SPATIAL EFFECTS OF URBAN GREEN SPACES ON REAL ESTATE: A CASE STUDY OF MUMBAI, INDIA

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July, 2021

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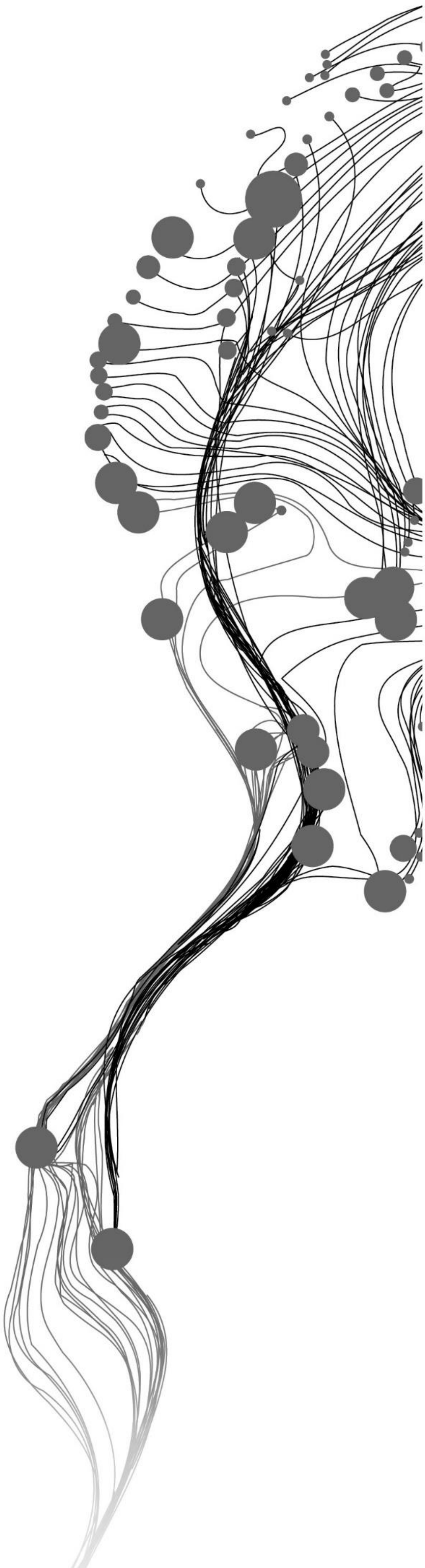

SPATIAL EFFECTS OF URBAN GREEN SPACES ON REAL ESTATE: A CASE STUDY OF MUMBAI, INDIA

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ABSTRACT

There is a vast literature present on the domain of Environmental Inequities and Valuations. The environmental inequities in the low socioeconomic status areas in the Global South cities are well documented. On the other hand, the Environmental Valuation studies have primarily been conducted in the cities of Global North. The results from the Global North valuation studies are not consistent with the few valuation studies conducted in the Global South. Especially in the cities of India, there is a massive shortage of studies in the domain of Environmental Inequities and Valuation. Mumbai, in particular, has seen a decline in quantities of urban green spaces over past decades, and the urban local bodies had not been able to meet the demands when compared to the National and Global standards. The strict supply and demand approach for the provision of urban green spaces and little emphasis on the spatial aspects have already led to greening displacements. This study attempted to identify the inequities present in the provision and access to the urban green spaces provision w.r.t low socioeconomic status areas and quantify the relationships of proximity to urban green spaces w.r.t. to the listing's prices properties. The urban green spaces are analyzed as managed and unmanaged types, derived from Yok, Wang, & Sia (2013). Through this study, the inequities and valuations of urban green spaces were coherently analyzed, unlike previous studies that assess one of these aspects in isolation using global(aspatial) and local (spatial) statistical models. The results from the local models in the study did not indicate the presence of inequities in provision and access to the types of urban green spaces w.r.t to the low socioeconomic status areas. However, the analysis highlighted areas where the urban green spaces have significant relationships present with the land values and the listing price of properties in rent and sale categories. The study serves as a guiding mechanism to the urban local body to identify areas with significant relationships concerning urban green spaces in cases of implementing further provisions/upgrades in DP 2034 and informing them to avoid future cases of greening displacements in the city.

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
AIC	Akaike Information Criterion
AICc	Corrected Akaike Information Criterion
ASR	Annual Statement of Rates
BMC	Brihanmumbai Municipal Corporation
CBD	Central Business District
DP	Development Plan
FDR	False Discovery Rate
GDP	Gross Domestic Product
GIS	Geographic Information System
GLM	General Linear Model
GTWR	Geographically-Temporally Weighted Regression
GWR	Geographically Weighted Regression
IGR	Inspector General of Registrations
IID	Independently and Identically Distributed
INR	Indian Rupees
KNN	K Nearest Neighbour
LWR	Locally Weighted Regression
MCGM	Municipal Corporation of Greater Mumbai
MGWR	Multiscale Geographically Weighted Regression
MMR	Mumbai Metropolitan Region
OLS	Ordinary least squares
RERA	Real Estate Regulatory Authority
RSS	Residual Sum of Squares
SAC	Spatial Autocorrelation
SES	Socio Economic Status
SH	Spatial heterogeneity
SRA	Slum Rehabilitation Authority
UDRI	Urban Design Research Institute
UGS	Urban Green Spaces
ULB	Urban Local Body
UT	Union Territory

KEY TERMS AND DEFINITIONS

Term	Definition
Managed Urban Green Spaces	The managed green spaces in this study include parks, playgrounds, gardens, and recreational complexes. Public authorities only manage this form of greenery (Hwang, Nasution, Amonkar, & Hahs, 2020; Yok et al., 2013).
Unmanaged Urban Green Spaces	Unmanaged urban green spaces in this study consist of urban forests and mangroves. These areas fall under either protected or unprotected categories designated by the local bodies. These types of greenery grow naturally and do not require intervention from humans (Hwang et al., 2020; Yok et al., 2013).
Land Values	Land Values is the worth of a piece of property, which encompasses the value of the land itself as well as any additions made to it, and is calculated by third-party immovable appraisers (Bhavana, 2021). The land values include rates of land plus the built-up residential rates per square meters (with survey information) controlled and released by the provincial governments for each financial year for geographical areas called land value sub-zones. The term land values have been synonymously used as market values of land in the thesis. The land values are also known as annual statement rates.
Listing prices of properties	The list price or asking price is the amount of money that the home seller plans to receive by selling their home. Variables such as the house's age, market trends, mortgage, features of the house, upgrades, and other factors affect the list price (Bankrate, 2021).
Notified Slum Clusters/Informal Land Use	As per the Census of India 2001 and 2011: "All specified areas in a town or city notified as 'Slum' by State/Local Government and Union Territory (UT) Administration under any Act including a Slum Act.'" (Chandramouli, 2010; Planning Tank, 2015).
Wards	According to Balk et al. (2019), "Wards are electoral units that are overseen by statutory-urban governing bodies. There is no automatic rule by which statutory towns and their constituent wards come into being based on well-defined demographic and economic criteria" (p.3).
Sub Zones	The geographical areas within the Brihanmumbai Municipal Corporation for which the rates of land and built-up have been arranged year-wise.
Green gentrification	Green gentrification is the displacement of low-income residents by further reducing the affordability of housing, from any area where new upgrades and provision to urban green spaces increased real estate prices and inducing inequities (Dooling, 2009; Sieg, Smith, Banzhaf, & Walsh, 2004).
Inequity	Inequity refers to the unjust and avoidable differences in the allocation of resources and services, in terms of quality/quantity or access, at a location where high/mid socioeconomic status areas or racial/ethnic groups are advantaged more than their low SES counterparts. The difference arises from failure in governance, cultural exclusion, and corruption (Pickett & Wilkinson, 2017; Rigolon, Browning, Lee, & Shin, 2018).

1. Introduction

1.1. Background and Motivation

1.1.1. Urban green spaces: benefits and types

Urban green Spaces form a significant component of green infrastructure, solving many urban and climatic challenges (Hiltrud Pötz & Pierre Bleuzé, 2016). There are several direct and indirect benefits associated with the presence of green spaces in urban environments (Leeds Ecosystem-Atmosphere and Forest (LEAF) Centre, the United Bank of Carbon (UBoC), Sustainable Cities Group at the & University of Leeds, 2015). The inconsistencies in defining and categorizing urban green spaces throughout literature create problems covered in a study by Taylor & Hochuli (2017). In some studies, urban green spaces have been used synonymously with open spaces, and in others, the distinctions are made based on the criteria of ownership or by considering/ignoring particular environmental features other than parks (Boulton, Dedekorkut-Howes, & Byrne, 2018). The categories defined by Yok et al. (2013) are managed and unmanaged vegetation in their study of urban green spaces in Singapore. This categorization has been used in many studies, including Blow, Geiger, Howell, & Wolfson (2009), Hwang, Nasution, Amonkar, & Hahs (2020), Jönsson, Thor, & Johansson (2011), Paillet et al. (2010) and others. The same categorization used by Hwang et al. (2020) will be considered for analysis in this M.Sc. project. Both managed and unmanaged urban green spaces face several challenges due to rapid urbanization and cities' densification, which need to be resolved.

1.1.2. Inequitable Provision and Access of urban green spaces

Urban green spaces face several challenges throughout the world's major cities, but the cities of developing/underdeveloped countries need more attention than their developed counterparts. More than half of the world's population lives in urban areas, with others estimating that by 2050 this will be closer to 68 percent, which means two out of every three people will live in cities (United Nations, Department of Economic and Social Affairs, 2018). More than 2/3rd of the increase in urbanization is anticipated to be occurring in the Global South. Due to the increasing burden on resources because of increasing populations in urban areas, environmental inequities are widely documented, including inequities in the distribution of urban green spaces in the Global South (Satterthwaite & Mitlin, 2013). There have been several studies conducted in developing regions within the past ten years, which talk about the inequitable distributions of green spaces in cities of underdeveloped/developing nations, forming a fraction of the broader domain of quantifying inequity in urban areas (Dadashpoor & Rostami, 2017; Lara-Valencia & García-Pérez, 2015a; Macedo & Haddad, 2016a; Willemse, 2013; Yu, Zhu, & He, 2020). In a study by Wolch, Byrne, & Newell (2014a) and Rigolon (2016), it is found in the cases of Global North that populations with low socioeconomic status face inequities with quantities and qualities of urban green spaces. According to an extensive and systematic literature review conducted by (Rigolon et al., 2018) proves that areas and populations with low socioeconomic status in the Global South: a) are not in closer proximity to parks(managed urban green space), b) Do not have access to more quantities of urban green spaces and c) Do not have the privilege to higher qualities of green spaces. From previous statements it becomes clear that the areas and populations with low socioeconomic status face unfair availability and access to urban green spaces. Some of the studies showed mixed or unclear results in inequity of urban green spaces. In rare cases that formed an insignificant proportion of literature, the studies found equitable distributions in quantity, accessibility, and quality of urban green spaces for populations with low socioeconomic status. The main reasons for the inequitable distributions are the lack of provision of urban green spaces, social/physical infrastructure by the urban local bodies in areas with low socioeconomic status (Breuste & Rahimi, 2015; Dupont, Jordhus-Lier, Sutherland, & Braathen, 2016; Lara-Valencia & García-Pérez, 2015a) and the other being ineffective planning for urban green spaces keeping low-income populations deprived (Dadashpoor & Rostami, 2017; Ouyang, Wang, Tian, & Niu, 2017; Wei, 2017; Wright Wendel, Zarger, & Mihelcic, 2012). Usually, the approach of the urban local bodies is to provide new patches of green spaces to meet gaps in demand and to reach standards defined by national and local authorities. However, this approach also seems to have problems attached in solving the issues.

1.1.3. Urban green spaces valuations and paradox

The issues mentioned related to inequities are often overlooked due to which urban green areas and other environmental amenities are often neglected and sacrificed. Urban development often comes at the cost of neglecting urban green spaces since urban areas can be measured in monetary terms and are valued higher than urban green areas. On the other hand, urban green spaces have mostly indirect and immeasurable benefits, which prove hard to quantify in monetary terms. As a result, urban green spaces are sacrificed for residential and commercial developments (Cilliers & Timmermans, 2012). To overcome the negative urban externalities, the government and local bodies strive to solve the problems by further providing green spaces to make the neighborhoods healthier and aesthetically pleasing. At the same time, this step can also raise housing costs and property values. The creation of new green spaces in compact cities to meet the gaps in demand and to fulfill the standards set in the development plans is a significant planning issue (Forestry, August, Haaland, & Bosch, 2015; Ramaiah & Avtar, 2019). However, just creating new urban spaces is not the solution as very recently, the problem of green gentrification has become evident, supporting the green space paradox by (Wolch, Byrne, & Newell, 2014b). The same study explained that providing new urban green spaces and real estate markets is paradoxical and an increasing cause of environmental inequities. More recently, examples of Green gentrification have been observed in cities such as Barcelona (Anguelovski, Connolly, Masip, & Pearsall, 2018), East Boston (Anguelovski et al., 2019), New York (Loughran, 2020), and others. Therefore, it becomes crucial to assess the impacts that managed and unmanaged green spaces have on the real estate market to arrive at statistical relationships. This M.Sc. project focuses on the economic valuation of urban green spaces besides other ecological and environmental benefits due to the difficulties in measuring them and the differences occurring in appraisal (Saraev, 2012). These benefits from urban green spaces are influenced by their characteristics related to availability and accessibility, aesthetics, amenities and equipment, and management (Churkina et al., 2016; Fuller & Gaston, 2009; Huang, Yang, & Jiang, 2018; World Health Organization, 2017).

1.1.4. Usage of appropriate models for environmental valuation

The previous paragraph clarifies that green gentrification affects property prices and diminishes housing affordability and how important it is to assess their relationships. These relationships can be assessed using a hedonic pricing model. Hedonic pricing models determine price factors based on the assumption that both the product's internal characteristics and external factors decide the price for its sale. Hedonic models have often been employed to estimate quantitative values for the ecosystem and environmental services that directly impact market prices for housing (Hargrave, 2020). The hedonic model has been previously employed in several studies to evaluate urban green spaces' spatial effects on property prices (refer to Table

1). The standard hedonic model approach does not utilize the spatial aspect of the variable, and often wrong models are chosen w.r.t the spatial unit of analysis (refer to Table 1). Table 1 also points out that the spatial unit of analysis in the studies is either at a neighborhood or a city level utilizing global econometrical models. These models only provide the global view of the study area, restricting spatial effects since spatial autocorrelation and spatial heterogeneity are also modeled locally. This part of the study has each point as a spatial unit for analysis, which will provide more comprehensive local effects to be evaluated using geographically weighted regression, which is more suitable as there are multiple local spatial units. Although both global and local spatial models' objective is to capture spatial patterns, and while both techniques have been used in housing valuation, minimal studies have been conducted utilizing local models, particularly for estimating effects from urban green spaces. These studies will be mentioned in the literature review section, which will help us select a suitable model for this study

1.2. Problem statement

Most of the cities in India are lagging much behind in terms of quality and quantity of urban green spaces compared to European and American cities or even Chinese cities. Some cities in Indian, like New Delhi, Chandigarh, and Gandhinagar, have shown promising improvements in the provision and management of urban green spaces, but still, the overall condition of urban green spaces in other cities is far from perfect (Chaudhry, Bagra, & Singh, 2011). From the literature review on environmental inequities (Section 2.1) and valuation of urban green spaces (Table 1), it is evident that there is a massive shortage of studies conducted in this domain, particularly in the case of Indian cities when compared to the Global North or Global South counterparts (e.g., China, Brazil, and South Africa). The main reason for this shortage is the scarcity of consistent and updated socioeconomic data in the public domain. The socioeconomic data gets released once every ten years when the census takes place. The last census took place in 2011, and the next was scheduled to be in 2022. The few studies that are relevant and conducted in India are mentioned in the following paragraphs.

The need for analyzing the inequities and valuation of urban green spaces also becomes essential as the urban local bodies in India still analyze the aspects relate to provision and management in a strict supply and demand sense, without the consideration of spatial aspects of the phenomenon. This is evident in the development plan documents where urban green spaces (including open spaces) are planned by checking the surplus/deficit in each administrative unit (wards), and the proposed layout for the urban green spaces is not described by any spatial logic (MCGM, 2017). Out of the few studies conducted in the Global South and India, the modeling approaches mostly follow standard hedonic regression framework without accounting for the spatial phenomenon of autocorrelation and heterogeneity, modifying the model to account for spatial effects (except for a very recent study conducted in Sao Paulo, Brazil by Panasolo et al., (2020). From a holistic perspective, the limitedness of studies using spatial models in the domain of urban green space effects on property prices in the Global South and not just India is visible, especially using spatial models in larger cities. Although the valuation studies in the Global South using spatial models are not conducted much in the first place, the study conducted by Cilliers & Timmermans (2012) is a good example when effects from developed nations are not observed in developing countries (refer to Table 1).

The significant studies on UGS Inequities in India are carried out by Hwang et al. (2020) and Sathyakumar, Ramsankaran, & Bardhan (2019). Both these studies were conducted using the satellite imageries and calculating landscape indices for urban green spaces, possibly due to the lack of vector data availability as the city of Mumbai does not have a dedicated spatial data infrastructure. The study by Hwang et al. (2020) quantified inequity between land values (as an overall indicator of socioeconomic status) and urban green spaces using a simple regression model which was aspatial in nature. Similarly, the study by Sathyakumar et al. (2019), also used an aspatial Multinomial Regression Model (MLR) for probabilistic analysis by defining SESI (socioeconomic status index) from the Census 2011 data with certain limitations about homogeneity in census sections, restriction of access in a census section and other issues. On the other hand, in the case of UGS valuations, the notable studies are conducted by Chaudhry, Sharma, Singh, & Bansal (2013) and Gupta, Mythili, & Hegde (2014), where both the studies do not include the unmanaged categories of urban green spaces and use simple hedonic regression approaches (weighted least squares and ordinary least square) with double log specifications for quantifying relationships between environmental variables with average prices in 176 urban residential plots and data form 578 housing transactions, respectively. Both the studies indicate an increase in property prices with a decrease in distance to urban parks and gardens. In all these studies, the usage of aspatial models raises the need for analyzing the relationships with more appropriate models. The spatial models will help to generate better insights and understanding the problem in a more comprehensive manner.

Due to the inconsistencies between the spatial unit of analysis and model structure, the literature relating to the spatial effects of urban green spaces on residential property prices have unclear and mixed effects. These unclear effects can increase or decrease the sale and the rent prices of residential properties) depending on the kind of green spaces (managed or unmanaged), characteristics of green spaces (size, proximity and shape), and residential property types (apartments, independent houses) that we are considering for analysis. Also, the regression models' variables differ between each study, depending on the types of data available and the study's focus. Apart from the inconsistencies in the spatial units and models, there are also inconsistencies present in the categorization of urban green spaces, which create a common misconception that all urban green spaces lead to the increment of surrounding property values, which is actually not the case every time. From the studies conducted by Anderson & Nafilyan (2018), Panduro & Veie (2013), and Wu, Ye, Du, & Luo (2017) , it becomes clear that effects on property types depend on the type of urban green spaces and unmanaged categories of urban green spaces (usually urban forests) tend to have a negative impact and do not increase property prices (refer to Table 1). The systematic literature review on the studies related to urban green space valuations and suitable model selection is provided in Chapter 2 (section 2.2. and 2.6. respectively).

Thus, this study attempts to analyze the aspects of inequities and valuations in the context of a city where the urban green resources are scarce, when compared to the Global North counterparts, utilizing most appropriate GWR models for both the sale and rent categories, unlike most studies that consider only one category (mainly sale transaction prices). Also, this study attempts to analyze the case of inequities and valuations in the case area coherently and not in isolation since these two aspects are interlinked with each other

1.3. Aim, Objectives, and Research Questions

The aim of the study is to study the spatial distributions, relationships, and effects of urban green spaces on residential real estate.

a. To study the spatial distributions and relationships of UGS with Land Values in the study area.
1. How are the urban green spaces spatially distributed by their types (managed and unmanaged)?
2. How are the land values spatially distributed?
3. Is there a relationship between the distribution of types of urban green spaces (areas and proportion of total UGS) with Land values over the study area?

b. To analyze the relationships of UGS with Slums Clusters in the study area.
1. How are the slum clusters spatially distributed?
2. Is there a relationship between distributive patterns of types of urban green spaces with slum clusters?
3. Is there a significant difference between the accessibility to urban green spaces between formal and informal residential land uses?

c. To estimate the spatial effects of urban green spaces by their types on list prices of residential properties (sale and rent prices) over the study area, using extended versions of hedonic regression models, i.e., geographically weighted regression techniques.
i. How do managed green spaces and their characteristics affect list prices of residential properties (sale and rent prices)?
ii. How do unmanaged green spaces and their characteristics affect list prices of residential properties (sale and rent prices)?
iii. How do the spatial patterns of the effects in c. i) and c. ii) differ for list prices of residential properties?
iv. Are the inferences derived from the local regression model complements the findings from objectives a. and b. across the study area?

d. To discuss policy implications from the results.
i. What are the potential policy implications of these findings?

1.4. Scientific and Societal Relevance

This M.Sc. research contributes to the domain of Environmental Inequities and Valuation in the context of the Global South. In terms of societal relevance, this study can help planners and policymakers better understand public urban green spaces' relationships with land uses and property prices and reveal gaps in quantities and location of new provisions and strategies that would not drive the exiting situation to become paradoxical. The topic is scientifically relevant as it emphasizes the need for using spatially local models which are underutilized in research. The study also attempts to assess the inequities and valuation of UGS in a coherent manner, including correlation, t-tests, and regression, unlike previous studies that use either one of the techniques and address the issues in isolation.

