MODELING LONGITUDINAL AND SPATIAL CHANGES IN URBAN GREEN SPACE DEVELOPMENT: A COMPARISON OF OLS AND MGWR

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ABSTRACT

How do multi-faceted factors impact urban green space (UGS) development over time in a city or region, and how is urban green space development associated with housing factors? This study assumes that the UGS development has had an inequitable impact on the communities where socially vulnerable populations face more challenges eventually, and thus aims to examine whether this inequitable impact varies spatially across the city over time, taking the City of Austin, Texas, as a case study. Further, this study compares the traditional, non-spatial global model (Ordinary Least Square, OLS) with the spatial local model (Multiscale Geographically Weighted Regression, MGWR) to discern a better way to understand the changes in UGS development in both longitudinal and spatial dimensions.

This study uses the City of Austin's green space spatial data, US Census data, U.S. Department of Housing and Urban Development (HUD) housing data, and Longitudinal Tract Database (LTDB) data from the years 2000 and 2020. Followed by analyzing how the change in observed differences in multiple variables and housing factors are associated with the change in UGS per capita between 2000 and 2020. The result shows that the city-wide greening strategy has become more equitable over time. However, housing affordability has become more negatively associated with UGS per capita over time. In addition, the MGWR outperforms the OLS model which provides greater explanatory power, and it provides more nuanced evidence for identifying spatial variation for each explanatory variable at the city scale. Therefore, the use of localized models, such as MGWR, is useful for lessening the problematic effect of aggregated data, especially when smaller unit data is not readily available. The results may offer insight into the potential polarization of UGS development and the re-arrangement of the flow of vulnerable populations to promote equity, as well as implications for policymakers, landscape design professionals, and city officials.

Keywords

Urban Green Space (UGS), Environmental Justice, Spatial-Longitudinal Analysis, Multiscale Geographically Weighted Regression (MGWR)

1 INTRODUCTION

Research has shown various benefits that Urban Green Space (UGS) can provide through the alteration of the physical urban environment. These include improved human health and well-being, better urban development, and a myriad of ecosystem services (Anguelovski et al., 2018; Harvey, 2001; Heynen, 2014; Swyngedouw & Heynen, 2003). Local and national governments worldwide are adopting more greening policies because of their acclaimed 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 denial of adequate city services in the past (Heck, 2021; Rigolon & Németh, 2018). In researching this inequity, some studies examined the procedural and recognitional injustice of marginalized communities that were excluded from decision-making processes, the misrecognition of their perception of green space, and policies that transmute environmental externalities into profiting opportunities (Checker, 2011; Curran & Hamilton, 2013; Dooling, 2009; McKendry & Janos, 2015). Other studies emphasizing distributional injustice demonstrated the potential economic and demographic spatial changes in the affected areas, such as increased adjacent property value and rental prices, increased tax payment, and the creation of new employment opportunities, as well as 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 to be helpful and constructive. The mounting empirical evidence provided us with insights into how socio-spatial inequities that were reproduced through UGS implementation might be overlooked (Anguelovski et al., 2020). Specifically, for distributional injustice, the cross-sectional focus on analyzing proximity and distance to UGS might be insufficient to answer the question of 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). However, such evidence is insufficient and scarce.

1.1 Park development and land value

Park creation in the United States has been historically interlinked with the social reproduction of both the bourgeois leisure class as well as the working class (Bachin, 2003; Birge-Liberman, 2010). One important aspect that much UGS research has been neglecting is that urban land is valuable, therefore, any modification to the built environment needs justification; this often involves both political and economic concerns in addition to the social and environmental standpoint. Because of the investment from both the public and private sectors, UGS has possessed the trait of the regional commodity that carries over the expectation of oftentimes elite class to resolve the potential shift in societal values and the urban ecological burdens (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. In addition, many of the current studies did not consider the complexity that various social, and economic factors, among others, will change during the operationalization of the problem (Anguelovski et al., 2022).

1.2 Fast-growing urban neighborhoods and UGS development in Austin

The city of Austin, Texas, is one of the fastest-growing cities in the United States with over two million residents living in the metropolitan area and almost one million within the city limit (Trust for Public Land 2022). As the city expands and new residents flourish, the city itself has experienced rapid development and transformed from a government- and university-based city in the 1990s into a metropolitan area that houses high-tech companies and industries nowadays (Connolly & Lira, 2021). In recent years, Austin has also been titled as a sustainable and equitable leader due to its efforts in pushing green and culturally progressive agendas while maintaining robust economic growth (Garcia-Lamarca et al., 2021; Long, 2016).

As Austin's population grows, it is no exception in terms of the expansion of park spaces. Since November 2018, the city of Austin Parks and Recreation Department (PARD) has made expansion and creation of 51 parks, equivalent to roughly about 200 acres of land across the city (PARD 2021). The Parkland Dedication Ordinance first passed in 1985 has made the mandates dedication for parkland along with new development applications; This has ensured an equitable and proportionate expansion of the city park system (PARD 2021). Despite the good intentions of the government's policy in allocating municipal bonds to prioritized communities, such as East Austin, to fill the gaps in Austin's Park system over generations, the inequity remains (Tretter, 2012). Though the policy itself is intentionally based on criteria such as income level, racial minorities, and young children ratio, the statistics of its efficacy say otherwise. According to the 2022 Trust for Public Land data, low-income residents enjoy 59% less access to park space per person compared to those who live in wealthier neighborhoods, although the city has allocated a $40 million municipal bond to help green space land acquisition in East Austin between 2000 and 2010 (Connolly and Lira 2021, Trust for Public Land 2022).

