HOW URBAN GREEN SPACE SPATIAL PATTERN AFFECTS ITS EQUITY: A BAYESIAN QUANTILE REGRESSION APPROACH

by

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ABSTRACT

Urban green space (UGS) is not evenly distributed in many urban areas. Marginalized communities often lack greenspace due to legacies of disinvestment. However, little is known regarding how the spatial pattern of UGS determine UGS equity at the regional level. Moreover, the potential nonlinearity and spatial heterogeneity in the USG pattern and equity relationship are obscure. Here, we explored how UGS equity varies among UGS spatial patterns and socioeconomic gradients in seven counties in Southeast Michigan. We quantified UGS equity by spatially explicit Gini coefficients and computed UGS spatial patterns by landscape metrics. A Bayesian quantile regression model was then applied to investigate the nonlinear relationship between landscape spatial patterns and UGS equity in the whole study area and three sub-regions with different population density.

Our results showed that at the regional scale, patch density and the large patch index have significantly negative effect on UGS equity at all levels. The mean patch shape index is negatively correlated with UGS equity in areas with a moderate equity level (0.52-0.92). At the sub-regional level, patch density is the most efficient predictor of USG equity in densely populated areas, while in areas with low population density, the large patch index also affects UGS equity. Therefore, we recommend regions with extremely poor equity should increase the amount of UGS instead of increasing the total area of UGS blindly. To enhance UGS equity in comparatively fair regions, government should avoid the fragmentation of existing UGS and develop new UGS with a more complex shape and longer circumferences to serve more communities

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Chapter 1 Introduction

Urban green space is the land that consists predominantly of unsealed, permeable soft surfaces such as soil, grass, shrubs, and trees (Swanwick, Dunnett, & Woolley, 2003). Generally, UGS includes public green space such as parks, sporting fields, community gardens, nature conservation areas, and private green space such as private yards, corporate campuses, and so on (Roy, Byrne, & Pickering, 2012; Wolch, Byrne, & Newell, 2014). In this paper, we consider UGS as a green space that has public access. UGS has both ecological and social benefits. Existing research has proven that UGS can provide ecosystem services such as reducing air pollution, temperature cooling, noise reduction, increasing carbon storage as well as stormwater management (Graça et al., 2018; Sikorska, Łaszkiewicz, Krauze, & Sikorski, 2020; Teresa, Lisa, Patrick, & Stephan, 2017; Yu et al., 2020; Yuchi, Sbihi, Davies, Tamburic, & Brauer, 2020). As for the social benefits, UGS has been proven essential for public health due to its positive impact on recovery from mental fatigue, lowing the stress level, and reducing respiratory disease, heart rate, mortality, and violence (Alcock et al., 2017; Berman et al., 2012; Beyer et al., 2014; Kondo, Fluehr, McKeon, & Branas, 2018; Ward Thompson et al., 2012). Multifunctionality in green infrastructure was addressed to emphasize the ability to provide various recreational functions for city dwellers (Gobster, Nassauer, Daniel, & Fry, 2007; Nassauer, 1995). Considering all these benefits, UGS is regarded as an essential resource for city dwellers. However, UGS was unevenly distributed in most cities (Wolch et al., 2014). Because of the disparity of green space resource and the related ecosystem service possession, the inequitable UGS distribution has been recognized as a critical environmental justice issue.

The mismatch between UGS demand and provision is a critical aspect of UGS equity, which has high spatial heterogeneity across socioeconomic gradients such as income, race and education (Dai, 2011). Many studies showed that population with lower socioeconomic status (SES) have less access to UGS. For example, it was found that white-majority census tracts generally enjoy significantly better UGS accessibility than minority-dominated census tracts (Liu, Kwan, & Kan, 2021). Also, the deprivation of access to UGS for African Americans was proved in a study in metropolitan Atlanta (Dai, 2011). As for income factor, environmental inequality is evident in Shanghai, China wherein wealthier communities benefit more from green space accessibility than disadvantaged communities (Yang Chen, Yue, & La Rosa, 2020). Besides, residents from low socioeconomic positions seem to suffer from double jeopardy; they lack both individual and community resources (Hoffimann, Barros, & Ribeiro, 2017). However, some studies found that sometimes the disparity of UGS equity among socioeconomic gradients was not significant. A case study of six cities in Illinois showed that racial/ethnic minorities had less tree canopy in their neighborhoods, but it did not find significant differences in terms of access to parks (Zhou & Kim, 2013). Moreover, significant differences among socioeconomic groups in terms of park access and changes in that access have not been detected in Hangzhou, China from 2000 to

2010 (Wei, 2017). Though the above factors which are associated with the UGS equity have been thoroughly studied, there are still some other factors receiving limited attention, especially those spatial factors.

The previous studies of the UGS spatial patterns and equity mainly focused on some intermediary variables such as urban dynamics and ecological function performance but did not directly establish the relationship between UGS spatial pattern and its equity. The development of UGS system is restricted by the built environment and thus displays differing spatial configurations (Huang, Yang, & Jiang, 2018). Also, the dynamics of urban development, land use type and diverse residential land type can affect the spatial distribution of UGS (C. Sun et al., 2019). One study in Munich indicates that the urban dynamic scenarios are significantly effective on UGS equity. Besides, the study found that among different urban dynamic scenarios, compact growth is the most favorable in terms of UGS equity (Xu, Haase, Pribadi, & Pauleit, 2018). Another study in Leipzig, Germany applied a Morphological Spatial Pattern Analysis approach to explore the relationship between green infrastructure spatial patterns and its equity and suggest more green infrastructure bridges to enhance structural connectivity as well as spatial equity (Wang, Xu, Pauleit, Kindler, & Banzhaf, 2019). In terms of ecological function performance, many researchers utilized landscape metrics to quantify the spatial pattern of UGS (Asgarian, Amiri, & Sakieh, 2015; Kong, Yin, & Nakagoshi, 2007; Sun et al., 2020) and then examined the correlation between UGS spatial pattern and ecological function performance. The spatial pattern of UGS has been proved to have significant effect on land surface temperatures which related to urban heat island and the combination of Patch density (PD) and edge density (ED) is proved to be the most deterministic factors of land surface temperature (Maimaitiyiming et al., 2014). A study in the region of Illinois-Indiana-Ohio also proved that optimizing UGS spatial pattern can help mitigate urban heat island effect (Li & Zhou, 2019). As the ecological function is a critical part of UGS benefits, the difference in ecological function performance in different areas can cause the disparity in UGS equity. With all the evidence, it is rational to consider improving the UGS equity by optimizing the UGS spatial pattern. Many previous studies have proved the inequity in UGS distribution on different levels, however, the spatial factors were missed in these studies and the direct linkage between UGS spatial pattern and UGS equity was still not completely established yet in the past research.

