 degrees of freedom

Multiple R-squared: 0.1067, Adjusted R-squared: 0.06044

F-statistic: 2.306 on 10 and 193 DF, p-value: 0.01399

Per Capita Green Space 2000-2010

Spatial Lag R results

```
Call:lagsarlm(formula = addedpc001 ~ hinc0010 + hval0010 + rent0010 +  
  pctwht0010 + pctblk0010 + pctcol0010 + pctold0010 + pctvac0010 +  
  pcthud0010 + popden0010, data = test_data, listw = W)
```

Residuals:

Min	1Q	Median	3Q	Max
-13.514013	-0.044038	0.062617	0.206257	0.708217

Type: lag

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-2.9041e-05	6.8134e-02	-0.0004	0.99966
hinc0010	-9.9219e-02	9.3622e-02	-1.0598	0.28924
hval0010	9.9749e-02	9.0734e-02	1.0994	0.27161
rent0010	8.7739e-02	8.1358e-02	1.0784	0.28084
pctwht0010	-1.7680e-02	9.3320e-02	-0.1895	0.84973
pctblk0010	8.5501e-03	8.1518e-02	0.1049	0.91647
pctcol0010	-3.2704e-02	8.4373e-02	-0.3876	0.69831
pctold0010	1.0780e-01	7.7599e-02	1.3892	0.16477
pctvac0010	1.4660e-01	7.0283e-02	2.0859	0.03699
pcthud0010	4.2547e-02	6.9599e-02	0.6113	0.54098
popden0010	1.8859e-02	8.1125e-02	0.2325	0.81617

Rho: -0.019788, LR test value: 0.029825, p-value: 0.86289

Asymptotic standard error: 0.11599

z-value: -0.1706, p-value: 0.86454

Wald statistic: 0.029103, p-value: 0.86454

Log likelihood: -283.9141 for lag model

ML residual variance (sigma squared): 0.94699, (sigma: 0.97313)

Number of observations: 204

Number of parameters estimated: 13

AIC: 593.83, (AIC for lm: 591.86)

LM test for residual autocorrelation

test value: 0.17935, p-value: 0.67193

Spatial Error R results

```
Call:errorsarlm(formula = addedpc001 ~ hinc0010 + hval0010 + rent0010 +  
  pctwht0010 + pctblk0010 + pctcol0010 + pctold0010 + pctvac0010 +  
  pcthud0010 + popden0010, data = test_data, listw = W)
```

Residuals:

Min	1Q	Median	3Q	Max
-13.516272	-0.043919	0.063246	0.210434	0.706728

Type: error

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.8498e-05	6.7294e-02	0.0003	0.99978
hinc0010	-9.8960e-02	9.3576e-02	-1.0575	0.29027
hval0010	9.9081e-02	9.0240e-02	1.0980	0.27222
rent0010	8.7361e-02	8.1316e-02	1.0743	0.28268
pctwht0010	-1.7246e-02	9.3042e-02	-0.1854	0.85295
pctblk0010	8.9519e-03	8.1267e-02	0.1102	0.91229
pctcol0010	-3.2365e-02	8.4248e-02	-0.3842	0.70085
pctold0010	1.0721e-01	7.7263e-02	1.3876	0.16527
pctvac0010	1.4584e-01	7.0044e-02	2.0821	0.03734
pcthud0010	4.2263e-02	6.9488e-02	0.6082	0.54305
popden0010	1.8598e-02	8.1046e-02	0.2295	0.81850

Lambda: -0.012536, LR test value: 0.011126, p-value: 0.91599

Asymptotic standard error: 0.11775

z-value: -0.10647, p-value: 0.91521

Wald statistic: 0.011336, p-value: 0.91521

Log likelihood: -283.9235 for error model

ML residual variance (sigma squared): 0.94711, (sigma: 0.9732)

Number of observations: 204

Number of parameters estimated: 13

AIC: 593.85, (AIC for lm: 591.86)

OLS R results

```
Call:
lm(formula = addedpc001 ~ hinc0010 + hval0010 + rent0010 + pctwht0010 +
    pctblk0010 + pctcol0010 + pctold0010 + pctvac0010 + pcthud0010 +
    popden0010, data = test_data)

Residuals:
    Min       1Q   Median       3Q      Max
-13.5168  -0.0470   0.0643   0.2044   0.7072

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.048e-17  7.006e-02   0.000    1.0000
hinc0010     -9.937e-02  9.626e-02  -1.032   0.3032
hval0010      9.858e-02  9.317e-02   1.058   0.2914
rent0010      8.800e-02  8.365e-02   1.052   0.2941
pctwht0010   -1.946e-02  9.595e-02  -0.203   0.8395
pctblk0010    8.221e-03  8.382e-02   0.098   0.9220
pctcol0010   -3.208e-02  8.673e-02  -0.370   0.7118
pctold0010    1.066e-01  7.969e-02   1.338   0.1826
pctvac0010    1.462e-01  7.216e-02   2.026   0.0441 *
pcthud0010    4.212e-02  7.155e-02   0.589   0.5567
popden0010    1.775e-02  8.336e-02   0.213   0.8316
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.001 on 193 degrees of freedom
Multiple R-squared:  0.04815,    Adjusted R-squared:  -0.001171
F-statistic: 0.9762 on 10 and 193 DF,  p-value: 0.4655
```

Per Capita Green Space 2010-2020

Spatial Lag R results

```
Call:lagsarlm(formula = addedpc102 ~ hinc1020 + hval1020 + rent1020 +
    pctwht1020 + pctblk1020 + pctcol1020 + pctold1020 + pctvac1020 +
    pcthud1020 + popden1020, data = test_data, listw = W)

Residuals:
    Min       1Q   Median       3Q      Max
-9.563942 -0.219706   0.028669   0.262040   7.299447

Type: lag
Coefficients: (asymptotic standard errors)
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.0011017  0.0644411   0.0171 0.9863593
hinc1020     -0.1342851  0.0735291  -1.8263 0.0678075
hval1020      0.0310018  0.0725019   0.4276 0.6689430
rent1020      0.0046649  0.0689584   0.0676 0.9460656
pctwht1020   -0.2921430  0.0815037  -3.5844 0.0003378
pctblk1020   -0.3369618  0.0713108  -4.7253 2.298e-06
pctcol1020    0.1220235  0.0781758   1.5609 0.1185510
pctold1020   -0.0519912  0.0708127  -0.7342 0.4628218
pctvac1020    0.0235118  0.0681865   0.3448 0.7302330
pcthud1020   -0.0254743  0.0666208  -0.3824 0.7021806
popden1020   -0.1867144  0.0690652  -2.7035 0.0068623

Rho: 0.04909, LR test value: 0.1729, p-value: 0.67755
Asymptotic standard error: 0.10979
z-value: 0.44714, p-value: 0.65478
Wald statistic: 0.19993, p-value: 0.65478

Log likelihood: -272.5843 for lag model
ML residual variance (sigma squared): 0.84714, (sigma: 0.9204)
Number of observations: 204
Number of parameters estimated: 13
AIC: 571.17, (AIC for lm: 569.34)
LM test for residual autocorrelation
test value: 4.1234, p-value: 0.042293
```

Spatial Error R results

```
Call:errorsarlm(formula = addedpc102 ~ hinc1020 + hval1020 + rent1020 +  
  pctwh1020 + pctblk1020 + pctcol1020 + pctold1020 + pctvac1020 +  
  pcthud1020 + popden1020, data = test_data, listw = W)
```

Residuals:

Min	1Q	Median	3Q	Max
-9.398450	-0.229374	0.016794	0.275682	7.291129

Type: error

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.0035388	0.0758104	0.0467	0.9627691
hinc1020	-0.1395949	0.0726884	-1.9205	0.0548004
hval1020	0.0076067	0.0753996	0.1009	0.9196415
rent1020	0.0250669	0.0679945	0.3687	0.7123804
pctwh1020	-0.2837556	0.0825887	-3.4358	0.0005909
pctblk1020	-0.3579281	0.0713591	-5.0159	5.279e-07
pctcol1020	0.1054795	0.0785793	1.3423	0.1794887
pctold1020	-0.0445369	0.0736442	-0.6048	0.5453402
pctvac1020	0.0189965	0.0682292	0.2784	0.7806884
pcthud1020	-0.0106001	0.0668200	-0.1586	0.8739553
popden1020	-0.1934023	0.0695451	-2.7810	0.0054198

Lambda: 0.154, LR test value: 1.3739, p-value: 0.24115

Asymptotic standard error: 0.11018

z-value: 1.3977, p-value: 0.1622

Wald statistic: 1.9536, p-value: 0.1622

Log likelihood: -271.9838 for error model

ML residual variance (sigma squared): 0.83903, (sigma: 0.91598)

Number of observations: 204

Number of parameters estimated: 13

AIC: 569.97, (AIC for lm: 569.34)

OLS R results

```
lm(formula = addedpc102 ~ hinc1020 + hval1020 + rent1020 + pctwh1020 +  
  pctblk1020 + pctcol1020 + pctold1020 + pctvac1020 + pcthud1020 +  
  popden1020, data = test_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-9.5787	-0.2096	0.0349	0.2593	7.2981

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.125e-17	6.629e-02	0.000	1.000000
hinc1020	-1.335e-01	7.564e-02	-1.765	0.079116 .
hval1020	3.480e-02	7.459e-02	0.467	0.641349
rent1020	1.634e-03	7.093e-02	0.023	0.981641
pctwh1020	-2.936e-01	8.384e-02	-3.502	0.000574 ***
pctblk1020	-3.339e-01	7.332e-02	-4.554	9.32e-06 ***
pctcol1020	1.242e-01	8.039e-02	1.545	0.123916
pctold1020	-5.007e-02	7.265e-02	-0.689	0.491520
pctvac1020	2.423e-02	7.015e-02	0.345	0.730151
pcthud1020	-2.803e-02	6.853e-02	-0.409	0.682953
popden1020	-1.857e-01	7.105e-02	-2.613	0.009679 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9469 on 193 degrees of freedom

Multiple R-squared: 0.1476, Adjusted R-squared: 0.1035

F-statistic: 3.342 on 10 and 193 DF, p-value: 0.0004937

Per Capita Green Space 2000-2020

Spatial Lag R results

```
Call:lagsarlm(formula = addedpc002 ~ hinc0020 + hval0020 + rent0020 +  
  pctwht0020 + pctblk0020 + pctcol0020 + pctold0020 + pctvac0020 +  
  pcthud0020 + popden0020, data = test_data, listw = W)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-11.916933	-0.149352	0.078568	0.280666	1.852561

Type: lag

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-2.2037e-05	6.4397e-02	-0.0003	0.999727
hinc0020	-1.5025e-01	9.1561e-02	-1.6410	0.100805
hval0020	1.7128e-01	9.0587e-02	1.8907	0.058660
rent0020	9.8390e-02	7.1523e-02	1.3757	0.168929
pctwht0020	-2.7243e-01	9.5413e-02	-2.8552	0.004300
pctblk0020	-3.5904e-01	7.7430e-02	-4.6370	3.535e-06
pctcol0020	8.0348e-02	8.8109e-02	0.9119	0.361809
pctold0020	1.1114e-01	7.9292e-02	1.4017	0.161010
pctvac0020	1.8263e-01	6.9656e-02	2.6219	0.008745
pcthud0020	2.1107e-02	6.6803e-02	0.3160	0.752032
popden0020	-1.1871e-02	7.7411e-02	-0.1533	0.878125

Rho: -0.0045057, LR test value: 0.0015901, p-value: 0.96819

Asymptotic standard error: 0.1112

z-value: -0.04052, p-value: 0.96768

Wald statistic: 0.0016419, p-value: 0.96768

Log likelihood: -272.4028 for lag model

ML residual variance (sigma squared): 0.84598, (sigma: 0.91977)

Number of observations: 204

Number of parameters estimated: 13

AIC: 570.81, (AIC for lm: 568.81)