1.3 Inequitable access to UGS in Austin

Austin has been racially segregated throughout the 20th century as the 1928 Master Plan set out a designated zone, East Austin, for minorities (Long, 2016). At the same time, this area was largely occupied by polluting industries and had limited access to green amenities. The later deed restriction made this segregation worse as it only allowed land use to be locked after the land was developed (Tretter, 2012). In addition, comprehensive plans developed before the year 1979 have no statutory enforcement power but only act as guidelines in directing city and zoning development. Even with the adoption of comprehensive plans 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 like East Austin has remained largely unchanged to this day.

In the early 1990s, grassroots environmental justice groups, such as People Organized in Defense of Earth and Her Resources (P.O.D.E.R.), in East Austin first started to advocate for a better environment and was successful in removing the Holly Street power plant. Around the same time, Austin started to brand itself as a leader in green and sustainable development. 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 (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.

1.4 The need for novel spatial models

To understand whether the distribution of UGS is associated with demographic and socio-economic factors at a city-wide level, spatial analysis is often used. Spatial analysis is a blend of inquiries, usually consisting of two parts; one is to map out the spatial patterns of research interest that are 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). Despite the ability to show the spatial patterns and reveal the potential mechanisms, spatial analysis is not immune from theoretical challenges. For example, the Modifiable Areal Unit Problem (MAUP), a form of Ecological Fallacy, posits that individual behavior cannot be explained at the aggregated level, therefore, the inferences made toward an observed phenomenon might be distorted and the outcome will be misrepresented (Baller et al., 2001; L. Li et al., 2017). Essentially, MAUP is concerned with the mismatch of scales between collected spatial data and the explanation processes (F. Li et al., 2017). Therefore, one common recommendation for solving the MAUP problem is to find the best possible scales where the underlying processes take place (Kwan, 2012). However, the data at the right scales is not always readily available, therefore, requiring researchers to find suitable novel models to address the potential problems with aggregated data at a local scale.

2 RESEARCH OBJECTIVES

Previous studies commonly use multivariate modeling to capture multifaceted factors that contribute to inequitable UGS development (Anguelovski et al., 2018; Rigolon, 2017; Stuhlmacher et al., 2022). Recent studies have expanded on the topic to include the association between green space development and housing factors (Anguelovski et al., 2018; Curran & Hamilton, 2013; Mullenbach & Baker, 2020; Stuhlmacher et al., 2022). A global model such as OLS is commonly used to explore the association between identified variables, including social, economic, and housing ones, with accessibility to green space, such as proximity (Anguelovski et al., 2018). However, a global model assumes spatial stationarity where variables are the same across space which might not be true in real life. The use of a local model, such as Multiscale Geographically Weighted Regression (MGWR), may better capture the local spatial variations for a better result.

Therefore, under the assumption that the UGS development is inequitable, and the socially vulnerable populations face more challenges over time, this study aims to model the longitudinal association between green space development and various socio-demographic, socio-economic, and housing factors at the city scale. Specifically, this study compares the differences between Ordinary Least Squares (OLS) and MGWR that predict UGS development in both longitudinal and spatial dimensions.

3 METHODS

3.1 Local and global model comparison

This study utilized both MGWR (local) and OLS (global) regression models to examine how identified variables are related to urban green space development in the two decades. The OLS is commonly used to examine the association between dependent variables and explanatory variables; This inferential technique provides a best-fit linear regression model between the variables of interest (Mansour et al., 2021). The regression coefficients associated with the model describe how the dependent variable changes with one unit change in the independent variables. However, some variables might be spatially correlated which will distort the result if such spatial dependence is not properly addressed in the model (Anselin, 2003).

The MGWR produces a local linear regression model that allows the selected area unit around each spatial feature to vary as some explanatory variable might operate on different spatial scales. This allows a more accurate estimation for variable coefficients that creates a weighted regression model for each spatial feature assuming a smooth change over the whole region. The reason for creating a local weighting matrix is due to the assumption that the neighboring features that are closer to the targeting feature have a larger impact on the results than the distant ones (Brunsdon et al., 1996). Compared to a global model, such as OLS, that assumes spatial stationarity, a local model like MGWR takes non-stationarity into account and allows for a more relaxed assumption made over space.

The spatial data was processed and visualized using ArcGIS Pro. The OLS model was performed with RStudio, and the MGWR was performed with ArcGIS Pro.

3.2 Data collection

The longitudinal dataset used in this study includes selected socio-demographic and socio-economic indicators, green space spatial data, and housing factors data from the year 2000 to the year 2020 (2000, 2010, and 2020). The socio-demographic and socio-economic data rely on the US Census and Longitudinal Tract Database (LTDB) developed by Brown University (Logan et al., 2014). The spatial green space data was obtained from the City of Austin Open Data Portal (City of Austin, n.d.). The housing factors were gathered from LTDB and the US Department of Housing and Urban Development (HUD) (HUD, n.d.).