2. Literature review

2.1. Urban green spaces inequities in the Global South

A systematic literature review conducted by (Rigolon et al., 2018) proves that areas and populations with low socioeconomic status in the Global South:

a) are not in closer proximity to parks(managed urban green space) in cities like Shenzhen, Macau, Wuhan, Beijing, Zhongshan, Shanghai in China (H. Li & Liu, 2016; Liang, Chen, & Zhang, 2017; Shen, Sun, & Che, 2017; Tu, Huang, & Wu, 2018; D. Wang, Brown, Zhong, Liu, & Mateo-Babiano, 2015; Q. Wang & Zhang, 2017; C. Wu et al., 2017a; W. Wu & Dong, 2014; Xing, Liu, Liu, Wei, & Mao, 2018; Xu, Xin, Su, Weng, & Cai, 2017; X. Yang, Li, & Webster, 2016; Ye, Hu, & Li, 2018; You, 2016), Tehran in Iran (Lotfi & Koohsari, 2011), Santiago de Chile in Chile (Krellenberg, Welz, & Reyes-Päcke, 2014), Hermosillo in Mexico (Lara-Valencia & García-Pérez, 2015a), Bogota in Columbia (Scopelliti et al., 2016), Cairo in Egypt (Mowafi et al., 2012), and Cape Town in South Africa (Willemse, 2013, 2018).

b) Do not have access to more quantities of urban green spaces in cities like Tehran and Hamadan in Iran (Bahrini, Bell, & Mokhtarzadeh, 2017; Dadashpoor, Rostami, & Alizadeh, 2016; Lotfi & Koohsari, 2011), Sheikhpura in Pakistan (Arshad & Routray, 2018), and other African (Donaldson, Ferreira, Didier, Rodary, & Swanepoel, 2016; Matthew McConnachie & Shackleton, 2010; Shackleton & Blair, 2013; Willemse, 2013, 2018), Latin American (Fernández-Álvarez, 2017; Lara-Valencia & García-Pérez, 2015b; Loret de Mola et al., 2017; Macedo & Haddad, 2016a) and Chinese (Chen & Hu, 2015; Chen, Hu, Li, & Hua, 2017; Gao et al., 2017; H. Li & Liu, 2016; Wan & Su, 2017; Q. Wang & Zhang, 2017; Xiao, Lu, Guo, & Yuan, 2017; J. Yang et al., 2015; X. Yang et al., 2016; You, 2016) cities.

c) Do not have the privilege to higher qualities of green spaces in cities like Curitiba in Brazil (Macedo & Haddad, 2016b), Santa Cruz in Bolivia (Wright Wendel et al., 2012), Buenos Aires in Argentina (Loret de Mola et al., 2017) with other African (Donaldson et al., 2016; Shackleton & Blair, 2013; Willemse, 2018) and Chinese cities (Jim & Shan, 2013; H. Li & Liu, 2016; Xu et al., 2017; W. Zhang, Yang, Ma, & Huang, 2015).

2.2. Urban green spaces valuation

The table below summarizes significant studies conducted in the domain of urban green spaces valuations:

Table 1: A literature review on studies examining the spatial effects of urban green spaces on property prices

S.No.	Result	Authors, Year	City	Objective	Data	Model	Unmanaged UGS present? (Y/N)	Spatial model? (Y/N)	Global South? (Y/N)	Spatial unit	Findings
1	**Significant positive effects of UGS on property prices**	Conway et al. (2008)	Vermont, USA	Examining effects of urban green space on residential property values	260 records, single-family residences,	standard hedonic model, spatial lag model	N	Y	N	Neighborhood	A significant positive effect of immediate proximate green space
2		Votsis A. (2016)	Helsinki Finland	Spatial effects of parks, forests, and fields on apartment prices	44300 apartments sale price records	spatial error model	**Y**	Y	N	City	Decreasing distance to UGS has the potential to increase price/sq.m.
3		Engstrom and Gren (2017)	Malmo, Sweden	Valuation of public parks on apartment prices	16655 records, sales price of apartments	linear regression, spatial lag, spatial error model	N	Y	N	City	Urban parks have a positive effect on property values, and the effect tends to increase with reduced distance to the parks
4		Trojanek et al. (2017)	Warsaw, Poland	Effects of proximity to urban green areas on property prices	43075 records, sale prices of apartments	hedonic model	N	N	N	City	Proximity to the urban green area is positively linked to an increase in apartment prices
5		Panasolo et al. (2020)	Curitiba, Brazil	Effects of urban green areas on real estate prices	2832 apartments, 2500 houses	spatial lag model	**Y**	Y	Y	Neighborhood	The proximity of urban green areas results in to rise in property prices
6	**Unclear or negative effects of UGS on**	Panduro and Veie (2013)	Aalborg (Denmark)	Approaches to hedonic pricing valuations	12928 records, single-family, and	spatial error model	**Y**	Y	N	City	Effects depend on UGA type and property type

	property prices				terraced houses						
7		Hendon (1972)	Fort Worth, (USA)	Impact of parks on property prices	700 records, Houses	correlation	N	N	N	City	Inconclusive relationship btw property value and parks
8		Weicher and Zerbst (1973)	Columbus (USA)	Externalities of neighborhood parks	Single-Family Houses	hedonic model	N	N	N	Neighborhood	Positive externalities for only those properties which face open space
9		Hammer, Coughlin & Horn (1974)	Pennypark (USA)	Effect of a large urban park on real estate value	4035 single houses, 6370 twin houses	hedonic model	N	N	N	Neighborhood	Statistically significant rise in property values with closeness to parks
10		Cilliers and Timmerman (2012)	Potchefstroom (South Africa)	Linking economic values to green spaces	Houses and apartments	direct valuation approach	N	N	Y	Neighborhoods	In developing countries, the green spaces' values are not realized compared to developed countries.
11		Wu et al. (2017)	Shenzhen, China	Spatial effects of accessibility to parks on housing prices	3047 housing units	hedonic model	**Y**	N	Y	City	Effects of parks on housing units are statistically significant, accessibility to forest parks have a negative effect
12		Anderson and Nafilyan (2018)	Great Britain	Estimating the impact of UGS on property prices	One million-plus property	hedonic model	**Y**	N	N	N/A	Unmanaged green spaces affect the prices negatively while managed one affect prices positively

2.3. Overview on variable relationships

The study discusses two different approaches to checking the relationship between two variables. The first approach is the more general approach which s quantified by Pearson's r.

2.3.1. Aspatial Relationships

The method used for quantifying the relationship using a non-spatial technique was chosen as Pearson's r. Pearson's r was chosen for the application in exploratory analysis when the spatial units were taken as wards to quantify the relationships between variables. Pearson's r quantifies the linear relationship between continuous variables on two measures. The first is the p-value which signifies if the relationship is existent between the variables, and the second is the correlation coefficient (r) which defines the strength of the relationship, whose values range from -1 (linear negative) to +1 (linear positive) (Samuels, 2015). There are several interpretations of the strength of relationships in different fields of science. In general, the closer variable is to the value of +1 or -1, the stronger the relationship between the two variables under observation.
There are many formulae for calculating r, but the most common formula is given below:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

(Source: https://www.gstatic.com/education/formulas2/355397047/en/correlation_coefficient_formula.svg)

where,

r = correlation coefficient
x_i = value of the x-variable in the sample
$\bar{x}$ = mean of the values of the x- variable
y_i = value of the y-variable in the sample
$\bar{y}$ = mean of the values of the y-variable

2.3.2. Spatial Relationships

For checking the relationships between the variables on a finer scale of land values subzones and local fishnet level, the methods of local bivariate relationships are selected, which works on the principles of calculating joint entropy of the variables using the Minimum spanning trees algorithm. The method allows the users to know if a significant relationship exists between the two spatial variables of interest and what is the strength and type of the relationship. The tool quantifies the relationship using permutation-based distribution estimation and testing. The pseudocode, as per Guo (2010) to generate the local entropy maps is as follows:
"
Input:
$D = \{x_i,y_i\}$, $|X| = n$, where x_i = vector of dimensionality d, observed at location s_i
Steps:

→Normalize variables [0,1]
→For each spatial unit or location s_i :
-Find KNN (k nearest neighbor)
-Construct MST (minimum spanning tree)
-Estimate local entropy *e*
-Randomly create 999 permutations, and for each permutation:
-Construct MST with edge power α
-Calculate and record the entropy
-Convert e to p-values as per the distributions of 999 random permutation e values
→Test for significance of the p-values

Output:
Generation of a local entropy map with the colors signifying the significant relationships by their types.
" (p.1377).

2.4. Overview on hedonic pricing models

The hedonic pricing model determines price factors according to the principle that both internal characteristics of the product being sold and extrinsic factors affecting the product decide its price (Hargrave, 2020). Multiple regression analysis is the most frequently used method to estimate the model. Structural characteristics of housing units (S_{il}) and Amenities characteristics (*A_{ik} and also including U_{in}*) are the factors constituting the price of real estate, and their relationship is explained by a price function P. There are both advantages and advantages associated with using hedonic price methods. Semi-log and log-log are the most common specifications of the hedonic model used in the real estate business. These specifications have their benefits related to the rectification of likelihood to heteroskedasticity and the position of benefit where costs change according to the number of residential attributes (Malpezzi, 2003). On the other hand, Standard hedonic regression models do not capture the underlying spatial processes and interactions and have some underlying assumption which does not work well with the particular case of geospatial data.
There are several studies that utilize the most common log-linear functional form of the hedonic model. The equation mentioned below for the hedonic model is the modification of the equation defined by Liu & Hite (2013):

Simple functional form:
$P = f(S, A, U)$ …...1)

Expansion form (log-linear hedonic model):
$\ln P_i = \beta_0 + \beta_l S_{il} + \beta_k A_{ik} + \beta_i U_{in} + \varepsilon$ …...2)

P = log of housing list price/rent price, P_i = housing price in nature log form.
S = structural/Physical characteristics of housing unit, taken from the database directly, S_{il} = Structural characteristics l of house i
U = urban green areas characteristics, U_{in} = urban green areas characteristics n of house i
A = Amenities characteristics include distance to transportation networks, A_{ik} = Amenities characteristics k of house i

2.5. Challenges with traditional hedonic pricing models

The hedonic model for consumers expresses willingness to pay or implicit marginal prices. The model quantifies the amount of money that the user agrees to pay for, based on its perception, about neighboring environmental features, which add or deduct from the value of property estimated by intrinsic characteristics (Hargrave, 2020). One of the significant problems of hedonic pricing models is their inability to account for spatial effects from environmental features such as open and green spaces induced in the model due to its location-specific nature *(Getis, 2010; Miron, 1984).* The major problems related to the spatial effects in standard hedonic models are spatial heterogeneity and spatial autocorrelation. The terms spatial heterogeneity and spatial autocorrelation are very often used together at the same time. This phenomenon depends on the scale considered for analysis and the type of research question related to the study. Spatial heterogeneity is often referred to as first-order and spatial autocorrelation as second-order spatial effects. Spatial heterogeneity refers to the irregular and unequal distribution of an event or process across regions. It suggests that the model's parameters and the functional forms differ across the study area, heteroskedasticity, or some other misspecification in the model. On the other hand, spatial autocorrelation refers to the patterns in the observations at the local scale, which change with distance, which causes one observation to be affected by the change in another observation (Getis, 1995). The result of not treating Spatial heterogeneity is incorrect variance and coefficient calculation and diminished efficiency in calculating OLS estimates. The spatial autocorrelation results in the incorrect calculation of the OLS coefficients and variance estimates due to omitted variable bias. In other cases, if spatial autocorrelation is present and untreated, it results in the unbiased but ineffective estimation of coefficients (Rey et al., 2011). Due to these challenges, the traditional ordinary least squares method is inefficient (Dubin, 1998). Therefore, these challenges should not be ignored while modeling spatial phenomenon (Can & Megbolugbe, 1997; LeSage James & Pace Robertelly, 2009; McMillen, 2010; Pace, Barry, & Sirmans, 1998).

2.6. Global vs. Local Spatial Models

The effects from global models are distorted on a local scale due to the homogeneity supposition on the variation over space amongst the parameters. This assumption is not a correct representation of reality which causes the subsequent misspecification in the model formulation (McMillen & Redfearn, 2010). The wrong choices of fixed effects result in the model misspecifications. The global estimation models include ordinary least squares, spatial lag model, spatial error model, and other variants depending on endogeneity and exogeneity assumptions. On the other hand, the local models have merits over the global model due to modeling spatial heterogeneity and spatial autocorrelation and automatically assuming regularly evolving price functions in spatial housing data (McMillen & Redfearn, 2010). The local models are either conditionally parametric or nonparametric in nature and are a part of locally weighted regression models. Geographically weighted regression is an adaptation of LWR, particularly for working with spatial data, and avoids the issues that arise in the discrete modeling of spatial heterogeneity.

Global models were developed to solve the problem of autocorrelation in the regression framework since this phenomenon is frequently observed in spatial data. Spatial regression models (global models) account for spatial autocorrelation making the regression framework flexible, and they do this by removing the assumptions of i.i.d. (independently and identically distributed) independent variables and unrelated *ε (error term)* (Leung, Mei, & Zhang, 2000). Since the focus of projects is to quantify the spatial effects of urban green spaces at the level of point data across the study area, the spatial regression model will be ineffective

in explaining the local variation and characteristics of the spatial processes. Spatial regression techniques model the average of the spatial process or event at hand, due to which they are not considered to be local models. In this case, Geographically Weighted regression techniques can prove to be effective alternatives because they also consider the interactions between response and independent variable across the study areas (A. Fotheringham, Brunsdon, & Charlton, 2002). GWR takes variables into account which are non-stationary in nature. Thus, the usage of GWR is more suited to the needs and focus of this study, and at the same time, it will also allow us to maintain coherence across objectives.
As mentioned in the problem statement, most of the studies estimating spatial effects are skewed towards global spatial econometric models, but only a few studies utilized local geographically weighted regression techniques. Most of the studies where geographically weighted regression is applied relate to modeling housing rents (Tomal, 2020), real estate market activity (Cellmer, Cichulska, & Bełej, 2020), urban warming, and cooling due to urbanization (Z. Wang, Fan, Zhao, & Myint, 2020) and other topics. The drawback of non-standard regression models, including spatial regression and geographically weighted regression, is that they can be computationally intensive.

2.7. Geographically Weighted Regression as an extension to hedonic pricing models

In geographically weighted regression, separate regression equations are acquired for each spatial zone in the study area. Then for the spatial weights kernel, which is generally a gaussian variant (other variations include square and tricube), bandwidth needs to be chosen, which can be computationally intensive since at each stage *n* number of regressions are required to be fitted. The bandwidth can be predefined, fixed, or adaptive (McMillen & Redfearn, 2010) and is generally taken by applying cross-validation methods (Farber & Páez, 2007). After the local kernel and bandwidth are selected, a distance decay function is used to add weights to the adjoining zones after the kernel (fixated on a zone) is adjusted (A. Fotheringham et al., 2002). The equations given by Fotheringham et al. (2002) are as follows:

Geographically weighted regression:
The standard regression equation: $Y = X\beta + \varepsilon$ is transformed to:
$Y = (\beta \otimes X)1 + \varepsilon$, …...3)

with least squares estimate of $\beta'n = (X^T W_n X)^{-1} X^T W_n X$ …...4)

and Variance $(\beta'n) = (X^T W_n^{-1} X)^{-1}$ …...5)

where W is the weighting matrix whose selection is made after the choice of the kernel type which can be adaptive or fixed. The weighting matrix is defined as e.g. $W_n = [[W_{n1}, 0, 0, 0], [0, W_{n2}, 0, 0],[0, 0, W_{n3}, 0], [0, 0, 0, W_{n4}]]$, where the element lying at places other than diagonal are zeros. A classic example of the kernel function with bandwidth as b and distance between centroid of spatial units n and m as d_{nm} is:

$w_{nm} = \exp [-(d_{nm}^2 / 2b^2)]$ …...6)

The GWR models can be implemented through software packages such as ArcMap, ArcGIS Pro, GWR 4.0, or programming languages for statistics such as R.

3. RESEARCH DESIGN AND METHODS

3.1. The rationale for selecting an Indian case study

As mentioned in section 2.1 and 2.2, studies related to estimating spatial effects and inequities of urban green spaces have already been conducted in China, Brazil, and South Africa, except for India. India is currently facing the challenge of managing and developing 35 urban agglomerations with a population of million-plus residents (Registrar General of India, 2013). These cities and urban agglomerations are further estimated to house 14% of the world's urban population by 2025 (McKinsey and Company, 2010). Delhi, Mumbai, and Kolkata are the 2nd, 8th, and 15th of the world's most populous urban agglomerations (Norzom & Jacob, 2019). This migration from rural and semi-urban areas to large cities brings several challenges such as air pollution, urban sprawl, and other harmful environmental externalities. Population rises have adversely affected the per capita green spaces in cities, with Mumbai and Chennai being the worst performing with 0.12 sq.m. (Aldous, 2011) and 0.46 sq.m. (Srivathsan A., 2012), respectively. The guidelines suggested by the FAO require at least nine sq.m. of green space per capita (Salbitano, Borelli, Conigliaro, & Chen, 2016), from which the seriousness of the situation can be inferred. Thus, better provision and management of existing urban green areas become extremely important to mitigate the adverse effects of urbanization sustainably, making cities more attractive, peaceful, and comfortable to live in (De Ridder et al., 2004).

3.2. Description of the study area Mumbai

Figure 1:Location map of Mumbai, India.

Mumbai is located on India's western coast along the Arabian Sea borders (19.0760° N, 72.8777° E) and is the largest metropolis in India. In the last decade, the population has risen more than 12 times, and just in 468 square kilometers of land, Mumbai has a population of almost 20 million people (MCGM, 2017).

According to a study by Sahana, Dutta, & Sajjad (2019), the built-up category increased from 55.2 percent to 70.90 percent of the total land cover over the past 25 years. Uncontrolled growth in population and insufficient infrastructural facilities have caused a massive loss to the open and green spaces in the city's built-up areas. In the case of Mumbai, the provision is far from perfect when compared to the guidelines of the United Nations and also from the guidelines suggested explicitly for Mumbai city, which aims at achieving four sq.m. per capita of green spaces (MCGM, 2017). According to Singh, Pandey, & Chaudhry (2010), in their study, when the urban population is considered when green cities are considered, an average of 15-25 sq.m. of green spaces are present, which is far from the current situation in Mumbai.

With the limited availability of urban green spaces, the property prices in Mumbai are the highest when compared to other large metropolitan cities such as Delhi, Bangalore, Chennai, Hyderabad and others (Swati Gaur, 2015). Mumbai metropolitan region has seen a 33% increase in property rates over the last decade. The average price observed in Mumbai in 2010 was around Rupees 7965 per square feet which incremented to Rupees 10610 per square foot in Quartile 1 of 2020, and from the decade 2001-2009, the city recorded a 67% increase in property prices, the highest amongst all Indian cities (Anil Urs, 2020). Apart from the statistics mentioned above, it also becomes imperative to note that the Municipal Corporation of Greater Mumbai is the richest in the country and Asia with a budget of INR 30000 Crores and about INR 75538 Crores in reserves, which is accumulated over the years (Agrahari Amit, 2019; Neogy Pubali, 2019). The real estate sector in Mumbai struggles with many problems such as unaffordable housing (Bhargava, 2020), high housing sale prices (Abhyankar et al., 2018), unaffordable rental housing (Tandel, Patel, Gandhi, Pethe, & Agarwal, 2016), informal housing for the poor (Desai & Yadav, 2008), ineffective rent control and slum management policies (Jagdale, 2015). Mumbai has also seen several instances of gentrification, documented in multiple studies related to the inner city gentrification (Chatterjee & Parthasarathy, 2018a), suburban gentrification (Bhattacharjee, 2019), displacement from textile mill areas (Chatterjee & Parthasarathy, 2018b), and green gentrification (Doshi, 2019). It becomes even more essential to analyze the scenario of urban green Spaces w.r.t. property prices in Mumbai to analyze if green spaces are a contributing factor in this phenomenon.

The urban areas (particularly in India), including large cities, metropolises, and megapolis, are divided into zones, which comprise various wards. Zones are areas where the city's urban local body divides the land, which has a set of development control and planning regulations assigned to it. The details are listed in Table 2, which specifies the administrative divisions of Brihanmumbai municipal corporation:

Table 2: Administrative divisions of Mumbai City.

<table>
<tr><th>DISTRICT</th><th>ZONE</th><th>WARDS</th><th>DISTRICT</th><th>ZONE</th><th>WARDS</th></tr>
<tr><td rowspan="7">MUMBAI CENTRAL</td><td rowspan="5">1</td><td>A</td><td rowspan="4">WESTERN SUBURBS</td><td rowspan="2">3</td><td>H (E, W)</td></tr>
<tr><td>B</td><td>K (W, E)</td></tr>
<tr><td>C</td><td rowspan="2">4</td><td>P (N, S)</td></tr>
<tr><td>D</td><td>R (N, S, C)</td></tr>
<tr><td>E</td><td rowspan="6">EASTERN SUBURBS</td><td rowspan="2">5</td><td>L</td></tr>
<tr><td rowspan="2">2</td><td>F (N, S)</td><td>M (W, E)</td></tr>
<tr><td>G (N, S)</td><td rowspan="3">6</td><td>N</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>S</td></tr>
<tr><td>T</td></tr>
</table>

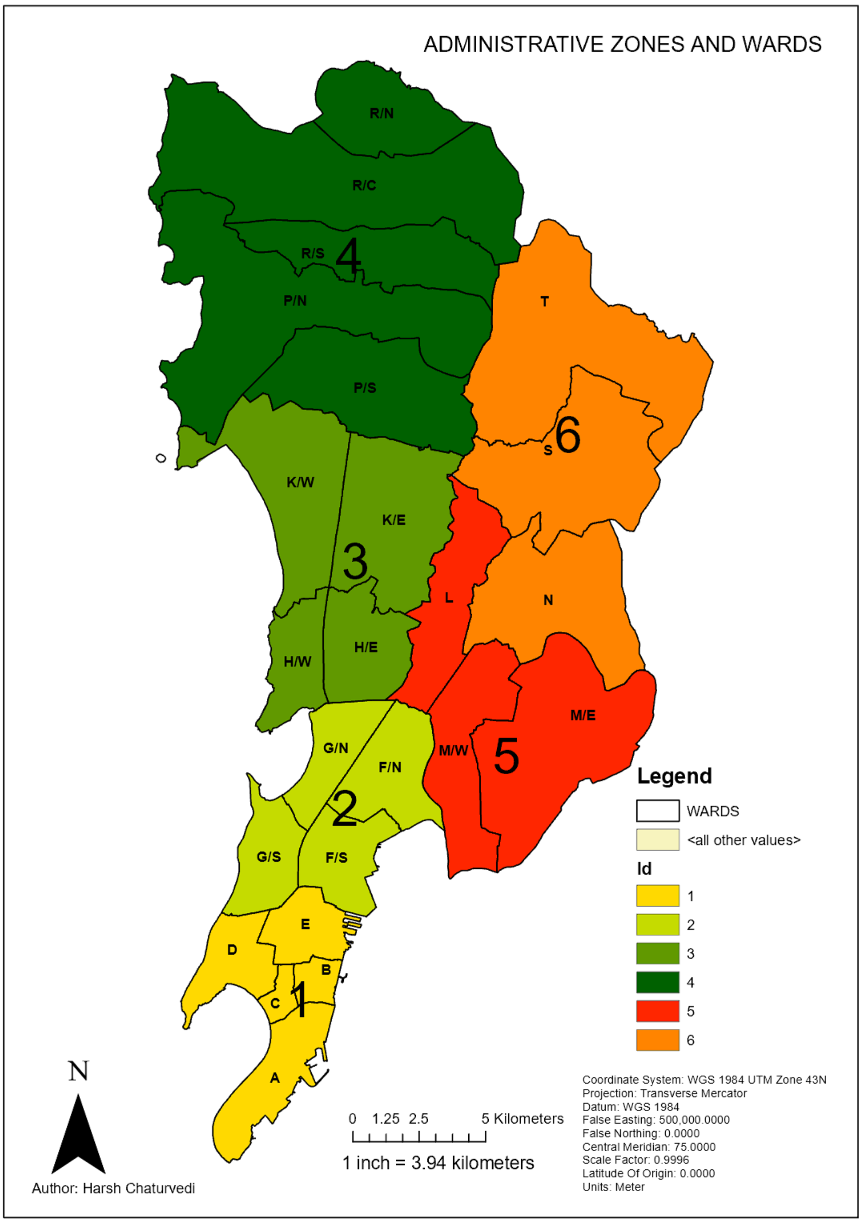


Figure 2: Map of Administrative zones and wards of Mumbai, India.