LM test for residual autocorrelation

test value: 9.3779, p-value: 0.0021962

Spatial Error R results

```
Call:errorsarlm(formula = addedpc002 ~ hinc0020 + hval0020 + rent0020 +  
  pctwht0020 + pctblk0020 + pctcol0020 + pctold0020 + pctvac0020 +  
  pcthud0020 + popden0020, data = test_data, listw = W)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-11.795617	-0.152265	0.067987	0.256709	1.783894

Type: error

Coefficients: (asymptotic standard errors)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.00076775	0.07343167	0.0105	0.991658
hinc0020	-0.15086518	0.09073613	-1.6627	0.096376
hval0020	0.15894021	0.09314947	1.7063	0.087954
rent0020	0.10746240	0.07100422	1.5135	0.130162
pctwht0020	-0.28603381	0.09758915	-2.9310	0.003379
pctblk0020	-0.39896866	0.07897098	-5.0521	4.37e-07
pctcol0020	0.07082645	0.08965243	0.7900	0.429521
pctold0020	0.09491986	0.08223179	1.1543	0.248379
pctvac0020	0.17823542	0.07082608	2.5165	0.011852
pcthud0020	0.03035096	0.06741687	0.4502	0.652567
popden0020	-0.02476490	0.07786187	-0.3181	0.750438

Lambda: 0.12644, LR test value: 1.0356, p-value: 0.30885

Asymptotic standard error: 0.11162

z-value: 1.1328, p-value: 0.25729

Wald statistic: 1.2833, p-value: 0.25729

Log likelihood: -271.8858 for error model

ML residual variance (sigma squared): 0.83937, (sigma: 0.91617)

Number of observations: 204

Number of parameters estimated: 13

AIC: 569.77, (AIC for lm: 568.81)

OLS R results

```
lm(formula = addedpc002 ~ hinc0020 + hval0020 + rent0020 + pctwht0020 +  
  pctblk0020 + pctcol0020 + pctold0020 + pctvac0020 + pcthud0020 +  
  popden0020, data = test_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-11.9174	-0.1493	0.0787	0.2801	1.8504

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-2.374e-17	6.621e-02	0.000	1.00000
hinc0020	-1.502e-01	9.409e-02	-1.596	0.11215
hval0020	1.709e-01	9.293e-02	1.839	0.06750 .
rent0020	9.854e-02	7.353e-02	1.340	0.18177
pctwht0020	-2.726e-01	9.808e-02	-2.779	0.00598 **
pctblk0020	-3.593e-01	7.907e-02	-4.544	9.71e-06 ***
pctcol0020	8.014e-02	9.058e-02	0.885	0.37741
pctold0020	1.107e-01	8.144e-02	1.359	0.17563
pctvac0020	1.824e-01	7.146e-02	2.552	0.01149 *
pcthud0020	2.126e-02	6.868e-02	0.309	0.75729
popden0020	-1.220e-02	7.955e-02	-0.153	0.87828

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9456 on 193 degrees of freedom
Multiple R-squared: 0.1498, Adjusted R-squared: 0.1058
F-statistic: 3.402 on 10 and 193 DF, p-value: 0.0004053

Appendix C - Qualitative Comparative Analysis

Sample Public PARD Meeting Minute

Minutes
Parks and Recreation Board
January 22, 1991

The regular meeting of the Parks and Recreation Board was held at the Parks and Recreation Department Board Room, 1500 W. Riverside Drive with Mrs. Beverly Griffith, Chair, presiding. Board Members present: Terry Colgan, Neil Iscoe, ErmaLinda Cruz-Torres, Beverly Griffith, Louise Nivison, Ron Carlidge, and Agnes Edwards. Staff present: Manuel Mollinedo, Jody Hamilton, Stuart Strong, Peter Marsh, Carolyn Kelley, Valleri Edelbrock and Donna Bohls.

CALL TO ORDER

The meeting was called to order at 6:30 p.m.

CITIZEN COMMUNICATIONS

Mr. Robert Simmons addressed the Board with a proposal for the installation of a carousel in Zilker Park. Mr. Simmons requested that the concessions RFP currently being prepared include a carousel concession. He provided Board Members with pictures of his proposed carousel which would have a Texas history theme.

SPECIAL PRESENTATIONS

Slide Show from Flag Football Programs

Robert Sopronyi, Acting Division Manager for Programs, made a presentation to the Board. He showed slides of the Department's At-Risk Youth flag football program including the cheerleaders. Mr. Sopronyi outlined the participation in both the flag football and basketball programs, funding for the programs and upcoming programs such as "Dare to Dance" and "High Adventure." He informed Board Members about the sponsorship of Pizza Hut, Pepsi and the Optimists Clubs in providing food for the sports banquets.

COMMITTEE REPORTS

None

CHAIR'S REPORT

Mrs. Griffith made a report on the RUDAT (Regional Urban Design Assistance Team) visit to Austin and their favorable report in regard to our downtown parks. She indicated that the Team stressed programming our resources.

ITEMS FROM PREVIOUS AGENDA

Approval of Conceptual Design of Gazebo at Lou Neff Point

David Santos, Project Manager, and Valleri Edelbrock, Horticulturalist, answered questions for Board Members regarding the gazebo project and the wisteria located on the site. Terry Colgan made a motion to approve the conceptual design of the project. ErmaLinda Cruz-Torres seconded the

Sample Civic Participation from the PARD Meeting Minute

CITIZEN COMMUNICATIONS

Mr. Robert Simmons addressed the Board with a proposal for the installation of a carousel in Zilker Park. Mr. Simmons requested that the concessions RFP currently being prepared include a carousel concession. He provided Board Members with pictures of his proposed carousel which would have a Texas history theme.

Civic Participation cases for each park across decades

Year	Year Acquired	Address	Location	1991	2000	2001	2010	2011	2020
1	1960	Parment Blvd., Austin, Texas	Laguna Oaks Neighborhood Park	23	20	20	34		
2	1971	Winkler Blvd., Austin, Texas	Monteleone Springs at Texas Motor Park	23	20	20	34		
3	1963	Yorkwood Dr., Austin, Texas	Baughman Oaks at Slough Creek Greenbelt	23	20	20	34		
4	1965	Farwell Dr., Austin, Texas	Long Creek Greenbelt	23	20	20	34		
5	1965	Winkler Blvd., Austin, Texas	Little Arroyo Neighborhood Park	23	21	20	34		
6	1965	Winkler Blvd., Austin, Texas	S. 15th St. at Austin Medical Center	23	21	20	34		
7	1975	Alameda Dr., Austin, Texas	High School Park	23	21	20	34		
8	1975	John Dr., Austin, Texas	San Antonio Park	23	21	20	34		
9	1931	Seaview St., Austin, Texas	Parque Atkinson Neighborhood Park	23	21	20	34		
10	1941	Seaview St., Austin, Texas	Seaview Park	23	21	20	34		
11	1974	Long Loop St., Austin, Texas	Long Loop Park, Dasher Park	23	21	21	34		
12	1974	Long Loop St., Austin, Texas	Long Loop Park	23	21	21	34		
13	1999	Bain Canyon Dr., Austin, Texas	Orion Creek Soccer Complex	23	21	21	34		
14	1999	Winkler Blvd., Austin, Texas	Winkler Blvd. at Austin Medical Center	23	21	21	34		
15	1946	S. Hall St., Austin, Texas	Highland Park	23	21	21	34		
16	1946	Winkler Blvd., Austin, Texas	Highland Park	23	21	21	34		
17	2006	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
18	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
19	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
20	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
21	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
22	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
23	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
24	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
25	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
26	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
27	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
28	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
29	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
30	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
31	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
32	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
33	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
34	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
35	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
36	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
37	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
38	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
39	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
40	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
41	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
42	1973	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
43	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
44	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
45	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
46	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
47	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
48	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
49	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
50	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
51	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
52	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
53	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
54	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
55	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
56	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
57	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
58	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
59	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
60	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
61	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
62	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
63	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
64	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
65	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
66	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
67	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
68	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
69	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
70	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
71	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
72	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
73	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
74	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
75	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
76	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
77	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
78	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
79	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
80	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
81	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
82	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
83	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
84	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
85	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
86	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
87	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
88	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
89	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
90	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
91	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
92	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
93	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
94	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
95	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
96	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
97	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
98	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
99	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		
100	1968	Chen Dr., Austin, Texas	Chen Dr. at Maple Run Preserve	23	21	21	34		

