Stat 276 Research Project
2nd Semester AY 2024-2025

I. **Proponent:** Sarra L. Maravilla

II. **Title:** Exploring the spatial variation of urban green space and its relation to societal composition: A case study of Quezon City, Metro Manila

III. Introduction

A. Background

An increasing number of studies suggest that urban green space (UGS) as one of the important factors in promoting sustainable urban development and livability (Aram, 2024; Haq, 2011; Hunter et al., 2019; Karade et al., 2017). Previous studies highlight its wide range of environmental benefits such as enhancing urban biodiversity, improving air and water quality, and mitigating urban heat islands (Aram et al., 2019; Castañeda et al., 2024; Nowak et al., 2006; Zhang et al., 2015). Socially, UGS serves an essential role in fostering community cohesion and improving physical and mental health by offering spaces for recreation and physical activity (Bertram & Rehdanz, 2015; Huang & Lin, 2023). Additionally, as urban areas face contentious challenges from climate change, the importance of UGS has been increasing due to their natural elements (Atiqul Haq et al., 2021; Cheng et al., 2021; Sturiale & Scuderi, 2019).

Considering all these benefits, UGS is an essential resource for urban dwellers, and they should have equitable access to it. The United Nations specified the need for "providing universal access to greenspace for urban residents" in the 11th Sustainable Development Goal of making cities and human settlements inclusive, safe, resilient and sustainable (United Nations, 2015). However, empirical evidence shows that UGS remains unevenly distributed within cities, which has been recognized as an issue of social equity and environmental justice (Rutt & Gulsrud, 2016; Wolch et al., 2014). Furthermore, disparities in UGS distribution are present among different characteristics of population distribution defined by income level, age, education, racial and ethnic background, and even immigration status (Dash & Chakraborty, 2023; Heo & Bell, 2023; Nesbitt & Meitner, 2016; Weigand et al., 2023; Wu & Kim, 2020; Wüstemann et al., 2017; Yang et al., 2022). Evidence often suggests that there are fewer UGS among socially disadvantaged neighborhoods than those with higher socio-economic status, mainly because there is a lack of political and economic resources to develop and maintain UGS in these neighborhoods (Łaszkiewicz et al., 2021; Rigolon, 2016; Yang et al., 2022). However, there are also studies that suggest otherwise, where disadvantaged groups have better access to UGS than the general population (Gilliland et al., 2006; Nicholls, 2001; Xiao et al., 2017). At present, study results are inconclusive regarding the equity of greenspace by sociodemographic groups, possibly due to the heterogeneity of how greenspace is defined and how social structure differ in each city. These varying results warrants examinations of UGS inequity on a local and targeted scale (Jennings & Gaither, 2015; Rigolon, 2016).

Metro Manila, the capital region of the Philippines, with a population of over 13 million residents (Philippine Statistics Authority., 2020), reflects the challenges of urbanization on green space availability and equity. Historical urban planning efforts, like the Burnham and Frost-Arellano plans envisioned expansive public green spaces to support societal needs. However, these plans were never fully realized due to land speculation, urban pressures, and shifting political priorities. As a result, green spaces in Metro Manila today are fragmented and unevenly distributed. Affluent communities often enjoy access to private parks and exclusive amenities, while low-income neighborhoods depend on overcrowded and limited public green spaces (Saloma & Akpedonu, 2021). Despite this, there remains a lack of formal studies quantifying the disparities in UGS availability among socio-demographic groups in Metro Manila. Existing studies on UGS have focused primarily on broader metrics, such as green space per capita and analysis on a larger spatial unit such as cities and municipalities (Olfato-Parojinog et al., 2024). While these studies provide valuable insights, these approaches often overlook disparities at smaller, more localized scales, such as within barangays (Yang et al., 2022).

Geographically Weighted Regression (GWR), as a varying coefficient model (Fotheringham et al., 2022), is a useful tool for capturing this spatial variation of barangay's greenness among its socio-economic composition (Yang et al., 2022). By analyzing spatial variation, GWR helps reveal patterns in the distribution of UGS in Metro Manila. Such analyses are essential for developing targeted strategies to enhance the availability, accessibility, and quality of UGS, ensuring that all residents can benefit equitably.

This paper employs the GWR model to investigate the spatial relationship between UGS availability and socio-economic disadvantaged in the barangays of Metro Manila, focusing on Quezon City as a pilot study area. The study aims to address the following questions: (1) How is UGS distributed among the barangays of Quezon City, Metro Manila? (2) Which of the vulnerable groups are suffering from UGS inequity? (3) What are the spatial variation characteristics of UGS inequity among the disadvantaged groups? This paper provides an overview of the current distributional equity of UGS to inform policymakers in promoting location-specific evaluations in order to pursue equally distributed UGS in different socio-economic groups, thereby mitigating broader issues of environmental justice and social inequity.

B. Research Problem and Motivation

Urban Green Spaces (UGSs) have been recognized as an important resource in promoting sustainable urban development, offering environmental, social, and health benefits to urban population. However, their distribution often reflects underlying social inequities, leaving marginalized communities at a disadvantage. Despite the global recognition of the need for equitable access to UGS, disparities persist in many cities, driven by socio-economic, political, and historical factors. In Metro Manila, these inequities are particularly evident (Saloma & Akpedonu, 2021). Existing research on UGS in the region has focused on broad spatial scales, often neglecting granular assessments at smaller administrative levels such as barangays, where disparities may be most pronounced (Bao et al., 2023).