3.3. Data Sources and Description

3.3.1. Extracted Data

The existing land use data for the development plan 2014-2034 of the Brihanmumbai Municipal Corporation has been hosted on Websites of Urban Design Research Institute (UDRI, 2014) and also a web tool AKOR (Kore, 2014) as a project of the Indian Institute of Technology, Mumbai. The shapefiles are a part of existing land use data. The Slum dataset was also available in the web services, but the updated data of 2016 has been used hosted by the Data meet group on GITHUB (and as a google group forum). The dataset is taken from the Slum rehabilitation authority and contains the features of the notified slum clusters. The Land values dataset has been taken from IGR Maharashtra for the financial year 2020-2021(12th September 2020 to March 31st, 2021) (IGR, 2021). The last dataset pertaining to the sale and rent categories of online property listings is extracted through web scraping from housing.com for the date 27th March 2021 (Elara Technologies, 2021). The data contains all the properties that are available for sale or rent on that date. Some of the properties are added months back, and some are added recently.

3.3.1.1. Administrative boundaries dataset:

The administrative boundaries for the Municipal Corporation (city boundary), administrative zones, and the wards under administrative zones were acquired from the exiting land use data (Kore, 2014). Original source: Development Plan for Greater Mumbai 2014-2034 Existing Land Use Maps and Report. Mumbai: MCGM, 2012.

3.3.1.2. Land Values Dataset:

The rate of land and building are prepared under Maharashtra stamp rules 1995, since 1989. According to the provision in Rule 4, Joint Director (Town planning Valuation Maharashtra State) prepares this ASR with the help of the Deputy Director/Assistant Director which works at divisional levels under their jurisdictions and submits it to the Chief Controller Revenue Authority every year before October 31, after the ASR gets approved, they are made available from April 31st to March 31.
The dataset was obtained using web scraping techniques and had information such as zone, sub-zone, landmark, price data, etc. The vector files containing polygons of subzones of land value division were not obtained since the data provider has only listed the tabular data for each zone and not in the desired vector format. The variables extracted are mentioned in table 3 below:

Table 3: Variable extract for Market Values of Land Uses

S.No.	Variable name	Remarks
1	Sub Zone number	The tract of land with subcategories of values.
2	Village name	Sub zones come under separately defined villages.
3	Zone name	Villages come under Zones such as Central, Andheri, Borivali, and Kurla.
4	Land Values	Used for analysis.
5	Residential Built-Up Value	Used for analysis.
6	Office	**Not Used for analysis as out of scope.**
7	Shop	
8	Industrial	

3.3.1.3. Urban Green Spaces dataset:

Both the managed and unmanaged categories of urban green spaces were acquired from the existing land use data containing the polygons in each category. Within both the managed and unmanaged categories, there are some subcategories present, as mentioned in the definition but they were grouped under relevant categories. The feature attribute table for the unmanaged urban green spaces category contained 1,680 polygons, and for the unmanaged category, it was 398 polygons.

3.3.1.4. Slums Clusters and Residential dataset

The residential land use shapefile is acquired from the existing land use data, and the slum clusters shapefile is acquired from the dataset of Slum Rehabilitation Authority, 2016, and published by Data meet (Datameet, 2016). In the case of slum clusters and ward shapefile, the data was recorded in Geographic Coordinate System, and for calculating the statistics for each ward, it was converted into a Projected Coordinate System for the study area. The number of polygons in the slum clusters was 2,542, and for the residential land use shapefile, it was 16,172.

3.3.1.5. Property Listings Dataset:

The analysis's explanatory variables were taken from the standard hedonic pricing approach by Basu & Thibodeau (1998). In most of the studies, the analysis variables are directly mentioned and plugged in the hedonic model altogether, which makes it challenging to distinguish amongst them based on their types. In a study conducted by Maslianskaïa-Pautrel & Baumont (2016), urban green space variables are grouped in a broader environmental category with structural attributes. Liu & Hite (2013) also defines a similar grouping of variables. The types mentioned in Table 3 are taken from literature based on the availability from the housing database and have been divided into structural, urban green spaces spatial effects, and amenities variables.

The data was scraped from housing.com for both categories. The website was chosen due to the consistency of its database. Because of the data accuracy, the success rate of selling or acquiring a property is high. The website contains real estate property listings in other location than India as well (LandCraft, 2019). The original number of records in rental listings was 49,344, and for the sales listings, the number was 1,17,773. The number of records also varies in each category. The data was extracted on 27th March 2021. After the extraction of the data, for both rent and sale categories, the geolocation of the property listing is recorded as longitude and latitude. The longitude and latitude were added to the GIS using Add X, Y point data to the map. EPSG 32643 was then defined for the point shapefiles. The total number of variables extracted are as follows:

Table 4: List of extracted variables of property listings for Rent and Sale Categories

S. No.	Intrinsic variable	Remarks (intrinsic Variables)	Reference	Extrinsic/Amenities variables	Remarks (extrinsic Variables)	Reference	Location Variable
1	price	Dependent variable, INR	(Conway, Li, Wolch, Kahle, & Jerrett, 2010; Engström & Gren, 2017; Liu & Hite, 2013; Maslianskaïa-Pautrel & Baumont, 2016; McCord et al., 2014;	Closest Distance to Airport	Used for analysis as they are the most crucial reference variables from literature. Unit in meters	(Conway et al., 2010; Hwang, Nasution, Amonkar, & Hahs, 2020; Liebelt, Bartke, & Schwarz, 2018; Conway, Li, Wolch, Kahle, & Jerrett, 2010; Engström & Gren, 2017; Liu & Hite, 2013; Maslianskaïa-	Longitude X
2	builtup_area	Explanatory variable, Used for analysis, unit in square meters		Closest Distance to Bus stop			Latitude Y
3	bedroom	Explanatory variable, Used for analysis		Closest Distance to Railways			-----
4	parking	Explanatory variable, Used for analysis		Closest Distance to the grocery store	Considered for analysis, dropped as a subset, and		

5	balcony	Explanatory variable, Used for analysis	Reserve et al., 2020; Trojanek, Gluszak, & Tanas, 2018; Votsis, 2017)	Closest Distance to hospital	stepwise regression model did not indicate improved performance. Unit in meters	Pautrel & Baumont, 2016; McCord et al., 2014; Reserve et al., 2020; Trojanek, Gluszak, & Tanas, 2018; Votsis, 2017)	
6	age	Explanatory variable		Closest Distance to Mall			
7	security	Explanatory variable, Used for analysis, INR		Closest Distance to Park			
8	brokerage	Explanatory variable, Used for analysis, INR		Closest Distance to Pharmacy			
9	totalfloors_building	Explanatory variable, used for analysis, Total floors in the building, the count variable		Closest Distance to Restaurant			
10	furnished	Explanatory variable, Used for analysis		Closest Distance to Bank			
11	society amenities	Explanatory variable, Score from 1-13 depending on the amenities included		Closest Distance to Theatre			
12	property type	The variables are not used for analysis as they are categorical. A binary-encoded variable of the same type caused problems in parameter estimation hence dropped Varied Units	-----	Closest Distance to Managed UGS	Used for analysis. Unit in meters	(Conway et al., 2010; Engström & Gren, 2017; Liu & Hite, 2013; Maslianskaïa-Pautrel & Baumont, 2016; McCord et al., 2014; Reserve et al., 2020; Trojanek et al., 2018; Votsis, 2017)	
13	sale type			Closest Distance to Unmanaged UGS			
14	listed by			Area of closest Managed UGS			
15	RERA compliant			Area of closest Unmanaged UGS			

16	furnishings			The shape of the closest Managed UGS	Dropped as highly correlated with the area variable in the regression model. Also, the possibility of discrepancies of vertices in the shapefile. Count variable		
17	facing direction			The shape of the closest Unmanaged UGS			
18	floor listings			-----			
19	possession status						
20	project name	Text data, not used for analysis					
21	address						
22	description						
23	added_info(time)	Time data, limitation of study					
24	carpet area	Highly correlated with built-up area					
25	bathrooms	Highly correlated with bedrooms					
26	average price (per unit of measurement)	Dynamically calculated on webpages, varied units, not considered for analysis					
27	EMI (equated monthly installments)						

3.3.2. Data Pre-processing

Tools used:
The software used for the processing and analysis of data is ArcMap 10.8.1, ArcGIS Pro, and QGIS 3.18 as GIS tools. Apart from the GIS tools, Excel, Octoparse, and Python have been used for the tasks of data processing and extracting. These tools have been utilized simultaneously depending on the functionalities and the type of tasks.

Figure 3 summarizes the steps taken for acquiring the data and the pre-processing steps to mold the data into a form ready for analysis:

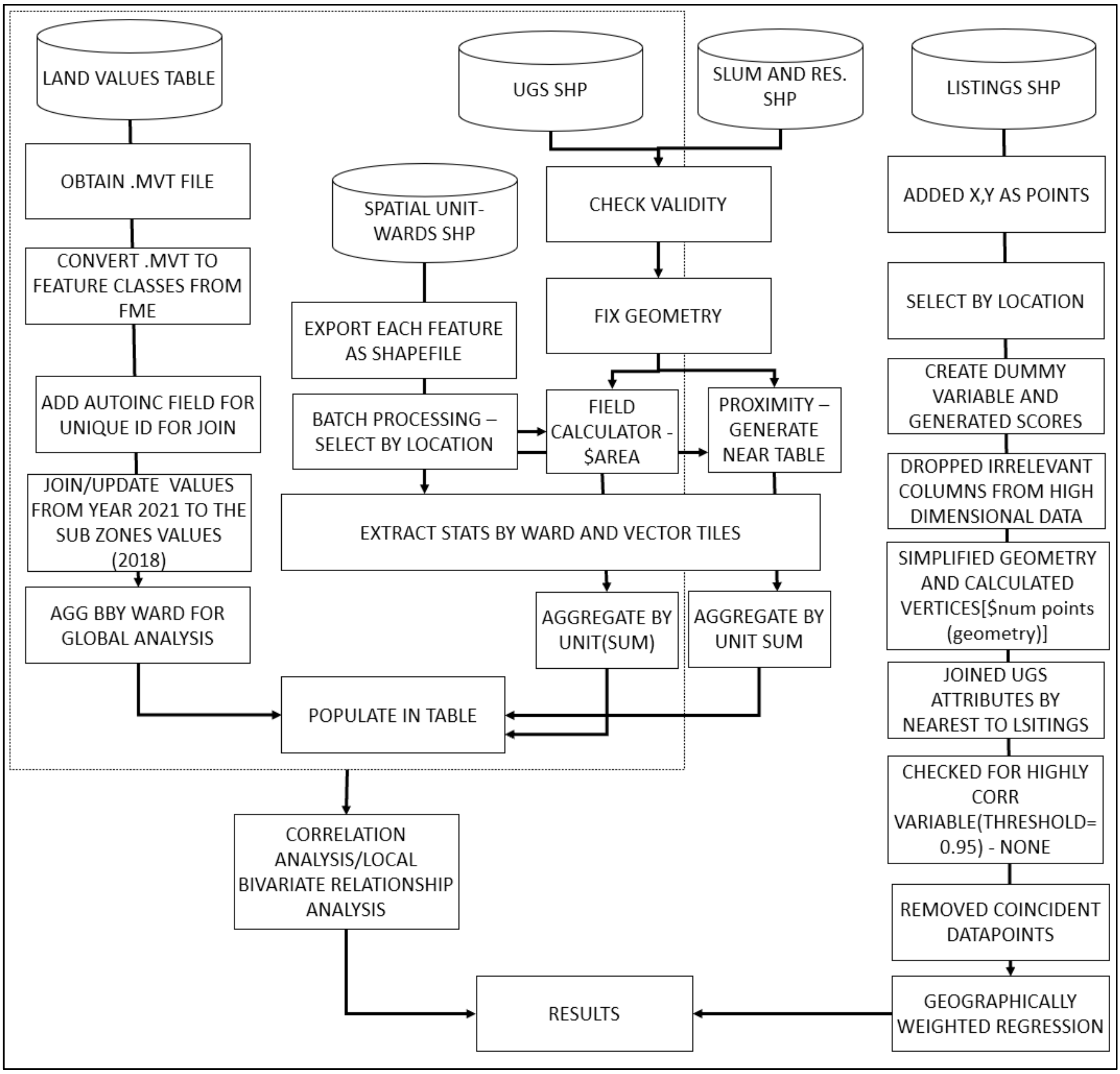


Figure 3: Framework of Data pre-processing

Matching Land Value subzones to wards

The land values subzone dataset shapefile was also extracted form the UDRI's loginmumbai.org website in the for of .mvt file (mapbox vector tile). The file contained the polygon with the relevant sub-zone number. The subzone numbers were then matched with the data extracted for the current year through SQL.

The data was then aggregated as average for each ward for the analysis at global(aspatial) level. With this step, the average land values with residential built-up were obtained for each ward. There was a total of 842 records obtained by web scraping, out of which 730 were taken for aggregation. The other records related to different land value sub-zone outside the BMC city boundary and for those reasons were dropped. While merging the tables, there were some duplicate values, which were deleted. They were also some unmatching records present which did not relate to the extracted table, so they were dropped. These unmatched records were present outside the administrative boundary of Brihanmumbai Municipal Corporation.

Fixing Geometries

Also, within each shapefile, some of the polygons were topologically incorrect and had deformities such as self-intersection and ring self-intersection. Managed urban green spaces shapefile had no invalid geometries present. In the unmanaged category, there were 13 invalid geometries present. The slum clusters contained 21 invalid geometries, and the residential use contained 201 invalid geometries. The (in)validity of polygons was arrived at by the Check Validity tool within the vector processing toolbox of QGIS. These topologically incorrect polygons returned an error while calculating the proximity geoprocessing operations. These incorrect features were corrected using the Fix geometry tool within the vector processing toolset of QGIS. After the correction of invalid geometries, the process of obtaining proximity stats for features was uninterrupted. The proximity from each feature of slum clusters and residential land use was calculated to each feature of managed and unmanaged urban green spaces. Then the values were sorted again for each ward using the FID of polygons and aggregated as the average value for each ward.

While calculating the nearest distance to each type of urban green spaces from residential and slum clusters was done using Generate near table tool of ArcMap, for the property listing, it was not the case. For the property listings, it was done using the 'Join attributes by nearest' tool in QGIS as in the ArcMap. The attributes of the features are not joined during the calculation of the proximity value. Only the closest features were selected in both cases. There was a slight difference in both the tools where in ArcMap, the tool allows calculation of distance by geodetic value but in QGIS, it only allowed the calculation by Planar method. Since the study area is only restricted to the extent of a city, the assumption is that these two methods would not cause significant differences in the calculation of proximity. Also, while calculating proximity variables for property listings, the tool recorded multiple instances of the listing being closest to 2 nearest features than 1. This expanded the number of records in both the sale and rent files. These attributes were joined to the original file using left join using Unique ID of listings, which resulted in the retention of only one closest feature.

Area Calculations

Using the Field Calculator tool in Arc GIS, the area of each polygon within the shapefile was calculated. The area of the shapefiles was then selected by location and feature of each unit (ward/land value subzone or fishnet vector tile) using the Select by location tool in Arc GIS and using Topology argument 'have their center in' for each spatial unit. This process sorted the features in each shapefile as per the spatial unit and saved the data in separate .csv files. After obtaining the features and their areas within each spatial, they were aggregated as the sum of the areas of managed UGS, unmanaged UGS, slum clusters, and residential land use. The stats for each spatial unit in terms of the calculation of areas of features or the proximity tables was done using the batch processing operations within the software packages.

Under objective a.3., the spatial unit of analysis was performed on both wards and land value subzones. Also, in the statistical analysis framework of a development plan, wards are considered as the standard unit through which the land uses and other variables of interest are analyzed. However, for analyzing the correlations between variables under research question b.2., an analysis on a finer level was possible due to the proper availability of vector data. It was performed by dividing the study area into rectangular grids using the fishnet tool, and the fishnet was created as a bounding box on the boundary of Brihanmumbai Municipal corporation. The Rows by columns values were 41*41. In order to use the local bivariate tool to understand the local relationships between variables, the maximum input vector records are set as 1000 (minimum 30). After clipping the fishnet from the extent of the bounding box to the extent of the BMC boundary polygon, the number of tiles remained at 948 within the study boundary. More rationale is provided in Section 3.4.3.

Again, using the tool of extract layer by location, the polygons in shapefiles of urban green spaces (managed and unmanaged) and residential land use (formal and informal) were extracted based on the intersecting criteria within each tile and stored as a separate file. These separate files contained the information on quantities (area) of variables under each tile. Previously while analyzing the level of the spatial unit, the aggregation of values was a concern as the local variations within the wards would not be captured but using this technique, the local variation is captured, and the types of relationship within each local zone is also arrived. This approach solves out the problem of aggregation on a coarser scale when the dataset is available for finer scale.

The values from each separate .csv file were populated in the table for each tile and then analyzed using the local bivariate tool. Since the quantities of the urban green spaces and residential land use also depend on the size of the spatial unit of interest, they were analyzed as proportions. For Example, the area of managed urban green spaces in a tile/total area of the tile, and similarly for other variables. Unlike Pearson's r-value, this tool analyses for statistically significant relationships by classifying each record in one of the six available categories. The categories are Not Significant, Positive Linear, Negative Linear, Concave, Convex and Undefined Complex.

Selection/Sorting of Listing Data by location

The data that is scraped from housing.com for both rent and sale categories have been sorted from the website using the keyword Mumbai from the domain. Since the data is collected from a private entity, their rule in the grouping of property listings using the Mumbai keyword is for the whole Mumbai Metropolitan Region (MMR), which is much beyond the spatial extent of our study area. So, the records having latitude and longitude values were sorted again using the Select by Location tool of ArcMap, and all the points that returned valid within the extent of Brihanmumbai Mumbai municipal corporation boundary were collected by making a subset of the original data file and stored separately for analysis. The number of rental listings after the selection of data points by location was 42965 records, and for the sale listings, the number of records was 38665 records. The number of columns in rent categories is not identical to the sale and fewer in number. Other processing and data wrangling/cleaning operations are mentioned in the previous table.

Apart from the areas, the number of vertices in the urban green space features was used as a parameter for shape as it describes the polygonal complexity of a feature. As there were some issues present in the urban green space's dataset related to geometries, before calculating the vertices, the features simplified using the snap to grid method as it matches the original shape more closely than other methods. The method snap to grid is not very efficient in terms of compressing the file size as compared to the other methods, but the file size was not the priority, so the factor was not considered. After the simplification of the polygons, the vertices of the features were calculated using the $num points(geometry) function under the field calculator of QGIS. This function returned the number of vertices as a column for the urban green space features which are to be used in the GWR model.

Data issues with listings records:

The issues with this particular data set were that of overlapping and duplicate points, which were verified and removed by GIS using the Delete Identical tool. The irrelevant data in the form of columns were removed (as mentioned in the previous table). There were also some issues in terms of the data types for a few variables, especially with the date variables, so they were transformed to the number of days (but ultimately not considered for the analysis). At few places in the model (exploratory regression), the whitespaces in the header created a problem (ultimately, the tool crashed). Other columns were transformed into dummy variables to make use of them, since, in the geographically weighted regression, any random categorization scheme for categorical variables should not be followed, and instead, the data should be encoded as a dummy variable, to be analyzed; otherwise, the model misinterprets the levels of classification (for example class 1, class2, class3 and so on). Some of the fields had strings attached to the numerical value; in those cases, the string from the number was separated, and then some columns were dropped if the string had many levels (for example, the columns of average price). Out of the variables chosen for analysis, they were checked for the high correlation between them with the threshold set as 0.95.

3.4. Analytical Methods

3.4.1. Analytical Structure and Framework

For the first part of the analysis, land values for the financial year 2020-2021 are being considered in this study as a proxy indicator for socioeconomic status due to the data from the district census handbook being outdated. Due to the scarcity of socioeconomic data, land values have been used in several studies as a substitute criterion to approximate the socioeconomic status of the population, and in many instances, its relationship with other measures of equity is noted (Kolbe, Schulz, Wersing, & Werwatz, 2015; S. Li, Li, & Ouyang, 2017; Zhu, Yang, & Xiaodong, 2003; Źróbek, Cellmer, & Kuryj, 2005). Land values have also been used as a proxy indicator for socioeconomic status in other domains such as health (Coffee et al., 2013), education (Ware, 2019), and other domains (Barnard & Oranje, 2014; Kristiawardani & Sampe, 2017). Utilizing the last census data would cause a mismatch in the timeline of different datasets, thus not considered for this study. The suggestions from Hwang et al. (2020) are considered as follows: A] Low-income areas (Notified Slum clusters area per unit area) will be considered for checking correlation with UGS areas by types. B] Social Amenities variables will be incorporated in the geographically weighted regression model to add further detail to evaluating spatial effects.

For the second part of the analysis, notified slum clusters within the study area represent the population that is deprived and has a low socioeconomic status. The slum clusters present in the study are notified and designated in the ELU map by the urban local body. Correlation analysis of these clusters by their areas will be made with urban green spaces to check if there exists inequity in the provision of managed and unmanaged urban green spaces. This analysis will allow us to check whether there are significant relationships between urban green spaces with the broader measure of socioeconomic status and the actual indicator of populations with low socioeconomic status. In summary, the first and second parts of the analysis will enable us to verify the inequities present with the spatial distribution pattern of urban green spaces with land values and slum clusters. At the same time, Land Value is also a real estate indicator, and Slum Clusters also provide us with the locational aspect of areas with a low socioeconomic population. Both these variables, to a reasonable extent, serve as indicators for both the issues of inequity and valuation.