All variables were calculated for their respective decadal change (10 years) in percentage for the span of twenty years (from 2000 to 2020). Table 1 provides an overview of the variables used in this study, descriptions, data sources, and respective types. The unit of analysis used in this study is the census tract.

Table 1. Variables and data sources.

Variable name	Description	Source	Type
Change of UGS per capita	Percentage change in per capita public park space (2000, 2010, and 2020)	Austin GIS Portal	DV
Percent College	Education Level: Percentage of population with at least a bachelor's degree (2000, 2010, and 2020)	US Census, LTDB	IV
Income	Income: Median household income (2000, 2010, and 2020)	US Census, LTDB	IV
Percent White	Race: Percentage of non-Hispanic white population (2000, 2010, and 2020)	US Census, LTDB	IV
Percent Black	Race: Percentage of non-Hispanic African American population (2000, 2010, and 2020)	US Census, LTDB	IV
Rent	Housing: Median gross rent (2000, 2010, and 2020)	US Census, LTDB	CV
Home value	Housing: Median home value for occupied units (2000, 2010, and 2020)	US Census, LTDB	CV
Change of population density	Population: Percentage of population density change over time (2000, 2010, and 2020)	US Census	CV
Change of vacant housing	Housing: Percentage of vacant housing change over time (2000, 2010, and 2020)	US Census, LTDB	CV
Change of old housing units	Housing: Percentage of old housing units 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

Note: DV (dependent variable), IV (independent variable), and CV (control variable).

Dependent variable: The dependent variable in this study is the percentage change in UGS per capita (percentage change of UGS in square feet over ten years at the census tract level). To calculate this change, the study utilized a commonly used assumption that each green space has a service area – a catchment boundary where residents within the radius of the selected threshold will likely use the green amenity. The threshold chosen in this study is 800 meters or approximately 10 minutes of walking distance. Following the similar approach used in previous studies, an 800-meter Euclidean distance buffer was created around each park, and all the new park service boundaries were summed for each tract for later green space change calculation (Anguelovski et al., 2022).

To determine the number of parks added during the corresponding decades, the study refers to the acquisition date information for each park stored in the Austin PARD's GIS file as the year of inauguration. For example, Lynnbrook Park was acquired by the City of Austin in 2001, therefore, the addition of this park size plus the 800-meter catchment area size will be calculated for the years 2000 and the year 2010. The two periods overlap with the decadal census data, that is, from the year 2000 to the year 2010, and from the year 2010 to the year 2020.

Independent and control variables: This study includes key socio-economic and socio-demographic factors that may be associated with the UGS changes and residents' social vulnerability, such as their 'educational level (Percent College)', 'race (Percent White and Percent Black)', and 'income level (Median Household Income)' (Table 1). Similar to previous studies that have explored the potential association between urban green space development and housing factors (Anguelovski et al., 2018, 2022; Stuhlmacher et al., 2022), the percentage of vacant housing, the percentage of HUD units, the percentage of old housing units, population density, median rent value, and median home value at the census tract level were used as control variables.

4 RESULTS

The results are presented below in four parts. The first part provides a visualization of the changes in UGS per capita and the key explanatory variables over two decades. The second part provides an overview of descriptive statistics of all the study variables for MGWR modeling for both decadal periods. The third part provides the interpretations for MGWR performed for each decadal period, as well as the spatial analysis of each variable in association with the changes of UGS per capita green for each decadal period. The last part compares the results from MGWR and OLS models.

4.1 Visualization of decadal changes for UGS and core explanatory variables

Decadal changes in UGS per capita, race (Percent White and Percent Black), educational level (Percent College), and income level (Median household income) at the census tract level are displayed below (Figure 1). In general, the increase in UGS per capita (Figure 1A) shows a decadal trend from around the city center to the fringe of the city. The increase in Percent White (Figure 1B) shows a general trend of expanding into Central and East Austin for the periods 2000-2010 and 2010-2020. At the same time, more neighborhoods in the second decadal period (2010-2020) are seeing an increase in the Percent White compared to the first decadal period (2000-2010). There are significantly more neighborhoods showing a decrease in the Percent Black (Figure 1C) during the first decade compared to the second decadal period. For the Percent College (Figure 1D), neighborhoods closer to the city center are seeing a bigger increase in the second decadal period. For the Income (Figure 1E), compared to the more spread-out pattern in the first decade, the second decade is seeing more increase in neighborhoods that are closer to the city center.