This paper aims to bridge this research gap and contribute to actionable insights to urban planning and policy-making in Metro Manila. By employing GWR, the study aims to find spatial patterns of UGS availability and inequity among socio-demographic groups in Quezon City, Metro Manila. These insights will help identify vulnerable populations most affected by the unequal UGS distribution and guide targeted interventions to improve green space accessibility. Ultimately, the research seeks to support evidence-based strategies for achieving equitable and sustainable urban development, addressing issues of environmental justice and social equity at large.

C. Research Objectives

This paper aims to explore the spatial variation of urban green space availability with particular focused on the disadvantaged groups. Specifically, the objectives of this research are as follows:

1. *To analyze the distribution of urban green spaces (UGS) among the barangays of Quezon City, Metro Manila*: This objective aims to map and quantify the availability of UGS in different barangays, providing a detailed understanding of how green spaces are spatially distributed within the city.
2. *To identify the socio-economic groups most affected by UGS inequity*: This involves examining the relationship between UGS availability and various socio-economic factors particularly age, education, and housing. The goal is to identify which vulnerable groups have limited access to green spaces.
3. *To investigate the spatial variation characteristics of UGS inequity among disadvantaged groups*: Using GWR, this objective seeks to discover patterns and variations in UGS distribution related to socio-economic disparities. This analysis will help reveal localized inequities and inform targeted interventions.

By achieving these objectives, the study aims to contribute to the broader goals of achieving social equity, environmental justice, and sustainable development in urban areas.

D. Significance of the Study

This study contributes to the growing body of research on UGS by addressing the critical issues of distributional equity in Metro Manila, particularly in Quezon City. By examining the spatial distribution of UGS and their availability among different socio-economic groups, this research provides valuable insight into the disparities that exists at a localized level, highlighting disparities that broader spatial analyses often overlook. Understanding these localized inequities is crucial for developing targeted strategies that can enhance the availability of UGS, ensuring that all urban residents, regardless of socio-economic status, can benefit from the benefits of UGS.

Additionally, this study employs GWR, an analytical tool that captures spatial variations in UGS distribution. This approach allows for a nuanced understanding of how socio-economic factors influence availability to UGS within specific barangays.

IV. Methodology

A. Study Area

Quezon City is situated on the northeastern portion of Metro Manila, located at approximately 14˚39’00” North latitude and 121˚02’51” East longitude. It covers a land area of 16,112.58 hectares, making up approximately one-fourth of NCR’s size which makes it the largest city in Metro Manila (Quezon City, 2018). According to the 2020 census, the City had a population of 2,960,048 comprising nearly one-fourth (21.95%) of Metro Manila’s population (13,484,462). The city ranks first among the thirty-three highly urbanized cities with the largest population in the country. For the period of 2015-2020, the city registered an annual population growth rate of 0.17%, lower than the NCR’s rate of 0.97%, as well as, the national growth rate of 1.63% (Philippine Statistics Authority., 2020) .

Quezon City’s actual land use pattern remains predominantly residential with a combined total of 5,100 hectares, representing 31.6% of the city’s land area. On the other hand, the city’s open parks occupy 1.29%, showing a diminishing trend from 2009 to 2018 with a decrease of 14.21 hectares. According to the city’s 2018 Ecological Report, there are 588 developed, partially developed, and underdeveloped parks. Major parks in the city include the Quezon Memorial Circle (25 hectares) and the Ninoy Aquino Parks and Wildlife Nature Center (19.29 hectare). Additionally, there are so-called “special” parks which include the 2,700-hectare La Mesa Watershed and the UP Arboretum (3.57 hectares) (Quezon City, 2018).

Figure 1. Location Map of Quezon City, Metro Manila

B. Data and Methods

i. General Approach

Regression analysis has long been used to explore the association between greenspace availability and socioeconomic status. However, because spatial dependence often exists in the relationship between socioeconomic factors and UGS distribution, traditional regression models may not be sufficient. With the advancements in Geographic Information System (GIS), spatial analyses have gained popularity offering a better explanatory measure for examining UGS and socio-economic factors.

In addition to addressing spatial dependence, it is important to consider spatial non-stationarity when analyzing these relationships. To capture the spatial variation in UGS inequity, a focus on local spatial relationship is required. GWR is a useful method for examining such local variations, allowing for a more nuanced approach of UGS distribution among different socio-economic variables at the neighborhood level particularly barangay level.

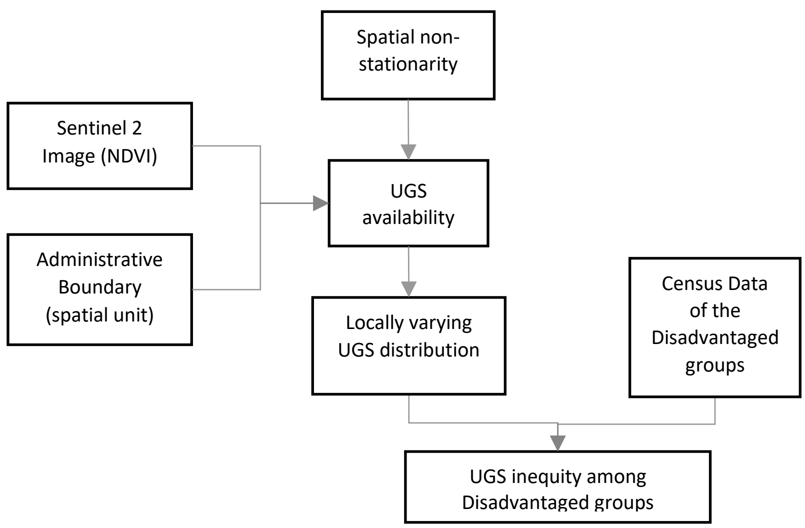

Figure 2. General approach for exploring UGS inequity

ii. Urban Green Space Metric

Remotely sensed images from the European Space Agency's Sentinel-2 mission and the Normalized Difference Vegetation Index (NDVI) were used to compute for the availability of UGS in each barangay. The Sentinel-2 Level 2A satellite images provide a 10-meter resolution and are already atmospherically corrected. Between January 1 to December 31, 2020, three satellite images with less than 10% cloud cover were identified. The satellite image with the least cloud cover in the study area, dated February 22, 2020, was used in the processing.