The third part of the analysis's focus would be on quantifying the spatial effects of urban green spaces on residential property prices and establishing the relationships between them. For this, online property listing on real estate websites would be analyzed using a regression model. Online property listings have been used as a proxy for property market indicators (Ali, Haase, & Heiland, 2020; Kristiawardani & Sampe, 2017). Thus, list price from the online property listings proves as a valid and viable alternative to assess the spatial effects of urban green spaces on property prices. This price can be mentioned in online databases for both selling and rental purposes by the owner. The database is chosen based on the accuracy of its data and reputation in the real estate market (refer to Table 4). This part of the study has each point as the spatial unit for analysis, which will provide more comprehensive local effects to be evaluated using geographically weighted regression, which is more suitable as there are multiple local spatial units.

Figure 4 summarizes the overall methodological framework for the M.Sc. research project as follows:

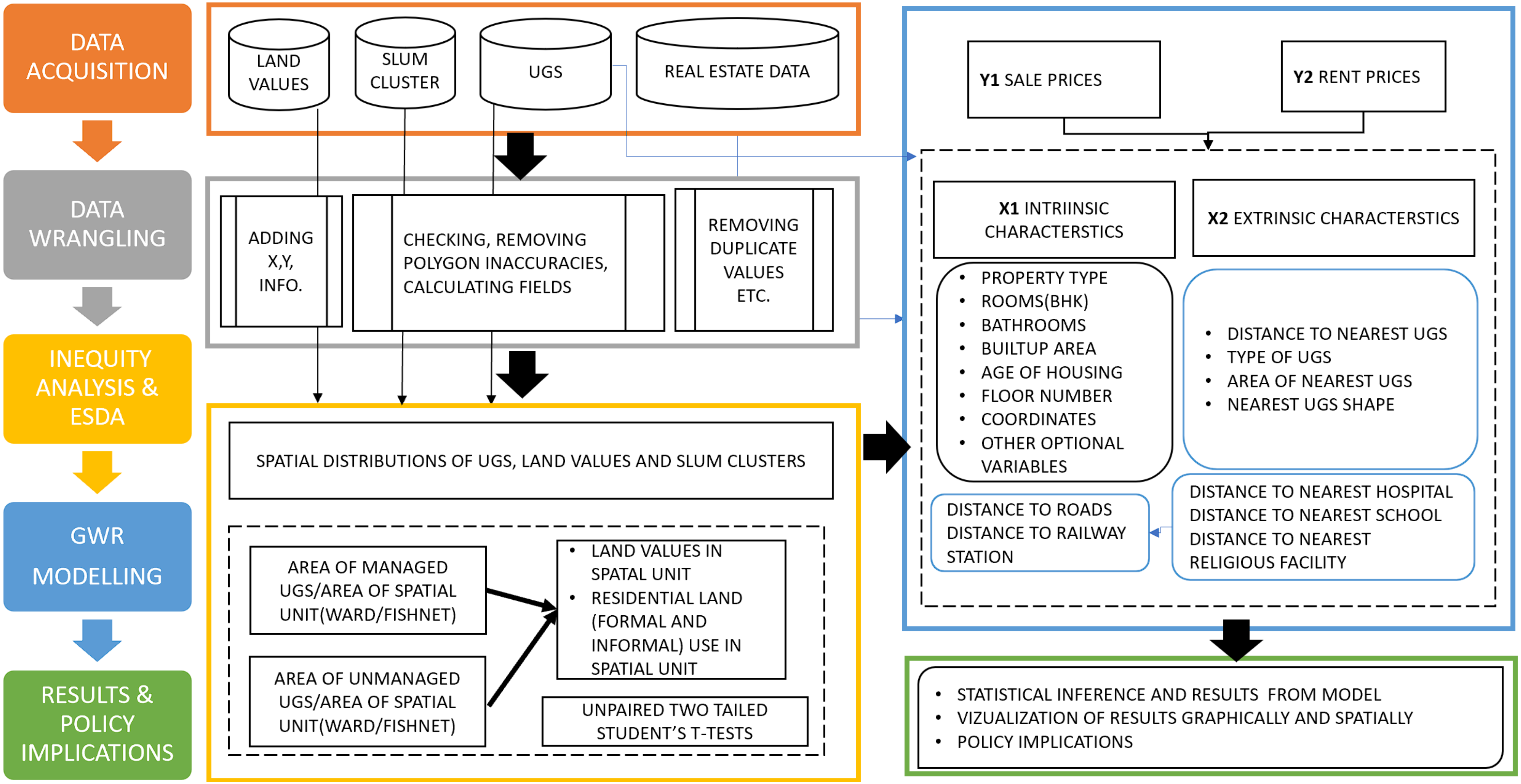


Figure 4: Methodological Framework for the M.Sc. project.

3.4.2. Spatial unit of analysis

The distribution of urban green spaces, residential land uses are mapped in GIS and overlayed with the pie charts (proportional quantity maps) describing the quantities of the variable present in each ward. Also, bar charts are included sorting the values in the wards from high - low for each shapefile. Land values are mapped in a categorized choropleth visualization.

The spatial unit of analysis in the study are varied and depend on the level of detail present in the available dataset. Overall, wards are used to analyze the relationships at a global level, and apart from wards, the analysis is conducted by land value sub-zone polygons, and a fishnet grid clipped to the study area's extent. For the GWR, the analysis is made on point level as the listings are recorded as point values.
For the ward level, Pearson's correlation coefficient was calculated for the variables to check the strength of their relationships after the pre-processing data tasks in the first place. Also, a t-test was performed to check the difference in mean values of nearest urban green spaces (by types) from the informal and formal residential land uses. The aggregation caused improper estimations and a failure to detect the local relationships between features, so the whole study area was divided into vector tiles. As a result, an alternative method of analyzing the data locally in space was made using the Local Bivariate Relationships, which calculates the relationships using the joint entropy of the variables. The land values sub-zones were used as the unit of local analysis apart from the fishnet grid. The descriptive statistics for the land values subzones are as follows:

Table 5: Descriptive statistics for the Land value variables.

S.No.	Type	Description	Mean	SD	Min	Max
i	Open Land	The average rate of land (in INR) for subzone /sq.m.	95031.70732	66886.93	0	475400
ii	Residential Built-Up	The average rate of Built-up (in INR) for a subzone/sq.m.	178371.8157	119407.4	0	861000
iii	Open Land +Residential built-up	Average rate of open land + residential built-up for a subzone /sq.m.	275114.2877	183547.3	0	1321240

3.4.3. Local Bivariate Relationships

Local Bivariate Relationships

The study area was divided into a fishnet of rectangular cells (default output) of 41*41 tiles as a bounding box of the study area. The tiles were extracted for the study area, which contained 948 vector cells in the study areas. The resolution of an average cell is 532 m (Width)*1040 m (Height) (except for the ones touching the boundary, as they are clipped to fill the area). The reason for dividing the study area into 41*41 tiles was:

1) In the case of utilizing a large number of neighbors from the Local Bivariate Relationships tool, the maximum number of neighbors is 1000, so the number of tiles within the administrative boundaries should be less than the maximum number of neighbors (selectable).
2) Due to topological reasons, the 'Intersect' topology was used to extract the variable polygons from the vector tiles and the land value polygons. The intersect topology was the best option to choose,

but more advanced options in other software exist, such as 'have_their_center_in' in the ESRI GIS suite. However, the options of batch processing and iterating over features were not possible in the ESRI GIS suite; therefore 'intersect' option was exercised from QGIS. This option creates problems of redundancy in some cases when a polygon is overlapped on the clipping boundary. Due to the larger of Residential and Unmanaged UGS vector polygons, creating vector cells on a finer scale would further cause problems; therefore, the chosen fishnet was considered for analysis.

The number of neighbors selected for the analysis is 30 for the model to remain as local as possible. The tool allows the user to select the number of neighbors from 30 to 1000, which has its own implications. Using a large number of neighbors results in significant relationships in the model but makes the model less local in the study area. Using many neighbors also increases the computational complexity and execution time-lapsed of the tool by many folds. Using many neighbors would fail in detecting local relationships in the study area and will oppose the inherent purpose of the tool, i.e., to detect local relationships. For a point process where the data points are in the range of several thousand, a greater number of neighbors can be used. The level of confidence/alpha of the model is taken as 0.95, which is a standard practice in the scientific domain. The number of permutations that are used to calculate the pseudo p values is 99, 199, 499, and 999. As an exploratory step, the problem can be explored by assigning a small number of permutations first, for e.g., setting the default to 99. As the best approach, the number of permutations was set to 999 to be able to calculate the best possible pseudo p values. The processing time increases as a greater number of permutations are selected. For more accurate results, the False Discovery Rate correction factor (alpha) was set to 0.5, controlling for the Type I errors in the model. The output was saved in a shapefile with the significance values in the fishnet vector tiles. After the selection of these parameters, the tool returns the relationship between variables in six categories. The limitation of the tool is that it is only able to detect linear and quadratic relationships, and in cases of other types of functions/relationships, it categorizes them as undefined complex. The categories are as follows:

i. Positive linear – Direct linear relationship.
ii. Negative Linear – Inverse relationship
iii. Concave - When the explanatory variable increases, the dependent variables change in the form of a concave function.
iv. Convex - When the explanatory variable increases, the dependent variables change in the form of a convex function.
v. Undefined complex – when the relationship between the variables is statistically significant but not falling under the other categories defined in this list.
vi. Not significant – returns true when the relationship is not significant between the variables.

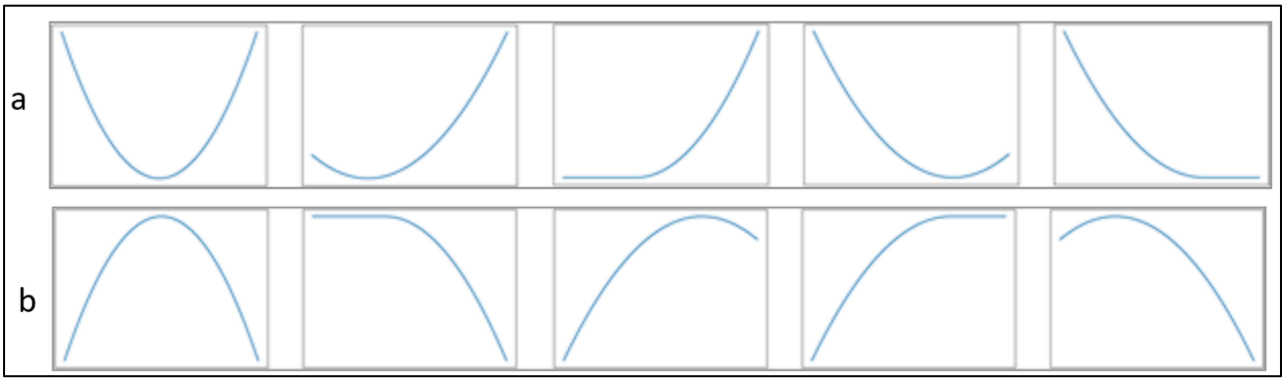


Figure 5: Types of quadratic relationships, convex (a) and concave (b) curves (Image Source: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/GUID-D774E151-E448-43B8-8DE1-C122D981EAFE-web.png)

From the introduction and problem statement section, it was clear that areas with low socioeconomic status have faced inequity in access to the urban green spaces in the city, which is taken as the baseline assumption. This research question has been analyzed to find out if there is a significant difference in access to the types of green spaces in each ward. As explained in the previous section on the data pre-processing, the nearest distance from the informal and formal residential land uses has been calculated to both managed and unmanaged categories of urban green spaces. After that, the distance to each category from informal and formal residential land use has been checked for the significant difference using a t-test. Since we are not sure of the directionality, a two-tailed unpaired t-test has been used. Since the variances of the samples are unequal, a heteroscedastic test s performed (tested for the variances using f-test and thus chosen the configuration). The descriptive statistics in the case of urban green spaces and residential land uses are not represented since they are varying in the spatial scale of analysis. Also, the use of intersecting topology caused the proportions of urban green spaces and residential land use in some wards to be very high.

3.4.4. Geographically Weighted Regression

The problem of coincident data points kept returning errors during the model run. When we select the number of neighbors in the tool, the coincident features must be less than the minimum number of neighbors chosen. After the selection of point data by location, there were several property listings that had the same longitude and latitude information. This can be due to two reasons:

1. They are actual duplicates, and somehow, the database is designed with redundancy.
2. The property type falls under the apartment category, and in a building, there are several different apartments listed for sale, hence the same geolocation (unlikely).

The coincident data points were removed using the Delete identical toolset under the Data Management of ESRI GIS suite. As the input, the longitude and latitude values were used, and the identical data points were deleted (can be checked from UID). This reduced the number of data points to 12194 under the sales category and 13454 under the rent category.

After the removal of coincident data points, the exploratory regression tool (stepwise regression) was tested to arrive at suitable variables for the geographically weighted regression model. At the start of this process, due to the size of the dataset, the computing limit of the tool was exceeding (1 million combinations. The spatial weights matrix was calculated as an input to the exploratory regression model with KNN as the conceptualization of spatial relationships. The value at K was taken as 200 as roughly there are 40000(n) rows for both sales and rent categories. So, the square root of n is 200. As a rule of thumb, the square root of n is taken for the calculation of the value of K in the KNN algorithm (S. Zhang, Li, Zong, Zhu, & Cheng, 2017). The tool generated the spatial weights matrix for both sale and rent categories. Due to the high dimensionality and the size of the dataset, the tool kept returning errors in the beginning. Finally, the list of variables was returned with their significance values. The results of this tool were not used as the size of the dataset was enormous, and the OLS model would not be effective in identifying the significant variables anymore.

The maps below provide the extracted dataset belonging to the sale and rent categories as follows:

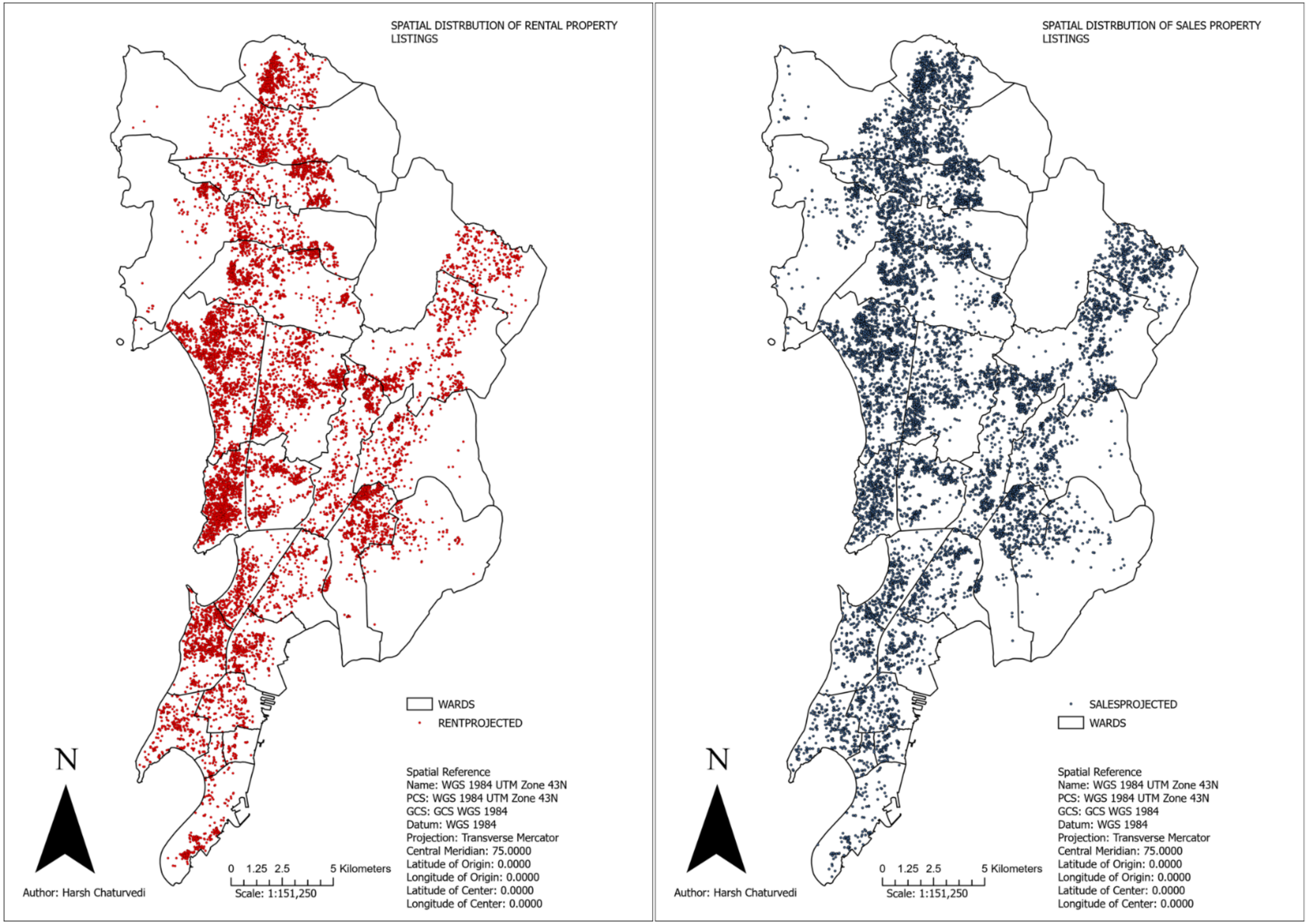


Figure 6: Spatial Distributions of Property Listings, Rent (left) and Sale (right) (generated from housing.com data)

Running the GWR returned error again due to multicollinearity, so highly correlated features were rechecked on the modified dataset with unique non-coincident data points. The correlation matrix is not attached below (due to size [rows by columns]). In both the cases for Sale and Rent, there were two variables that were highly correlated with other variables hence dropped (In bold):

a) **Carpet area** with built-up area
b) **UnmanagedUGS_vertices** with UnmanagedUGS_area.

The highly correlated variables were sorted as a result of running a correlation matrix on the dataset and sorting the highly correlated variables out, but since the dataset is in the form of points and the GWR is calculated locally for points, there is a high chance that the subsets of the dataset (while calculating local equations) contain highly correlated variables. Local VIF and VDP are calculated by the MGWR implementation; hence the global model was not used to calculate VIF.
The variables used for analysis are as follows:

Table 6: Descriptive Statistics for variables in Rent category

RENTAL PROPERTY LISTINGS					
Variable	Unit	Mean	SD	Min	Max
Dependent Variables					
Total_price	INR	55414	64770	3500	130000
Explanatory Variables					
Intrinsic/Structural variables					
builtup_area	square metres	896	589	100	7600
bedroom	n/a	2	1	1	6
parking	n/a	1	1	0	5
balcony	n/a	1	1	0	12
age	n/a	10	9	0	99
security	n/a	209437	275682	0	500000
brokerage	n/a	50637	65259	0	1300000
total_floors	n/a	11	9	0	90
furnishing	n/a	10	2	0	12
society amenity	n/a	3	3	0	13
Extrinsic variables					
nearest_dist_airport	metres	8499	4724	700	2160
nearest_dist_busstop	metres	597	622	0	3000
nearest_dist_railways	metres	1205	772	0	6300
UGS variables					
nearest_dist_managed_ugs	metres	251	219	0	2304
area_nearest_managed_ugs	square metres	3221	7012	0	72370

Nearest_dist_unmanaged_ugs	metres	1454	1317	0	7103
Area_nearest_unmanaged_ugs	square metres	551798	1311458	151	11860675

Table 7: Descriptive statistics for variables in Sale category

SALE PROPERTY LISTINGS					
Variable	Unit	Mean	SD	Min	Max
Dependent Variables					
Total_price	INR	35534367	97281813	200000	990000000
Explanatory Variables					
Intrinsic/Structural variables					
builtup_area	square metres	996.7323	781.6154	100	24000
bedroom	n/a	1.898615	0.967014	1	10
parking	n/a	0.739347	0.693107	0	8
balcony	n/a	0.543857	1.003162	0	9
age	n/a	9.415394	10.94243	0	99
brokerage	n/a	175472.5	623468.8	0	50000000
total_floors	n/a	13.88627	10.96965	0	85
society amenity	n/a	3.42951	3.145161	0	11
Extrinsic variables					
nearest_dist_airport	metres	9197.523	4761.945	700	21700
nearest_dist_busstop	metres	655.5575	688.2218	0	3000
nearest_dist_railways	metres	1184.1	792.0912	0	7600
UGS variables					
nearest_dist_managed_ugs	metres	262.0224	237.2468	0	3003.696384
area_nearest_managed_ugs	square metres	3644.552	8640.672	0	72370
Nearest_dist_unmanaged_ugs	metres	1298.29	1192.184	7074.178	14623937.17
Area_nearest_unmanaged_ugs	square metres	790960.8	1755748	151	10268603

The spatial kernel of the model was chosen as 'adaptive' to choose the bandwidth from a set of neighbours and the weighting function was selected as standard 'bisquare'. The bandwidth searching method was selected as 'Golden Search' which minimized the AICc score to arrive at the optimal bandwidth for the gaussian model. The optimal bandwidth for the rent model was 208 neighbours and for the sale model the optimal bandwidth for the sale model was arrived at 1024 neighbours. The variables were also log transformed and GWR was performed to check the relationships, but the transformation did severely degrade model performance and poorly explained the variability in price w.r.t explanatory variables. Hence, the variables were only standardized in model calibration and not transformed as the case with the hedonic pricing equation. Out of the complete dataset which contained data for different categories of housing, only apartments were chosen for analysis as they are the most common housing unit in the study area. Analysing different property types would require a most robust machine learning technique if the goal of the analysis is to predict housing prices, but machine learning regression methods do not capture the spatial structure of the underlying process.

4. RESULTS

4.1. Research Question a.1, a.2, and b.1 (Objectives a & b)

To study the spatial distributions of Urban green spaces, Land Values and Residential Land use over the study area.

a.1. How are the urban green spaces spatially distributed by their types (managed and unmanaged) across each ward?

In the study area, the highest amount of managed green spaces is present in ward A. Ward A is the second largest ward in Mumbai Central in terms of area after ward F/N (second highest quantities of managed UGS). In general, the wards located within Mumbai Central enjoy higher proportions of managed urban green spaces than other wards from Western and Eastern Suburbs (As illustrated in Figure 7). Other wards from Eastern suburbs such as Ward T, N, and L have relatively higher quantities of managed urban green spaces than the Western suburbs. On the other hand, Wards B, C (relatively small area when compared to other wards), H/E, G/N, and P/N (more patches of unmanaged UGS), constitute the least quantities of managed urban green spaces. The managed urban green spaces are present in the forms of fragmented patches, which are smaller in size and are dispersedly located over the study area (Hwang et al., 2020).