Park, Pre#2, City, 2000, 2020, 2030, 2040

Park, Pre#2, City, 2000, 2020, 2030, 2040

3

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86	1970	S 6th St., Austin, Texas	74	1926	Joe Kelly Ave., Austin, Texas	85	1926	Elmer (Deep Edg) Neighborhood Park	20	34
87	1992	West Oltorf St., Austin, Texas	75	1927	Ben Houston Dr., Austin, Texas	86	1927	Ben Houston Dr., Austin, Texas	20	34
88	1982	St. Harford Dr., Austin, Texas	76	1928	Harford Ave., Austin, Texas	87	1928	Harford Ave., Austin, Texas	20	34
89	1982	Red Creek Ave., Austin, Texas	77	1928	Lamar St., Austin, Texas	88	1928	Lamar St., Austin, Texas	20	34
90	1982	Red River St., Austin, Texas	78	1930	Harwood Ave., Austin, Texas	89	1930	Harwood Ave., Austin, Texas	20	34
91	1977	Parmer Lane Dr., Austin, Texas	79	1930	Harwood Ave., Austin, Texas	90	1930	Harwood Ave., Austin, Texas	20	34
92	2009	Burress Hill, Austin, Texas	80	1932	14th Spring Rd., Austin, Texas	91	1932	14th Spring Rd., Austin, Texas	20	34
93	1989	Payson Dr., Austin, Texas	81	1932	14th Spring Rd., Austin, Texas	92	1932	14th Spring Rd., Austin, Texas	20	34
94	1989	Payson Dr., Austin, Texas	82	1934	14th Spring Rd., Austin, Texas	93	1934	14th Spring Rd., Austin, Texas	20	34
95	1989	Payson Dr., Austin, Texas	83	1934	14th Spring Rd., Austin, Texas	94	1934	14th Spring Rd., Austin, Texas	20	34
96	2013	Exton Dr., Austin, Texas	84	1934	14th Spring Rd., Austin, Texas	95	1934	14th Spring Rd., Austin, Texas	20	34
97	1982	01 Big T, Austin, Texas	85	1934	14th Spring Rd., Austin, Texas	96	1934	14th Spring Rd., Austin, Texas	20	34
98	1982	01 Big T, Austin, Texas	86	1934	14th Spring Rd., Austin, Texas	97	1934	14th Spring Rd., Austin, Texas	20	34
99	1982	01 Big T, Austin, Texas	87	1934	14th Spring Rd., Austin, Texas	98	1934	14th Spring Rd., Austin, Texas	20	34
100	1982	01 Big T, Austin, Texas	88	1934	14th Spring Rd., Austin, Texas	99	1934	14th Spring Rd., Austin, Texas	20	34
101	1982	01 Big T, Austin, Texas	89	1934	14th Spring Rd., Austin, Texas	100	1934	14th Spring Rd., Austin, Texas	20	34
102	1982	01 Big T, Austin, Texas	90	1934	14th Spring Rd., Austin, Texas	101	1934	14th Spring Rd., Austin, Texas	20	34
103	1982	01 Big T, Austin, Texas	91	1934	14th Spring Rd., Austin, Texas	102	1934	14th Spring Rd., Austin, Texas	20	34
104	1982	01 Big T, Austin, Texas	92	1934	14th Spring Rd., Austin, Texas	103	1934	14th Spring Rd., Austin, Texas	20	34
105	1982	01 Big T, Austin, Texas	93	1934	14th Spring Rd., Austin, Texas	104	1934	14th Spring Rd., Austin, Texas	20	34
106	1982	01 Big T, Austin, Texas	94	1934	14th Spring Rd., Austin, Texas	105	1934	14th Spring Rd., Austin, Texas	20	34
107	1982	01 Big T, Austin, Texas	95	1934	14th Spring Rd., Austin, Texas	106	1934	14th Spring Rd., Austin, Texas	20	34
108	1982	01 Big T, Austin, Texas	96	1934	14th Spring Rd., Austin, Texas	107	1934	14th Spring Rd., Austin, Texas	20	34
109	1982	01 Big T, Austin, Texas	97	1934	14th Spring Rd., Austin, Texas	108	1934	14th Spring Rd., Austin, Texas	20	34
110	1982	01 Big T, Austin, Texas	98	1934	14th Spring Rd., Austin, Texas	109	1934	14th Spring Rd., Austin, Texas	20	34
111	1982	01 Big T, Austin, Texas	99	1934	14th Spring Rd., Austin, Texas	110	1934	14th Spring Rd., Austin, Texas	20	34
112	1982	01 Big T, Austin, Texas	100	1934	14th Spring Rd., Austin, Texas	111	1934	14th Spring Rd., Austin, Texas	20	34
113	1982	01 Big T, Austin, Texas	101	1934	14th Spring Rd., Austin, Texas	112	1934	14th Spring Rd., Austin, Texas	20	34
114	1982	01 Big T, Austin, Texas	102	1934	14th Spring Rd., Austin, Texas	113	1934	14th Spring Rd., Austin, Texas	20	34
115	1982	01 Big T, Austin, Texas	103	1934	14th Spring Rd., Austin, Texas	114	1934	14th Spring Rd., Austin, Texas	20	34
116	1982	01 Big T, Austin, Texas	104	1934	14th Spring Rd., Austin, Texas	115	1934	14th Spring Rd., Austin, Texas	20	34
117	1982	01 Big T, Austin, Texas	105	1934	14th Spring Rd., Austin, Texas	116	1934	14th Spring Rd., Austin, Texas	20	34
118	1982	01 Big T, Austin, Texas	106	1934	14th Spring Rd., Austin, Texas	117	1934	14th Spring Rd., Austin, Texas	20	34
119	1982	01 Big T, Austin, Texas	107	1934	14th Spring Rd., Austin, Texas	118	1934	14th Spring Rd., Austin, Texas	20	34
120	1982	01 Big T, Austin, Texas	108	1934	14th Spring Rd., Austin, Texas	119	1934	14th Spring Rd., Austin, Texas	20	34
121	1982	01 Big T, Austin, Texas	109	1934	14th Spring Rd., Austin, Texas	120	1934	14th Spring Rd., Austin, Texas	20	34
122	1982	01 Big T, Austin, Texas	110	1934	14th Spring Rd., Austin, Texas	121	1934	14th Spring Rd., Austin, Texas	20	34
123	1982	01 Big T, Austin, Texas	111	1934	14th Spring Rd., Austin, Texas	122	1934	14th Spring Rd., Austin, Texas	20	34
124	1982	01 Big T, Austin, Texas	112	1934	14th Spring Rd., Austin, Texas	123	1934	14th Spring Rd., Austin, Texas	20	34
125	1982	01 Big T, Austin, Texas	113	1934	14th Spring Rd., Austin, Texas	124	1934	14th Spring Rd., Austin, Texas	20	34
126	1982	01 Big T, Austin, Texas	114	1934	14th Spring Rd., Austin, Texas	125	1934	14th Spring Rd., Austin, Texas	20	34
127	1982	01 Big T, Austin, Texas	115	1934	14th Spring Rd., Austin, Texas	126	1934	14th Spring Rd., Austin, Texas	20	34
128	1982	01 Big T, Austin, Texas	116	1934	14th Spring Rd., Austin, Texas	127	1934	14th Spring Rd., Austin, Texas	20	34
129	1982	01 Big T, Austin, Texas	117	1934	14th Spring Rd., Austin, Texas	128	1934	14th Spring Rd., Austin, Texas	20	34
130	1982	01 Big T, Austin, Texas	118	1934	14th Spring Rd., Austin, Texas	129	1934	14th Spring Rd., Austin, Texas	20	34
131	1982	01 Big T, Austin, Texas	119	1934	14th Spring Rd., Austin, Texas	130	1934	14th Spring Rd., Austin, Texas	20	34
132	1982	01 Big T, Austin, Texas	120	1934	14th Spring Rd., Austin, Texas	131	1934	14th Spring Rd., Austin, Texas	20	34
133	1982	01 Big T, Austin, Texas	121	1934	14th Spring Rd., Austin, Texas	132	1934	14th Spring Rd., Austin, Texas	20	34
134	1982	01 Big T, Austin, Texas	122	1934	14th Spring Rd., Austin, Texas	133	1934	14th Spring Rd., Austin, Texas	20	34
135	1982	01 Big T, Austin, Texas	123	1934	14th Spring Rd., Austin, Texas	134	1934	14th Spring Rd., Austin, Texas	20	34
136	1982	01 Big T, Austin, Texas	124	1934	14th Spring Rd., Austin, Texas	135	1934	14th Spring Rd., Austin, Texas	20	34
137	1982	01 Big T, Austin, Texas	125	1934	14th Spring Rd., Austin, Texas	136	1934	14th Spring Rd., Austin, Texas	20	34
138	1982	01 Big T, Austin, Texas	126	1934	14th Spring Rd., Austin, Texas	137	1934	14th Spring Rd., Austin, Texas	20	34
139	1982	01 Big T, Austin, Texas	127	1934	14th Spring Rd., Austin, Texas	138	1934	14th Spring Rd., Austin, Texas	20	34
140	1982	01 Big T, Austin, Texas	128	1934	14th Spring Rd., Austin, Texas	139	1934	14th Spring Rd., Austin, Texas	20	34
141	1982	01 Big T, Austin, Texas	129	1934	14th Spring Rd., Austin, Texas	140	1934	14th Spring Rd., Austin, Texas	20	34
142	1982	01 Big T, Austin, Texas	130	1934	14th Spring Rd., Austin, Texas	141	1934	14th Spring Rd., Austin, Texas	20	34
143	1982	01 Big T, Austin, Texas	131	1934	14th Spring Rd., Austin, Texas	142	1934	14th Spring Rd., Austin, Texas	20	34
144	1982	01 Big T, Austin, Texas	132	1934	14th Spring Rd., Austin, Texas	143	1934	14th Spring Rd., Austin, Texas	20	34
145	1982	01 Big T, Austin, Texas	133	1934	14th Spring Rd., Austin, Texas	144	1934	14th Spring Rd., Austin, Texas	20	34
146	1982	01 Big T, Austin, Texas	134	1934	14th Spring Rd., Austin, Texas	145	1934	14th Spring Rd., Austin, Texas	20	34
147	1982	01 Big T, Austin, Texas	135	1934	14th Spring Rd., Austin, Texas	146	1934	14th Spring Rd., Austin, Texas	20	34
148	1982	01 Big T, Austin, Texas	136	1934	14th Spring Rd., Austin, Texas	147	1934	14th Spring Rd., Austin, Texas	20	34
149	1982	01 Big T, Austin, Texas	137	1934	14th Spring Rd., Austin, Texas	148	1934	14th Spring Rd., Austin, Texas	20	34
150	1982	01 Big T, Austin, Texas	138	1934	14th Spring Rd., Austin, Texas	149	1934	14th Spring Rd., Austin, Texas	20	34
151	1982	01 Big T, Austin, Texas	139	1934	14th Spring Rd., Austin, Texas	150	1934	14th Spring Rd., Austin, Texas	20	34
152	1982	01 Big T, Austin, Texas	140	1934	14th Spring Rd., Austin, Texas	151	1934	14th Spring Rd., Austin, Texas	20	34
153	1982	01 Big T, Austin, Texas	141	1934	14th Spring Rd., Austin, Texas	152	1934	14th Spring Rd., Austin, Texas	20	34
154	1982	01 Big T, Austin, Texas	142	1934	14th Spring Rd., Austin, Texas	153	1934	14th Spring Rd., Austin, Texas	20	34
155	1982	01 Big T, Austin, Texas	143	1934	14th Spring Rd., Austin, Texas	154	1934	14th Spring Rd., Austin, Texas	20	34
156	1982	01 Big T, Austin, Texas	144	1934	14th Spring Rd., Austin, Texas	155	1934	14th Spring Rd., Austin, Texas	20	34
157	1982	01 Big T, Austin, Texas	145	1934	14th Spring Rd., Austin, Texas	156	1934	14th Spring Rd., Austin, Texas	20	34
158	1982	01 Big T, Austin, Texas	146	1934	14th Spring Rd., Austin, Texas	157	1934	14th Spring Rd., Austin, Texas	20	34
159	1982	01 Big T, Austin, Texas	147	1934	14th Spring Rd., Austin, Texas	158	1934	14th Spring Rd., Austin, Texas	20	34
160	1982	01 Big T, Austin, Texas	148	1934	14th Spring Rd., Austin, Texas	159	1934	14th Spring Rd., Austin, Texas	20	34
161	1982	01 Big T, Austin, Texas	149	1934	14th Spring Rd., Austin, Texas	160	1934	14th Spring Rd., Austin, Texas	20	34
162	1982	01 Big T, Austin, Texas	150	1934	14th Spring Rd., Austin, Texas	161	1934	14th Spring Rd., Austin, Texas	20	34
163	1982	01 Big T, Austin, Texas	151	1934	14th Spring Rd., Austin, Texas	162	1934	14th Spring Rd., Austin, Texas	20	34
164	1982	01 Big T, Austin, Texas	152	1934	14th Spring Rd., Austin, Texas	163	1934	14th Spring Rd., Austin, Texas	20	34
165	1982	01 Big T, Austin, Texas	153	1934	14th Spring Rd., Austin, Texas	164	1934	14th Spring Rd., Austin, Texas	20	34
166	1982	01 Big T, Austin, Texas	154	1934	14th Spring Rd., Austin, Texas	165	1934	14th Spring Rd., Austin, Texas	20	34
167	1982	01 Big T, Austin, Texas	155	1934	14th Spring Rd., Austin, Texas	166	1934	14th Spring Rd., Austin, Texas	20	34
168	1982	01 Big T, Austin, Texas	156	1934	14th Spring Rd., Austin, Texas	167	1934	14th Spring Rd., Austin, Texas	20	34
169	1982	01 Big T, Austin, Texas	157	1934	14th Spring Rd., Austin, Texas	168	1934	14th Spring Rd., Austin, Texas	20	34
170	1982	01 Big T, Austin, Texas	158	1934	14th Spring Rd., Austin, Texas	169	1934	14th Spring Rd., Austin, Texas	20	34
171	1982	01 Big T, Austin, Texas	159	1934	14th Spring Rd., Austin, Texas	170	1934	14th Spring Rd., Austin, Texas	20	34
172	1982	01 Big T, Austin, Texas	160	1934	14th Spring Rd., Austin, Texas	171	1934	14th Spring Rd., Austin, Texas	20	34
173	1982	01 Big T, Austin, Texas	161	1934	14th Spring Rd., Austin, Texas	172	1934	14th Spring Rd., Austin, Texas	20	34
174	1982	01 Big T, Austin, Texas	162	1934	14th Spring Rd., Austin, Texas	173	1934	14th Spring Rd., Austin, Texas	20	34
175	1982	01 Big T, Austin, Texas	163	1934	14th Spring Rd., Austin, Texas	174	1934	14th Spring Rd., Austin, Texas	20	34
176	1982	01 Big T, Austin, Texas	164	1934	14th Spring Rd., Austin, Texas	175	1934	14th Spring Rd., Austin, Texas	20	34
177	1982	01 Big T, Austin, Texas	165	1934	14th Spring Rd., Austin, Texas	176	1934	14th Spring Rd., Austin, Texas	20	34
178	1982	01 Big T, Austin, Texas	166	1934	14th Spring Rd., Austin, Texas	177	1934	14th Spring Rd., Austin, Texas	20	34
179	1982	01 Big T, Austin, Texas	167	1934	14th Spring Rd., Austin, Texas	178	1934	14th Spring Rd., Austin, Texas	20	34
180	1982	01 Big T, Austin, Texas	168	1934	14th Spring Rd., Austin, Texas	179	1934	14th Spring Rd., Austin, Texas	20	34
181	1982	01 Big T, Austin, Texas	169	1934	14th Spring Rd., Austin, Texas	180	1934	14th Spring Rd., Austin, Texas	20	34
182	1982	01 Big T, Austin, Texas	170	1934	14th Spring Rd., Austin, Texas	181	1934	14th Spring Rd., Austin, Texas	20	34
183	1982	01 Big T, Austin, Texas	171	1934	14th Spring Rd., Austin, Texas	182	1934	14th Spring Rd., Austin, Texas	20	34
184	1982	01 Big T, Austin, Texas	172	1934	14th Spring Rd., Austin, Texas	183	1934	14th Spring Rd., Austin, Texas	20	34
185	1982	01 Big T, Austin, Texas	173	1934	14th Spring Rd., Austin, Texas	184	1934	14th Spring Rd., Austin, Texas	20	34
186	1982	01 Big T, Austin, Texas	174	1934	14th Spring Rd., Austin, Texas	185	1934	14th Spring Rd., Austin, Texas	20	34
187	1982	01 Big T, Austin, Texas	175	1934	14th Spring Rd., Austin, Texas	186	1934	14th Spring Rd., Austin, Texas	20	34
188	1982	01 Big T, Austin, Texas	176	1934	14th Spring Rd., Austin, Texas	187	1934	14th Spring Rd., Austin, Texas	20	34
189	1982	01 Big T, Austin, Texas	177	1934	14th Spring Rd., Austin, Texas	188	1934	14th Spring Rd., Austin, Texas	20	34
190	1982	01 Big T, Austin, Texas	178	1934	14th Spring Rd., Austin, Texas	189	1934	14th Spring Rd., Austin, Texas	20	34
191	1982	01 Big T, Austin, Texas	179	1934	14th Spring Rd., Austin, Texas	190	1934	14th Spring Rd., Austin, Texas	20	34
192	1982	01 Big T, Austin, Texas	180	1934	14th Spring Rd., Austin, Texas	191	1934	14th Spring Rd., Austin, Texas	20	34
193	1982	01 Big T, Austin, Texas	181	1934	14th Spring Rd., Austin, Texas	192	1934	14th Spring Rd., Austin, Texas	20	34
194	1982	01 Big T, Austin, Texas	182	1934	14th Spring Rd., Austin, Texas	193	1934	14th Spring Rd., Austin, Texas	20	34
195	1982	01 Big T, Austin, Texas	183	1934</						