To measure green exposure, NDVI values were utilized to identify all types of green spaces. The NDVI is calculated as:

$$\boldsymbol{NDVI} = \frac{\boldsymbol{NIR} - \boldsymbol{Red}}{\boldsymbol{NIR} + \boldsymbol{Red}}$$

where NIR and Red are the near-infrared and red wavelength bands, respectively. Pixels with NDVI values equal and larger than 0.1 were considered as green spaces following the previous studies using the same dataset (Wu & Kim, 2020; Yang et al., 2022). The mean of value of these ranges was used to determine the barangay greenness. The processing of the barangay greenness was done in ArcGIS Pro 3.4.

iii. Key variables of disadvantaged groups

The socioeconomic variables used in this paper was collected from the 2020 Census of Population and Housing (CPH) of Philippine Statistics Authority (PSA), with the barangay as the smallest spatial unit of census data. For this paper, we employ a more focus analysis on the “disadvantaged groups” in the Philippine society. Disadvantaged or marginalized sectors are defined by the Republic Act No. 8425 also known as Social Reform and Poverty Alleviation Act as the following: farmer, fisherfolk, workers in the formal sector and migrant workers, workers in the informal sector, indigenous peoples and cultural communities, women, differently abled persons, senior citizens, victims of calamities and disasters, youth and students, children, and urban poor. Considering the availability of census data and the definition of disadvantaged groups in the context of the Philippines, we then established a set of socioeconomic indexes to express the level of barangay deprivation including three variables: age, education, and housing which are composed of four indicators.

Variables	Indicator	Description
Age	Underage (U)	Percentage of people aged below 18 (%)
	Elderly (E)	Percentage of people aged 65 and above (%)
Education	Illiterate (I)	Percentage of people that are illiterate (%)
Housing	Living below 50 sqm. (H)	Percentage of people living in a house with less than 50 sqm in area (%)

Table 1. Key variables for disadvantaged groups

To examine how these four variables correlate to the UGS metric we use the Pearson correlation analysis. When the absolute value of the correlation coefficient between two socio-economic variables exceeded 0.7, one variable was excluded from the model to avoid multicollinearity (Yang et al., 2022). The remaining variables were then standardized to a mean of 0 and a standard deviation of 1, allowing us to identify the most significant contributor to inequity (Yang et al., 2022). Among the variables, Underage (U) and Elderly (E) exhibited showed a strong correlation, with a coefficient of 0.83, exceeding the threshold of 0.7 as shown in Figure 3. For the follow up model, the variable Underage (U) was retained. Other variables exhibited correlation coefficients below 0.7. Finally, the model used Underage (U), Illiteracy (I), and Housing (H) as the explanatory variables. The pre-pre-processing and data clean up was done in R 4.4.2.

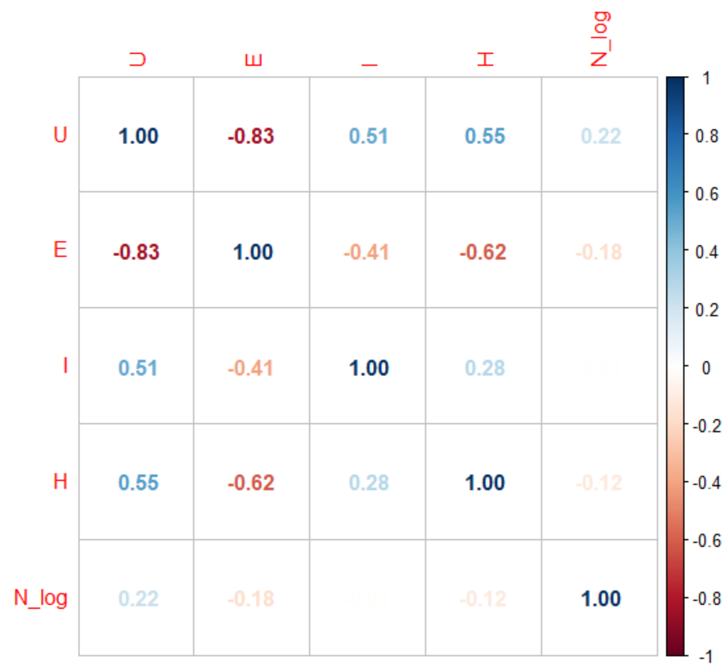

Figure 3. Pearson correlation analysis

iv. Statistical Analysis

Two statistical models were employed for this paper, the ordinary least squares (OLS) and geographically weighted regression (GWR). First, OLS was used to investigate the global relationship between the UGS and socio-economic status through the study area. The OLS model helps in understanding the overall trend and determine which of the socioeconomic variables have a significant impact on the barangay greenness.

However, the limitation of OLS model is its assumption of spatial stationarity which overlooks spatial heterogeneity and may restrict its descriptive and predictive analysis (Yang et al., 2022). Also, Moran's I statistics was used to measure the spatial autocorrelation of the dependent variables, barangay greenness. This step confirmed the need to account for spatial dependency within the data.