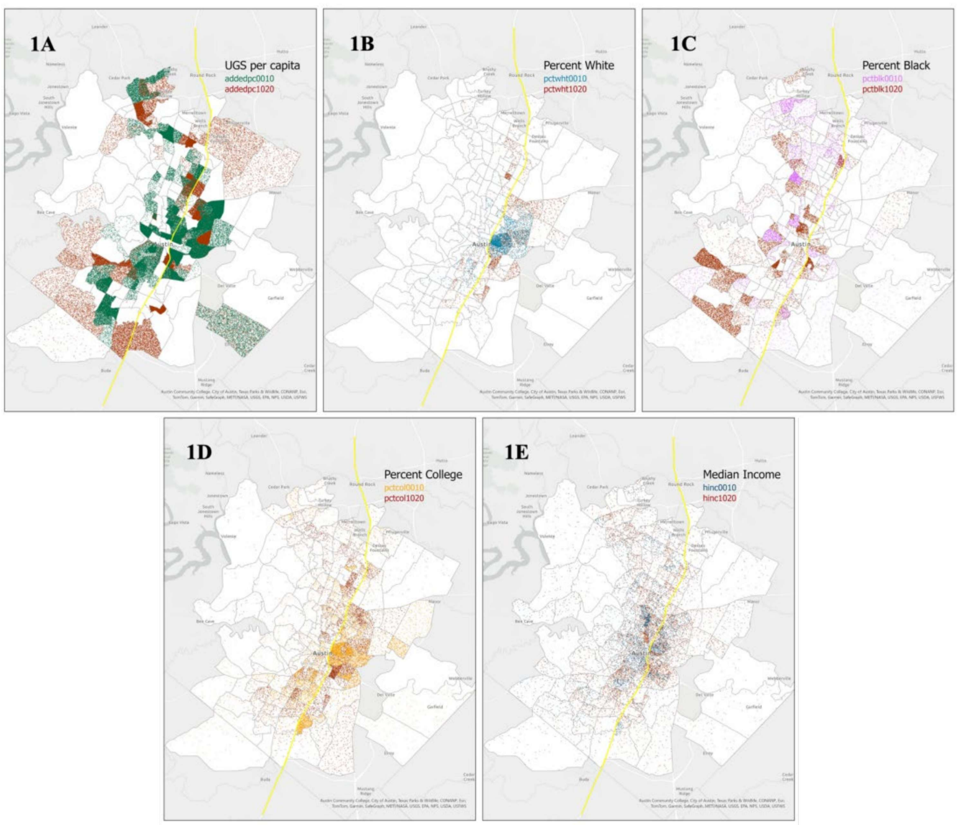

Figure 1. Green Space and Core Explanatory Variables 2000-2010 and 2010-2020 maps (created by the authors using ArcGIS)

(A) UGS per capita Added, (B) Percent White Change, (C) Percent Black Change, (D) Percent College Change, (E) Median Household Income Change

4.2 Descriptive statistics for MGWR

The descriptive statistics for all variables of both decadal periods are shown in Table 2. The mean value of each coefficient reflects the association between the explanatory variables and the dependent variable. The standard deviation explains the spatial variation of each explanatory variable with a smaller value indicating a better OLS fit. When performing the regression analysis, the model uses scaled data, therefore, the values for each explanatory variable can be compared across the table.

For the period of the year 2000 to the year 2010, there is a negative association between the Percent White and UGS per capita. The small standard deviation for Percent White indicates a low spatial variability in Austin. When compared between the two decades, explanatory variables such as Percent College have changed from a negative association to a positive relationship with the UGS per capita. Percent HUD Units, on the other hand, changed from a positive association to a negative association with the UGS per capita. Among all the explanatory variables, Percent Black and Population Density have relatively high standard deviations across the two decades, indicating the general pattern of high spatial variations for both variables across the city.

Table 2. Descriptive Statistics for variables 2000-2010, 2010-2020.

Year	Variables	Neighbors	Mean	Std Dev	Minimum	Maximum	Median
2000-2010	Percent White	161 (79.7%)	-0.006	0.006	-0.030	0.002	-0.004
	Percent Black	30 (14.9%)	0.040	0.250	-0.077	2.095	-0.002
	Percent College	30 (14.9%)	-0.018	0.089	-0.917	0.117	-0.0003
	Median Household Income	32 (15.8)	-0.010	0.103	-0.778	0.054	0.006
	Median Gross Rent	61 (30.2%)	-0.011	0.044	-0.102	0.280	-0.020
	Median House Value	30 (14.9%)	-0.051	0.199	-2.180	0.176	-0.014
	Population Density	59 (29.2%)	-0.760	1.934	-11.981	0.018	-0.372
	Percent Vacant Units	30 (14.9%)	0.009	0.113	-0.354	1.024	-0.002
	Percent Old Units	202 (100%)	-0.006	0.003	-0.013	-0.002	-0.005
	Percent HUD Units	202 (100%)	0.009	0.006	0.0003	0.019	0.008
Year	Variables	Neighbors	Mean	Std Dev	Minimum	Maximum	Median
2010-2020	Percent White	52 (25.5%)	-0.077	0.064	-0.329	0.029	-0.060
	Percent Black	30 (14.7%)	0.016	0.353	-2.051	0.672	0.009
	Percent College	204 (100%)	0.009	0.002	0.003	0.013	0.010
	Median Household Income	38 (18.6%)	-0.003	0.048	-0.331	0.071	0.004
	Median Gross Rent	36 (17.7%)	0.037	0.136	-0.064	1.194	0.003
	Median House Value	31 (15.2%)	-0.025	0.088	-0.475	0.137	-0.009
	Population Density	30 (14.7%)	-0.348	0.435	-1.950	-0.020	-0.173
	Percent Vacant Units	30 (14.7%)	-0.032	0.123	-1.077	0.403	-0.010
	Percent Old Units	71 (34.8%)	-0.256	0.263	-0.690	0.006	-0.137
	Percent HUD Units	204 (100%)	-0.008	0.001	-0.010	-0.006	-0.008