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Park, Pw20, CR, 2000, 2000, 2000					23	20	34	Park, Pw20, CR, 2000, 2000, 2000					23	20	34
					23	20	34						23	20	34
7															
246	1939	Lease Center Dr., Austin, Texas	Zeller Nature Preserve	27	27	37	286	2052	Jena Creek Co., Austin, Texas	Bushy Creek Greenbelt	23	20	34		
247	1971	1515 W. Austin, Texas 7	Wilmette Creek Central Greenbelt	27	21	37	287	1975	Harmon Ave., Austin, Texas 7	Elgin Ridge Park	23	20	34		
248	1971	1515 W. Austin, Texas 7	Chase Station Park	27	21	37	288	1975	Harmon Ave., Austin, Texas 7	Newton Railroad Park	23	20	34		
249	1971	1515 W. Austin, Texas 7	Trailhead Neighborhood Park	27	20	34	289	1975	Harmon Ave., Austin, Texas 7	Plum Creek Cemetery	23	21	46		
250	1971	1515 W. Austin, Texas 7	Travis Lake Forest Park	27	20	34	290	1975	Harmon Ave., Austin, Texas 7	Rocky Creek Greenbelt	23	20	34		
251	1975	Lease Center Dr., Austin, Texas	Patton Estate Camp & Neighborhood Park	27	20	34	291	1980	Lawrence Ave., Austin, Texas	Old Oakley and Ferguson	23	20	34		
252	1975	Lease Center Dr., Austin, Texas	Lawrence Ave. Neighborhood Park	27	20	34	292	1982	Lawrence Ave. Neighborhood Park	Lower Bull Creek Greenbelt	24	21	36		
253	1977	Jack Reed Rd., Austin, Texas	Neufuss Nature Creek Greenbelt	27	22	37	293	1979	Jack of Texas Hwy., Austin, Texas	Lower Bull Creek Greenbelt	24	21	36		
254	1977	Lease Center Dr., Austin, Texas	Lawrence Ave. Neighborhood Park	27	20	34	294	1982	Lawrence Ave. Neighborhood Park	Vol. Memorial Park	23	27	34		
255	2014	San Antonio Rd., Austin, Texas	Winnburg Neighborhood Park	23	20	34	295	1984	Amador Springs Rd., Austin, Texas	Canyon Vista Park	23	20	34		
256	1981	Lease Center Dr., Austin, Texas	Douglas Creek Neighborhood Park	23	20	34	296	1984	Chenoweth Rd., Austin, Texas	Chenoweth Middle Neighborhood Park	23	20	34		
257	1981	Reynolds Dr., Austin, Texas	Autismthon Showup at Town Lake Motor Park	23	43	36	297	1987	Silk Oak Cntry., Austin, Texas	Silk Oak Neighborhood Park	23	20	34		
258	1983	Cherry Hill Rd., Austin, Texas	Compton Field Ranch Motor Park	23	21	34	298	1989	Chenoweth Cntry., Austin, Texas	North Loop Greenbelt	23	20	34		
259	1983	Howard Rd., Austin, Texas	Compton Field Ranch Motor Park	23	21	34	299	1974	Jeffrey Pkwy., Austin, Texas	Oakhill Neighborhood Park	23	20	34		
260	1983	Howard Rd., Austin, Texas	Compton Field Ranch Motor Park	23	21	34	300	1974	Jeffrey Pkwy., Austin, Texas	Phyllis Wood Neighborhood Park	23	20	34		
261	2020	Howard Pkwy., Austin, Texas	Barnwood Neighborhood Park	23	20	34	201	1989	Jeffrey Pkwy., Austin, Texas	J.J. Neillwood Greenbelt	23	20	34		
262	1983	Howard Pkwy., Austin, Texas	Red Bull Park	23	20	34	202	1989	Jeffrey Pkwy., Austin, Texas	Jeffrey Pkwy. Greenbelt	23	20	34		
263	1973	Lease Center Dr., Austin, Texas	Autism High, Texas Center	23	24	34	203	1929	W. 60 St., Austin, Texas 78	Duncan Neighborhood Park	23	20	34		
264	1973	Lease Center Dr., Austin, Texas	Autism High, Texas Center	23	24	34	204	1929	W. 60 St., Austin, Texas 78	Duncan Neighborhood Park	23	20	34		
265	1987	J. Mackdon Dr., Austin, Texas	Kennedy Plaza Neighborhood Park	20	20	35	305	1984	Stanger Rd., Austin, Texas	Cleek & Smith on Stanger Greenbelt	23	21	35		
266	1987	Lease Center Dr., Austin, Texas	Travis Creek Neighborhood Park	23	20	34	306	1984	Stanger Rd., Austin, Texas	Cleek & Smith on Stanger Greenbelt	23	21	35		
267	1949	Lease Center Dr., Austin, Texas	Shoal Bouds at Town Lake Motor Park	23	43	34	207	2014	1515 E. 45th Austin, Texas 7	Gray Rock Golf Course	23	20	34		
268	1949	Lease Center Dr., Austin, Texas	Shoal Bouds at Town Lake Motor Park	23	43	34	208	2017	Luther King Jr. Blvd., Austin, Texas	M.E. Smith Neighborhood Park	23	20	34		
269	1984	Lease Center Dr., Austin, Texas	Shoal Bouds at Town Lake Motor Park	23	43	34	209	1984	Lease Center Dr., Austin, Texas	Lease Center Neighborhood Park	23	20	34		
270	2000	Deer Ln., Austin, Texas	William H. Isbell-Kamel Greenbelt	23	20	34	210	2014	Lease Center Dr., Austin, Texas	Hightower Neighborhood Park and Wetland Park	23	20	35		
271	1983	Lease Center Dr., Austin, Texas	Lease Center Neighborhood Park	23	20	34	211	1983	Lease Center Dr., Austin, Texas	Lease Center Neighborhood Park	23	20	34		
272	1983	Lease Center Dr., Austin, Texas	Lease Center Neighborhood Park	23	20	34	212	1979	Lease Center Dr., Austin, Texas	Shiloh Valley Greenbelt	23	20	34		
273	2019	Lease Center Dr., Austin, Texas	Lease Center Neighborhood Park	23	20	34	213	1979	Lease Center Dr., Austin, Texas	Shiloh Valley Greenbelt	23	20	34		
274	2007	Crook Ave., Austin, Texas	Neighborhood Trail Greenbelt	23	20	34	214	1979	Lease Center Dr., Austin, Texas	Shiloh Valley Greenbelt	23	20	34		
275	1979	Lease Center Dr., Austin, Texas	Lawrence Ave. Neighborhood Park	23	20	34	215	1979	Lease Center Dr., Austin, Texas	Shiloh Valley Greenbelt	23	20	34		
276	1981	Lease Center Dr., Austin, Texas	North Gate Neighborhood Greenbelt	23	20	34									
277	1981	Lease Center Dr., Austin, Texas	North Gate Neighborhood Greenbelt	23	20	34									
278	1981	Lease Center Dr., Austin, Texas	North Gate Neighborhood Greenbelt	23	20	34									
279	1982	Palma Plaza Dr., Austin, Texas 78	Palma Plaza Pocket Park	23	20	34									
280	1982	Lease Center Dr., Austin, Texas	Shoal Bouds at Town Lake Motor Park	23	43	34									
281	2005	Browne Dr., Austin, Texas	Browne Neighborhood Park	23	20	34									
282	1981	Browne Dr., Austin, Texas	Browne Neighborhood Park	23	20	34									
283	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
284	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
285	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
286	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
287	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
288	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
289	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
290	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
291	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
292	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
293	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
294	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
295	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
296	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
297	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
298	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
299	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									
300	1978	Isola Creek Dr., Austin, Texas	Cook Island Park	23	20	34									

Civic Participation by census tract across decades

GEOTID0	S_ID	CH90	CH10	CH20	CH30	CH40	CH50	CH60
48450019001	1	0	34	0	4	491486077		
48450019002	2	29	20	34	4	4948468	3,892,086,947	5,439,401,618
4845001776	3	353	303	521	68	108,3818466	122,7714749	166,1352041
48450020425	4	23	41	68	522,7272727	14,92537313	15,86089572	
4845001915	5	827	919	1777	598,4383952	44,78857055	831,150968	
4845001777	6	478	1060	1810	88,18481848	192,5872093	310,8897288	
4845001770	7	48	143	411	1,898353561	12,42375653	31,59857071	
4845001775	8	48	41	103	15,68579834	8,92888059	12,4231006	
4845001772	9	0	21	34	0	7,444168734	7,104244654	
48450020428	10	92	101	272	36,311503	16,52496911	32,8865782	
4845001984	11	0	0	0	0	0	0	
4845001946	12	46	44	71	20,3533823	18,08466913	28,10788013	
4845001725	13	95	88	142	30,6300264	21,22015815	25,73329224	
4845001781	14	309	280	456	120,4208885	117,2529213	174,3119268	
4845001784	15	23	21	36	11,76278889	3,733997155	5,850868473	
4845001752	16	188	278	150	347,773	87,32248186	123,5505558	
4845001918	17	1064	886	1390	284,2639584	231,5129344	352,3447452	
4845001918	18	97	89	152	39,86351195	37,87234043	60,07985138	
4845002318	19	829	873	1421	175,7100468	115,7871398	196,950797	
4845003007	20	552	494	836	310,8108108	286,2108922	459,3409593	
4845002025	21	373	823	1002	452,82008	420,4152022	208,4142563	
4845003005	22	170	285	444	83,79748835	80,81732325	107,4778881	
4845003026	23	445	398	707	174,0208988	123,1343284	208,4814815	
4845001783	24	46	45	72	11,48277584	8,192244975	13,52112878	
4845001917	25	293	230	434	62,06312222	49,75124378	84,32098367	
4845001402	26	343	449	7817	519,230095	1650,496147	3109,38743	
4845001308	27	468	412	686	134,7150259	147,7231983	224,6224447	
4845001307	28	467	488	782	119,7128941	136,3899442	209,8705432	
4845001728	29	29	26	46	22,8078037	14,88778035	26,22902126	
4845002500	30	138	120	204	26,87176803	22,01834862	33,88509106	
4845001782	31	841	560	948	116,08113	108,0678179	178,8341822	
4845002028	32	118	101	450	439,3707483	463,0969167	517,9781444	
4845002011	33	26	40	71	26	19,50268162	23,13487152	
4845003006	34	755	659	1073	62,00809237	298,4547351	244,31151452	
4845001855	35	253	480	831	148,9988221	77,95288034	90,18884306	
48450020435	36	0	0	272	0	11,93139448	32,70016831	
48450020034	38	242	208	347	75,86298897	63,63790524	110,3807978	
48450020317	39	2850	3151	3965	816,6189112	633,8764836	602,4920225	
4845001774	40	23	82	136	7,014333638	10,31057463	16,25821877	