To address the limitation of OLS and account for the spatial autocorrelation, GWR was employed in this study. GWR allows for the coefficients to vary with geographical position accounting for spatial heterogeneity. Compared with OLS, the coefficients in GWR are functions of spatial location. To consider the variable relationship between barangay greenness and socioeconomic variables from the local perspective, we modeled the local-scale inequity using GWR. The formula to calculate GWR is given below (Fotheringham et al., 2022):

$$y_i = \beta_{i0} + \sum_{k=1}^{m} \beta_{ik} x_{ik} + \varepsilon_i$$

where y_i is the dependent variable at barangay i; x_{ik} is the kth independent variable at barangay i; m is the number of the independent variables; β_{i0} is the intercept parameter at barangay i, β_{ik} is the local regression coefficient (weight) for the kth independent variable at barangay i; and ε_i is the random error at barangay i.

GWR is relatively insensitive to the choice of weighting function but they are sensitive to the bandwidth of the particular weighting function chosen. In GWR, there are two types of kernels to choose from: fixed and adaptive. Akaike Information Criterion (AIC) was used to compare models using fixed and adaptive kernels. The adaptive kernel, which showed a lower AIC, was chosen for our model. The statistical analysis was done in R 4.4.2.

V. Results and Discussion

i. Spatial pattern of greenness

Figure 4 shows the spatial distribution of barangay greenness in Quezon City. Areas with low level of green exposure are concentrated in the eastern and central parts of the city. High levels of greenness are predominantly found in the northern part of the city, including the barangay where the La Mesa Watershed and University of the Philippines are located.

ii. Global regression analysis using OLS

The result of the OLS model is shown in Figure 5. The NDVI mean value of each barangay was first transformed using logarithm to achieved normality in the data distribution. On the figure, the coefficients provide insights into the individual effects of each socioeconomic variables on green exposure. The residuals indicate that the prediction errors are well distributed, with the median residual close to zero, suggesting that the model's predictions are relatively accurate.