As urban issues are usually complicated and tend to be non-linear, the relationship between UGS equity and spatial patterns can be possible to have the quantile effect and be sensitive to the quantiles. Lacking theoretical foundation, there is no plausible reason for such a simplification linking UGS equity only to the conditional mean of the response variable, which may over- or underestimate or incorrectly assume that no correlation exists (Marco, Nadja, Hannah, Paulien, & Peter, 2018). To our best knowledge, there is no research on how UGS spatial pattern affects UGS equity for points other than the mean of the response distribution. Yet, it is rational to assume that the upper, central, and lower quantiles of the response variable may be affected differently by UGS. Previous studies have proved that the effect of the available amount of UGS on human well-being is non-linear with the marginal utility of UGS first increasing and then decreasing (Christine & Katrin, 2015). A non-linear association of greenness with self-rated general health among older adults was investigated in China (Baishi et al., 2022). Also, the non-linear association between quality adjusted UGS and subjective well-being for different levels of self-assessed subjective well-being was examined (Farahnaz, Andi, & Wendy, 2021). Considering all the complexity of urban related issues, it can be more realistic to make the hypothesis of a non-linear effect in this study.

Besides, the UGS equity is also sensitive to the population density. Urban population growth is leading to growing concerns about land use change, sustainable utilization of land, and the loss of UGS. With the increase of urban population density, the demand of UGS increases. However, the infill development intensified the shortage of potential UGS provision and thus increased the mismatch between UGS provision and demand. The population density of central urban areas is higher than that of the periphery in cities (Corner, Ongee, & Dewan, 2014), while land available for green space construction in central urban areas is scarce (Chang et al., 2017). The mismatch between the spatial patterns of green spaces and population will lead to people in different locations enjoying a different amount of ecosystem services provided by green spaces and thus cause a spatial heterogeneous equity issue. Thus, how to target the hot spots of UGS inequity and apply a smart planning and design for specific regions based on different context still need to be studied and explored.

In this study, we apply a novel Bayesian quantile regression (BQR) approach to study UGS equity, with the hypothesis that the urban spatial pattern effect on UGS equity is different according to the level of equity. We investigate the nonlinear effect of UGS spatial pattern on UGS equity in Southeast Michigan where cities are confronting severe urban sprawl and equity issue and hold massive vacant lots to be revitalized. We aim to (1) quantify the green space equity with Gini coefficient and describe its spatial distribution, (2) examine the non-linear effect of green space spatial pattern and SES on green space equity. (3) investigate if the effect is different in three sub-regions with different population densities.

Chapter 2 Methodology

2.1. Study Area

Southeast Michigan is a region comprising seven counties located in the lower peninsula of Michigan, bordered by Lake St. Clair and Lake Erie. It covers a total area of 4,598 square miles with a population of 4.7 million inhabitants (United States Census Bureau, 2010). Urban sprawl is a growing problem in the region, especially in Detroit. This leads to the mass movement of people from the inner city to suburban areas. Despite this, most inhabitants in Livingston, Macomb, Monroe, Oakland, Washtenaw, and Wayne Counties still live in urban areas. Our study area encompasses all categorized urban areas in Southeast Michigan by the United States Census Bureau (2010) as shown in Fig. 1. This includes both urbanized areas of over 50,000 inhabitants and urban clusters of over 5,000 inhabitants (Southeast Michigan Council of Governments, 2018). Fig. 1 shows that relatively large patches of UGS are mainly distributed in the outer edges of the region or along rivers. The central area of Detroit shows numerous vacant lots and small, fragmented UGS.

To better study the spatial variations of UGS equity in the study area, we divide it into three sub-regions based on population density. The first class is the fringe area with a density of fewer than 500 people per square mile. The second class is the middle area with a density of fewer than 1000 people per square mile but more than 500 people per square mile. The third class is the core area with a density of more than 1000 people per square mile.

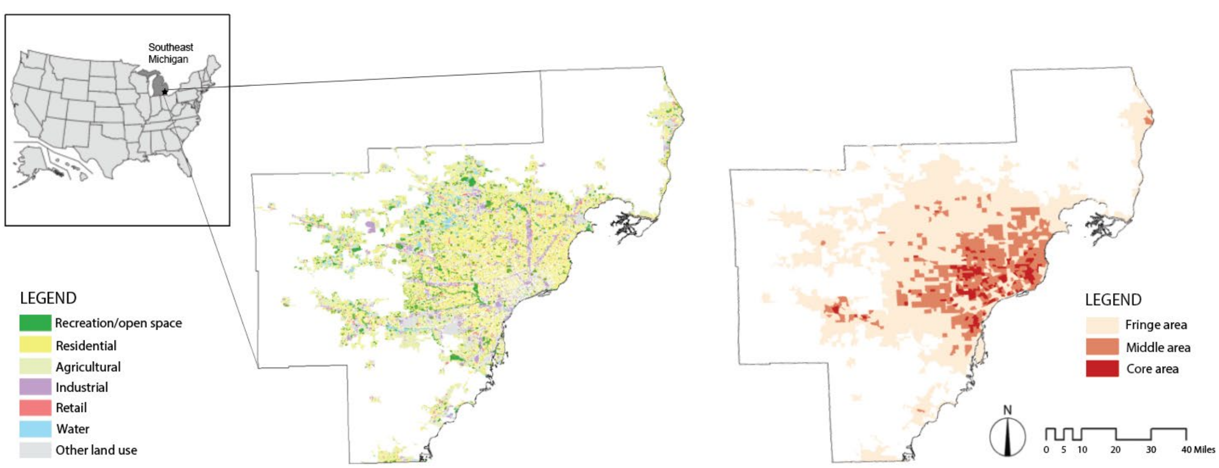

Figure 1. *Study area and its sub-regions. The left figure shows the location of our study area and main categories of land use in urban areas of Southeast Michigan. The green color represents the recreation/open space category which is defined as UGS in our study. The right figure shows the sub-*

regions of our study. The sub-regions were defined by the population density. The light red color represents fringe area with a population density of fewer than 500 people per square mile. The red color represents middle area with a density of fewer than 1000 people per square mile but more than 500 people per square mile. The dark red color represents core area which has a density of more than 1000 people per square mile.