For the unmanaged urban green space, figure 7 clearly shows that Eastern and Western suburbs have the most quantities of unmanaged urban green spaces, with the highest quantities being in Wards T, N, L, R/S, R/C, respectively. Wards situated with Mumbai Central have either nil or negligible amounts of unmanaged urban green spaces, which is evident from Figure 7. The results are also consistent with the findings from Hwang et al. (2020), which indicate that unmanaged UGS are present in larger quantities in the northern peripheral areas of the city.

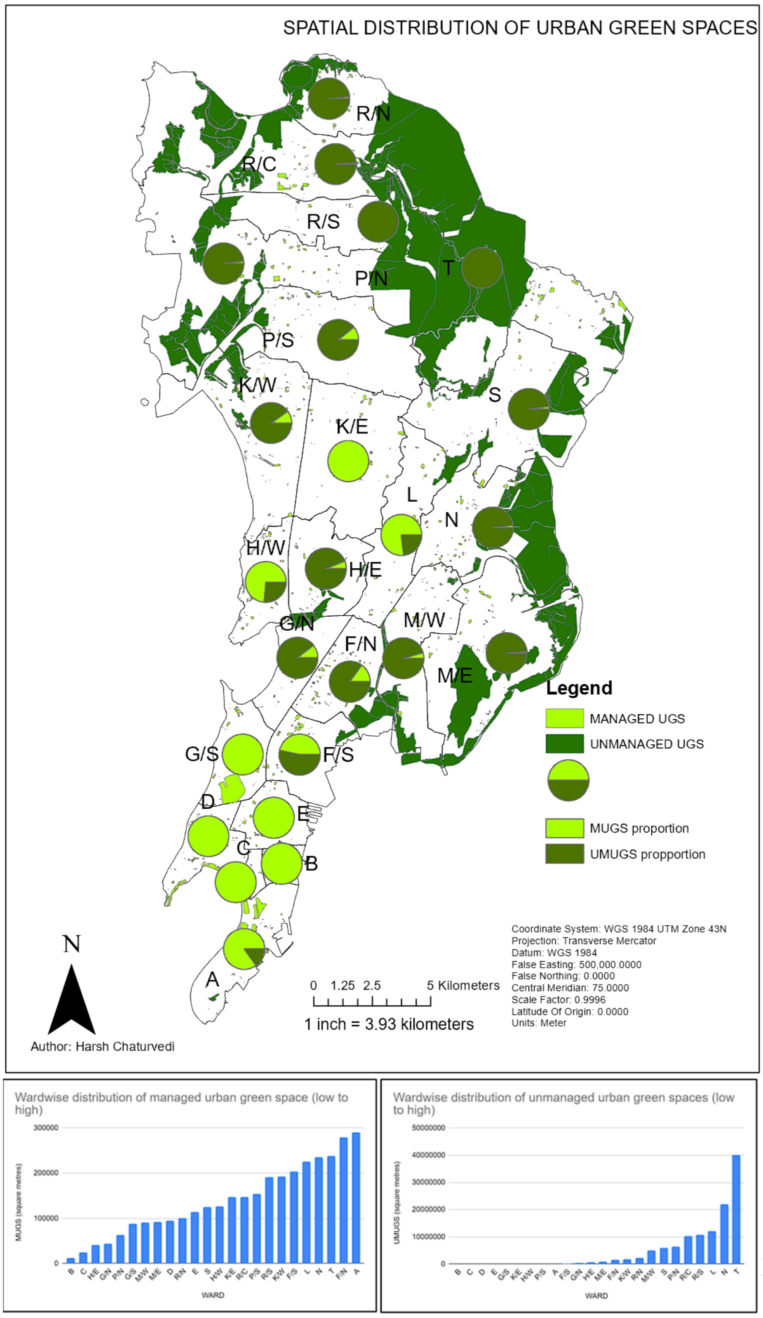


Figure 7: Spatial Distributions of Urban green spaces by types across the study area

a.2. How are the current land values spatially distributed across each ward?

From figure 8**,** it is evident that the values of land plus the values residential built up are highest in the wards situated in Mumbai Central (southern part of the city) because of the presence of coastline and higher elevation in those wards. In the Western suburbs, the values almost follow an inverse function of distance where the farther one moves from Mumbai Central; the values keep decreasing. In the Eastern suburbs, the values are the lowest because of the higher concentration of unmanaged UGS (mangroves) in the wards with a significant portion of classified land use along with port infrastructure and higher proportions of informal land use (MCGM, 2017).

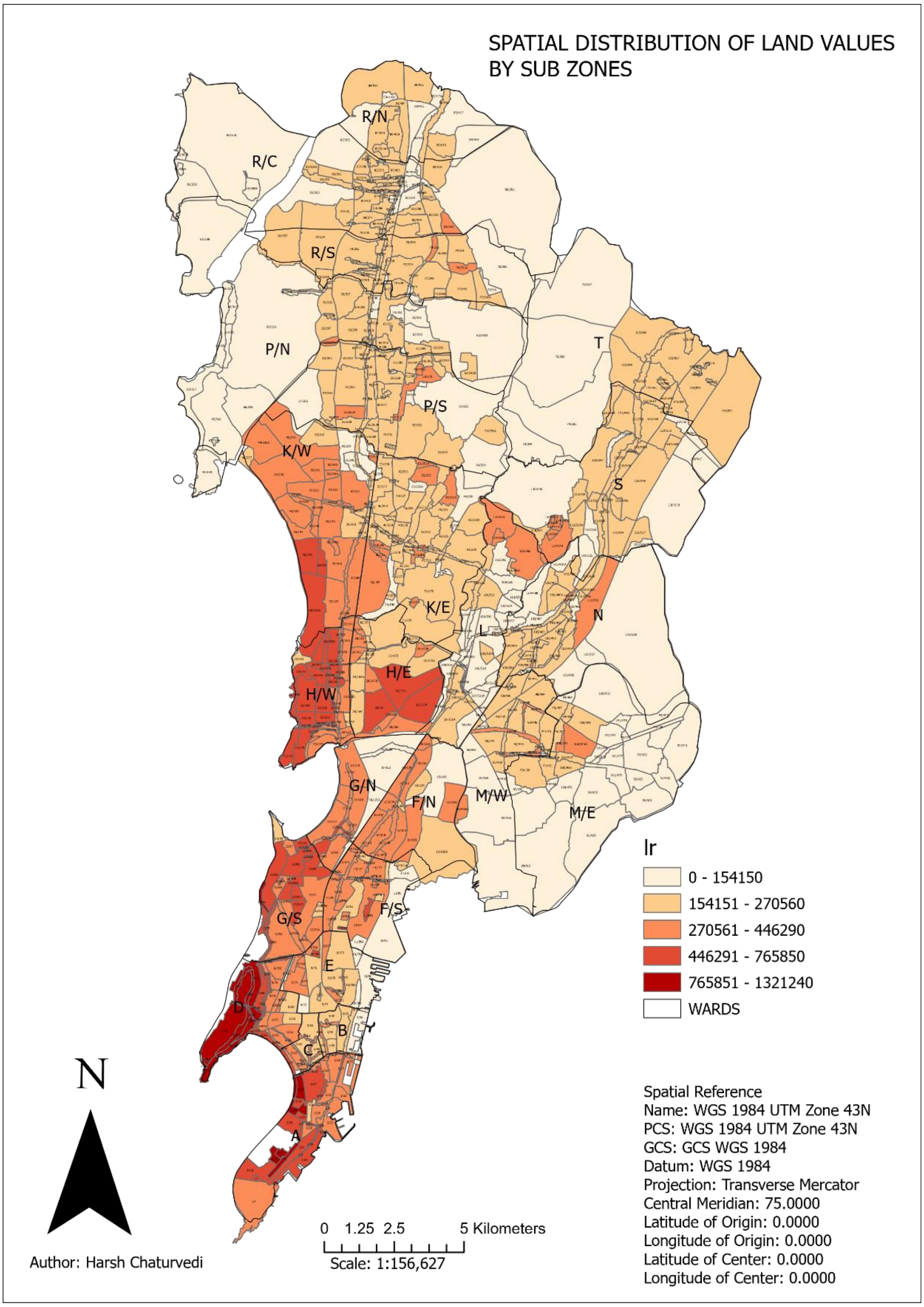


Figure 8: Spatial Distribution of Land Values by subzones across the study area

b.1. How are the informal (notified slum clusters) and formal (designated) residential land uses and spatially distributed across each ward?

The informal residential land use (slum clusters) is primarily concentrated in the wards situated within the Eastern and Western suburbs. The quantities of informal residential land uses are the lowest in the wards situated within Mumbai Central due to the higher land values. The eastern and Western Suburbs have, due to the presence of higher proportions of informal settlements than Mumbai Central district, are subject to lower land values. The wards situated in the suburbs also contain high proportions of unmanaged urban green spaces, which raises the need to check inequities in access to managed urban green spaces from informal settlements.

Note: Due to the scaling issues between areas of managed and unmanaged UGS , scatterplots are not used to plot the quantities I a single graph. Instead, separate bar graphs are used to depict wards with higher or lower quantities of urban green spaces and residential land use.

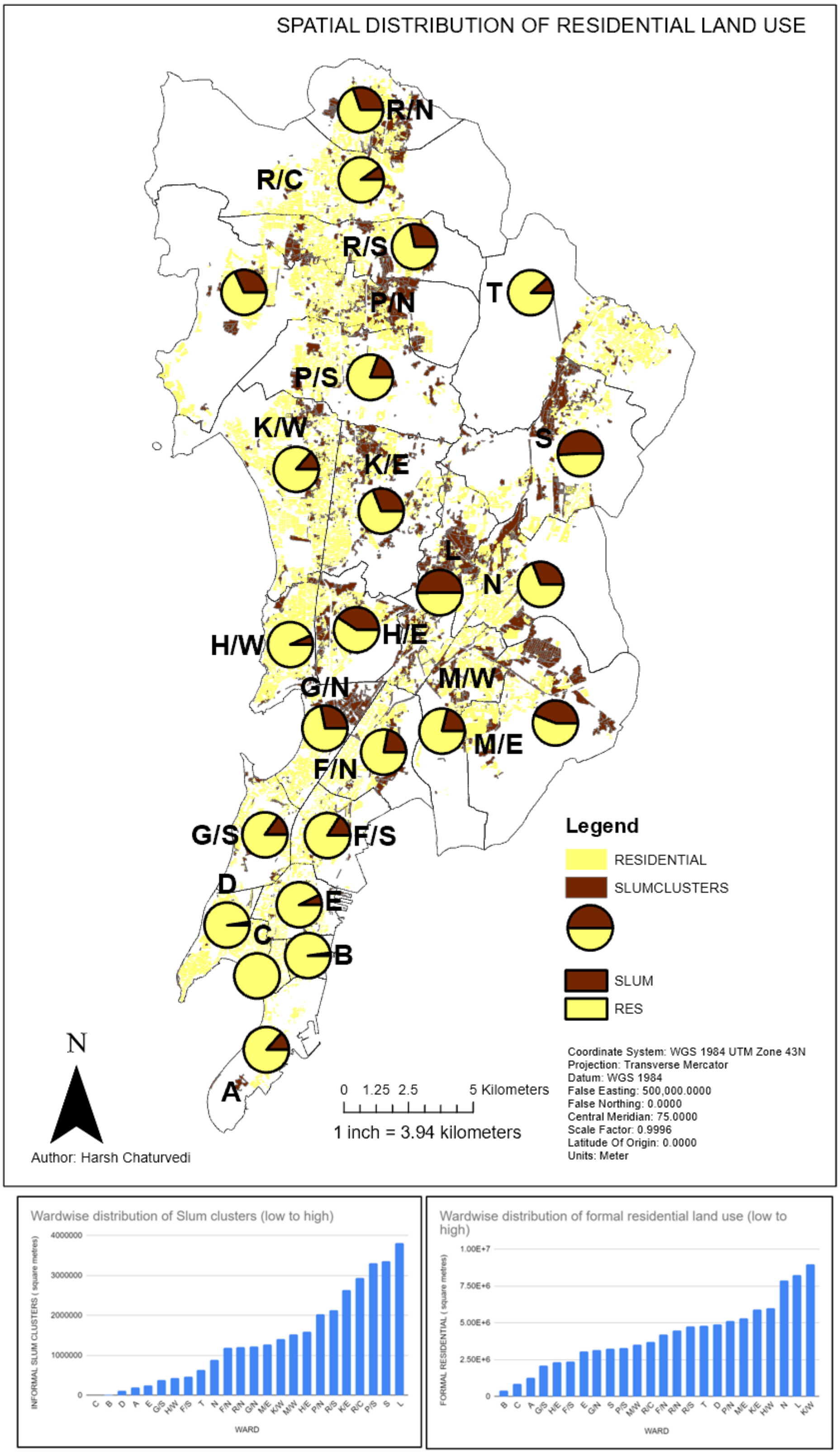


Figure 9: Spatial Distribution of Residential Land uses by types across the study area

4.2. Research Question a.3, b.2, b.3 (Objective a & b):

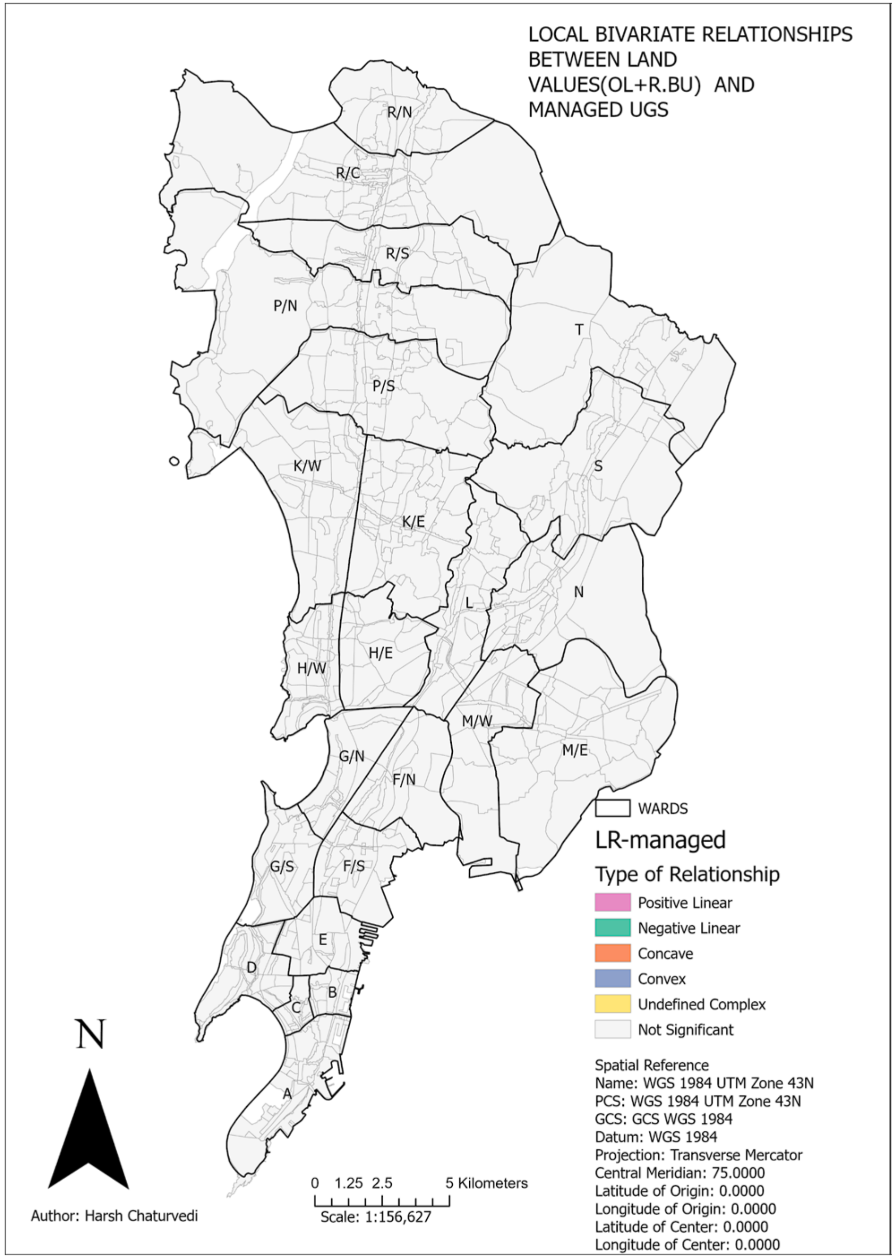
To analyze the relationships of UGS with Land Values in the study area.
To analyze the relationships of UGS with Slums Clusters in the study area.

a.3. Is there a relationship between the distribution of types of urban green spaces (the total area of managed urban green space/total ward/sub-zone area) with Land values over the study area (market value of open land + market value of residential built up in each ward/sub-zone)?

The method uses neighboring polygons from a specific polygon of interest and calculates pseudo p values using permutations to detect the significant relationships. The categories of significance are mapped on the land values polygons. If a polygon represents a positive relationship and the surrounding polygons represent a concave relationship, it will imply the dependent variable (Land values, open land values, or residential built-up values) increasing in the form of concave function with the independent variable (managed or unmanaged UGS), which means if the unit in the independent variable is added or subtracted the dependent variable will increase or decrease linearly/quadratically with the associated function type.
Case 1: Dependent variable – Aggregated Land Values (Sum of Average Open Land Values and Average Residential built-up values for land values subzones, refer Table 5).
Case 2: Dependent variable – Average Open Land Values for land value subzones
Case 3: Dependent variable – Average Residential Built-up Values for land value subzones.
Independent Variable – Proportions of UGS (total area of managed/unmanaged UGS in a spatial unit (ward/land value subzone/fishnet) divided by Total area of the spatial unit.

Table 8: Results from relationships between land values and UGS by their types

S.no.	Hypothesis	Ward Level (Pearson's r)	Local subzone level
1	Proportions of Managed urban green spaces have a positive relationship with land values over the study area	Proportions of managed urban green spaces and average land values were found to be moderately positively correlated (48) = 0.57, $p = 0.003$ (The result is significant at $p < 0.05$).	The relationship of land values, when including the market values of open land plus the market values of residential built-up, do not reveal any significant relationship with the urban green spaces (both managed and unmanaged) over the study area. This is due to the aggregation scheme of the land values where the residential built-up values are also added to the base values of open land.
2	Proportions of unmanaged urban green spaces have a negative relationship with land values over the study area.	Proportions of unmanaged urban green spaces and average land values were found to be moderately negatively correlated r (48) = -0.51, $p = 0.10$ (The result is not significant at $p < 0.05$).	



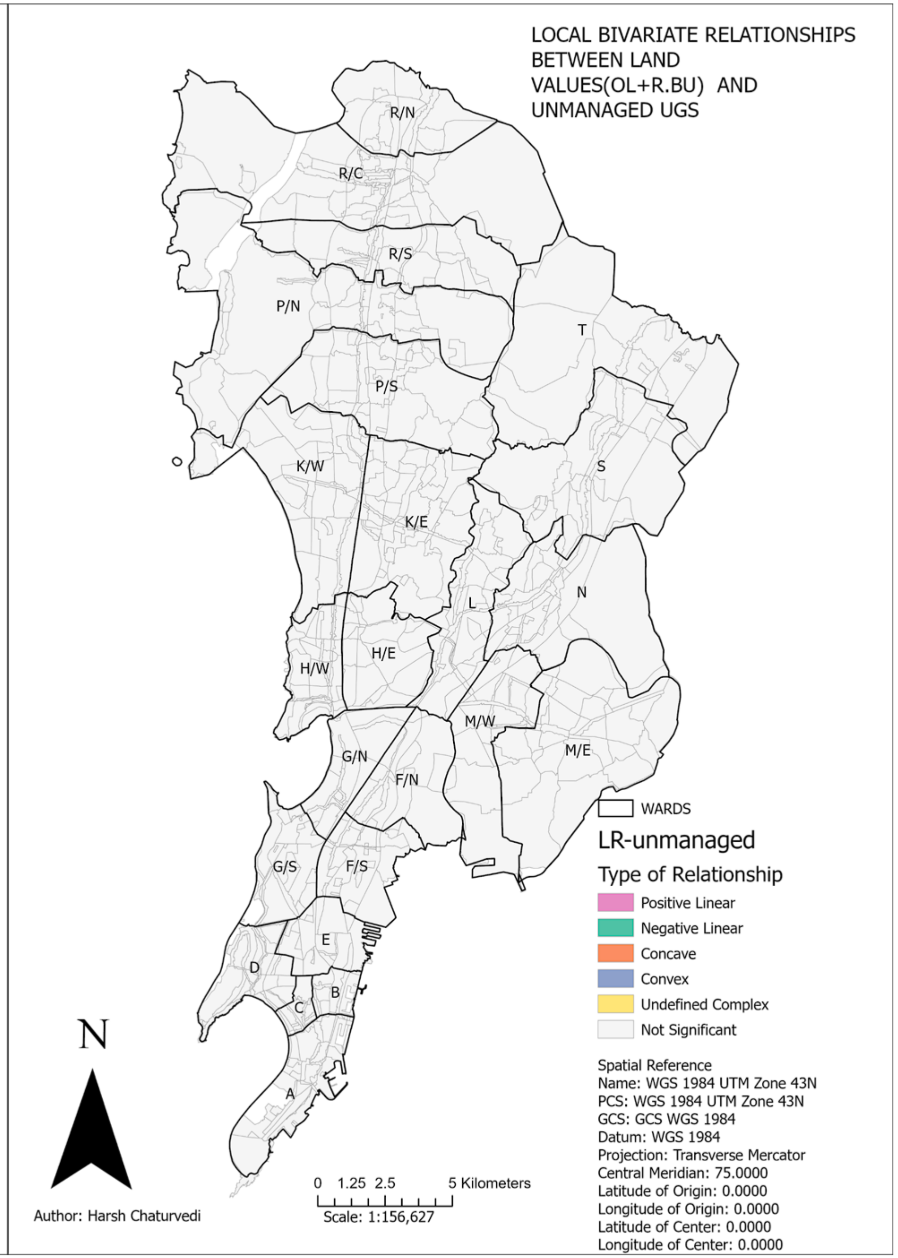


Figure 10: Local Bivariate relationships between Land values and Urban green Spaces (managed -left, unmanaged-right)