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4845001829	81	94	84	146	35,51190226	31,07658158	59,37372916	
4845001828	82	278	254	428	18,14124614	18,3237469	18,3237469	
4845001840	83	512	485	785	114,1837948	81,22007448	93,85071514	
4845001826	84	580	522	1268	275,6653992	246,4885954	454,8003128	
4845001845	85	513	814	814	163,4471003	150,310559	254,5203803	
4845001844	86	420	374	639	112,8122482	104,5568912	153,7166228	
48450020419	87	714	636	1100	240,898435	156,2299713	222,4489181	
4845001823	88	164	104	1094	451	81,94726451	145,2891453	
4845001822	89	575	740	1258	84,97913244	103,971899	185	
4845001821	90	529	463	760	81,86002322	77,95288034	90,18884306	
4845001820	91	529	640	1088	71,35149717	88,11785763	141,0605471	
4845001819	92	1656	2180	4148	434,189827	444,6257393	970,8727828	
4845001818	93	207	180	306	124,58891593	32,25894552	45,57607951	
4845001817	94	46	40	68	10,68278107	10,94607505	16,5601464	
4845001813	95	299	300	2890	88,30732220	45,68210048	387,0881329	
4845001812	96	276	400	468	37,30738037	32,2322422	53,71778144	
4845001811	97	115	100	272	30,78892597	30,56234719	83,46118441	
4845001810	98	127	120	212	17,00802617	16,00802617	24,00802617	
4845001805	99	920	1120	2584	122,4461108	239,880058	557,8537855	
4845001804	100	782	680	2784	126,3782654	114,3625897	409,4572739	
4845001728	101	799	1307	83,66017271	107,88071025	170,70902804	261,88071025	
4845001750	102	380	427	778	80,18589318	88,00626144	160,4445457	
48450020004	103	292	408	716	119,2323397	201,5888779	282,079063	
4845001841	104	0	0	34	0	0	0	
4845001713	105	23	20	34	22,93120638	17,68845696	27,91963347	
4845001719	106	103	82	103	31,58603917	27,65039822	41,96029807	
4845001718	107	1340	1184	2131	241,4414414	171,3873526	343,2929564	
4845001713	108	210	181	581	51,52109912	47,14769871	129,39686637	
4845001712	109	285	240	67	67,28297445	62,15119229	193,1005019	
4845001707	110	276	240	408	62,872728	50,90137858	77,18501703	
4845001706	111	484	404	688	132,1937322	113,35578	178,682075	
4845001705	112	1306	1148	1940	292,3000957	255,802024	384,4692685	
4845001605	113	214	1781	14330	2350,180505	2125,136811	3671,3871129	
4845001604	114	270	246	436	71,4653953	64,5461008	97,13120208	
4845001603	115	7452	6474	10957	1782,989488	1403,445455	2092,42796	
4845001602	116	3608	3328	5090	893,8602974	1069,433576	1504,1817712	
4845001305	117	2874	2634	43108	5102,3148937	6099,747425	8630,024961	
4845001304	118	1525	1325	1828	446,5502972	494,6791818	684,9533698	
4845001303	119	21900	21930	28496	7246,850386	8761,486217	5585,130571	
4845001200	120	38448	39060	57595	12795,12518	9230,387324	9851,832158	

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4845001728	161	1528	1740	2958	358,1808958	368,0203046	582,8571429	
4845001728	162	785	880	1122	126,4044944	97,1016525	155,0901846	
4845001745	163	161	276	454	87,2799564	108,661473	200,8186478	
48450020421	164	23	92	135	8,125166445	13,32753035	12,58820601	
48450020423	165	580	820	104	0312094	83,0702745	136,507408	
48450020314	166	0	21	71	0	4,39238653	13,16785579	
4845001748	167	117	488	819	51,04712042	80,0072171	125,584234	
4845001912	168	46	45	72	15,80506084	11,42825105	17,43735923	
4845001725	169	165	161	273	71,42151188	41,95609522	69,4584948	
4845001760	170	23	0	34	6,075013201	1,93589848	1,877728446	
4845001847	171	92	80	136	20,88540146	11,20762118	19,41913753	
4845001848	172	161	144	362	41,64511123	30,08147085	65,45200287	
4845001755	173	884	795	1300	179,6017879	136,2835025	208,3687254	
4845001758	174	353	316	520	78,7594237	78,50931077	113,48758	
4845001727	175	799	1054	1992	155,5983115	101,33641	184,6607285	
4845001740	176	750	1430	2428	298,6857826	327,2311213	483,5595909	
4845001765	177	0	0	0	0	0	0	
4845001714	178	119	108	276	20,44322281	9,127735325	18,38327345	
4845001403	179	1589	1781	2174	1021,208226	1345,301757	1295,788184	
4845001733	180	20	136	2	7,877609090	5,58869219	31,27814885	
4845001769	181	23	102	2	4,87804878	3,990877993	14,59645108	
4845001722	182	46	40	68	13,45226338	10,14455998	17,88990935	
4845001761	183	29	24	39	5,46460887	3,518029003	4,742856711	
4845001751	184	115	100	170	54,81410887	51,38746146	77,16749887	
4845001716	185	437	387	640	107,8479753	83,0529981	87,17928285	
4845001842	186	92	84	522	22,4494141	11,6870229	38,30420811	
4845001850	187	298	232	820	72,2255512	54,1949933	218,8184962	
4845001838	188	115	106	421	30,67486653	18,7592153	41,38917426	
4845001401	189	13835	18720	23780	5385,363955	6273,458445	7494,484715	
48450020422	190	419	365	613	81,1858187	69,53705468	100,9846579	
48450020413	191	979	1038	1433	292,0643931	13,87103988	284,0436079	
48450020412	192	1559	1372	2350	271,3664056	235,6578495	381,1841038	
48491020408	193	0	0	68	0	0	15,19213584	
48491020411	194	0	0	0	0	0	0	
48491020409	195	0	0	68	0	0	13,69035635	
48491020508	196	0	0	68	0	4,35304571	13,49911981	
48491020311	197	0	20	102	0	6,722888076	14,32181971	
48491020318	198	23	20	34	3,187803188	2,364668194	3,743256633	
48491020408	199	23	20	34	5,453494701	3,087123466	10,21941869	
48491020405	200	71	64	104	12,51888777	11,0491932	16,2881754	

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48450020430	41	1227	1067	2702	389.4001904	314.1008771	1042.036251
48450020427	42	1071	929	1596	156.576835	119.2660812	198.393433
48450020429	43	210	180	304	74.800851	208.650164	186.182101
48450020424	44	3077	2273	1056	896.7991038	522.91307	1055.98144
48450020433	45	40	103	14	14.483872	1.7679804	10.8920514
48450020208	46	8313	3411	1001	101.1521701	101.1521701	101.1521701
48450020432	47	92	81	306	52.3219568	40.9354523	102.6156402
48450020114	48	942	727	1530	22.7489865	126.3414634	232.467488
48450020139	49	3093	252	137	2592.1871	185.011923	202.101923
48450020207	50	95	120	209	27.869885	147.2768717	21.0281594
48450020137	51	6897	1320	1001	105.813788	105.813788	105.813788
48450020410	52	161	142	244	40.90447154	36.78851372	55.21911224
48450020409	53	466	404	692	122.4243582	120.620796	182.871075
48450020414	54	364	638	156	15.166014	145.274774	145.274774
48450020402	55	345	308	538	60.7693126	48.2786207	62.7202251
48450020403	56	1289	1289	1289	159.0743165	204.651141	204.651141
48450020308	57	1053	909	1892	203.8722168	156.185607	292.262192
48450020307	58	92	121	604	17.26253308	21.7752574	101.5638137
48450020315	59	21	19	10	0.4337886	0.4337886	0.4337886
48450020424	60	397	340	578	199.4870381	98.048122	148.281698
48450020316	61	721	671	801	159.0584129	151.875725	203.192982
48450020304	62	14184	14184	14184	14184.14184	14184.14184	14184.14184
48450020173	63	23	41	68	6.809050051	7.62484085	11.16584165
48450020172	64	3276	653	1187	11.44881843	11.44881843	11.44881843
48450020112	65	371	464	996	63.73459976	90.96553148	133.560834
48450020110	66	3243	3831	3998	102.8744782	96.88105415	3003.956408
48450020109	67	2687	2727	3019	152.927872	152.927872	152.927872
48450020108	68	567	838	1432	166.5716116	195.6317257	350.804272
48450020107	69	743	215	108	40.6989362	40.6989362	40.6989362
48450020106	70	1021	139	397	1.1658442	19.91328157	155.450787
48450020105	71	28	29	35	5.121352709	3.749313939	6.876227698
48450020104	72	42	69	33	3.92026433	3.92026433	3.92026433
48450020073	73	263	224	386	65.878197	68.8134426	92.5050892
48450020072	74	203	343	372	12.1455458	12.1455458	12.1455458
48450020055	75	258	457	499	45.1521804	37.8704674	137.410119
48450020213	76	23	82	367	17.2296249	11.6288217	86.5112249
48450020054	77	295	723	739	1374.119077	1290.199819	1290.199819
48450020019	78	2056	1780	3140	30.5215567	34.0137365	567.26979
48450020018	79	210	140	40	40.2686612	40.2686612	40.2686612
48450020182	80	138	126	213	50.9977827	42.14546823	70.7406173