2.2. Measuring the Spatial Equity of Urban Green Space

In this study, we indexed the general equity level of every census tract in our study area with the Gini coefficient (Zhang, Lu, & Holt, 2011). The original Gini coefficient is generally used to measure the income inequality within a nation or a social group in economics. Considering its ability to describe the inequality in a specific zone among values of a frequency distribution, a growing number of studies bring it into urban development equity studies and adapt it to a new context (Yi Chen et al., 2022; Wang et al., 2019; Wüstemann, Kalisch, & Kolbe, 2017). There are many other ways to examine the accessibility of UGS considering the distance to, e.g., UGS, time-consuming, and park acreage. However, the definition and components of access are not well conceptualized yet (Rigolon, 2016), and there is little consistency between studies in terms of methodology and definitions (Mears, Brindley, Maheswaran, & Jorgensen, 2019). The provision of UGS for residents' regular recreational activities is supposed to be no further than the walkable distance, and we define walking distance as not exceeding 300m (Wüstemann et al., 2017). The Gini coefficient ranges from 0 to 1, with 0 representing perfect equality and 1 representing maximal inequality, as shown in Eq. (1):

$$G = 1 - \sum_{i=1}^{n} \frac{p_i}{p}(\theta_i + \theta_{i-1}) \tag{1}$$

with Eq. (2) being:

$$\theta_i = \frac{x_i^{green}}{x^{green}} \tag{2}$$

where x_i^{green} is the absolute amount of UGS in a 300m buffer around grid cell as the dependent variable; x^{green} is the total amount of UGS in the census tract where grid cell n locates; P is the total population of the census tract, and P_i is the population within grid cell i.

We calculated the Gini coefficient as follows: Firstly, we created a 100m × 100 m grid layer with only centroids and intersected with the study region in ArcGIS 10.6. To avoid incomplete grid cells and buffers, we selected the grid centroids located in the study area. Based on these selected centroids, we created a 100m × 100 m square buffer and a 300m round buffer. Then, we calculated the amount of UGS in each 300m buffer and the population within each grid cell. The population data for Gini coefficient calculation is provided by the Dasymetric Population for the Conterminous United States data from an EnviroAtlas dataset by the United States Environmental Protection Agency. This dataset intelligently reallocates the 2010 population from census blocks to 30m-sized pixels based on land cover and slope. Considering the subsequent mathematical calculations, we then removed grid cells with a population less than 1 or without any existing UGS. Finally, the Gini coefficient was calculated for each census tract.

2.3. Landscape Metrics and Socioeconomic Variables

In this research, we applied landscape metrics to quantify UGS spatial patterns. Many studies considered UGS as one category of urban land cover and calculated different landscape structure metrics based on a Fragstats method from extracted remote sensing images, analyzing the overall pattern of vegetation (Huang et al., 2018). Here, we mapped UGS based on the land use category of "recreation/open space". Private gardens within housing areas are not considered as UGS in this study (Wüstemann et al., 2017). There are some other land use categories that also have the potential to serve as UGS. However, considering a "golf course" lacks public accessibility and "agricultural" or "cemetery" has limited recreational functions, we exclude these land use categories (Kabisch, Strohbach, Haase, & Kronenberg, 2016; Xu et al., 2018). With a series of landscape metrics such as percentage of landscape, patch density, and mean patch shape index, we are enabled to quantify the composition and configuration of landscapes and thus describe the spatial pattern of UGS. The selection of appropriate landscape structure metrics can be ambiguous and be adjusted based on different research purpose

In order to capture the impact of the UGS spatial pattern on UGS equity in 2010, five landscape metrics are selected to quantify the spatial pattern of UGS (Table. 1): (1) Class area (CA), (2) Patch density (PD), (3) Largest patch index (LPI), (4) mean Euclidean nearest neighbor distance (ENN_MN), and (5) mean Patch shape index (SHAPE_MN) (Huang et al., 2018). With these landscape metrics, we can quantify the abundance, fragmentation, large patch dominance, isolation, and shape complexity of UGS in the study area. As the overall UGS change is not obvious from 2010 to 2020, we estimate the situation in 2010 with land use data from 2020. Regional land use data recorded in 2020 are provided by the Southeast Michigan Council of Governments (SEMCOG). We then calculated the landscape metrics of UGS in Fragstats (version 4.2) for each census tract.

We deployed four socioeconomic indices as control variables (Table. 1) as race, income, and other socioeconomic factors are likely to affect UGS distribution and equity (He, Wu, & Wang, 2020; Hoffimann et al., 2017; Łaszkiewicz, Kronenberg, & Marcińczak, 2021). Four socioeconomic variables are the minority, median household income, housing unit, and high school. The socioeconomic data in this study are derived from the 2010 US government census and the American Community Survey of 2010.

Table 1. Descriptive variables.

Category	Variable	Description	Unit	Data Source
UGS equity	Gini coefficient	The index of inequity level	None	SEMCOG, 2020, land use; EnviroAtlas dataset

Landscape metrics	Class area (CA)	CA equals the sum of the areas (m^2) of all patches of the corresponding patch type divided by 10,000 (to convert to hectares)	Hectares	SEMCOG, 2020, land use
	Patch density (PD)	PD equals the number of patches of the corresponding patch type divided by total landscape area (m^2), multiplied by 10,000 and then by 100 (to convert to 100 hectares).	Number per 100 hectares	SEMCOG, 2020, land use
	Largest patch index (LPI)	LPI equals the area (m^2) of the largest patch of the corresponding patch type divided by total landscape area (m^2), multiplied by 100 (to convert to percentages)	Percent	SEMCOG, 2020, land use
	Mean Euclidian nearest neighbor distance (ENN_MN)	ENN equals the distance (m) mean value over all urban green space patches to the nearest neighboring patch, based on the shortest edge-to-edge distance from cell center to cell center; FRAGSTATS computes the mean in ENN (ENN_MN)	Meters	SEMCOG, 2020, land use
	Shape index (SHAPE_MN)	SHAPE equals patch perimeter (m) divided by the square root of the patch area (m^2), adjusted by a constant to adjust for a square standard; FRAGSTATS computes the mean in SHAPE (SHAPE_MN)	None	SEMCOG, 2020, land use

Socioeconomic data	Minority	Percentage of major minorities, including African American, Hispanic, and Asian	Percent	United States Census Bureau, 2010, summary file 1
	Median household income	Estimated median household income (in inflation-adjusted USD for 2010)	Dollar	American Community Survey, 2010, data profile
	Household unit	Number of housing units in each census tract	Number	United States Census Bureau, 2010, summary file 1
	High school	Percentage of the population with a high school diploma	Percent	American Community Survey, 2010, data profile