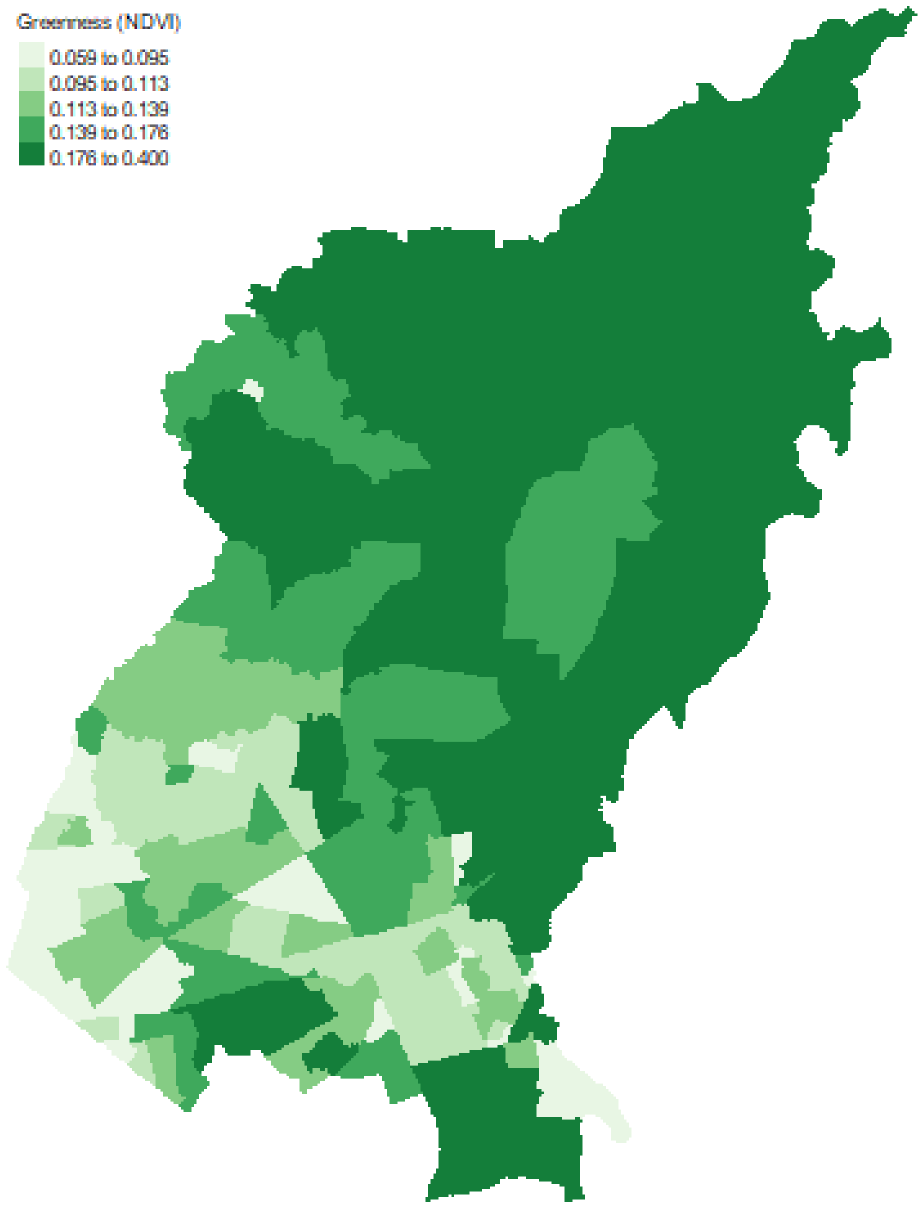

Figure 4. Barangay greenness pattern in Quezon City

Given that all data were standardized to a mean of 0 and a standard deviation of 1, the coefficients represent the change in the standardized dependent variable for a one standard deviation change in each standardized independent variable. The positive coefficient for U at 0.4954 shows a statistically significant positive relationship with green exposure, highlighting that areas with higher underage population tend to have greater green exposure. Conversely, H variable has a negative coefficient of -0.3419, also statistically significant, indicating that higher percentage of household with living area less than 50 sqm in area are associated with lower green exposure. Illiteracy (I) variable presents a negative coefficient of -0.1627 suggesting a negative relationship with green exposure, but this relationship is not statistically significant at the 0.05 level but significant at the 0.1 level. The variable (I) was still used in the succeeding model

The model summary indicates a residual standard error of 0.9314, an R-squared value of 0.151 (suggesting 15.1% of the variability in standardized green exposure can be explained by the independent variables), and an adjusted R-squared value of 0.1325. The F-statistic of 8.181 with a p-value of 4.732e-05 signifies that the overall model is statistically significant. The model accounts for a modest portion of the variance in green exposure, and the overall statistical significance underscores the relevance of these predictors in understanding the dynamics of green exposure.

```
lm(formula = N_log ~ U + H + I, data = shp)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.3512 -0.5312  0.0528  0.6010  2.5425 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -3.677e-16  7.816e-02   0.000 1.000000    
U            4.954e-01  1.050e-01   4.717 5.79e-06 ***
H           -3.419e-01  9.399e-02  -3.638 0.000388 ***
I           -1.627e-01  9.141e-02  -1.779 0.077371 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9314 on 138 degrees of freedom
Multiple R-squared:  0.151,	Adjusted R-squared:  0.1325 
F-statistic: 8.181 on 3 and 138 DF,  p-value: 4.732e-05
```

Figure 5. Results of the OLS model

Despite the illiteracy (I) variable not achieving statistical significance at the 0.05 level in the OLS regression model (p-value = 0.077371), it is important to consider its potential impact on green exposure. It’s p-value it is close to the conventional threshold of 0.05, suggesting that there may still be an underlying effect that warrants further investigation. Appendix A provides the estimated coefficients and confidence interval of various OLS model combining different socioeconomic variables.

We also examined the residuals of the OLS model, which shows the uneven distribution over predicted values, indicating a violation of homoscedasticity (same variance), see Figure 6. This implies the presence of residual autocorrelation. This is further supported by the large inferred variation (mean sigma = 0.93). As a result, the OLS model fit provides biased estimates in the parameters without accounting for the residual autocorrelation. To check for spatial autocorrelation, Moran’s I statistic was used. We utilized the “queen” contiguity matrix for computing for Moran’s I value, which resulted in a slightly higher value (0.539) compared to the “rook” contiguity matrix (0.535). To perform hypothesis testing we use the Monte Carlo Method. The density plot, along with the resulting Moran's I value, is overlaid in Figure 7. The plot shows the Moran's value lies to the right of the density curve, confirming the presence of spatial autocorrelation in the dependent variable, barangay UGS.