4.3 Model diagnostics for MGWR model

As introduced before, this study used MGWR, a local form of linear regression, as the primary model for studying the spatially varying longitudinal association between UGS development (UGS per capita) and explanatory variables. The selected model diagnostics, as shown below in Table 3, compared several indicators with the automatically produced Geographically Weighted Regression (GWR) model. For the years 2000 to the year 2010, the MGWR model outperforms the GWR model as indicated by the higher R-squared value, as well as the lower AICc value. Similarly, for the years 2010 to the year 2020, despite having similar R-squared values, MGWR is still the preferred model as it has a lower AICc value which indicates a better model fit.

Table 3. MGWR Model Diagnostics.

Year	Statistics	GWR	MGWR
2000-2010	R-Squared	0.885	0.960
	Adjusted R-Squared	0.799	0.934
	AICc	351.542	197.237
2010-2020	R-Squared	0.976	0.968
	Adjusted R-Squared	0.931	0.938
	AICc	310.157	257.838

4.4 A comparison of OLS and MGWR models

This section shows the differences in results for both OLS and MGWR models. The results from both models show that the MGWR model outperformed the OLS model with an increase in both R^2 and the adjusted R^2 value. For the first decade, the OLS model (see Table 4) does not show significance overall and the small R-squared value indicates a poor coverage of the UGS per capita that the explanatory variables can predict. In the MGWR model (see Table 2 and Figure 2), the Percent White does not show significance and shows a negative trend with the UGS per capita at a regional level (161 out of 202 features). The Percent Black shows a positive relationship with the increase in the UGS per capita in the easter fringe of the city at a local level (30 out of 202 features). Similarly, both Median Household Income and the Percent College show a negative association with the increase in the UGS per capita in the eastern fringe of the city at a local level (30 and 32 out of 202 features, respectively).

For the second decade, the OLS model (see Table 4) shows significance with a relatively small R-squared value; Only Population Density shows significance among all the explanatory variables. In the MGWR model (see Table 2 and Figure 2), the Percent White shows a negative association with the UGS per capita in West Austin closer to the city center at a regional level (52 out of 204 features). The Percent Black shows a positive association with the UGS per capita, also in West Austin, at the local level (30 out of 204 features). The Percent College shows a positive trend with the UGS per capita at a global level (204 out of 204 features). The Median Household Income shows a negative association with the UGS per capita in the east fringe at a local level (38 out of 204 features).

Table 4. OLS analysis for 2000-2010, 2010-2020.

Year	Variables	Estimates	Std Dev	Pr (>| t |)
2000-2010	Percent White	218.76	150.71	0.15
	Percent Black	25.64	102.36	0.80
	Percent College	-330.36	139.78	**0.02***
	Median Household Income	-275.93	365.12	0.45
	Median Gross Rent	391.84	301.75	0.20
	Median House Value	-92.01	159.09	0.56
	Population Density	-6.01	23.82	0.80
	Percent Vacant Units	20.52	26.05	0.43
	Percent Old Units	4.24	16.54	0.80
	Percent HUD Units	5.01	11.94	0.68
		p-value: 0.22, adjusted R-Squared: 0.02		
Year	Variables	Estimates	Std Dev	Pr (>| t |)
2010-2020	Percent White	-30.9830	51.5880	0.5488
	Percent Black	5.8948	6.8123	0.3879
	Percent College	5.4623	34.3629	0.8739
	Median Household Income	-64.6383	63.3569	0.3089
	Median Gross Rent	58.1530	57.8693	0.3162
	Median House Value	-24.4817	52.1887	0.6395
	Population Density	-463.7630	60.4508	**$8.17e^{-13}$***
	Percent Vacant Units	-7.5321	11.5210	0.5140
	Percent Old Units	-7.5349	7.9001	0.3414
	Percent HUD Units	0.5043	8.8418	0.9546
		p-value: $2.8e^{-08}$, adjusted R-Squared: 0.21*		