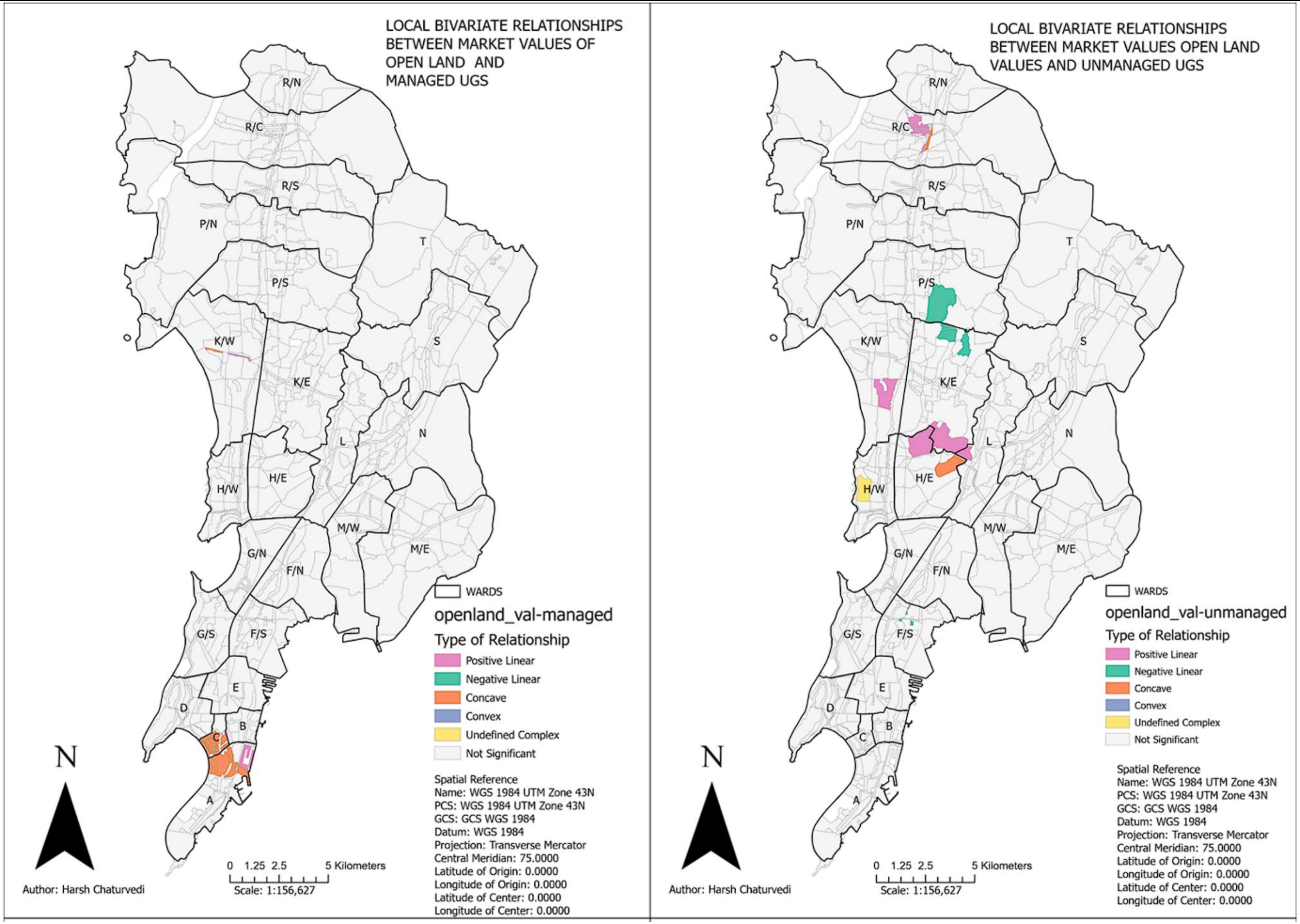


Figure 11: Local Bivariate Relationships between market values of open land and urban green spaces (managed -left, unmanaged-right).

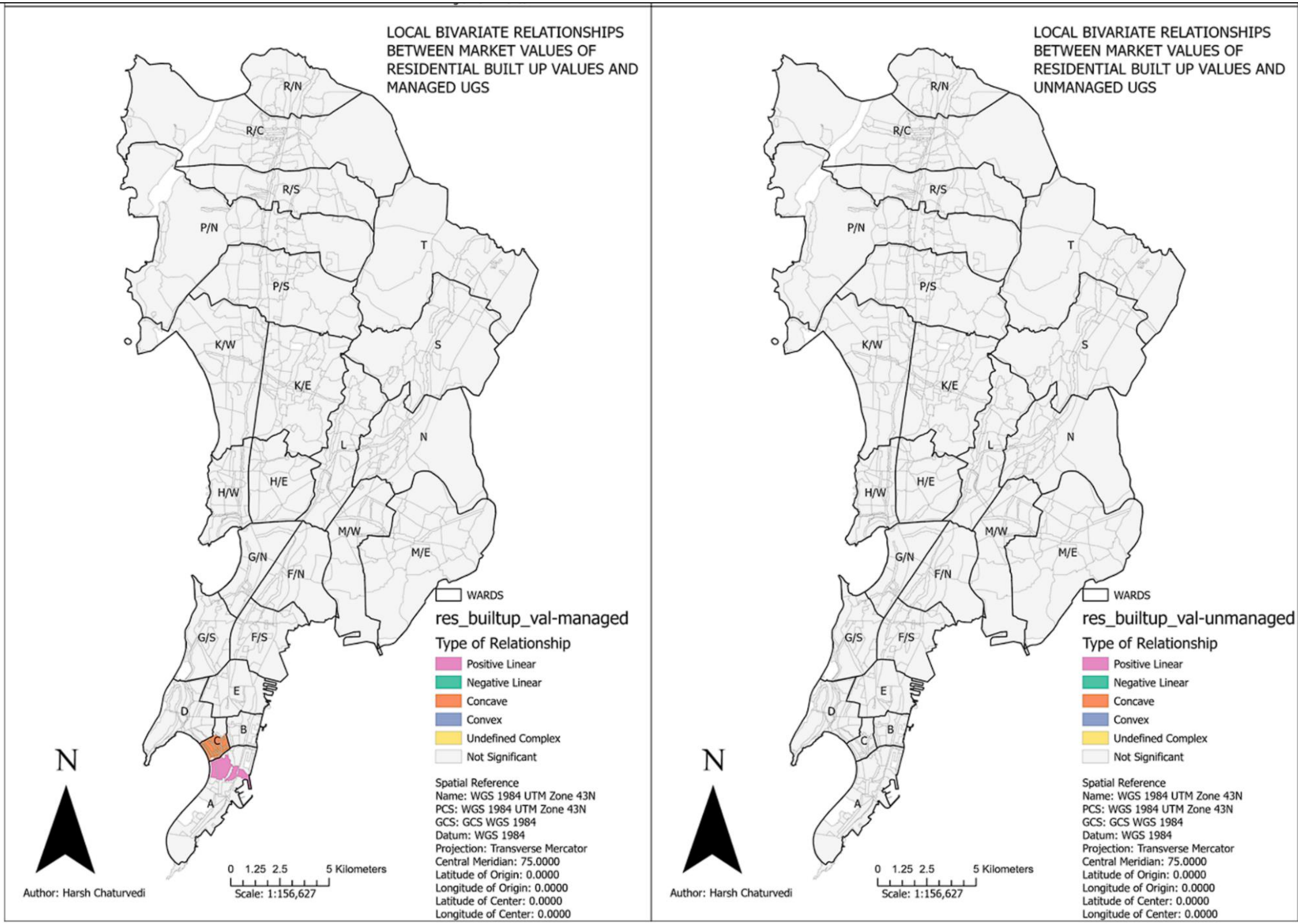


Figure 12: Local Bivariate Relationships between market values of residential built-up and urban green spaces (managed -left, unmanaged-right

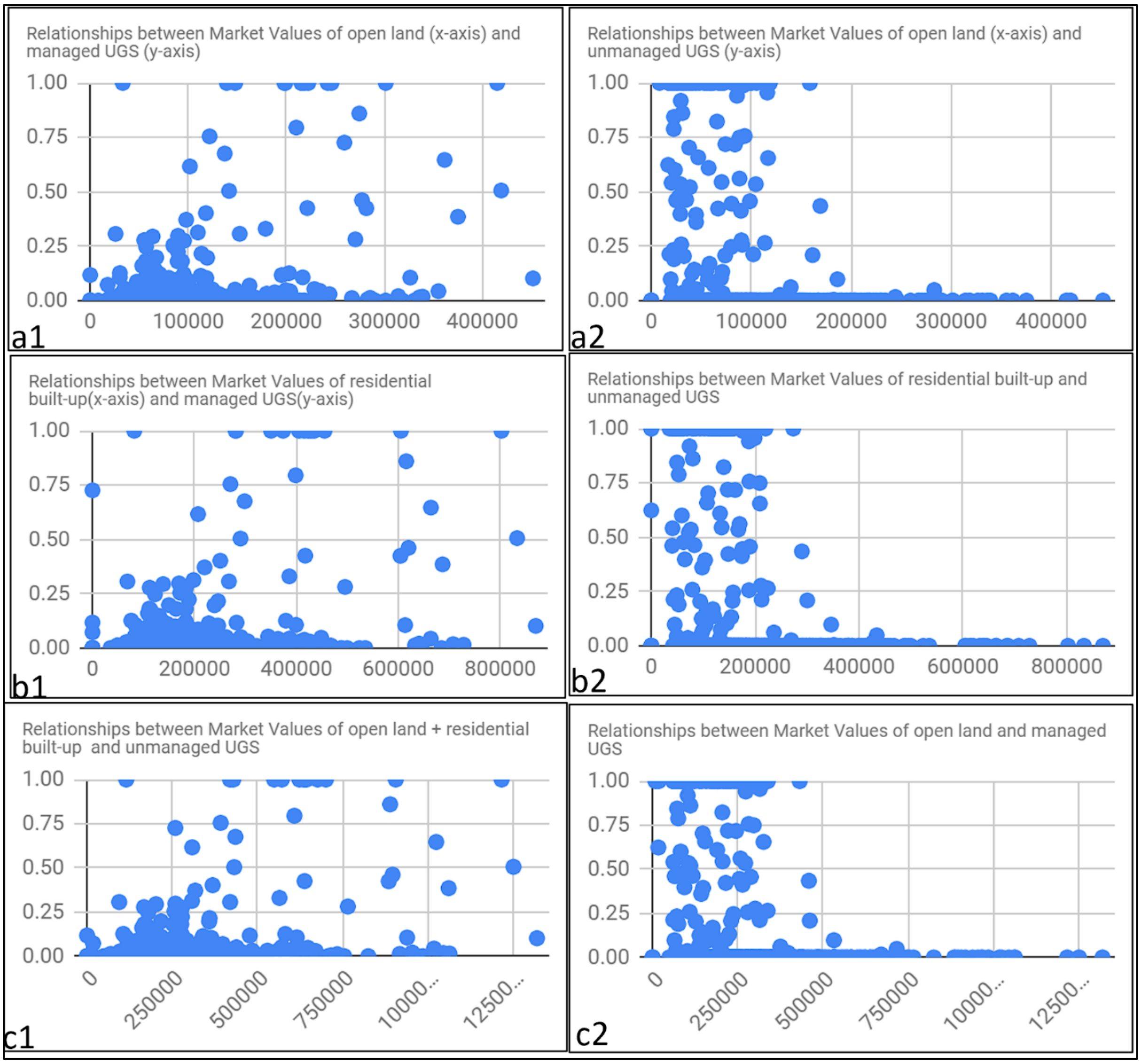


Figure 13: Scatterplot depicting relationships between land values (aggregated and disaggregated) with UGS

On the other hand, when the analysis is carried out using individual market values of either open land or residential built-up, there are significant relationships with managed urban green spaces detected over some land value sub-zones polygons. The results from previous case 1 do not prove a significant relationship with the aggregated land values making it difficult to conclude that urban green spaces are related to the indicator of SES denoting equity/inequity. However, disaggregation of the market values of open land and residential built-up did reveal some significant positive relationships with managed urban green spaces as hypothesized. Both the market values of open land and residential built-up showed positive linear and quadratic relationships with managed urban green spaces in the wards belonging to the Mumbai Central area. In the case of unmanaged UGS, there were significant linear positive /negative relationships observed with market values of open land. These relationships were positively significant in zones that were closer to the Central Business District and negatively significant in zones farther from the Central Business District. However, there were no relationships observed between unmanaged urban green spaces and the market values of residential built-up. These relationships are similar to the results from further analysis.

Table 9: Results from local bivariate relationships between market values of open land and residential built-up with urban green spaces (by their types)

S.no.	Hypothesis	Local subzone level
1	Proportions of Managed urban green spaces have a positive relationship with open land values over the study area	In the case of analyzing the average values of open land with proportions of managed urban green spaces, the relationship is significant in zone 1, particularly in wards A, B, and C, where the proportions of managed urban green spaces are higher when compared to other parts of the city.
2	Proportions of managed urban green spaces have a positive relationship with market values of residential built-up over the study area.	Similarly, the relationship between the average market values of residential built-up and proportions of managed urban green spaces was found significantly positive at the same location as Case 1.
3	Proportions of Unmanaged urban green spaces have a negative relationship with market values of open land over the study area	On the other hand, the relationship of average open land values with proportions of unmanaged urban green spaces revealed significant relationships with the subzones bordering or lying in close proximity to unmanaged urban green spaces.
4	Proportions of Unmanaged urban green spaces have a negative relationship with market values of residential built-up over the study area.	However, the average market values of residential built-up did not reveal any significant linear or quadratic relationship with the proportions of unmanaged urban green spaces over the study area.

b.2. Is there a relationship between distributive patterns of types of urban green spaces (the total area of managed/unmanaged urban green space/total area of ward/fishnet) with residential land use (the total area of slum clusters/total area of ward/fishnet)?

In both the cases of checking inequities in the provision and access to the managed and unmanaged UGS w.r.t formal and informal residential land uses, the results produced a lot of false positives due since including the tiles with null values highly contributed to the skewing of results and resulted in significant relationships in the tiles where either type of UGS was not present at all. Therefore, only those vector tiles were selected that contained non-null values for the quantities and access to UGS.

The analysis for checking the relationship between inequities in the provision of urban green spaces for low SES areas, i.e., Informal residential land use, did not reveal any significant relationship, which proves that there is no sufficient evidence to conclude the case for inequities, as hypothesized earlier. On the other hand, the relationship between the proportions of managed urban green spaces was significantly negative with the formal residential land use in the Central Business District, which is due to the presence of higher proportions of managed UGS and lower proportions of formal residential land use in the area. Again, no relationship was detected between unmanaged UGS and formal residential land use.

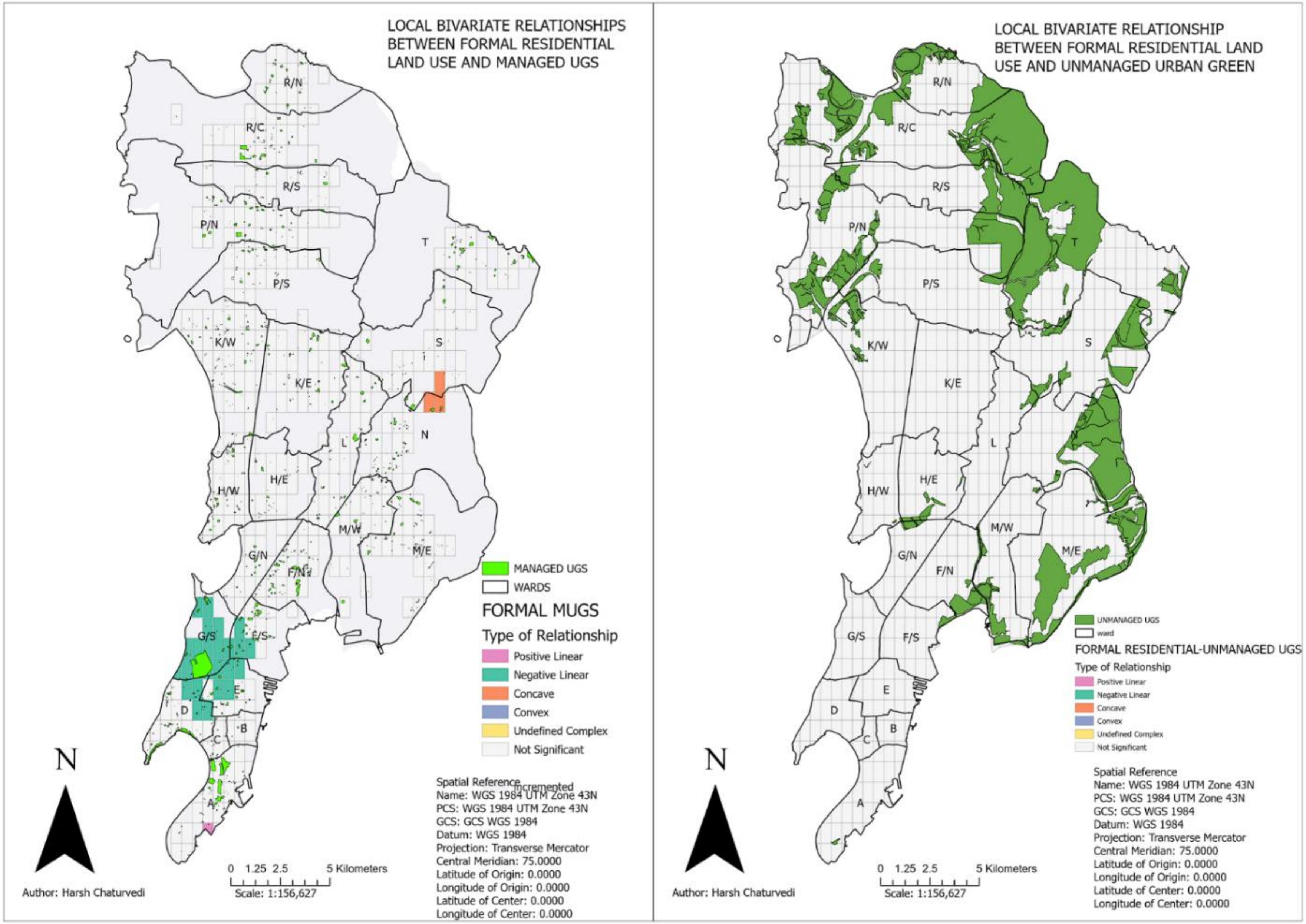


Figure 14:Local Bivariate relationships between Formal residential land use and urban green spaces (managed -left, unmanaged-right).

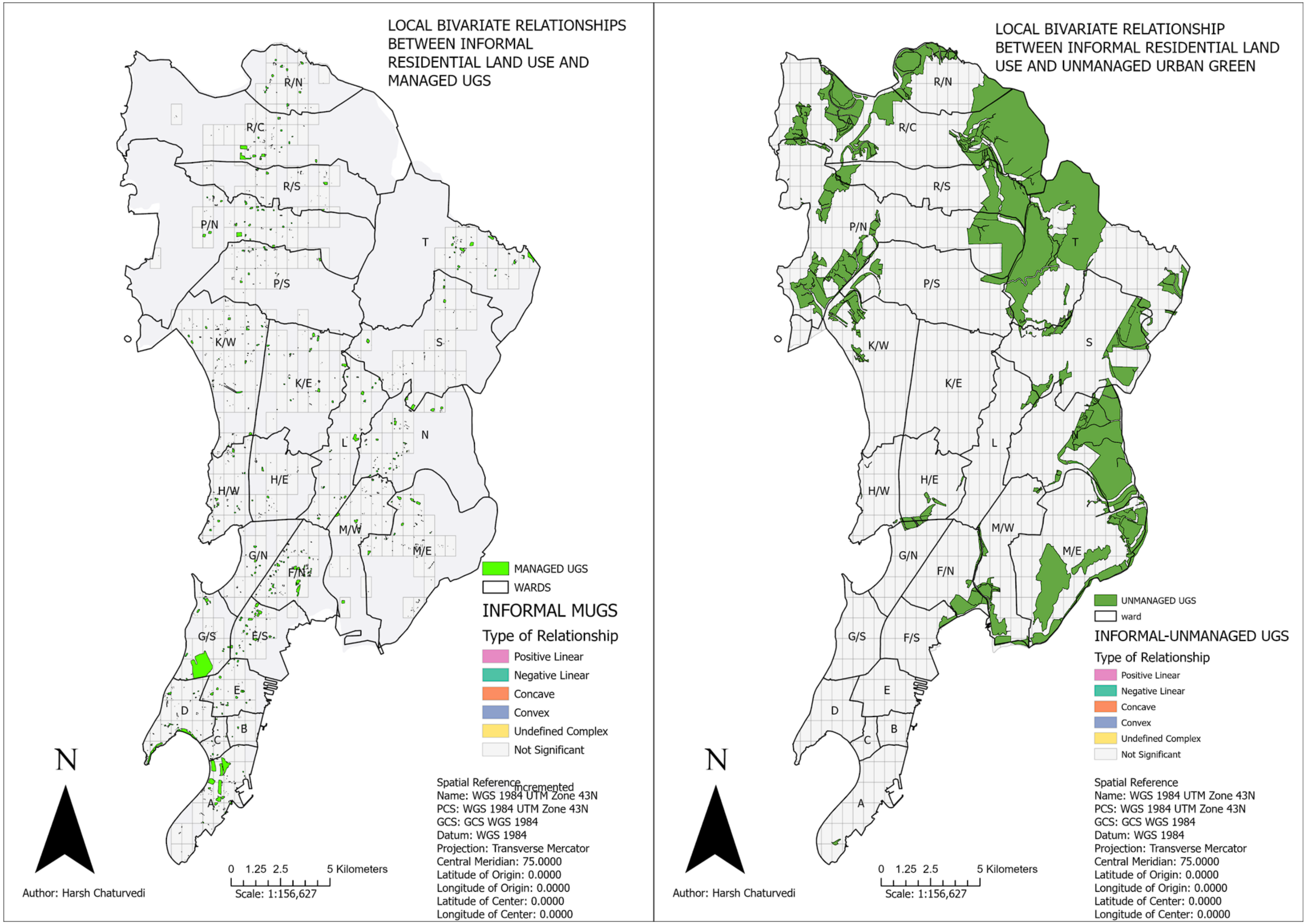


Figure 15: Local Bivariate relationships between Informal residential land use and urban green spaces (managed -left, unmanaged-right).