2.4. Bayesian Quantile Regression

In this study, we innovatively apply Bayesian quantile regression to investigate whether the effects of UGS spatial pattern change depending on the level of equity at the regional and sub-regional levels. In this field, quantile regression enables us to investigate whether the effects of UGS spatial pattern change depending on the levels of equity in the urban area, whereas mean regression estimates only a single effect for the average equity condition. A detailed mathematical formula derivation of the BQR method can be provided by the R package—bayesQR for reference. We built a regression model for the BQR analysis, as shown in Eq. (3) and Eq. (4):

$$Y_i = \alpha_1^p x_1 + \alpha_2^p x_2 + \alpha_3^p x_3 + \ldots + \alpha_n^p x_n + \epsilon_i^p \tag{3}$$

$$\alpha \sim N(\alpha_0, V_0) \tag{4}$$

the dependent variable Y_i represents the level of UGS equity. The independent variable x includes all the landscape metrics and socioeconomic data above. ϵ_i^p and α_n^p are the regression intercept and slope at the p quantile, respectively. α followed a normal distribution with α_0 as the average and V_0 as the variance. We standardized all the variables to keep the regression parameters on similar scales and removed the first 100 iterations to assure a more stable and accurate result.

Chapter 3 Results

3.1. Urban Green Space Equity Distribution

The Gini coefficient ranges from 0.52 to 0.99, indicating overall uneven UGS distribution in the study area. Over 70% of Gini coefficients are larger than 0.9, indicating extremely unequitable UGS in most census tracts. Fig. 2 clearly shows the spatial distribution of the Gini coefficient that the center of Detroit has extremely uneven UGS distribution, while the UGS distribution in the outer edges of the western region has comparatively more equity. Though there is no significant difference in the Gini coefficient between different sub-regions, the fringe area tends to have a lower Gini coefficient than the core area, which typically has a Gini coefficient larger than 0.9. In order to make the Gini coefficient and UGS spatial pattern look more intuitive, we extracted 9 examples with different percentages of urban green space from all the census tracts (Fig. 3).

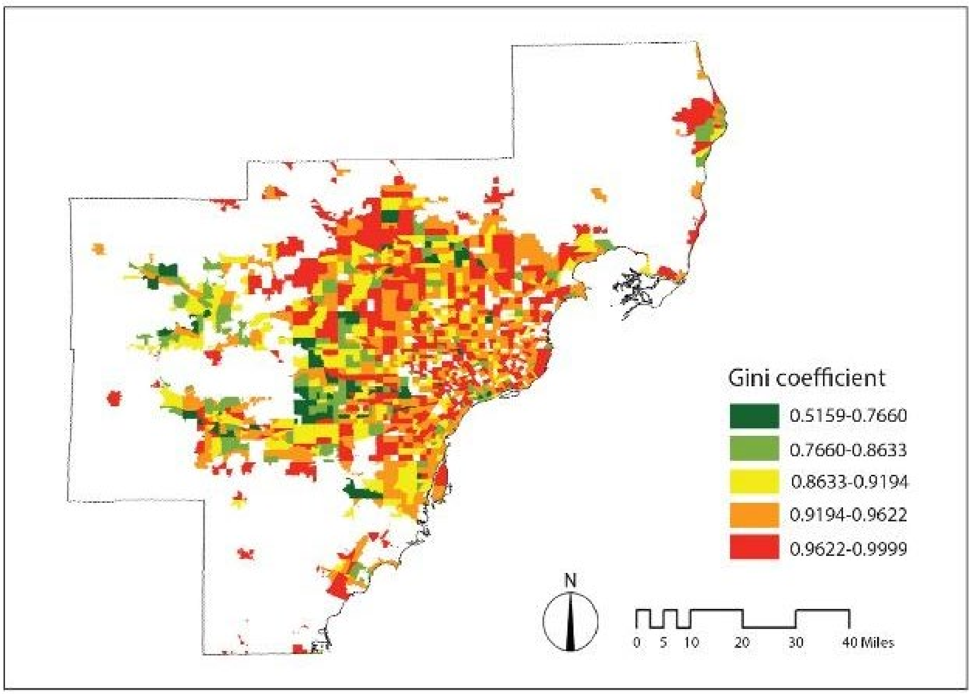

Figure 2. *Spatial distribution of the Gini coefficient. The figure shows the Gini coefficient for each census tract in our study area. From red color to green color, the Gini coefficient decreases and the equity level of UGS increases.*

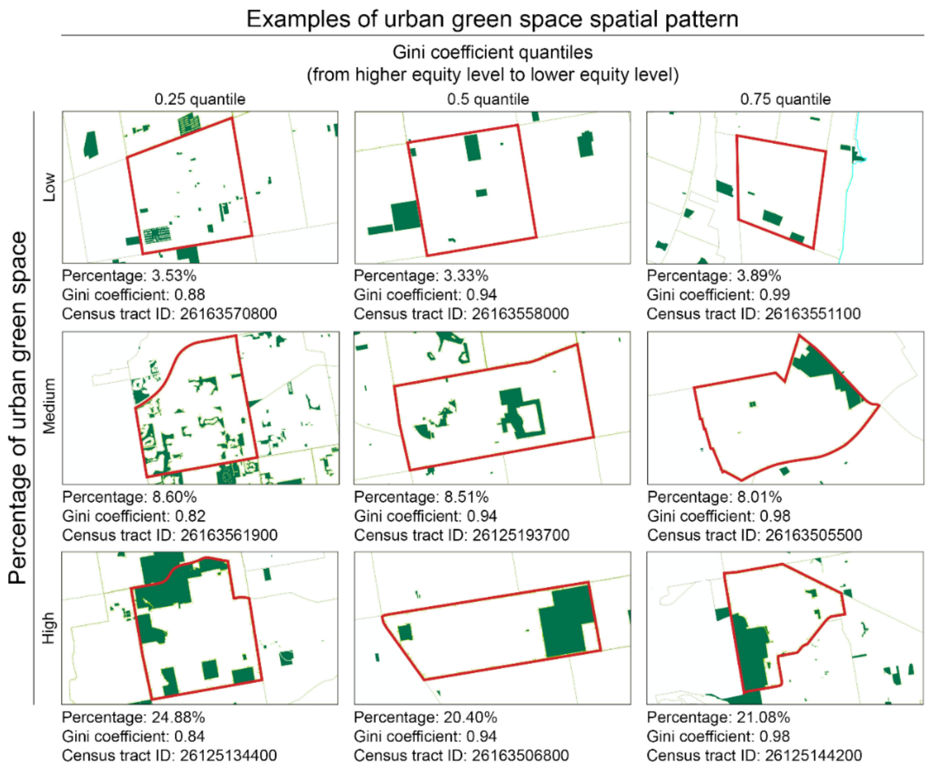

Figure 3. *Examples of urban green space spatial pattern. Nine examples were extracted from all the census tracts in the map. We controlled either the percentage of UGS or the Gini coefficient to better compare differences in UGS spatial pattern. The green patches are the UGS, and the red lines show the boundaries of the extracted census tracts.*

Table 2. Descriptive statistics.