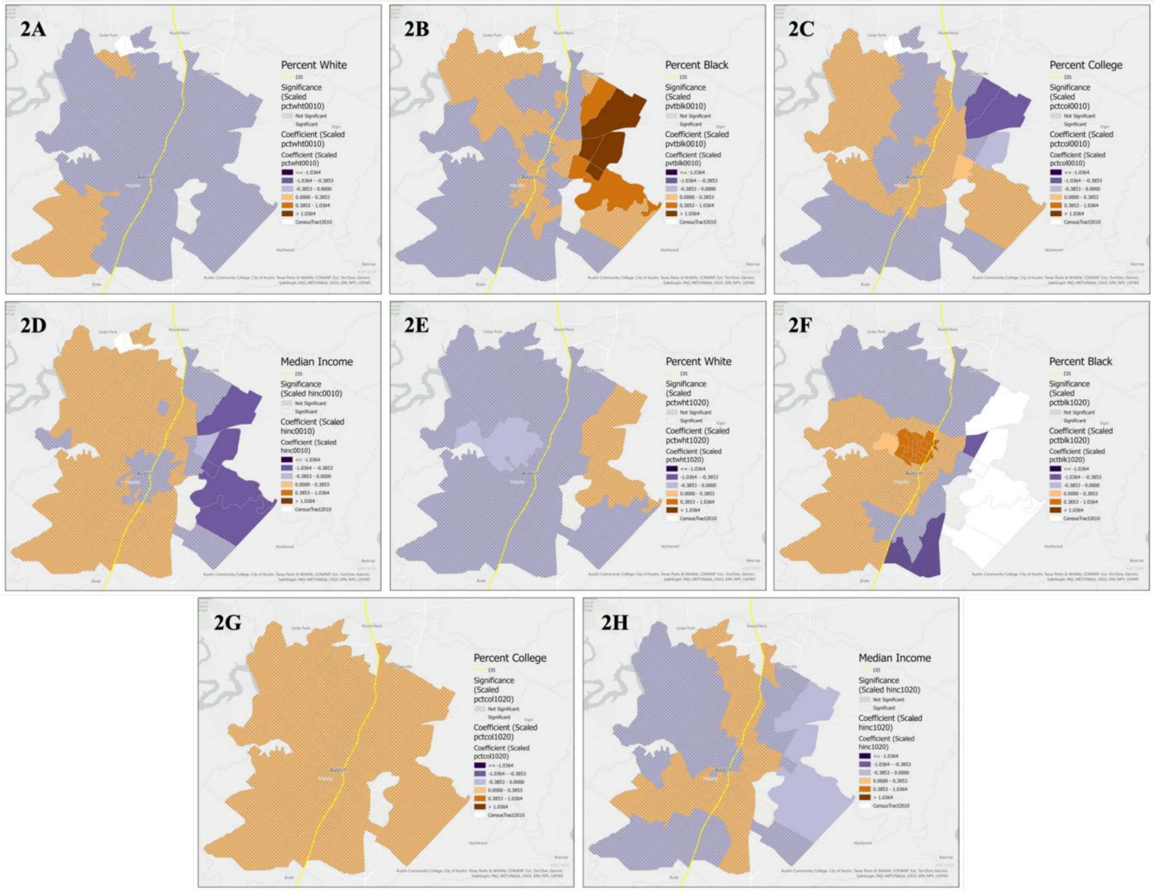

Figure 2. Core explanatory variables MGWR 2000-2010, and 2010-2020 (created by the authors using ArcGIS)

(A)(E) Percent White, (B)(F) Percent Black, (C)(G) Percent College, (D)(H) Median Household Income

5 DISCUSSION

This study investigated the spatial associations between UGS and various explanatory factors longitudinally. The study focuses on the UGS per capita (per capita green space size change in square feet) over time and contributes to the literature by using both local and global models. Unlike previous research that linked green space development and housing factors to gentrification, this study focuses on modeling the UGS development phenomena by controlling for several important housing factors that might be related to gentrification within the city. Greening agendas that "lead" to gentrification can be complex and possibly only part of the reasons that result in the inequity issues, what this study did is provide a different perspective of looking at the explanatory factors at a city-wide scale instead of focusing on "vulnerable" areas that are identified using prevalent criteria (Anguelovski et al., 2018, 2022; Stuhlmacher et al., 2022) (see Figure 3).

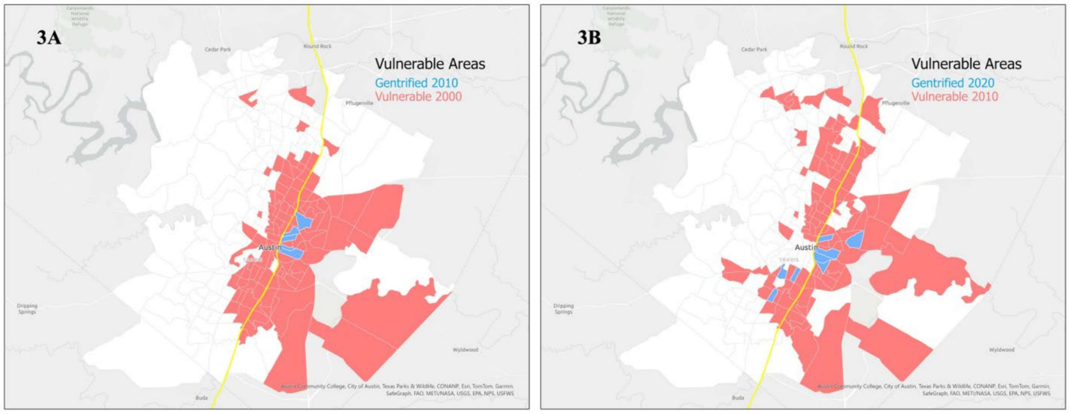

Figure 3. Vulnerable areas for each decade (created by the authors using ArcGIS)

(A) Vulnerable area at the beginning of the year 2000, (B) Vulnerable area at the beginning of the year 2010

Compared to the OLS model, MGWR provides a more nuanced perspective in terms of the developmental trend of UGS per capita with each of the explanatory factors (see Figures 2, 4, and 5). OLS provides an overall association between explanatory variables and UGS per capita, as well as the model fit; However, challenges may arise when interpreting OLS results as housing factors are included as control variables. MGWR, on the other hand, not only provides such information but also allows researchers to examine each variable's trend separately. A detailed interpretation of the MGWR model is presented below in two parts. The first part concerns key explanatory variables (race, education level, and income); The second part concerns all other control variables (housing and population).