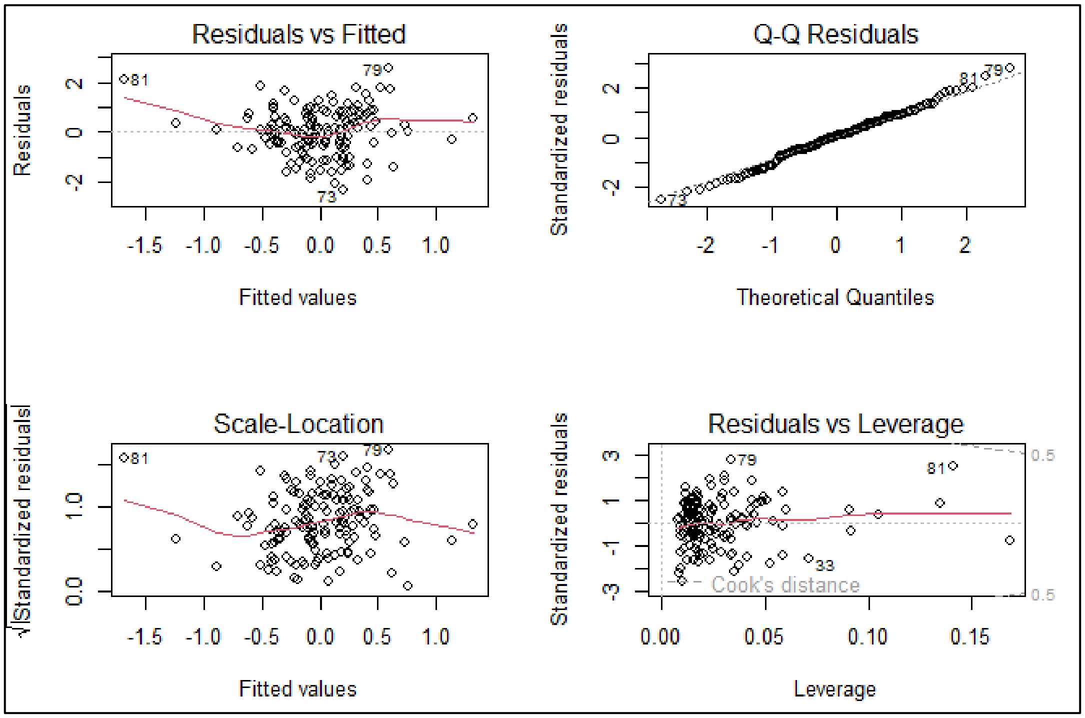

Figure 6. Residual plots of the OLS model

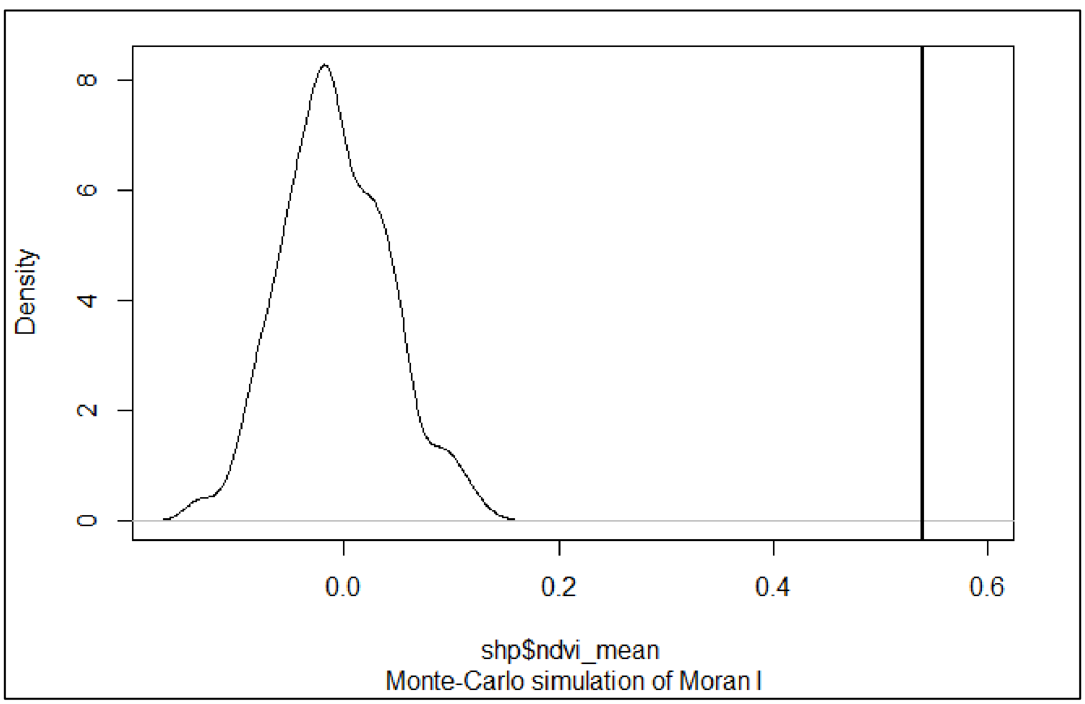

Figure 7. Density plot of permutation outcomes and the Moran's I

iii. Results of the Geographically Weighted Regression

Figure 8 shows the association between socio-economic status and barangay greenness based on the GWR model. The AIC of OLS was 388.73 while GWR model provides a lower AIC value which indicates better in identifying the local-scale association between barangay UGS and socioeconomic status. The map of spatial variations of each variable are shown in Figure 9.

```
gwr(formula = linear_model, data = shpgwr_sp, adapt = abw, hatmatrix = TRUE,
    se.fit = TRUE, predictions = TRUE)
Kernel function: gwr.Gauss
Adaptive quantile: 0.04224801 (about 5 of 142 data points)
Summary of GWR coefficient estimates at data points:
                   Min.    1st Qu.     Median    3rd Qu.       Max.  Global
X.Intercept. -1.3934839 -0.3538451 -0.1065479  0.1475754  1.5820787  0.0000
U            -0.5595685 -0.0054159  0.2346094  0.3843921  1.0129137  0.4954
H            -0.6933088 -0.4130895 -0.2339026 -0.0712636  0.1671327 -0.3419
I            -0.5337369 -0.2145272 -0.1461146 -0.0647925  0.2422777 -0.1627
Number of data points: 142
Effective number of parameters (residual: 2traceS - traceS'S): 51.34725
Effective degrees of freedom (residual: 2traceS - traceS'S): 90.65275
Sigma (residual: 2traceS - traceS'S): 0.6485223
Effective number of parameters (model: traceS): 38.25403
Effective degrees of freedom (model: traceS): 103.746
Sigma (model: traceS): 0.6062193
Sigma (ML): 0.5181688
AICc (GWR p. 61, eq 2.33; p. 96, eq. 4.21): 325.8299
AIC (GWR p. 96, eq. 4.22): 254.5156
Residual sum of squares: 38.12684
Quasi-global R2: 0.7295969
```

	Variable	+ (%)	+ sig. (%)	- (%)	- sig. (%)	SD	Mean
U	U	74.64789	28.87324	25.35211	0.000000	0.3080419	0.2119901
H	H	9.15493	0.00000	90.84507	38.028169	0.2072912	-0.2520573
I	I	11.26761	0.00000	88.73239	5.633803	0.1377680	-0.1398511