Calibrated variables for the 2000s

S_ID	AlCal	HincCal	WincCal	BincCal	DeHCal	ChiCal
1	0.05	0.86	0.92	0.05	0.05	0.05
2	0.61	0.78	0.42	0.74	0.08	0.06
3	0.57	0.69	0.49	0.52	0.57	0.51
4	0.58	0.4	0.63	0.59	0.04	0.84
5	0.05	0.82	0.85	0.08	0.07	0.65
6	0.6	0.68	0.47	0.54	0.63	0.5
7	0.05	0.92	0.84	0.16	0.1	0.06
8	0.05	0.92	0.89	0.08	0.06	0.08
9	0.05	0.92	0.39	0.44	0.06	0.05
10	0.05	0.69	0.89	0.12	0.05	0.14
11	0.05	0.34	0.48	0.64	0.12	0.05
12	0.05	0.84	0.9	0.15	0.09	0.09
13	0.05	0.68	0.67	0.5	0.21	0.12
14	0.05	0.93	0.91	0.09	0.31	0.51
15	0.05	0.91	0.9	0.05	0.05	0.07
16	0.05	0.84	0.87	0.12	0.22	0.5
17	0.05	0.97	0.95	0.03	0.22	0.96
18	0.05	0.97	0.96	0.04	0.07	0.15
19	0.05	0.03	0.09	0.73	0.88	0.53
20	0.54	0.21	0.61	0.64	0.52	0.57
21	0.05	0.14	0.49	0.29	0.8	0.5
22	0.07	0.16	0.82	0.14	0.72	0.22
23	0.68	0.14	0.92	0.18	0.6	0.53
24	0.05	0.91	0.92	0.04	0.07	0.07
25	0.05	0.99	0.93	0.05	0.14	0.77
26	0.52	0.53	0.75	0.19	0.67	0.83
27	0.13	0.16	0.17	0.18	0.84	0.51
28	0.5	0.14	0.23	0.52	0.73	0.51
29	0.05	0.58	0.72	0.5	0.63	0.09
30	0.6	0.7	0.64	0.19	0.56	0.1
31	0.61	0.83	0.8	0.11	0.56	0.51
32	0.05	0.69	0.12	0.67	0.06	0.63
33	0.05	0.26	0.11	0.76	0.06	0.1
34	0.58	0.21	0.07	0.73	0.06	0.67
35	0.05	0.71	0.49	0.63	0.04	0.52
36	0.05	0.41	0.16	0.5	0.05	0.05
38	0.85	0.16	0.46	0.13	0.84	0.36
39	0.05	0.03	0.25	0.66	0.31	0.72
40	1	0.92	0.7	0.36	0.17	0.06
41	0.77	0.4	0.13	0.58	0.13	0.48
42	0.58	0.4	0.1	0.61	0.63	0.53
43	0.05	0.4	0.66	0.09	0.05	0.7

87	0.05	0.17	0.37	0.59	0.74	0.55
88	0.12	0.15	0.1	0.81	0.78	0.12
89	0.14	0.24	0.16	0.74	0.84	0.5
90	0.06	0.53	0.3	0.67	0.68	0.49
91	0.51	0.16	0.14	0.72	0.95	0.33
92	0.07	0.18	0.13	0.72	0.88	0.61
93	0.5	0.33	0.26	0.48	0.76	0.13
94	0.19	0.39	0.77	0.22	0.6	0.07
95	0.54	0.27	0.16	0.88	0.52	0.26
96	0.05	0.07	0.07	0.71	0.91	0.14
97	0.08	0.17	0.08	0.83	0.83	0.12
98	0.1	0.11	0.14	0.73	0.92	0.37
99	0.14	0.1	0.13	0.68	0.84	0.53
100	0.8	0.14	0.19	0.6	0.86	0.51
101	0.53	0.86	0.8	0.16	0.52	0.42
102	0.14	0.57	0.46	0.24	0.2	0.4
103	0.05	0.14	0.37	0.52	0.86	0.51
104	0.05	0.76	0.49	0.56	0.21	0.05
105	0.05	0.79	0.83	0.18	0.1	0.09
106	0.5	0.98	0.94	0.05	0.18	0.12
107	0.59	0.64	0.9	0.07	0.56	0.56
108	0.54	0.56	0.48	0.45	0.56	0.21
109	0.06	0.24	0.5	0.26	0.64	0.3
110	0.59	0.58	0.9	0.1	0.56	0.27
111	0.86	0.73	0.93	0.09	0.45	0.51
112	0.55	0.87	0.95	0.06	0.22	0.57
113	0.52	0.57	0.93	0.06	0.7	0.96
114	0.8	0.86	0.97	0.04	0.37	0.33
115	0.4	0.89	0.96	0.04	0.58	0.9
116	0.99	0.14	0.44	0.1	0.5	0.74
117	0.36	0.15	0.29	0.6	0.63	1
118	0.94	0.36	0.82	0.22	0.65	0.81
119	0.65	0.5	0.75	0.12	0.81	1
120	0.69	0.38	0.74	0.26	0.4	1
121	0.92	0.5	0.46	0.73	0.24	1
122	0.5	0.06	0.06	0.08	0.67	0.95
123	0.21	0.06	0.04	0.85	0.61	0.87
124	0.2	0.28	0.85	0.09	0.69	0.52
125	0.51	0.42	0.87	0.07	0.53	0.56
126	0.67	0.17	0.41	0.35	0.36	0.51
127	0.55	0.74	0.95	0.05	0.46	0.57
128	0.66	0.14	0.04	0.93	0.71	1
129	0.68	0.03	0.04	0.98	0.79	0.97

44	0.05	0.38	0.1	0.89	0.07	0.74
45	1	0.41	0.36	0.53	0.05	0.07
46	0.05	0.26	0.09	0.94	0.12	0.5
47	1	0.38	0.26	0.16	0.04	0.21
48	1	0.52	0.92	0.06	0.09	0.53
49	0.05	0.26	0.09	0.82	0.04	0.96
50	0.51	0.52	0.15	0.87	0.05	0.11
51	0.51	0.26	0.06	0.68	0.51	0.51
52	0.51	0.16	0.23	0.54	0.92	0.16
53	0.52	0.48	0.24	0.59	0.85	0.51
54	0.5	0.48	0.18	0.28	0.29	0.52
55	0.12	0.34	0.19	0.56	0.56	0.26
56	0.67	0.1	0.05	0.51	0.25	0.53
57	0.69	0.11	0.25	0.52	0.57	0.54
58	0.05	0.11	0.21	0.54	0.81	0.08
59	0.18	0.85	0.16	0.85	1	0.96
60	0.52	0.39	0.33	0.52	0.45	0.51
61	0.93	0.64	0.15	0.55	1	0.52
62	0.05	0.09	0.11	0.52	0.98	0.8
63	0.54	0.58	0.46	0.5	0.86	0.96
64	0.21	0.47	0.13	0.96	0.69	0.3
65	0.21	0.15	0.06	0.88	0.93	0.28
66	0.73	0.09	0.04	0.97	0.24	0.77
67	0.05	0.12	0.04	1	0.46	0.72
68	0.59	0.16	0.04	1	0.26	0.52
69	0.54	0.14	0.06	0.97	0.16	0.51
70	0.05	0.48	0.21	0.8	0.69	0.14
71	0.14	0.58	0.16	0.89	0.83	0.06
72	0.64	0.39	0.31	0.63	0.81	0.08
73	0.51	0.14	0.17	0.28	0.67	0.29
74	0.06	0.3	0.52	0.12	0.7	0.34
75	0.05	0.16	0.32	0.56	0.91	0.19
76	0.05	0.13	0.28	0.59	0.4	0.06
77	1	0.35	0.81	0.05	0.28	0.91
78	0.53	0.55	0.89	0.1	0.59	0.59
79	0.51	0.4	0.21	0.86	0.83	0.2
80	0.64	0.56	0.51	0.74	0.63	0.2
81	0.5	0.51	0.77	0.45	0.56	0.14
82	0.52	0.79	0.81	0.51	0.63	0.29
83	0.95	0.53	0.51	0.51	0.14	0.51
84	0.22	0.58	0.58	0.55	0.16	0.58
85	0.62	0.58	0.69	0.49	0.41	0.52
86	0.34	0.56	0.43	0.67	0.95	0.51

130	0.66	0.07	0.06	0.99	0.55	0.99
131	0.51	0.01	0.04	0.99	0.67	0.82
132	0.59	0.22	0.65	0.59	0.46	0.86
133	0.55	0.09	0.7	0.51	0.25	0.99
134	0.52	0.01	0.68	0.99	1	0.57
135	0.18	0.01	0.79	0.06	1	0.55
136	0.52	0.02	0.44	0.52	1	0.23
137	0.32	0.05	0.81	0.99	0.98	0.51
138	0.5	0.07	0.17	0.95	0.66	0.8
139	0.54	0.16	0.64	0.48	0.58	0.8
140	0.52	0.09	0.79	0.99	0.8	0.51
141	0.29	0.24	0.91	0.1	0.56	0.64
142	0.54	0.02	0.71	0.62	0.15	0.79
143	0.52	0.64	0.84	0.21	0.53	0.13
144	0.14	0.85	0.96	0.05	0.11	0.58
145	0.59	0.63	0.96	0.05	0.37	0.59
146	0.07	0.77	0.77	0.09	0.06	0.09
147	0.54	0	0.68	0.85	0.24	0.68
148	1	0.59	0.47	0.43	0.56	0.56
149	0.93	0.15	0.05	0.99	0.09	0.52
150	0.66	0.41	0.04	0.51	0.09	0.52
151	0.05	0.08	0.04	0.85	0.16	0.58
152	0.05	1	0.95	0.06	0.08	0.28
153	0.57	0.89	0.94	0.64	0.15	0.64
154	0.05	0.5	0.35	0.84	0.06	0.52
155	0.33	0.95	0.85	0.09	0.05	0.09
156	0.05	0.52	0.17	0.67	0.67	0.12
157	0.54	0.81	0.24	0.79	0.14	0.96
158	0.64	0.59	0.89	0.06	0.28	0.5
159	0.27	0.57	0.66	0.4	0.35	0.2
160	0.86	0.64	0.49	0.56	0.74	0.37
161	0.68	0.63	0.47	0.5	0.48	0.59
162	0.53	0.69	0.54	0.51	0.59	0.51
163	0.05	0.79	0.83	0.32	0.17	0.3
164	0.86	0.66	0.37	0.52	0.11	0.06
165	0.05	0.68	0.33	0.54	0.7	0.5
166	0.05	0.06	0.23	0.67	0.55	0.05
167	0.05	0.75	0.8	0.2	0.1	0.2
168	0.05	1	0.95	0.05	0.07	0.07
169	0.05	0.15	0.5	0.11	0.97	0.19
170	0.52	0.96	0.9	0.99	0.05	0.06
171	0.53	0.69	0.4	0.59	0.5	0.09
172	0.05	0.67	0.36	0.57	0.36	0.16

173	0.27	0.96	0.85	0.86	0.16	0.53
174	0.6	0.76	0.88	0.15	0.71	0.39
175	0.95	0.92	0.83	0.1	0.14	0.52
176	0.05	0.89	0.75	0.28	0.13	0.57
177	0.05	0.84	0.92	0.14	0.05	0.05
178	0.2	0.95	0.89	0.1	0.08	0.09
179	0.05	0.35	0.45	0.4	0.67	0.77
180	0.05	0.84	0.91	0.05	0.05	0.06
181	0.57	0.7	0.86	0.09	0.12	0.06
182	1	0.52	0.81	0.13	0.41	0.07
183	0.51	0.99	0.93	0.06	0.06	0.06
184	0.96	0.84	0.96	0.05	0.48	0.23
185	0.05	0.98	0.92	0.09	0.06	0.5
186	0.79	0.63	0.67	0.55	0.05	0.09
187	0.05	0.39	0.44	0.59	0.69	0.34
188	0.52	0.75	0.19	0.77	0.11	0.12
189	0.57	0.34	0.86	0.07	0.65	1</