Variable	**Sub-region**	**Population Density**	**Min.**	**1st quantile**	**Mean**	**3rd Quantile**	**Max.**
	Fringe area	<500/mi^2	0.52	0.89	0.92	0.97	0.99
Gini coefficient	Middle area	>500/mi^2, <1000/mi^2	0.55	0.90	0.92	0.97	0.99
	Core area	>1000/mi^2	0.56	0.91	0.91	0.97	0.99
	Fringe area	<500/mi^2	0.09	6.30	39.54	47.07	619.65
CA	Middle area	>500/mi^2, <1000/mi^2	0.18	2.25	10.76	13.59	115.83
	Core area	>1000/mi^2	0.18	0.99	4.66	4.86	45.81
	Fringe area	<500/mi^2	0.07	0.91	2.27	2.89	93.19
PD	Middle area	>500/mi^2, <1000/mi^2	0.37	1.44	2.63	3.25	11.61
	Core area	>1000/mi^2	1.03	1.59	3.99	4.08	24.02
	Fringe area	<500/mi^2	0.02	0.82	4.48	5.42	57.62
LPI	Middle area	>500/mi^2, <1000/mi^2	0.04	0.74	3.56	3.98	34.55

	Core area	>1000/mi^2	0.07	0.61	2.74	3.02	20.43
	Fringe area	<500/mi^2	1.00	1.17	1.29	1.38	2.40
SHAPE_MN	Middle area	>500/mi^2, <1000/mi^2	1.00	1.09	1.23	1.32	3.00
	Core area	>1000/mi^2	1.00	1.05	1.15	1.23	1.58
	Fringe area	<500/mi^2	60.00	150.40	366.50	437.10	4355.00
ENN_MN	Middle area	>500/mi^2, <1000/mi^2	60.00	187.60	392.90	510.00	1793.20
	Core area	>1000/mi^2	70.14	153.15	400.26	577.06	1727.54

3.2. Effects of Urban Green Space Spatial Pattern on Its Equity

3.2.1. Effects at the medium equity level

Individual associations between UGS spatial pattern and equity at 0.5 quantile are given in Fig. 3 and Table 2, indicating that generally, areas with larger UGS patch density (PD), more large patches of UGS (LPI) and more UGS with complex shape (SHAPE_MN) are associated with higher level of equity. Patch density (PD), large patch index (LPI) and shape index (SHAPE_MN) have significant negative effects on Gini coefficient. Though not significant, class area (CA) has a negative effect on Gini coefficient, indicating that with more total areas of UGS, the area has lower Gini coefficient and thus has more equitable UGS distribution. Mean Euclidian nearest neighbor distance (ENN_MN) is also not significantly correlated with the Gini coefficient but has a positive tendency. With longer Euclidian nearest neighbor distance (ENN_MN), the UGS patches are more isolated, and may harm the UGS equity.

Table 3. Bayesian Quantile Regression model for Gini coefficient at the 0.5 quantile (CI: 95%)

Variable	Coefficient	Lower Range	Upper Range
CA	-0.09	-0.23	0.05
PD	-0.66*	-0.81	-0.52
LPI	-0.39*	-0.52	-0.25
SHAPE_MN	-0.12*	-0.21	-0.04
ENN_MN	0.04	-0.01	0.10
Minority	-0.01	-0.08	0.07
Income	-0.03	-0.14	0.07
Household Unit	0.01	-0.06	0.07
High school	-0.01	-0.10	0.07

3.2.2. Effects at Different Equity quantiles

However, the correlation between UGS spatial pattern and Gini coefficient differs at different equity levels, proving that the relationship between them is nonlinear (Fig 3). The negative effect of patch density (PD) on the Gini coefficient is significant across all quantiles and declines with the increase of quantiles. This indicates that patch density (PD) has less effect on UGS equity in areas with lower equity level. Large patch index (LPI) also has significant declining negative effect on the Gini coefficient across all quantiles and thus is also effective in areas with any equity levels. Shape index (SHAPE_MN) has a negative effect on the Gini coefficient at the 0.25 quantile (0.89) and 0.5 quantile (0.94). However, this effect loses its significance at the 0.75 quantile (0.97), indicating that the complexity of UGS patch shape can only improve the equity in areas with higher equity level. As covariates are standardized, our model additionally suggests that patch density (PD) has the largest impact on UGS equity of all selected variables, followed by (large patch index) LPI with a medium effect, and shape index (SHAPE_MN) with a relatively small impact.

All the socioeconomic factors are not significantly correlated with UGS equity but still have different tendencies. Income has a negative tendency towards the Gini coefficient and this tendency increases with the increasing of quantiles. This indicates that people with higher median household income tends to enjoy more equitable UGS resources especially in areas with lower equity level. At the 0.25 quantile (0.89), the number of household units has a positive influence on UGS equity, indicating that in more equal areas, UGS equity decreases with more population in the area. However, this effect tends to change to be negative at the 0.75 quantile (0.94). The minority and high school diploma don't show any potential effects on the Gini coefficient.