Figure 8. GWR model results

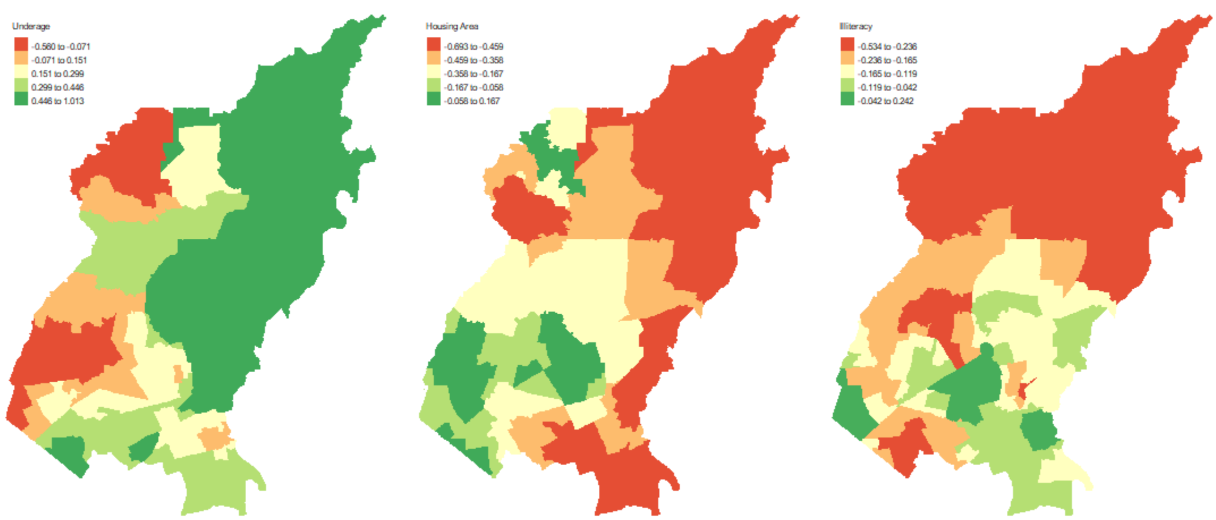

Figure 9. Spatial variation of each socio-economic variables

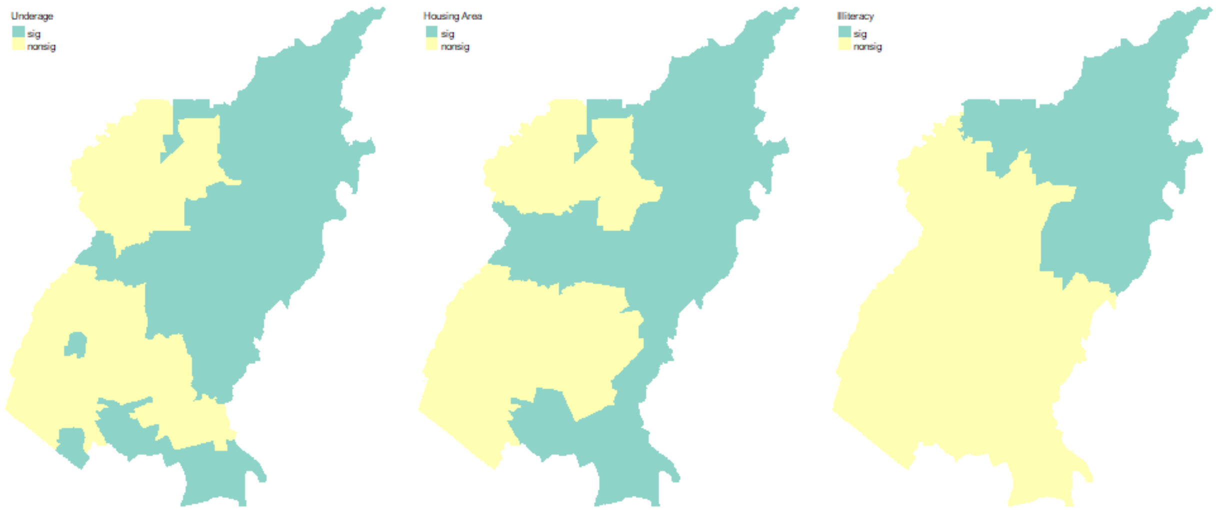

Figure 10. Map of significant and non-significant GWR results

a. Underage
   In terms of underage, both OLS and GWR reports a positive association between barangay UGS and the population of underage with mean value at 0.2119. The GWR reports a positive association at 74.65% with 28.88% of it being significant. This means that in most areas, an increase in the underage population is associated with an increase in green exposure.

b. Housing
   For housing, the GWR results indicates a negative coefficient indicating that in most area, an increase in the population of households with living area less than 50 sqm area is associated with a decrease in green exposure. The GWR results yield a mean value of -0.2521. It also indicates that 90.85% of the barangays have negative coefficients with 38.03% having significant values.

c. Illiteracy
   For illiteracy, the GWR results provides that 88.73% of the barangay have negative coefficient indicating that in most areas, an increase in illiteracy is associated with a decrease in green exposure. However, only 5.63% of these barangays show statistically significant negative coefficients.

The coefficients based on significance are mapped in Figure 10. For underage, most significant areas are located in the northwest. For households with living area less than 50 sqm, significant results are also in the northwest. For illiteracy, most significant results are in the northern part. Since the variables are standardized, we can compare the highest contributors to inequity. Based on the GWR results, the variable with the highest mean negative coefficient is Household with living area less than 50 sqm (-0.252), followed by illiteracy (-0.140). Underage, on the other hand, has a positive coefficient.

VI. Conclusion

This project builds on previous research into the complex spatial relationship between UGS and various socio-economic statuses. It identifies the disadvantaged groups suffering from UGS inequity and reveals the complicated spatial association by the GWR model. The regression results indicated that the disadvantage groups including households with living area below 50 sqm and those with illiteracy, are exposed to UGS inequity, with smaller households being the most affected. Various socio-economic dimensions of barangays show different spatial agglomeration characteristics of local-scale inequities.