Calibrated variables for the 2010s

S ID	AlCal	HincCal	WtrCal	BldCal	DensCal	ChrCal
1	0.05	0.92	0.92	0.12	0.03	0.05
2	0.54	0.6	0.25	0.89	0.15	0.05
3	0.58	0.72	0.77	0.69	0.36	0.51
4	0.53	0.66	0.16	0.22	0.47	0.08
5	0.05	0.44	0.69	0.09	0.06	0.6
6	0.6	0.62	0.51	0.69	0.67	0.53
7	0.52	0.95	0.81	0.12	0.19	0.07
8	0.05	0.3	0.86	0.05	0.05	0.06
9	0.05	0.63	0.41	0.56	0.07	0.06
10	0.05	0.5	0.33	0.5	0.06	0.08
11	0.05	0.27	0.33	0.84	0.1	0.05
12	0.05	0.82	0.87	0.1	0.07	0.08
13	0.05	0.49	0.36	0.73	0.3	0.09
14	0.05	0.81	0.95	0.86	0.23	0.51
15	0.05	0.86	0.87	0.05	0.06	0.05
16	0.05	0.88	0.91	0.37	0.19	0.49
17	0.05	0.97	0.96	0.89	0.19	0.54
18	0.05	0.87	0.84	0.05	0.05	0.15
19	0.05	0.05	0.07	0.66	0.98	0.51
20	0.53	0.56	0.72	0.54	0.47	0.56
21	0.05	0.23	0.91	0.34	0.72	0.51
22	0.07	0.12	0.91	0.05	0.71	0.44
23	0.66	0.56	0.93	0.33	0.7	0.51
24	0.05	0.47	0.86	0.05	0.06	0.06
25	0.05	0.98	0.93	0.05	0.1	0.21
26	0.5	0.51	0.81	0.39	0.65	0.85
27	0.15	0.25	0.33	0.34	0.69	0.52
28	0.5	0.13	0.53	0.55	0.65	0.51
29	0.1	0.52	0.87	0.11	0.74	0.19
30	0.59	0.55	0.64	0.26	0.55	0.1
31	0.82	0.9	0.5	0.22	0.52	0.51
32	0.05	0.49	0.07	0.63	0.09	0.52
33	0.05	0.24	0.64	0.83	0.06	0.08
34	0.56	0.59	0.4	0.72	0.12	0.56
35	0.05	0.69	0.15	0.92	0.03	0.41
36	0.05	0.27	0.1	0.84	0.04	0.07
37	0.05	0.25	0.1	0.84	0.04	0.07
38	0.82	0.18	0.63	0.19	0.81	0.31
39	0.65	0.01	0.1	0.9	0.5	0.05
40	1	0.84	0.66	0.22	0.86	0.07
41	0.7	0.18	0.08	0.4	0.53	0.56
42	0.55	0.17	0.05	0.3	0.73	0.51
43	0.05	0.12	0.6	0.5	0.05	0.55

44	0.05	0.55	0.07	0.62	0.06	0.62
45	0.99	0.55	0.13	0.79	0.03	0.06
46	0.05	0.1	0.05	0.92	0.1	0.51
47	1	0.12	0.14	0.53	0.03	0.36
48	1	0.77	0.92	0.06	0.08	0.51
49	0.05	0.52	0.08	0.86	0.03	0.6
50	0.23	0.4	0.07	0.96	0.04	0.08
51	0.51	0.11	0.04	0.69	0.53	0.5
52	0.51	0.09	0.26	0.4	0.89	0.15
53	0.52	0.32	0.19	0.31	0.75	0.51
54	0.5	0.24	0.32	0.52	0.23	0.52
55	0.19	0.19	0.26	0.57	0.59	0.2
56	0.61	0.05	0.04	0.05	0.48	0.53
57	0.71	0.12	0.36	0.84	0.6	0.52
58	0.05	0.07	0.19	0.53	0.8	0.09
59	0.11	0.06	0.07	0.61	1	0.06
60	0.52	0.23	0.31	0.39	0.37	0.5
61	0.91	0.03	0.07	0.39	1	0.52
62	0.05	0.09	0.08	0.31	0.79	0.96
63	0.53	0.53	0.37	0.66	0.72	0.06
64	0.5	0.54	0.15	0.96	0.58	0.5
65	0.35	0.1	0.1	0.05	0.96	0.5
66	0.68	0.06	0.04	0.97	0.37	0.71
67	0.93	0.09	0.06	1	0.36	0.68
68	0.7	0.05	0.05	0.99	0.4	0.53
69	0.54	0.17	0.11	0.97	0.47	0.52
70	0.05	0.51	0.24	0.78	0.67	0.12
71	0.13	0.04	0.08	0.72	0.82	0.05
72	0.65	0.53	0.3	0.8	0.78	0.06
73	0.51	0.22	0.23	0.51	0.6	0.59
74	0.05	0.63	0.73	0.12	0.6	0.37
75	0.05	0.15	0.23	0.37	0.85	0.5
76	0.05	0.08	0.09	0.74	0.63	0.68
77	1	0.51	0.86	0.15	0.2	0.98
78	0.79	0.61	0.95	0.08	0.42	0.57
79	0.51	0.27	0.09	0.75	0.66	0.16
80	0.65	0.23	0.25	0.84	0.65	0.17
81	0.45	0.49	0.69	0.49	0.54	0.13
82	0.51	0.82	0.68	0.46	0.53	0.34
83	0.8	0.46	0.31	0.75	0.15	0.44
84	0.18	0.55	0.22	0.79	0.12	0.54
85	0.6	0.58	0.38	0.67	0.35	0.52
86	0.18	0.26	0.38	0.89	0.92	0.5

87	0.51	0.05	0.11	0.72	0.86	0.52
88	0.11	0.05	0.05	0.6	0.82	0.5
89	0.12	0.07	0.06	0.77	0.86	0.5
90	0.07	0.24	0.16	0.73	0.7	0.51
91	0.53	0.07	0.08	0.7	0.93	0.5
92	0.07	0.05	0.04	0.79	0.99	0.6
93	0.49	0.37	0.33	0.1	0.7	0.13
94	0.21	0.28	0.86	0.51	0.5	0.07
95	0.52	0.07	0.05	0.6	0.82	0.19
96	0.05	0.04	0.05	0.85	0.88	0.13
97	0.08	0.08	0.05	0.88	0.72	0.12
98	0.1	0.04	0.09	0.79	0.89	0.52
99	0.14	0.08	0.09	0.71	0.87	0.54
100	0.61	0.08	0.09	0.61	0.81	0.51
101	0.53	0.84	0.52	0.66	0.43	0.5
102	0.13	0.56	0.74	0.13	0.17	0.49
103	0.05	0.06	0.64	0.1	0.74	0.53
104	0.05	0.66	0.15	0.8	0.57	0.05
105	0.05	0.54	0.69	0.4	0.08	0.08
106	0.42	0.96	0.94	0.09	0.14	0.11
107	0.59	0.68	0.89	0.09	0.32	0.54
108	0.55	0.39	0.84	0.31	0.51	0.2
109	0.06	0.27	0.62	0.28	0.57	0.29
110	0.59	0.65	0.92	0.14	0.57	0.22
111	0.96	0.58	0.92	0.25	0.42	0.51
112	0.55	0.87	0.97	0.09	0.18	0.55
113	0.52	0.73	0.85	0.09	0.63	0.91
114	0.41	0.96	0.97	0.05	0.32	0.3
115	0.37	0.93	0.96	0.15	0.6	0.82
116	0.61	0.42	0.66	0.19	0.28	0.75
117	0.43	0.59	0.46	0.51	0.59	1
118	0.94	0.52	0.92	0.86	0.66	0.61
119	0.66	0.74	0.86	0.13	0.49	1
120	0.66	0.57	0.88	0.24	0.57	1
121	0.61	0.8	0.84	0.59	0.54	1
122	0.46	0.85	0.11	0.39	0.52	0.99
123	0.19	0.08	0.08	0.18	0.59	0.84
124	0.17	0.35	0.86	0.07	0.67	0.51
125	0.5	0.59	0.91	0.07	0.81	0.53
126	0.69	0.26	0.55	0.57	0.3	0.51
127	0.55	0.61	0.94	0.07	0.43	0.55
128	0.66	0.10	0.25	0.78	0.73	0.98
129	0.69	0.06	0.16	0.67	0.73	0.97

130	0.66	0.37	0.24	0.96	0.51	0.99
131	0.51	0.02	0.05	0.99	0.65	0.78
132	0.58	0.16	0.07	0.65	0.32	0.82
133	0.56	0.14	0.86	0.05	0.16	0.99
134	0.52	0.01	0.86	0.1	1	0.54
135	0.14	0	0.49	0.12	1	0.52
136	0.52	0	0.43	0.55	1	0.15
137	0.28	0.07	0.83	0.09	0.96	0.53
138	0.59	0.12	0.44	0.89	0.58	0.61
139	0.54	0.15	0.77	0.52	0.5	0.99
140	0.52	0.07	0.84	0.1	0.8	0.95
141	0.51	0.39	0.89	0.16	0.55	0.84
142	0.52	0.23	0.88	0.28	0.39	0.64
143	0.53	0.55	0.77	0.52	0.46	0.13
144	0.54	0.97	0.88	0.07	0.08	0.96
145	0.54	0.63	0.97	0.07	0.33	0.57
146	0.07	0.71	0.48	0.16	0.06	0.1
147	0.54	0	0.75	0.68	0.19	0.64
148	1	0.56	0.66	0.13	0.55	0.57
149	0.52	0.05	0.03	0.98	0.14	0.49
150	0.56	0.36	0.12	0.03	1	0.06
151	0.05	0.08	0.07	0.77	0.11	0.6
152	0.05	1	0.96	0.05	0.07	0.2
153	0.56	0.97	0.91	0.05	0.11	0.6
154	0.05	0.51	0.18	0.84	0.09	0.34
155	0.08	0.71	0.68	0.11	0.05	0.06
156	0.05	0.35	0.08	0.81	0.77	0.12
157	0.53	0.46	0.12	0.84	0.23	0.05
158	0.64	0.41	0.68	0.16	0.37	0.36
159	0.23	0.5	0.61	0.46	0.43	0.5
160	0.89	0.72	0.37	0.59	0.66	0.38
161	0.67	0.64	0.59	0.15	0.51	0.58
162	0.54	0.62	0.72	0.51	0.62	0.5
163	0.91	0.79	0.86	0.52	0.15	0.51
164	0.73	0.51	0.36	0.62	0.18	0.07
165	0.85	0.55	0.24	0.23	0.73	0.45
166	0.88	0.05	0.13	0.71	0.63	0.05
167	0.05	0.72	0.66	0.2	0.26	0.5
168	0.05	0.97	0.84	0.11	0.05	0.07
169	0.05	0.05	0.36	0.54	0.96	0.17
170	0.14	0.94	0.89	0.1	0.08	0.05
171	0.51	0.7	0.21	0.76	0.72	0.07
172	0.05	0.4	0.28	0.75	0.46	0.12

173	0.21	0.98	0.59	0.06	0.16	0.51
174	0.43	0.71	0.81	0.19	0.62	0.47
175	0.81	0.9	0.79	0.08	0.35	0.5
176	0.05	0.7	0.66	0.24	0.22	0.57
177	0.89	0.67	0.91	0.24	0.04	0.05
178	0.11	0.72	0.71	0.26	0.13	0.06
179	0.05	0.15	0.61	0.07	0.55	0.8
180	0.05	0.92	0.94	0.17	0.04	0.06
181	0.57	0.69	0.8	0.05	0.11	0.05
182	1	0.36	0.75	0.51	0.48	0.07
183	0.4	0.84	0.84	0.05	0.05	0.05
184	0.98	0.88	0.95	0.51	0.38	0.22
185	0.05	0.9	0.94	0.05	0.05	0.45
186	0.75	0.54	0.16	0.63	0.05	0.07
187	0.05	0.14	0.25	0.72	0.77	0.24
188	0.51	0.54	0.19	0.79	0.15	