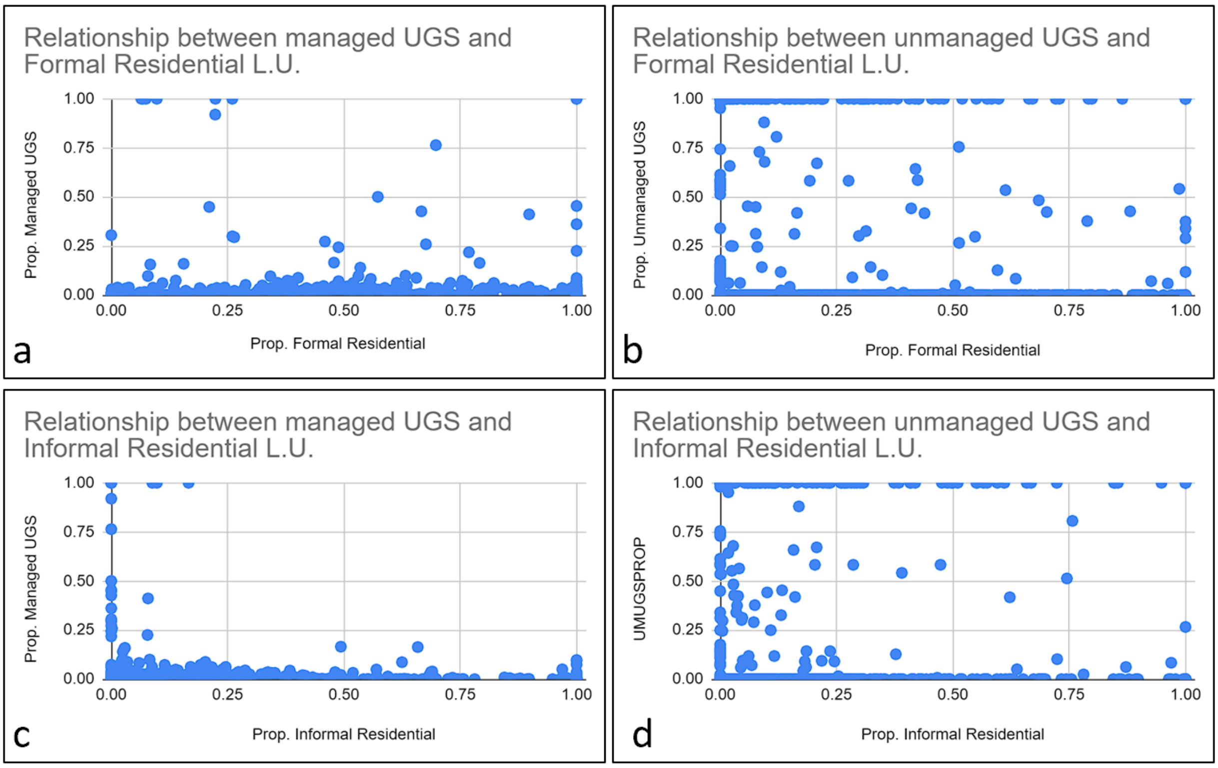


Figure 16: Scatterplot depicting relationships between residential land use (formal - managed[a], formal-unmanaged[b], informal-managed[c], informal-unmanaged[d] and UGS

Table 10: Results of local bivariate relationships between formal and informal residential land use and urban green spaces by their types

S.no.	Hypothesis	Ward Level (Pearson's r)	Local fishnet level
1	Proportions of managed urban green spaces have a negative relationship with proportions of informal residential land use (slum clusters) over the study area.	The variables managed urban green spaces and informal residential land use was found to be moderately negatively correlated r (48) = -0.21, p = 0.32 (The result is not significant at $p < 0.05$).	The relationship between informal residential land use and managed urban green spaces was found non-significant over the study area and did not exhibit negative relationships as it was hypothesized.
2	Proportions of managed urban green spaces have a positive relationship with proportions of formal residential land use over the study area	The variables managed urban green spaces, and formal residential land use was found to be moderately positively correlated r (48) = 0.33, p = 0.11 (The result is not significant at $p < 0.05$).	The relationship at the local level between managed urban green spaces and formal residential land used contains patches with negative-linear relationships contrary to the original hypothesis.
3	Proportions of unmanaged urban green spaces have a positive correlation with proportions of informal	The variables unmanaged urban green spaces and informal residential land use were found to be weakly/poorly negatively correlated r (48) = -0.04, p =	Insignificant. This is due to the reason that unmanaged urban green spaces are clustered mainly in the eastern and western

	residential land use (slum clusters) over the study area	0.03 (The result is significant at $p < 0.05$).	suburbs. Their presence in the tiles must be in a significant amount with insignificant quantities of other variables in the same analyzed tiles.
4	Proportions of unmanaged urban green spaces have a negative relationship with proportions of formal residential land use over the study area.	The variables unmanaged urban green spaces and formal residential land use were found to be moderately negatively correlated $r(48) = -0.35$, $p = 0.09$ (The result is not significant at $p < 0.05$).	

b.3. Is there a significant difference between the accessibility to urban green spaces between formal and informal residential land uses?

On average, over the study area, in terms of accessibility, formal residential land uses are closer to managed urban green spaces than informal residential land uses by (Ward level = 20 m, Local fishnet level = 12 m). Also, the formal residential land uses are farther to unmanaged urban green space than informal residential land uses (Ward level = 336 m, Local Fishnet Level = 190m). These figures reflect the overall inequity present in the study areas for the informal and low-income areas when compared to the formal designated residential areas. However, the results from the t-test show that there is not enough evidence to reject the null hypothesis and prove that there is no statistically significant difference between the two cases.

Table 11: Results from the t-test analyzing inequities in access to urban green spaces from residential land uses.

S.no.	**Hypothesis**	**Ward Level,** Df = (n1+n2) – 2 = 46	**Local fishnet level,** Df = (n1+n2) – 2 = 1894
1	There exists a significant difference between the mean nearest distance to managed urban green spaces from formal and informal residential land uses across the study area with wards as a unit.	There was no significant difference between the nearest distance to unmanaged urban green spaces, $t(46) = 0.21$, $p = 0.82$, despite informal residential land use (M = 233, SD = 52) had a higher distance to unmanaged urban green spaces than formal residential land use (M = 213, SD = 60).	There was no significant difference between the nearest distance to managed urban green spaces, $t(1894) = 0.49$, $p = 0.22$, despite informal residential land use (M = 288, SD = 272) had a higher distance to managed urban green spaces than formal residential land use (M = 276, SD = 308).
2	There exists a significant difference between the mean nearest distance to unmanaged urban green spaces from formal and informal residential land uses across the study area with wards as a unit.	There was no significant difference between the nearest distance to unmanaged urban green spaces, $t(46) = 0.36$, $p = 0.71$, despite formal residential land use (M = 2095, SD = 1716) had a higher distance to unmanaged urban green spaces than informal residential land use (M = 1759, SD = 510).	There was no significant difference between the nearest distance to unmanaged urban green spaces, $t(1894) = 0.02$, $p = 0.91$, despite formal residential land use (M = 1459, SD = 1512) had a higher distance to unmanaged urban green spaces than informal residential land use (M = 1269, SD = 1340).

4.3. Research Questions c.1, c.2, c.3 and c.4 (Objective c)

To estimate the spatial effects of urban green spaces by their types on list prices of residential properties (sale and rent prices) over the study area, using extended versions of hedonic regression models, i.e., geographically weighted regression techniques.

c.1. How do urban green spaces by their types and characteristics (proximity, area) affect list prices of rental properties?

The table below lists the model diagnostics from both global and local models used for analyzing rent property listings:

Table 12: Diagnostic measures comparing results from Global and Local regressions model for Rent category

S.No.	Diagnostic Measure	Global Model	Local Model
1	Residual sum of squares	1126.58	344.189
2	Log-likelihood	-2610.236	4975.607
3	AIC	5260.471	-4629.56
4	AICc	5262.543	-3231.644
5	R2	0.912	0.973
6	Adj R2	0.912	0.966

Table 13: Coefficient estimates of the proximity to urban green space variables for the rent category.

RENT		OLS	GWR					
S.No.	Variable	Estimate	Mean	STD	Min	Median	Max	% of Significant Listings (total = 12795)
1	Near_M.UGS_dis	0.003	0.008	0.084	-0.296	0.002	1.193	7% (1004)
2	Near_UM.UGS_dis	0.002	0.002	0.02	-0.147	0.002	0.153	6% (848)

Note: The list of all the variables with the coefficient estimates (in both the sale and rent category) is mentioned in the appendices.

The goodness-of-fit of the regression model explained by the residual sum of squares is less in the case of the local model when compared to the global model—also, the AICc and Adj. R^2 scores are better in the case of the local model, with a value of 0.96. the variability in the response variable of rental prices of the property listings is well explained (96%) by the explanatory variables chosen for the model. In the case of the local model, since the coefficients (and associated s.e., t-values and p-values) are calculated locally, both positive and negative effects of the covariates vary across the study area. The distance to the nearest managed UGS is affecting the rental prices of property listing again in wards where the proportions of managed UGS are present in higher quantities.

On the other hand, the nearest distance to unmanaged UGS in wards that are closer to the Mumbai Central region is significantly affecting the rental property prices of the apartments. The rental listing prices are having a positive relationship in areas with closer proximity to unmanaged UGS, which was contrary to the expected results. The location and position of the urban green spaces are playing a pivotal role in determining their impacts on rental listing prices.

The nearest distance to managed urban green spaces and unmanaged urban green spaces variables were significantly affecting 7% and 6%, respectively, of the total property listings in the rent category.

Table 14: Monetary effects of urban green spaces on rental listing prices.

DESCRIPTIVE STATS	**MANAGED UGS**		**UNMANAGED UGS**	
	POSITIVE (INR)	**NEGATIVE(INR)**	**POSITIVE (INR)**	**NEGATIVE (INR)**
avg	19306.91085	9865.061377	4214.69024	11396.13824
min	413.01865	9929.1807	377.727744	5270.87925
max	729923.4423	12616.778615	64017.41905	54721.4486
median	10850.59534	1254.307498	2672.866968	8376.36681
stdev	36220.65896	16621.76531	6381.88156	10872.62208

The proximity to both the managed and unmanaged urban green spaces affected the rent prices of the property listings both positively and negatively, which means in cases where positive relationships are observed, a unit change increase in the independent variable (distance to urban green space, in meters) variable, would increase the dependent variable (rent prices) by the values of the beta coefficient. For example, if the beta coefficient is positive, the increase in the distance to the urban green spaces would cause an increase in the rent prices of properties and vice versa. In the case of managed urban green spaces, where the positive relationship was observed, with the decrease in the nearest distance to managed urban green spaces, the property prices in the rent category also decreased up to INR 729923. In the cases of a negative relationship, with the decrease in the nearest distance to managed UGS, the listing prices of properties in the rent category increased up to INR 12616.

On the other hand, in the case of unmanaged urban green spaces, where the positive relationship was observed, with the decrease in the nearest distance to managed urban green spaces, the property prices in the rent category also decreased up to INR 64017. In the cases of a negative relationship, with the decrease in the nearest distance to managed UGS, the listing prices of properties in the rent category increased up to INR 54721.

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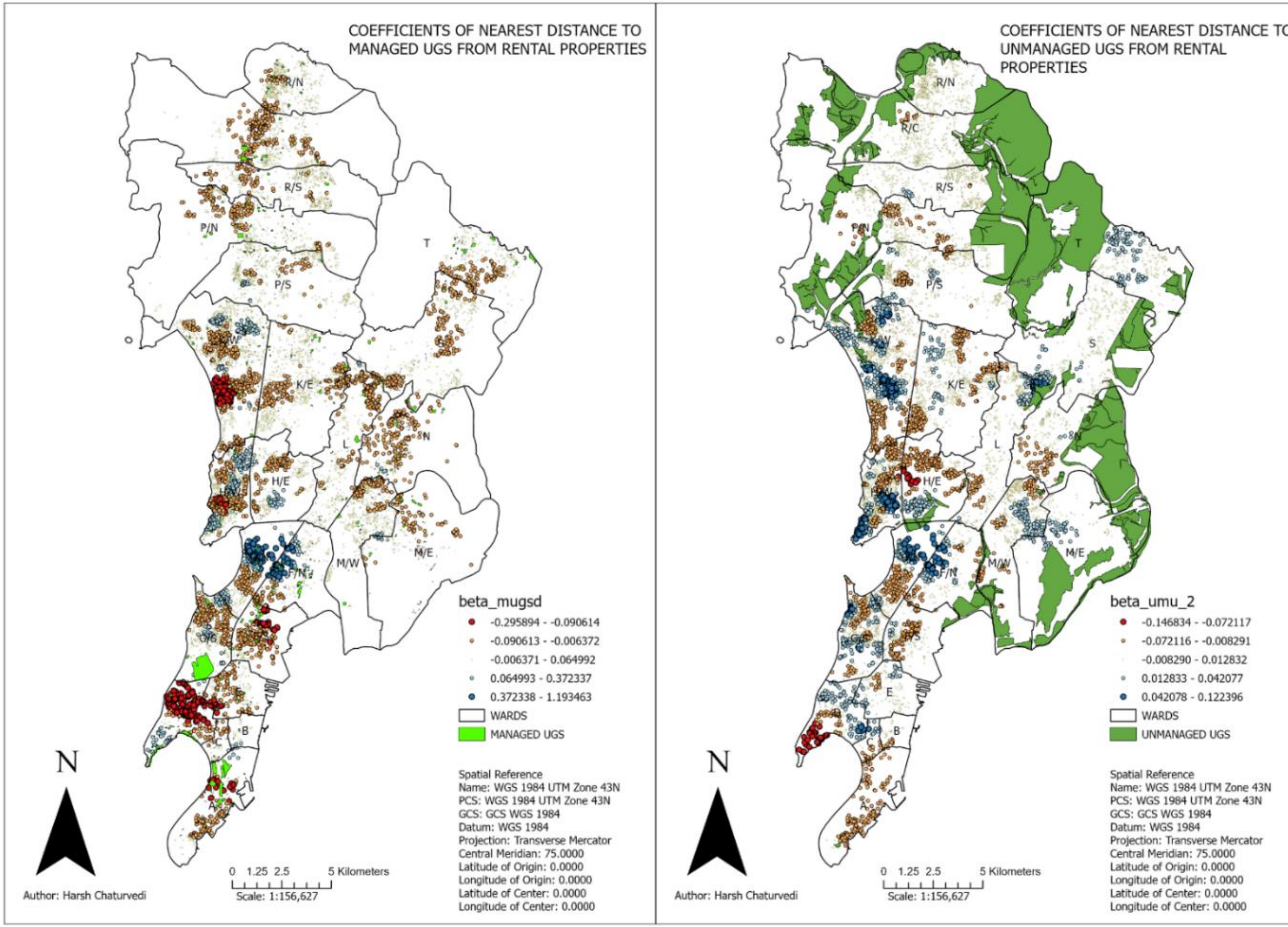

Figure 17: Coefficients of nearest distance to managed (left) and unmanaged (right) UGS from rental property listings.

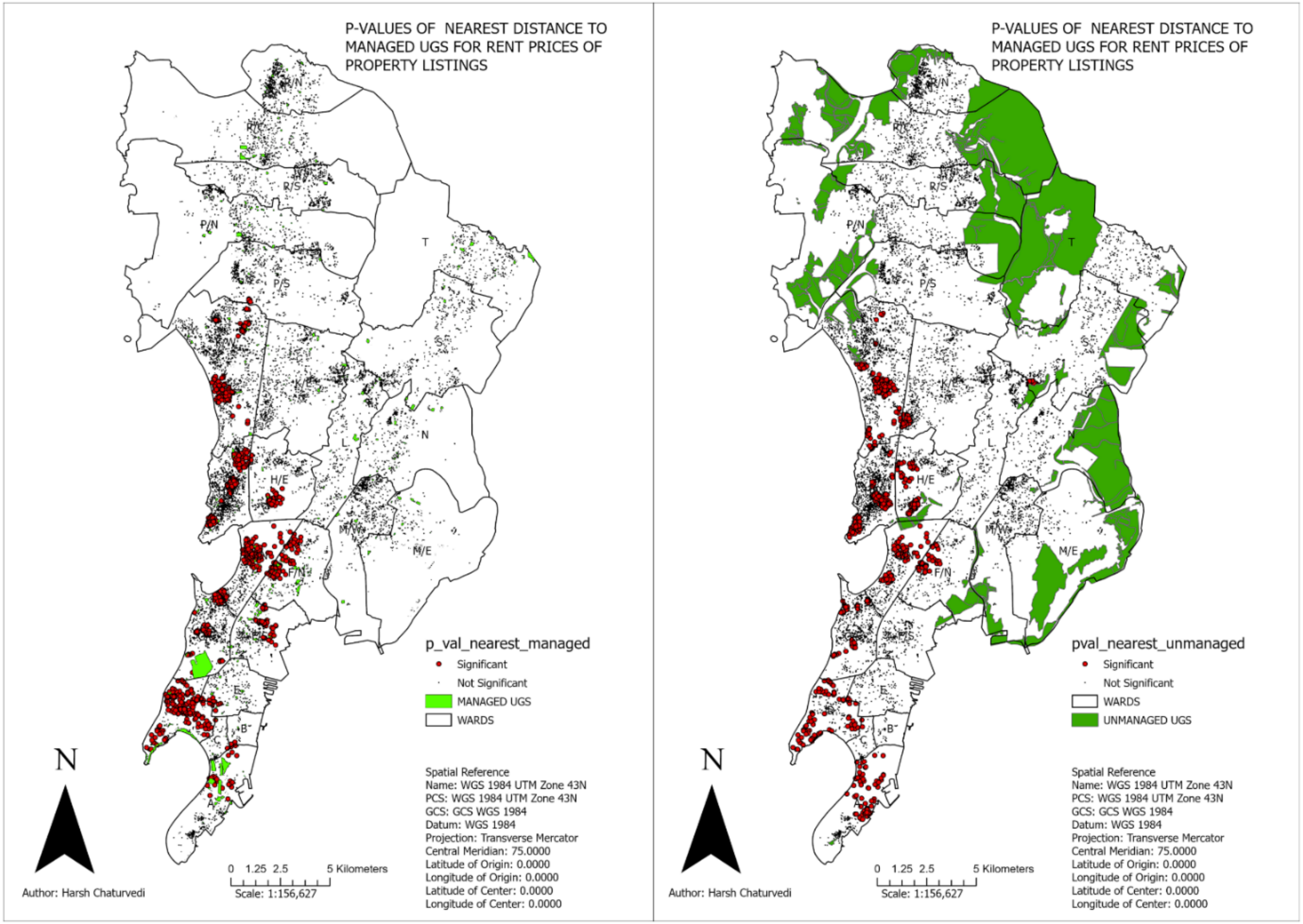

Figure 18: P-values of nearest distance to managed (left) and unmanaged UGS (right) from rental property listings.

c.2. How do urban green spaces by their types and characteristics affect list prices of sale properties?

The table below lists the model diagnostics from both global and local models used for analyzing sale property listings:

Table 15: Diagnostic measures comparing results from Global and Local regressions model for Sale category

S.No.	Diagnostic Measure	Global Model	Local Model
1	Residual sum of squares	10520.736	9124.349
2	Log-likelihood	-15598.463	-14796.457
3	AIC	31234.926	30509.203
4	AICc	31237	30548.14
5	R2	0.066	0.19
6	Adj R2	0.064	0.156

Table 16: Coefficient estimate of the proximity to urban green space variables for the sale category.

SALE		OLS	GWR					
S.No.	Variable	Estimate	Mean	STD	Min	Median	Max	% of Significant Listings (total = 11264)
1	Near_M.UGS_dis	-0.012	-0.025	0.051	-0.206	-0.02	0.144	7% (830)
2	Near_UM.UGS_dis	-0.014	-0.02	0.039	-0.207	-0.011	0.076	8% (908)

Note: The list of all the variables with the coefficient estimates (in both the sale and rent category) is mentioned in the appendices.

In the case of listing prices of sale properties, the goodness-of-fit explained by the residual sum of squares is poor in both the global and local models. Although the local model more significantly explains the proportion of variations in sale property listing prices than the global mode through the Adj. R^2 criterion. Still, the explanatory variables do not prove sufficient, making it challenging to capture the significant local variations precisely. This is due to the effects of other macroeconomic variables over the study area, which is further discussed in Section 5.3. The intrinsic and extrinsic variables do explain the local variations from the GWR model, but it is not necessary that the effects of urban green spaces on prices are insignificant. For checking the significance, the p-values are mapped in order to assess the reliability of generated coefficients.

The distance to the nearest managed UGS is positively affecting the list prices in the wards G/S (no unmanaged UGS present in the ward), L (high proportion of managed UGS), and H/E (proximity to UGS in the ward L). Significant negative effects due to proximity are visible in Ward R (C, N, and S) due to the presence of a very high proportion of unmanaged UGS. The sale prices from unmanaged UGS are getting positively affected in clusters located in the northern parts of Wards K/E and K/W extending to the central parts of Wards P/S. Similarly, the positive effects are visible in R/S and T due to the high proportion of unmanaged UGS being present in the wards.

The nearest distance to managed urban green spaces and unmanaged urban green spaces variables were significantly affecting 7% and 8%, respectively, of the total property listings in the sale category.

Table 17: Monetary effects of urban green spaces on sale listing prices of properties.

DESCRIPTIVE STATS	MANAGED UGS		UNMANAGED UGS
	POSITIVE (INR)	NEGATIVE(INR)	NEGATIVE (INR)
avg	1642786.596	789318.033	7871399.435
min	932841.1625	158787826	191578065.9
max	2200016.816	1714831.9456	1500800.8309
median	1682093.238	2201867.55	1856943.908
stdev	380687.7861	25452373.55	26238702.92

The proximity to the managed urban green spaces affected the sale prices of the property listings both positively and negatively. In cases where the positive relationship was observed, with the decrease in the nearest distance to managed UGS, the property prices in the sale category also decreased up to INR 2200016. In the cases of a negative relationship, with the decrease in the nearest distance to managed UGS, the listing prices of properties in the sale category increased up to INR 1714831.

On the other hand, in the case of unmanaged urban green spaces, only negative relationships were observed between the distance to the nearest unmanaged UGS and the sale prices of the property listings. The negative relationships increased the listing prices of properties in the sale category up to INR 1500800.