Several avenues for future research are highlighted by this project. Future research should aim to enhance the precision of green space accessibility assessment and environmental equity evaluation. This study focused on the inequity experienced by disadvantaged groups, particularly regarding barangay green exposure. Future research might consider additional variables related to disadvantaged groups and other explanatory variables associated with green space. Additionally, while this project focused on the availability of green space using the NDVI mean value, future studies could explore other metrics, such as publicly available spaces or accessibility measures, like the distance from public green spaces.

Compared to the OLS model, GWR model provides a better data fitting. It identified vulnerable areas and provided a detailed map of local-scale UGS inequity among various socio-economic indicators. Distinguishing these inequities across multiple socio-economic dimensions is crucial for equitably distributing scarce public resources and effectively promoting green space-based environmental justice. Prioritizing disadvantaged groups in future UGS planning is essential to ensure equity in vulnerable areas. This paper provides a fresh perspective on UGS inequities study specifically for Metro Manila and highlights key areas that should be prioritized for alleviation in future urban green space system planning and policymaking.

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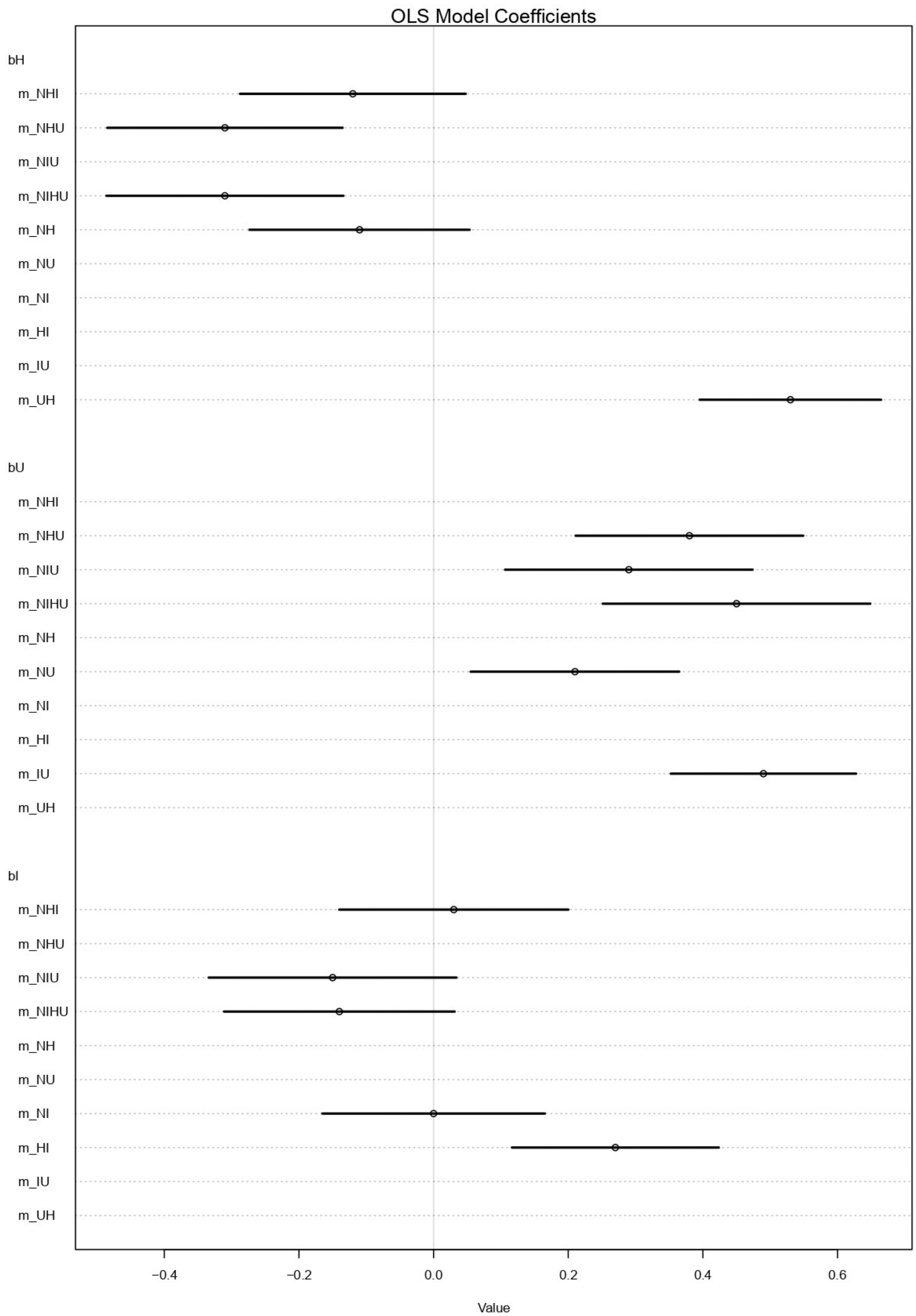
Appendix A.


OLS Model Coefficients
bH
m_NHI
m_NHU
m_NIU
m_NIHU
m_NH
m_NU
m_NI
m_HI
m_IU
m_UH
bU
m_NHI
m_NHU
m_NIU
m_NIHU
m_NH
m_NU
m_NI
m_HI
m_IU
m_UH
bI
m_NHI
m_NHU
m_NIU
m_NIHU
m_NH
m_NU
m_NI
m_HI
m_IU
m_UH
−0.4
−0.2
0.0
0.2
0.4
0.6
Value