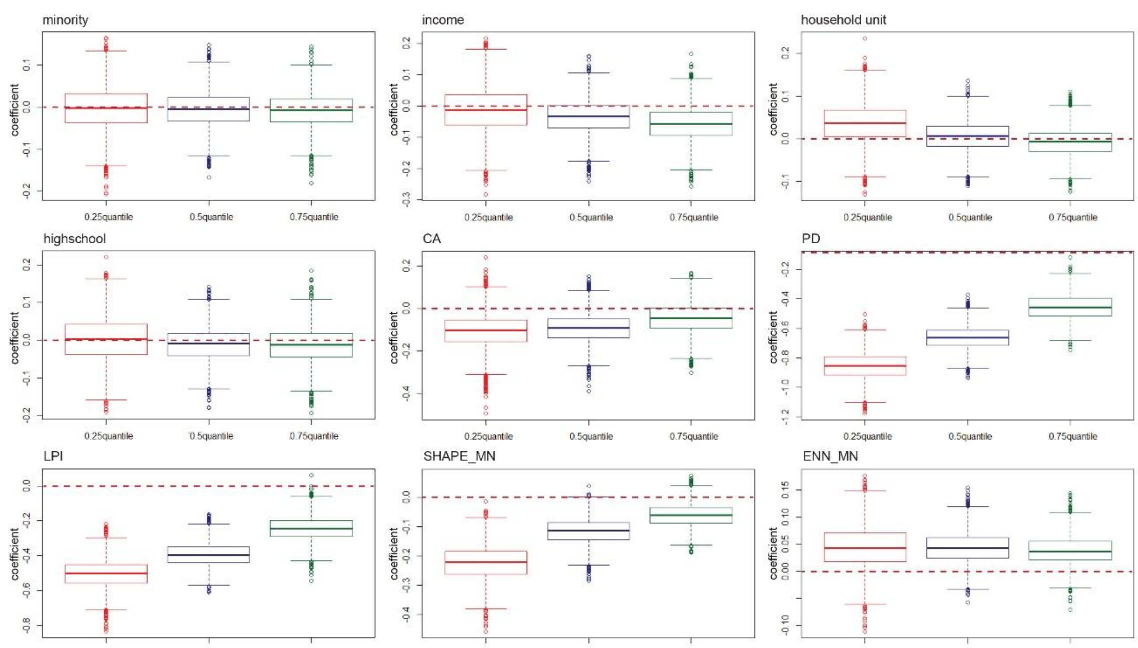

Figure 4. *Coefficient distribution of independent variables for different quantiles. We extracted all the coefficients from 5000 iterations of Bayesian quantile regression model and burnt in the first 100 iterations. The Confident interval of our result is 95%. The red, blue and green colors represent the results at the 0.25, 0.5 and 0.75 quantiles. The dash line at 0 is a standard of significance.*

3.3. Relationship Between Urban Green Space Landscape Metrics and the Gini Coefficient in Sub-regions

Among all sub-regions, the fringe areas tend to have more significant UGS spatial pattern-equity association than the core areas. In the middle area, the results seem to be more complicated due to the heterogeneity in this sub-region. The variance of coefficients in the core area tends to be more dispersed with less significance.

Patch density (PD) is the most effective variable of all the independent variables. In fringe area and middle area, patch density (PD) has a significant negative impact on the Gini coefficient across the quantiles. In core area, patch density (PD) keeps the significant negative effect at the 0.25 quantile (0.89) and the 0.5 quantile (0.94) but lose the significance at the 0.75 quantile (0.97). Thus, in core area, the increase of patch density of UGS can improve UGS equity in census tracts with higher equity level and may not be as effective as that in less equal areas. Large patch index (LPI) has a significant negative effect on the Gini coefficient in fringe area at the 0.25 quantile (0.89) and the 0.5 quantile (0.94). Thus, in fringe area, census tracts with more large UGS patches are more equal especially in areas with higher equity level. In fringe area, Shape index (SHAPE_MN) has a significant negative effect on Gini coefficient at the 0.25 quantile (0.89) and the 0.5 quantile (0.94). In middle area, shape index (SHAPE_MN) has a significant negative effect on Gini coefficient at only 0.25 quantile (0.89). In this way, census tracts with more complex UGS patches have better UGS equity in both fringe and middle areas, especially in areas with higher equity level. Though not significant, class area (CA) has a negative tendency toward Gini coefficient across all the quantiles in fringe, middle and core areas, indicating that in all the sub-regions, census tracts with larger total area of UGS tends to have higher UGS equity. In both fringe area and middle area, mean Euclidean nearest neighbor distance (ENN_MN) has a positive tendency towards the Gini coefficient across all the quantiles, while in core area, it loses this tendency. Thus, the isolation and fragmentation of UGS patches may harm the UGS equity in fringe and middle areas.