Calibrated variables for the 2020s

S ID	AtCal	HiresCal	Wincal	BisCal	Descal	CRICal
1	0.05	0.7	0.95	0.07	0.03	0.05
2	0.53	0.52	0.35	0.78	0.16	0.05
3	0.57	0.65	0.63	0.56	0.46	0.5
4	0.53	0.51	0.19	0.46	0.69	0.06
5	0.05	0.39	0.6	0.12	0.06	0.62
6	0.59	0.72	0.61	0.52	0.67	0.53
7	0.52	0.86	0.69	0.04	0.19	0.09
8	0.05	0.95	0.61	0.54	0.07	0.06
9	0.05	0.57	0.4	0.15	0.11	0.05
10	0.05	0.61	0.33	0.11	0.07	0.09
11	0.05	0.18	0.56	0.76	0.08	0.04
12	0.05	0.85	0.91	0.07	0.07	0.07
13	0.05	0.41	0.29	0.63	0.42	0.07
14	0.05	0.5	0.67	0.54	0.22	0.5
15	0.05	0.9	0.61	0.1	0.05	0.05
16	0.05	0.63	0.91	0.16	0.21	0.36
17	0.05	0.58	0.91	0.04	0.16	0.54
18	0.05	0.88	0.96	0.04	0.05	0.13
19	0.05	0.07	0.07	0.62	0.98	0.51
20	0.52	0.68	0.9	0.06	0.43	0.55
21	0.05	0.51	0.62	0.14	0.78	0.51
22	0.07	0.36	0.94	0.26	0.62	0.29
23	0.69	0.63	0.94	0.22	0.7	0.51
24	0.05	0.92	0.95	0.07	0.06	0.06
25	0.05	0.99	0.94	0.04	0.1	0.2
26	0.43	0.79	0.03	0.07	0.37	0.89
27	0.18	0.31	0.61	0.15	0.72	0.51
28	0.51	0.38	0.5	0.53	0.64	0.51
29	0.1	0.55	0.34	0.11	0.79	0.15
30	0.58	0.5	0.79	0.53	0.56	0.08
31	0.83	0.97	0.51	0.06	0.44	0.5
32	0.05	0.57	0.11	0.63	0.17	0.57
33	0.05	0.53	0.08	0.9	0.07	0.07
34	0.54	0.67	0.7	0.53	0.55	0.52
35	0.05	0.68	0.17	0.97	0.54	0.27
36	0.18	0.29	0.05	0.56	0.04	0.08
38	0.87	0.33	0.93	0.05	0.79	0.3
39	0.63	0.64	0.1	0.58	0.6	0.58
40	1	0.6	0.5	0.55	0.54	0.06
41	0.73	0.18	0.08	0.2	0.27	0.65
42	0.58	0.69	0.04	0.56	0.73	0.51
43	0.05	0.17	0.18	0.73	0.1	0.51

44	0.05	0.33	0.07	0.71	0.08	0.84
45	0.96	0.32	0.05	0.6	0.04	0.05
46	0.05	0.2	0.07	0.75	0.1	0.55
47	1	0.55	0.14	0.28	0.03	0.27
48	1	0.88	0.92	0.08	0.07	0.51
49	0.05	0.6	0.05	1	0.03	0.54
50	0.23	0.2	0.05	0.83	0.04	0.07
51	0.51	0.06	0.04	0.58	0.58	0.49
52	0.51	0.19	0.28	0.29	0.84	0.12
53	0.52	0.48	0.41	0.3	0.8	0.51
54	0.5	0.42	0.52	0.12	0.22	0.51
55	0.22	0.31	0.37	0.62	0.73	0.14
56	0.58	0.06	0.08	0.63	0.6	0.53
57	0.7	0.15	0.3	0.64	0.62	0.53
58	0.06	0.1	0.28	0.8	0.82	0.26
59	0.09	0.04	0.14	0.54	1	0.09
60	0.53	0.07	0.26	0.75	0.78	0.05
61	0.94	0.05	0.16	0.79	1	0.51
62	0.05	0.56	0.5	0.11	0.8	0.88
63	0.53	0.4	0.26	0.76	0.78	0.05
64	0.5	0.53	0.4	0.88	0.56	0.5
65	0.38	0.06	0.17	0.86	0.89	0.51
66	0.7	0.09	0.1	0.86	0.28	0.91
67	0.92	0.18	0.22	0.99	0.44	0.78
68	0.7	0.08	0.06	1	0.3	0.54
69	0.52	0.22	0.18	0.86	0.5	0.58
70	0.06	0.66	0.27	0.71	0.59	0.5
71	0.11	0.07	0.14	0.76	0.79	0.05
72	0.64	0.58	0.49	0.08	0.8	0.07
73	0.51	0.08	0.31	0.43	0.65	0.23
74	0.09	0.52	0.63	0.38	0.68	0.27
75	0.05	0.5	0.58	0.2	0.91	0.43
76	0.05	0.07	0.12	0.88	0.58	0.21
77	1	0.5	0.63	0.1	0.16	0.84
78	0.73	0.62	0.83	0.05	0.46	0.56
79	0.5	0.25	0.1	0.84	0.78	0.12
80	0.6	0.21	0.42	0.91	0.82	0.18
81	0.47	0.12	0.9	0.26	0.4	0.13
82	0.5	0.75	0.86	0.51	0.56	0.26
83	0.62	0.41	0.46	0.56	0.24	0.23
84	0.18	0.3	0.44	0.76	0.16	0.55
85	0.57	0.31	0.73	0.25	0.26	0.52
86	0.21	0.34	0.31	0.63	0.96	0.5

87	0.5	0.05	0.05	0.86	0.94	0.51
88	0.12	0.06	0.04	0.87	0.85	0.46
89	0.14	0.06	0.09	0.62	0.95	0.51
90	0.08	0.18	0.15	0.55	0.65	0.51
91	0.53	0.63	0.06	0.71	0.95	0.44
92	0.07	0.05	0.1	0.68	0.98	0.64
93	0.47	0.2	0.17	0.07	0.51	0.1
94	0.22	0.24	0.88	0.25	0.5	0.06
95	0.52	0.06	0.05	0.63	0.65	0.54
96	0.05	0.64	0.08	0.68	0.91	0.12
97	0.18	0.05	0.1	0.95	0.7	0.2
98	0.11	0.06	0.06	0.58	0.94	0.61
99	0.27	0.04	0.11	0.62	0.87	0.42
100	0.8	0.05	0.13	0.69	0.87	0.55
101	0.53	0.8	0.87	0.12	0.37	0.5
102	0.15	0.25	0.34	0.12	0.14	0.5
103	0.05	0.13	0.58	0.86	0.82	0.51
104	0.05	0.57	0.18	0.8	0.54	0.05
105	0.05	0.52	0.41	0.44	0.08	0.07
106	0.45	0.93	0.94	0.04	0.14	0.1
107	0.58	0.61	0.89	0.29	0.55	0.53
108	0.54	0.59	0.62	0.23	0.54	0.39
109	0.05	0.35	0.63	0.5	0.61	0.51
110	0.58	0.57	0.8	0.22	0.59	0.18
111	0.95	0.64	0.87	0.73	0.41	0.5
112	0.44	0.87	0.87	0.17	0.54	0.54
113	0.52	0.85	0.98	0.05	0.65	0.92
114	0.37	0.97	0.99	0.13	0.28	0.29
115	0.28	0.85	0.95	0.07	0.63	0.8
116	0.6	0.56	0.63	0.09	0.27	0.72
117	0.5	0.57	0.85	0.64	0.56	0.1
118	0.9	0.74	0.92	0.98	0.76	0.59
119	0.61	0.59	0.8	0.1	0.85	0.98
120	0.61	0.68	0.94	0.06	0.72	0.1
121	0.71	0.69	0.95	0.51	0.82	1
122	0.48	0.51	0.39	0.17	0.44	0.97
123	0.21	0.23	0.22	0.65	0.57	0.82
124	0.19	0.44	0.96	0.05	0.69	0.51
125	0.42	0.77	0.88	0.08	0.78	0.53
126	0.67	0.32	0.63	0.54	0.31	0.54
127	0.54	0.77	0.97	0.1	0.49	0.54
128	0.64	0.69	0.3	0.87	0.86	0.96
129	0.66	0.63	0.16	0.97	0.77	0.97

130	0.65	0.69	0.66	0.83	0.83	0.99
131	0.51	0.07	0.2	0.89	0.68	0.86
132	0.57	0.14	0.22	0.29	0.37	0.82
133	0.54	0.54	0.21	0.48	0.04	0.16
134	0.51	0	0.42	0.5	1	0.54
135	0.14	0	0.5	0.5	1	0.52
136	0.5	0.17	0.01	0.39	0.88	0.13
137	0.51	0.11	0.84	0.05	0.95	0.53
138	0.39	0.25	0.44	0.87	0.73	0.63
139	0.5	0.85	0.43	0.85	0.24	0.6
140	0.52	0.31	0.85	0.39	0.77	0.56
141	0.51	0.46	0.91	0.09	0.52	0.85
142	0.51	0.51	0.69	0.7	0.6	0.99
143	0.53	0.35	0.87	0.5	0.46	0.11
144	0.73	0.88	0.88	0.05	0.07	0.57
145	0.64	0.73	0.96	0.04	0.38	0.56
146	0.07	0.58	0.57	0.33	0.07	0.19
147	1	0	0.18	0.91	0.03	1
148	0.53	0.64	0.82	0.57	0.96	0.8
149	0.75	0.07	0.03	0.94	0.13	0.41
150	0.96	0.15	0.04	1	0.07	0.54
151	0.05	0.17	0.12	0.84	0.14	0.71
152	0.05	0.99	0.92	0.04	0.06	0.19
153	0.54	0.89	0.95	0.06	0.11	0.89
154	0.05	0.43	0.19	0.87	0.13	0.34
155	0.09	0.7	0.66	0.21	0.05	0.07
156	0.05	0.23	0.1	0.56	0.85	0.1
157	0.52	0.41	0.15	0.81	0.28	0.95
158	0.05	0.51	0.54	0.46	0.4	0.27
159	0.22	0.6	0.32	0.37	0.53	0.5
160	0.67	0.56	0.35	0.25	0.71	0.3
161	0.65	0.29	0.28	0.5	0.35	0.06
162	0.54	0.58	0.65	0.38	0.64	0.49
163	0.94	0.72	0.95	0.15	0.11	0.51
164	0.65	0.29	0.28	0.5	0.35	0.06
165	0.05	0.43	0.48	0.51	0.71	0.42
166	0.83	0.18	0.19	0.77	0.67	0.06
167	0.05	0.61	0.66	0.32	0.29	0.37
168	0.05	0.95	0.92	0.25	0.05	0.06
169	0.05	0.05	0.34	0.16	0.97	0.16
170	0.13	0.96	0.87	0.06	0.08	0.06
171	0.51	0.56	0.32	0.82	0.68	0.06
172	0.05	0.41	0.25	0.9	0.45	0.15

173	0.24	0.98	0.44	0.13	0.15	0.51
174	0.6	0.81	0.84	0.1	0.66	0.31
175	0.61	0.53	0.88	0.54	0.3	0.51
176	0.65	0.76	0.73	0.51	0.23	0.56
177	0.09	0.93	0.92	0.08	0.04	0.04
178	0.12	0.74	0.61	0.39	0.15	0.06
179	0.05	0.31	0.66	0.21	0.7	0.69
180	0.05	0.86	0.88	0.2	0.64	0.08
181	0.55	0.75	0.77	0.06	0.13	0.06
182	1	0.44	0.84	0.1	0.37	0.06
183	0.42	0.95	0.91	0.09	0.05	0.05
184	0.67	0.87	0.98	0.05	0.4	0.18
185	0.05	0.81	0.59	0.62	0.06	0.21
186	0.89	0.18	0.07	0.67	0.07	0.09
187	0.05	0.25	0.65	0.64	0.67	0.51
188	0.5	0.5	0.09	0.86	0.3	0.1
189	0.56	0.6	0.93	0.09	0.71	0.99
190	0.63	0.26	0.34	0.52	0.43	0.06
191	0.06	0.05	0.05	0.73	0.84	0.52
192	0.06	0.26	0.04	0.5	0.08	0.54
193	0.05	0.18	0.77	0.17	0.07	0.08
194	0.05	0.76	0.76	0.53	0.08	0.04
195	0.05	0.7	0.7	0.5	0.19	0.06
196	0.05	0.29	0.29	0.59	0.21	0.06
197	0.13	0.65	0.41	0.25	0.2	0.06
198	0.32	0.66	0.73	0.22	0.31	0.05
199	0.24	0.24	0.7	0.5	0.73	0.05
200	0.05	0.22	0.38	0.6	0.66	0.06
201	0.05	0.62	0.82	0.07	0.45	0.04
202	0.29	0.62	0.62	0.35	0.25	0.76
203	0.05	0.84	0.58	0.34	0.46	0.05
204	0.05	0.56	0.73	0.58	0.84	0.05
205	0.05	0.34	0.34	0.54	0.64	0.05