For racial disparities (Percent White and Percent Black), part of West Austin has become significant in the second decadal period (2010-2020) and is negatively associated with UGS per capita (Figures 2E and 2F). Most parts of the city except for the West and East fringe are showing a negative trend with UGS per capita, for each decadal period, respectively. Similarly, the Percent Black shows a significant positive relationship with UGS per capita in West Austin closer to downtown Austin in the second decadal period. For individuals' education level (the Percent College), the second decadal period shows a trend of being positively related to the UGS per capita in the second decade. For individuals' income level (Median Household Income), despite both decades showing most of the city being insignificant, a larger portion of West Austin has shifted from a positive trend to a negative trend (Figures 2D and 2H). This means income has become less important in predicting per capita green space, at least from the years 2000 to the year 2020. Overall, more socially vulnerable populations (racial minorities and low-income) are seeing a more equitable developmental trend regarding UGS per capita over time except for individuals' education level.

For the Median House Value (see Figures 4A and 5A), the trend has changed from a mostly negative relation to around half of the city being positively related to the UGS per capita. For the Median Gross Rent (Figures 4B and 5B), the positive trend has encroached on the neighborhoods closer to the city center, and the East fringe shows a significant and positive association with the increase in the UGS per capita. For the Percent Vacant (Figures 4C and 5C), fewer neighborhoods in the Northeast fringe show a positive association with the UGS per capita, and more neighborhoods in the Southeast fringe become negatively associated with the UGS per capita in the second decade. For the Percent Old (Figures 4D and 5D), a large part of the neighborhoods closer to the city center, and all neighborhoods in the Southeast fringe become negatively associated with the increase in per capita green space in the second decade. Lastly, for the Percent HUD (Figures 4E and 5E), despite not showing significance in either decade, it changed from a positive trend to a negative trend, both at a global level. The results from the association between the housing factors and the change in per capita green space to some extent support there exists a city-wide, aggregated trend, that explains gentrification might be related to urban greening. It thus suggests the housing affordability situation in Austin is becoming more evident, with neighborhoods of higher housing value and rent, lower vacant rates, lower percentage of old housing, and lower percentage of subsidized housing units enjoying more per capita green space over time (Tang & Ren, 2014).

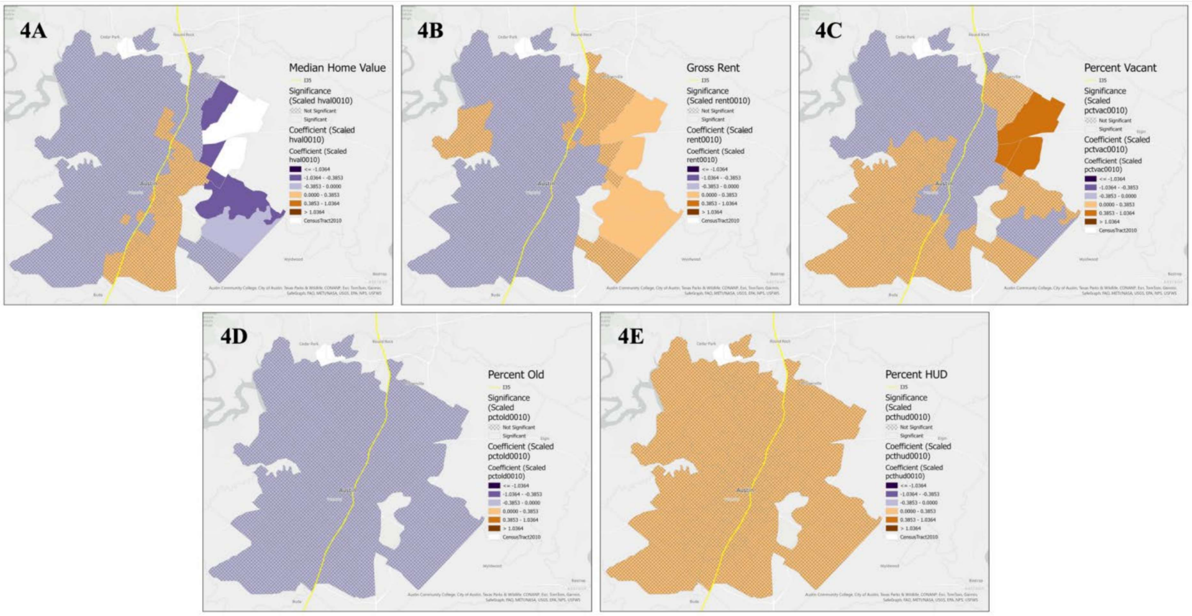

Figure 4. Housing variables MGWR 2000-2010 (created by the authors using ArcGIS)