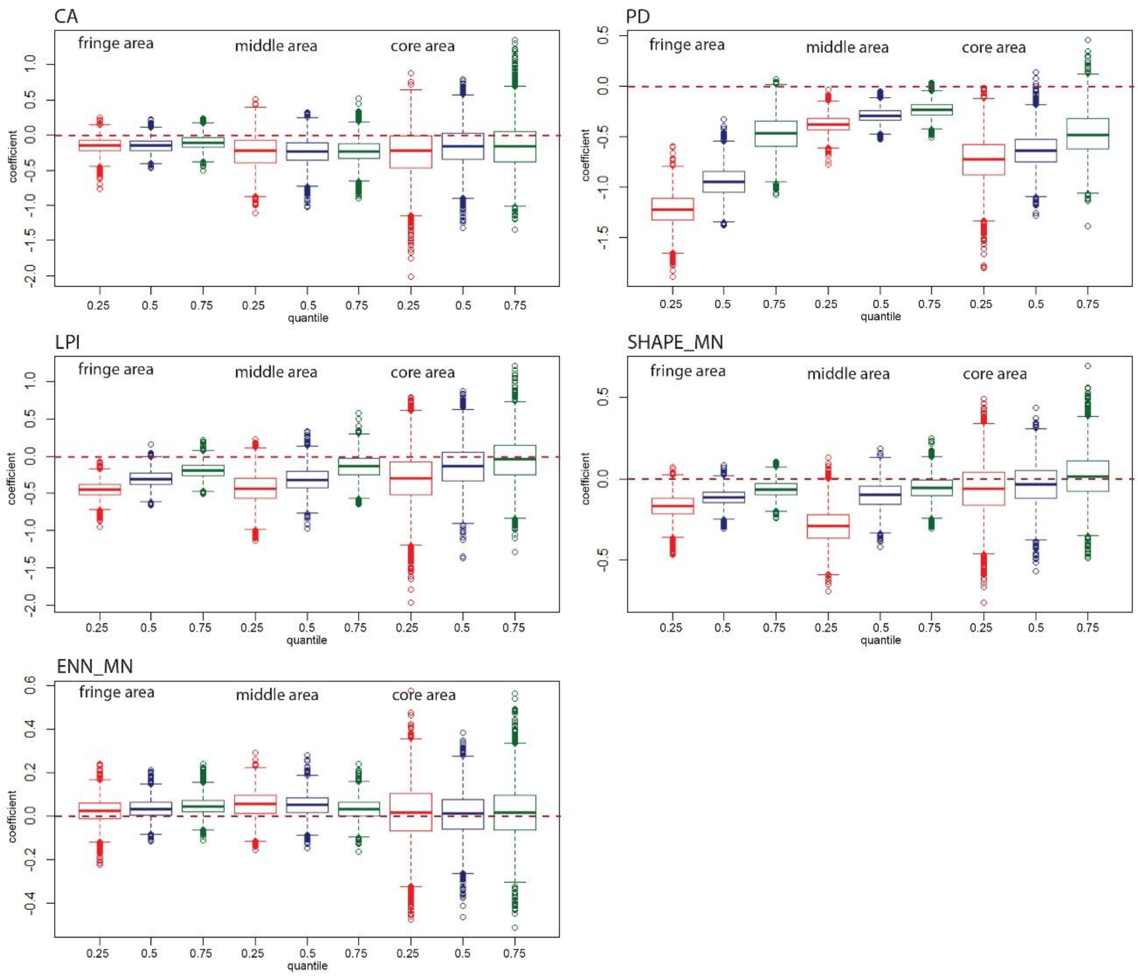

Figure 5. *Coefficient distribution of landscape metrics in sub-regions for different quantiles. The box plots show the distribution of all the coefficients of landscape metrics and Gini coefficient. The Confident interval of our result is 95%. The red, blue and green colors represent the results at the 0.25, 0.5 and 0.75 quantiles. The dash line at 0 is a standard of significance. By comparing the result in different sub-regions, we can explore the spatial heterogeneity and bring up particular strategies for each sub-region.*

Though all the socioeconomic variables don't meet the significance, there are still some tendencies that need to be pointed out. The minority tends to have a negative effect at 0.25 quantile (0.94) in the middle area. Income tends to have a positive effect at the 0.25 quantile (0.89) in the fringe area, but the effect turns to be negative at the 0.75 quantiles (0.97). Income then keeps the negative tendency across all the quantiles in both middle and core areas. Household unit tends to have a positive effect at all quantiles in fringe area. This positive effect decreases with the increase of quantile. High school diploma has a positive tendency at 0.25 quantile (0.89) in fringe area, indicating that in fringe area, census tracts with a larger high school education rate tend to have more equitable UGS distribution, especially in areas with higher equity level.

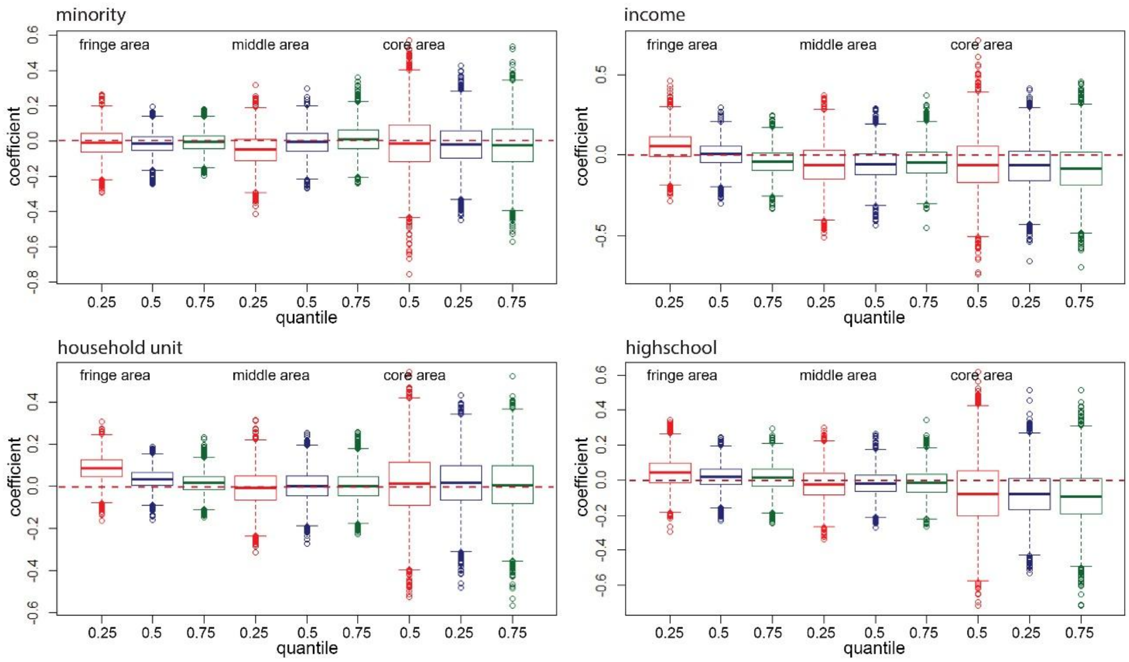

Figure 6. *Coefficient distribution of socioeconomic variables in sub-regions for different quantiles. The box plots show the distribution of all the coefficients of socioeconomic variables and Gini coefficient. The Confident interval of our result is 95%. The red, blue and green colors represent the results at the 0.25, 0.5 and 0.75 quantiles. The dash line at 0 is a standard of significance. In this study, the relationship between socioeconomic variables and Gini coefficient is not significant.*

Chapter 4 Discussion

4.1. Spatial and Socioeconomic impacts on UGS Equity

In this article, we partially addressed the issue that how the spatial pattern of UGS affects its equity in a non-linear way by calculating the Gini coefficient and landscape metrics of every census tract and applying the BQR model. Combine the results from this study with Figure 2, it's clear that with the similar percentages of UGS, the decrease in patch density increases the Gini coefficient and decreases the equity. With more patches of UGS, the supply of UGS increases, therefore more residents can get the accessibility to a UGS. In this way, the increase of patch density can largely affect the UGS equity. Besides, the UGS patches with more complex edge can increase the equity level because they could serve more residents with longer perimeter. Large patch dominance also contributes to the UGS equity. For two areas with similar percentage of UGS, the area where large patches dominant can be more equitable. This is the first time that BQR model is applied in UGS equity study. It is proved that the spatial pattern of UGS has a significant effect on UGS equity and varies across the quantiles. The sufficient provision of UGS is considered to be a critical aspect for social and ecological benefits (Wüstemann et al., 2017), but counterintuitively, total area of UGS is not the factor that has the greatest impact on the UGS equity, especially in areas where the UGS is less equally distributed. Instead, patch density, large patch index and shape index play more important roles in the equal distribution of UGS. This result demonstrates that the quantity of UGS area is not as important as the configuration of UGS for UGS equity. Therefore, regions with limited areas of UGS can also improve the equity via smart planning. In other words, without reasonable planning, a region with large areas of UGS is likely to be unevenly distributed and fail to provide equitable services for residents.

Since areas with high Gini coefficients generally have few UGS, a large portion of Gini coefficients is above 0.9. The difference is relatively small at a high quantile of the Gini coefficient. This probably caused the result that with the increase of quantile, the impacts of landscape metrics decreased. In contrast, the impact of income increases with the increase of quantile though not significant enough, indicating that overall, income has more impact on UGS equity in areas with a more inequitable distribution of UGS. In these areas, people with higher median household income tend to possess more UGS provision while those with lower income have limited access to UGS. This result basically reached an agreement with former research that UGS disparity was usually present in socioeconomically disadvantaged areas. (Pauleit, Ennos, Golding, & planning, 2005; Sathyakumar, Ramsankaran, Bardhan, & Sensing, 2019).