(A) Median House Value, (B) Median Gross Rent, (C) Percent Vacant, (D) Percent Old, (E) Percent HUD

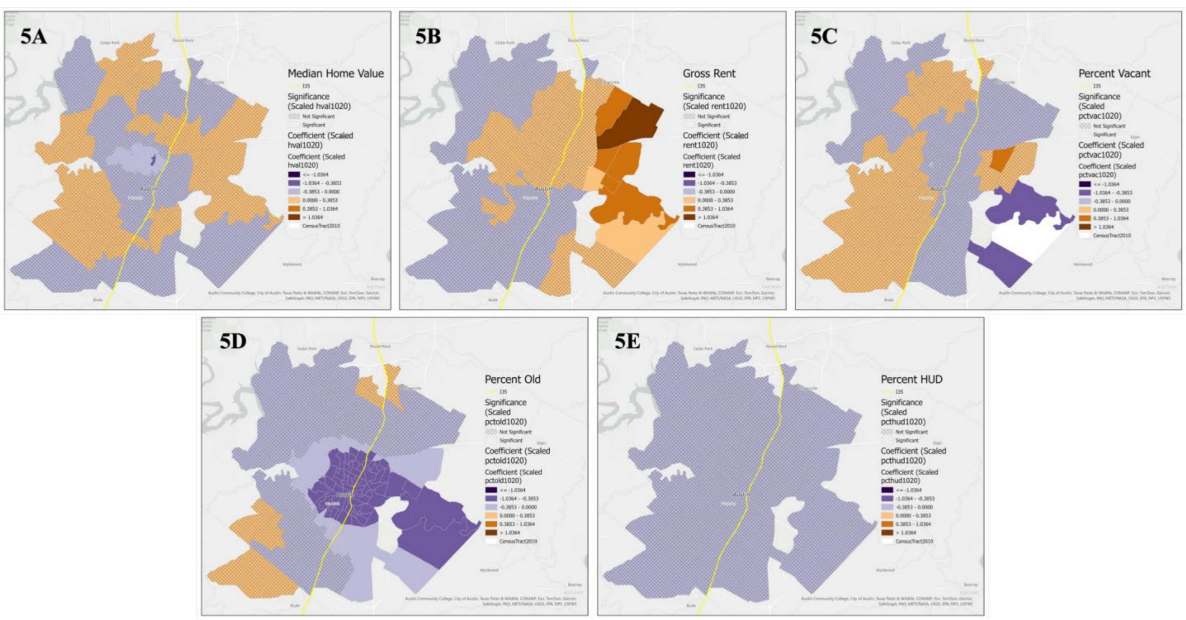

Figure 5. Housing variables MGWR 2010-2020 (created by the authors using ArcGIS)

(A) Median House Value, (B) Median Gross Rent, (C) Percent Vacant, (D) Percent Old, (E) Percent HUD

6 CONCLUSION

This study utilized both OLS and MGWR models in longitudinal and spatial analysis on green space development in Austin, TX as a case study. Several limitations should be considered when reading the interpretations of this study. First, this study only explored the publicly owned green space, that is, supervised by the Austin Department of Parks and Recreations; This study does not include private parks or any other green space, such as street trees, that provide amenities to the citizens as well (Hunter et al., 2019). As a result, it does not necessarily mean a census tract that has a smaller UGS per capita will enjoy fewer green amenities. Second, UGS per capita is closely related to the population density of that census tract, therefore, the smaller number may not indicate inequity, but rather a higher traffic in the parks for that area. It is possibly better to also combine the analysis of proximity to the nearest parks using walking distance as complementary evidence. Lastly, urban green space equity is a complex issue that no simple measurements can cover the entirety. For example, most of the explanatory variables in the OLS model did not show any significance in the first decadal period (2000-2010). In comparison, the MGWR model was able to explain several variables at the local or regional level. This indicates a global model like OLS barely accounts for space variance and may be less suitable for tackling complex issues such as UGS inequity. However, MGWR is not free from limitations. For example, the underlying logic of an MGWR model is that there exists spatial non-stationarity, which should theoretically work well for complex issues like UGS inequity. Because the study only focuses on the census-tract level and all the explanatory variables might not have that many varying scale differences, the result can pose a risk of over-fitting. Despite potential limitations, this study contributes to the application and comparison of OLS and MGWR models, and it seeks to expand on exploring the use of MGWR in landscape architecture to test for variation in the relationship across space by creating a weight matrix for closer observations in UGS research. We suggest the comparison of spatial models can shed light on the problems associated with aggregated data, and the growing body of research on the longitudinal study regarding UGS inequity. The significance of equitable access to UGS has been recognized both in practice, such as American Society of Landscape Architects (ASLA), and in research, notably in the field of landscape architecture where growing attention to environmental justice is being paid recently by addressing unequal distribution of resources against vulnerable communities (Chang, 2018; Miller et al., 2022). In seeking to align with these efforts to enhance environmental justice in UGS, the findings of this study will provide valuable insights and methodological alternatives for landscape architecture practitioners, policymakers, and city officials, who want to understand how existing UGS inequity issues have evolved spatially and temporally and what statistical methods can be used to efficiently target the most needed communities.

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