4.2. Improving Urban Green Space Equity in Diverse Regions

The application of the BQR model enabled us to identify the regions that need improvement urgently and provide targeted strategies for diverse regions. In this study, the results helped to identify the most effective UGS spatial pattern indicators for the UGS equity at both regional and sub-regional levels. Thus, strategies that are adapted to local conditions can be introduced to the study area and this method can be applied to any region.

4.2.1. Improving Urban Green Space Equity in regions with different equity levels

With the results at the regional level, we could propose effective planning strategies to promote UGS equity in urban areas with differing UGS equity. For regions with extremely inequitable distribution of UGS, the most efficient way to achieve equity is enlarging the largest UGS patch in the region together with adding many small UGS patches. Usually, the governments focus on planning a large park with a larger service radius and higher quality, however, it is less likely for people to take daily recreational activities in a large park despite its accessibility (Kabisch et al., 2016). More UGS patches rather than larger UGS patches will provide more accessible UGS for residents within their walkable distance and thus help promote the UGS equity in the region. In regions with moderate levels of UGS equity, we should consider the impact of shape complexity additionally. A rectangular park with a thin and long shape will serve more community than a round shape park with the same area.

4.2.2. Improving Urban Green Space Equity in regions with different population density

The population density map (Fig. 1) shows that the population distribution in the study area is uneven, concentrated in the central area around Detroit and decentralized in the rest of the area. When compared to the fringe and middle areas with lower population density, the core area has relatively less area of UGS, less shape complexity, smaller largest patch, more isolation degree but larger PD. Though the equitable distribution of UGS in the study area does not significantly correspond with population density, the core area tends to have higher Gini coefficients and is more concentrated in the interval above 0.9. Despite this, the BQR model results revealed the difference between sub-regions and put forward meaningful suggestions for urban development.

Like other metropolitans, the metropolitan core of Detroit has been through a prosperous time with high-intensity land development and high-density population influx. Rapid urbanization has been eroded considerable open spaces, not only causing the fragmentation of natural habitats but also the insufficiency of UGS provision for humans (Dinda, Das Chatterjee, & Ghosh, 2021; Sathyakumar, Ramsankaran, & Bardhan, 2020). In the study area, core areas are densely developed with residential lands and other land use. Limited by the densely built environment and large need of residents, retails and transportation, core areas need more efforts to keep existing UGS or create new UGS. Since the last century, urban planners and designers have started to bring UGS back into the city and tried to provide sufficient services for residents. However, it still needs a long way to go for areas with dense populations to provide equitable UGS for residents. Not only in the metropolitan area of Detroit, but all the large cities are confronting the serious problem: how to provide sufficient and equitable UGS for the growing population demand with limited land resources in a densely built-up environment (Xu et al., 2018).

Our study indicates that PD contributes the most to the UGS equity among three sub-regions and it is the most significant variable in core areas. In other words, bringing more UGS into the built environment is the priority for areas with dense populations regardless of the shape and the size of UGS. Even a small pocket park or a rain garden near the corner counts in this context. Detroit itself is suffering from urban sprawl and population loss, with large amounts of developed lands abandoned as vacant lands. This tendency harms the development of cities but also provides an opportunity for bringing more equitable UGS to urban areas. UGS has the potential to be introduced into vacant lands and brownfields for revitalization as well as provide cultural services for residents (Nassauer & Raskin, 2014).

With more continuous UGS, larger patches and more undeveloped parcels, the fringe areas have more potential and more equitable distribution of UGS when compared to the core area. And yet, the positively correlated trend between the household units and the Gini coefficient indicates that the UGS in fringe areas is also under the pressure of growing housing demand (Xu et al., 2018). This is consistent with the fact that more inhabitants are dispersing from the center of the city to its surrounding areas, causing the urban area to expand with a loss of UGS. As evidenced by the result, PD and LPI are the most effective impact on UGS equity in the fringe area. Thus, how to develop land in a more efficient way and avoid the fragmentation of existing UGS is a major challenge for the fringe area.

4.3. Limitations and Outlook

We identified four limitations to this study. Firstly, the Gini coefficient can only show the overall situation of UGS equity in one census tract without reflecting where the inequity occurs. Areas with the same value could indeed have different situations. Also, the Gini coefficient describes the relative degree of equity regardless of sufficiency. Thus, we can only analyze the equity of UGS distribution in the study area. High equity in this research does not equal sufficiency, whereas areas with low equity are also likely to have more UGS. Secondly, since a large portion of the calculated Gini coefficient is concentrated in a small interval above 0.9, the BQR results cannot be significant enough in a higher quantile. Thirdly, we define the UGS based on land use classification and thus some potential UGS may not be included in this classification. We may combine the land use data with land cover data and extract the UGS more precisely in future studies. Finally, the result can be largely changed with the modification of accessible distance. In this study, as we only focus on the urban areas where people would prefer to regularly utilize UGS by walking, we define the accessible distance as a walkable distance no further than 300m. In future studies, we could conduct a community survey and define the distance according to the actual preference of residents in different regions. Also, we could involve the assessment of other UGS characters such as quality and study several specific zones to deepen the understanding of the mechanism behind UGS equity.

Chapter 5 Conclusion

To the best of our best knowledge, this is the first time a study identifies which characters of UGS spatial patterns specifically affect UGS equity and how these characters affect equity across equity levels and sub-regions. The analysis of the UGS spatial pattern and UGS equity in Southeast Michigan enables us to develop a new understanding of the spatial variability of UGS equity and the impact of UGS spatial pattern on UGS equity at the regional level and sub-regional levels.

From our results, it is apparent that PD and LPI have significantly positive effects on UGS equity in areas of any equity level. SHAPE_MN is positively correlated with UGS equity in areas with a moderate equity level. In densely populated areas, PD seems to be the most effective factor for UGS equity while in fringe areas with less population, LPI contributes together with PD in moderately equitable areas. In summary, this study implies that the spatial pattern of UGS has varying impacts on UGS equity at different equity levels and in areas with different population densities. Specific planning and design of the UGS distribution need to be taken into consideration to promote the equity, for instance, increasing the number of UGS in extremely inequitable areas and densely populated areas, and avoiding the fragmentation of existing UGS in areas at moderate equity level and areas with less population density.

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