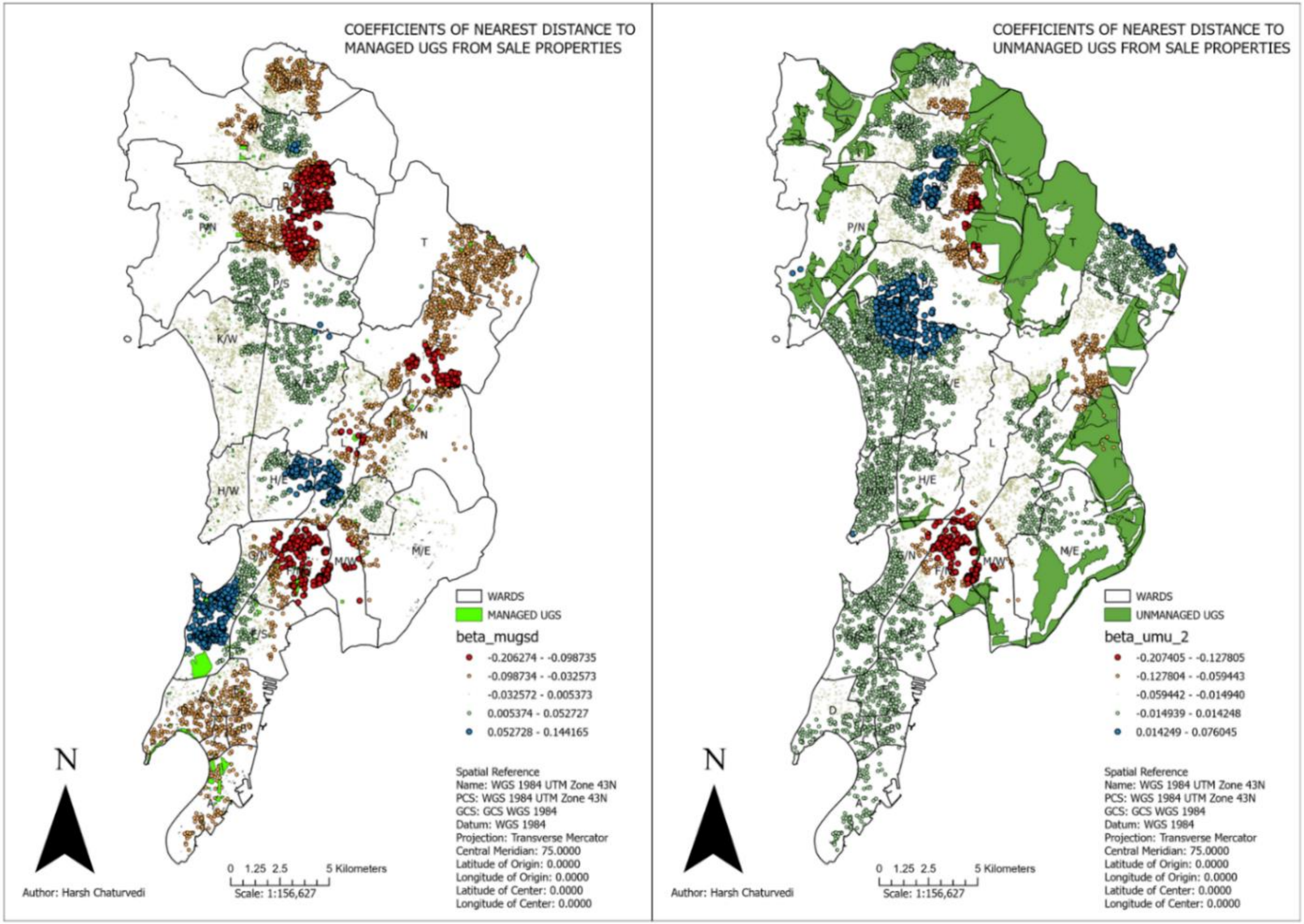

Figure 19: Coefficients of nearest distance to managed (left) and unmanaged UGS (right) from sale property listings.

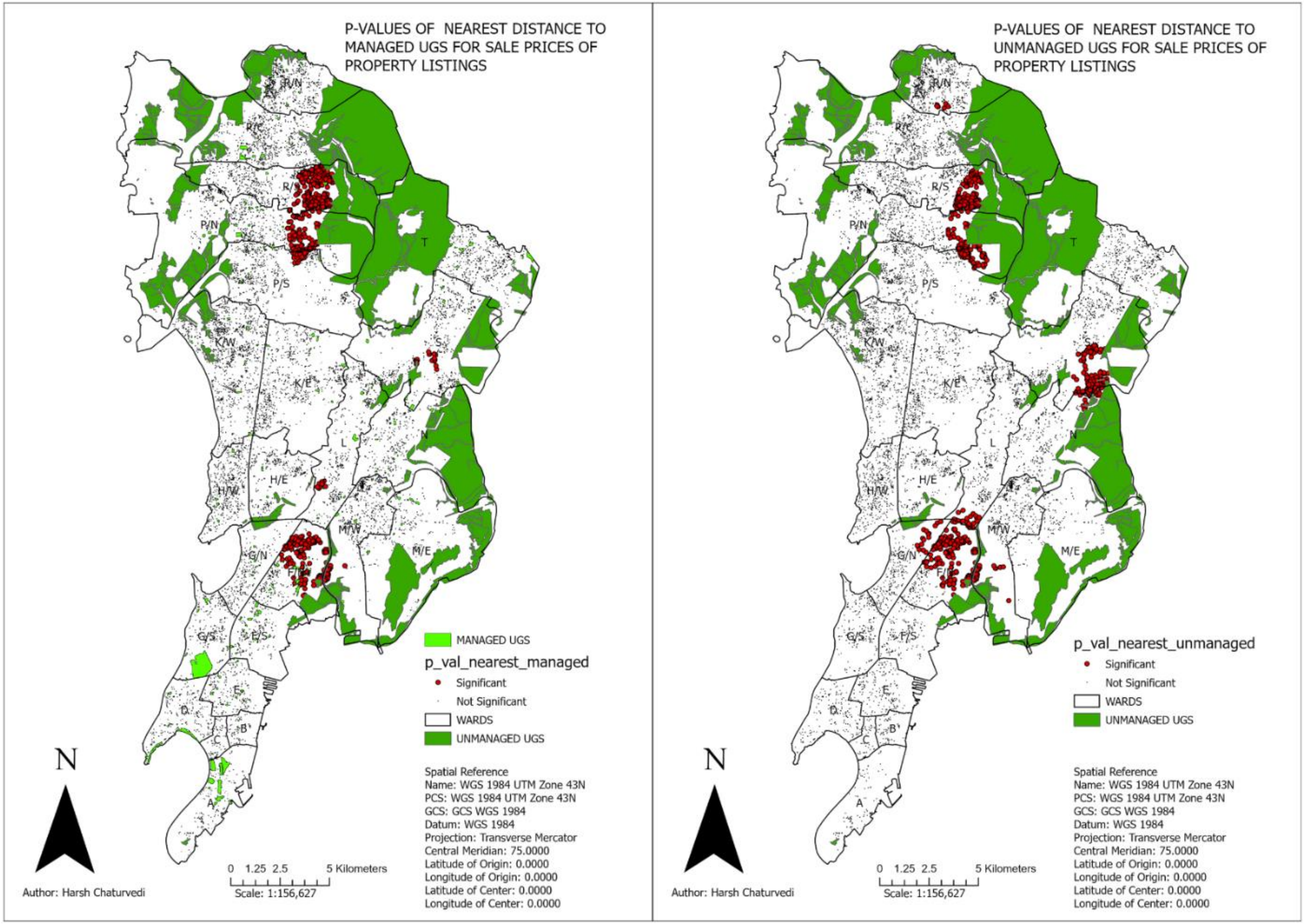

Figure 20: P-values of nearest distance to managed (left) and unmanaged (right) UGS from sale properties.

c.3. How do the spatial patterns of the effects in c.1 and c.2? differ across wards for list prices of residential properties?

In both, the cases of rent and sale categories, the significant properties for both managed and unmanaged urban green spaces are clustered in the same location. These significant clusters of coefficients contain the positive or negative relationship of the UGS variables with the listing prices. These relationships can be traced back from the map of the coefficient to check the type and strength of the relationship. In both cases, the coefficients and significance of the variables on a local scale are different. Thus for each variable from the local model, beta and p values are not presented.

In the regression model for rent prices, the pattern of the significant coefficient is almost identical in cases of managed and unmanaged urban green spaces. In both cases, a significant relationship is found in Wards A, D, G/S, G/N, F/N, H/W, H/E, and K/W. The effects, either positive or negative, are not homogenous across the wards.

In the regression model for sale prices, the pattern of the significance of nearest distance to managed and unmanaged UGS is also identical. Parts of Ward F/N, G/N, S, P/N, and R/S are significantly affected by the proximity component of managed and unmanaged UGS. This implies that the sale properties are significantly negatively impacted in the wards which have closer proximity to unmanaged urban green spaces.

The areas and vertices of the nearest UGS were also included in the model for both cases. However, while mapping the values of the variables, the results were biased. The reasons for that are as follows.

- Due to one optimal bandwidth for the model (for rent or sale category) and not adjusting bandwidths with confidence intervals for each separate variable, the results from area and vertices were biased. This was due to their dependence on the distance to the nearest UGS variable, which resulted in erroneous results. The logic for the interpretation of the result did not prove to be correct. Previous studies that included the area of the nearest UGS were conducted on a much smaller spatial unit, so scaling must not have been an issue there, as it proves in this study.
- There was a high correlation between these two variables, so the variable containing vertices was removed beforehand. There were also discrepancies present in the features in terms of digitization (referring to over completeness of the vertices digitized); thus, vertices were not considered.

c.4. Are the inferences derived from the local regression model complements the findings from objectives a. and b. across the study area?

The local regression model for the rent category also revealed results that are complementing to the earlier objective of checking overall inequity using market values of open land and urban green spaces. The result from the rent model revealed that the rent prices are significantly affected by wards with higher proportions of managed urban green spaces, and farther the proximity of managed UGS, lesser the prices of rent in the area and vice versa. In the case of unmanaged UGS, our hypothesis was confirmed by the results, which reflected that unmanaged UGS had a significant positive relationship with the rent prices of properties in areas closer to the CBD. This meant that farther the proximity to unmanaged UGS in CBD, higher the rental prices of properties and vice versa, which proved that unmanaged UGS does not contribute to the increase in rental values of properties.

On the other hand, the performance of the model for the sale category did not explain the variation in sale prices very well in terms of the diagnostic measures over the whole study area. Still, the results of the model cannot be discarded as due to the nature and local structure of the model, the model did reveal the property listings which were being significantly affected by the presence of urban green spaces. Both the variables accounting for the nearest distance to managed and unmanaged urban green spaces were highly influenced by the proximity to unmanaged UGS. The nature of the relationship was negative, which meant farther the distance to unmanaged UGS, lower the sale prices of property listings, and vice versa. This was contrary to our hypothesis that proximity to unmanaged UGS does not significantly increase property prices. The influence of macroeconomic factors is also described in the results section, which indicates that the housing market is not just limited to the intrinsic and extrinsic characteristics of the properties, and the fact that the purchase of housing units in Mumbai is considered as lucrative investments leaving little room for environmental amenities to play a significant factor in variations in sale prices.

5. DISCUSSION AND LIMITATIONS

5.1. Model Structures

The spatial resolution of the input data for the analysis was taken on the ward level (global) and subzones/fishnet/point level for property listings (local). The model resolution for analyzing these datasets was also based on global/aspatial (Pearson's r/Linear Regression) and local (Local Bivariate relationships/ GWR) modeling techniques. The study was conducted using two model calibrations, where the analysis was done using: 1) global mean modeling/aspatial techniques such as Pearson's r on ward level data in cases of checking inequities, 2) local bivariate relationships/spatial technique on subzones/fishnet level. In the case of property listings, the dataset was only analyzed on its original point resolution using both global (OLS) and local (GWR) modeling techniques. There were also other possibilities of calibrating the models for checking inequities in two different ways where 1) the global modeling techniques (Pearson's r/Linear Regression) could be applied to the dataset with a local spatial resolution (Fishnet/Subzones) and 2) where the local modeling techniques (Local Bivariate relationships/ GWR) could be applied on the datasets with a global spatial resolution (aggregated on ward level). The first case of the alternative modeling approach is used in the research by Hwang et al. (2020) and Sathyakumar et al. (2019), as also mentioned in the introduction section, which utilized simple linear and multinomial logistic regression, respectively, arose the need to use a more appropriate local modeling technique that takes in consideration the location and values of the nearest neighbors and renders the model 'spatial.' The main problem with these two alternative model calibrations is the inherent mismatch of the spatial resolution of the dataset with the spatial resolution of the modeling techniques, hence not considered for analysis in this study.

The first part of the analysis where global mean modeling/aspatial techniques such as Pearson's r on ward level data in cases of checking inequities was conducted as an exploratory step in the analysis process. This preliminary analysis was conducted keeping in mind that previous research used similar types of models in quantifying the inequities. This type of analysis also allowed us to check whether the results turned out as hypothesized earlier. The results from these models for the research questions were as it was hypothesized in most cases (refer to section 4.2.), but the results cannot be considered reliable as 1) there was an aggregation scheme imposed on the dataset resulting in loss of information and local variations while analysis and 2) the statistical models had the assumption of homogeneity of parameters over space which is considered misspecification in model formulations (McMillen & Redfearn, 2010). Therefore, more emphasis is given on the analysis and results that use local modeling techniques on datasets with local spatial resolution due to the nonparametric nature and assumptions of nonstationary independent and independent variables (A. Fotheringham et al., 2002). The main disadvantage of using the local modeling techniques was the high cost of computation when compared to other techniques. Nonetheless, the wards' boundaries were overlayed with the results of the appropriate local analysis to serve as the standard unit of interpretation of results since wards serve as the most basic unit of analysis in the development plans in the study area.

5.2. Overall Inequities and inequities in provision and access

As discussed in section 5.1., that the techniques used in the literature for assessing inequities of green space provision and access between high and low socioeconomic status areas use aspatial (such as correlation and simple linear regression) and do not consider the phenomenon of spatial autocorrelation and heterogeneity. Therefore, it would not be justifiable to compare the results of this study directly with other studies in terms of statistical measures due to the difference in techniques and model structures. Still, the results are comparable conceptually w.r.t inequity, equity, or mixed/insignificant results.

The results of this study when checking the overall inequity of urban green spaces provision with land values (refer Section 4.2., research question a.3.) were not consistent with the results in Hwang et al. (2020) when the same aggregation scheme for land values was used (sum of market values of open land and residential built-up). The results with the aggregation scheme did not reveal any significant relationship with managed or unmanaged UGS over the study area, contrary to the positive relationship being found in the study by (Hwang et al., 2020) between areas of unmanaged urban green spaces and the lower land values districts on the fringes. The reason for this inconsistent result of this study with the literature again indicates the factors of aggregation scheme and the usage of global aspatial models. However, the analysis was conducted again by disaggregating the land values and analyzing the relationships of market values of open and market values of residential built up with the managed and unmanaged urban green spaces. The results proved that in the wards with a higher proportion of managed UGS (Mumbai Central), there was a significant positive relationship present with both market values of open land and residential built-up. On the other hand, unmanaged UGS only had significant relationships with market values of open land only in the suburban wards.

In many cases from the literature review, the inequity is quantified in terms of the racial/ethnic demography of an area, which is not the case in this study. Only the formal (48% of the city's population) and informal residential land uses (52% of the city's population) are used as a proxy for the population and SES status. Also, land values have already been used as a rough indicator of SES status and also as a real estate indicator. While checking for inequities in the provision of urban green spaces with informal residential land uses (refer Section 4.2., research question b.2.), the results of this study were also consistent with 7.5 % of the results of the literature review. Some of the studies in the literature review used indices such as green space numbers per capita, green space area per capita and green space area per area. The indicator such as green space area per capita and green space numbers per capita was available in the study area aggregated on the ward level, which would further result in loss of information, thus not considered for analysis. Instead the indicator green space area per area was used.

In terms of the inequities in proximity for the low SES areas (refer Section 4.2., research question b.3.), the results of this study resonate with 19% of the studies in the literature review, which points toward mixed or insignificant findings when compared to the high SES areas. This study did not include any buffers or threshold distance to measure inequity in access when compared to the literature. The studies that did include buffers or threshold distance in the literature reported inequity in access more frequently than other studies. Nevertheless, in terms of the average distance to urban green spaces, the results of this study did reveal the difference between formal and informal residential land use as hypothesized. On average, informal residential land uses were farther from the managed categories of urban green spaces and closer to the unmanaged urban green spaces when compared to the formal residential land use over the study area. These results resonate with the findings from another study by Sathyakumar et al. (2019), which uses remote sensing data and SESI (socioeconomic status index), which indicates that residents of low SES areas are subject to lesser degrees of access when compared to the residents of high SES areas. The results of the same study were carried out on changing resolutions with the assumptions of homogeneity in Socioeconomic status across the census sections as the information on sub-sections of the census were not available. Although the study does not make a distinction between the managed and unmanaged categories of urban green spaces, it gave recommendations on categorizing the urban green spaces as accessible or not accessible for future research.

5.3. Relationships w.r.t listing prices of sale and rent category of properties

In the domain of valuation of urban green spaces, the models that are not calibrated on the local spatial scale (spatial or non-spatial) report mixed findings, with some of the studies indicating significant positive effects on the surrounding property prices (Conway et al., 2010; Engström & Gren, 2017; Panasolo et al., 2020; Trojanek et al., 2018; Votsis, 2017) and others indicating unclear/mixed-effects (Anderson & Nafilyan, 2018; Cilliers & Timmermans, 2012; Hammer, Coughlin, & Horn, 1974; Hendon, 1971; Panduro & Veie, 2013; Weigher & Zerbst, 1973; C. Wu et al., 2017a). Some of these studies that do analyze the unmanaged categories of urban green spaces(Anderson & Nafilyan, 2018; Panasolo et al., 2020; Votsis, 2017; C. Wu, Ye, Du, & Luo, 2017b) do not explicitly mention it or make a distinction. In most of these studies, the analysis is only conducted for the sale prices of the surrounding property prices, ignoring the effects of urban green spaces on the rental prices of the properties. Out of the few studies that utilized global model for modeling sale prices and included unmanaged urban green spaces, the results from Panasolo et al. (2020) and Votsis (2017) were consistent with the results of this study in the sale category, that decreasing distance to unmanaged urban green spaces has the potential to increase property prices. On the other hand, the studies by Anderson & Nafilyan (2018) and C. Wu et al. (2017) suggested otherwise that the proximity to urban green spaces such as forests in the unmanaged categories decreased the prices (sale/transaction) of properties. In comparison to these studies following traditional techniques, the studies utilizing the local GWR models reveal both positive and negative effects on the property prices over the study area, same as the case in this study (Cho, Bowker, & Park, 2006; Du, Wu, Ye, Ren, & Lin, 2018; Hiebert & Allen, 2019; W. Li & Saphores, 2012; Nilsson, 2014; Nur, Abdul-Rahim, Mohd Yusof, & Tanaka, 2020). Therefore, the interpretation of results from these previous studies with this study can be done broadly on the level of inferences and not statistical metrics. The following paragraph outlines the results of this study with other GWR utilizing studies.

In the case of the regression model for the rent category, both managed and unmanaged categories of urban green spaces had varying degrees of effects locally and had substantial differences from area to area, with the relationship with rental prices being significant at some locations and insignificant at others. These results were consistent with the studies conducted by Cho et al. (2006), Du et al. (2018), Hiebert & Allen (2019), Nilsson (2014), and Nur et al. (2020). The results were clustered around the Mumbai Central area, which consists of the CBD and the properties listings that moved farther from the CBD to the fringes had a decaying effect on the variation in rental prices due to the proximity with urban green spaces. The results for the rent category are similar to the results from Nilsson (2014), which explains that in the fringe or suburban areas of the city, the unmanaged green spaces such as forests (and in this study's case-mangroves) do have the economic effects as positive as the effects observed in the City Central Area. Also, the results from the rent model resonate with the findings from Tyrväinen & Miettinen (2000), which states that the addition in values of the properties is notably lesser, which are located in suburban and peri-urban areas when compared to the properties located in core urban areas. As hypothesized, the unmanaged UGS, which were located closer to the Central area, has a positive relationship, which meant that with the increase in distance to the nearest unmanaged UGS, the rent prices of the listings were also increasing. In terms of model performance, the results generated from the local regression model were significantly better than the results from the global OLS model, which were also consistent with the studies by Cho et al. (2006) and Nur et al. (2020) that systematically compared the results of the local models with the global models.

On the other hand, the results from the regression model for the sale category were significant and clustered at locations in the suburban areas, through which we understand that only larger patches and vectors of unmanaged green spaces significantly affected the sale prices of the property listings. The results of the sale model were not related to the findings from Cho, Jung, & Kim (2009), which states that the preference of suburban populations is inclined more towards scattered patches of unmanaged green spaces (forests) when compared to the larger units. The results from the sale category did not resonate with the results from the rent category, as the model performance affected the explainability in local variations. The significant results from sale properties only suggested that the sale prices of property listings were increasing with decreased distance to unmanaged urban green spaces (negative coefficients) and did not result in positive coefficients over the study area, as the case observed in the rent category.

For the sale property listings regression model, the intrinsic variables do not prove to be sufficient in explaining the variations in Sale prices of properties. This is due to the fact that macroeconomic factors play a significant role in deciding the sale prices. This is due to the reason that Mumbai's housing market has transformed into an investment market, and even though in recent years, the demand for buying houses in Mumbai has lowered drastically even though the city hosts more than 500,000 vacant apartments (THE HINDU, 2018). In another study of macroeconomic factors affecting the House Price Index, the macroeconomic factors explain 98% of the variability in housing prices w.r.t factors such as Inflation, GDP, Exchange Rates, Housing credits, and interest rates (Prabhu Parrikar, 2019). Another research also disproves the supply and demand theory from microeconomics taking the case of the housing market in Mumbai (Abhyankar et al., 2018).

5.4. Limitations

There were realized limitations of the study, some due to the availability of datasets and other due to the methodological and processing limitations. One of the major limitations of the study is the lack of consistency in the temporal dimension of the datasets, which restricts the temporal analysis of the phenomena. In particular, there is a slight mismatch in the data of shapefiles where the urban green spaces (managed and unmanaged) with the formal residential land use relates to the year 2014, whereas the shapefile for informal land use (slum clusters) related to 2016. The other datasets are for the current year 2021, including land value polygons and data of property listing. The data of property listings extracted from the database are added by the owners or agents on different dates, some up to 2 or 3 months back from the date of extraction (27th March 2021), which is not consistent thus not used in the analysis. The assumption made was about the stationarity of the shapefiles from 2014 and 2016 with the current year, as no significant changes are expected in the features. Other limitations were related to the lack of update socio-economic data and qualitative data on the urban green spaces. Also, Within the analysis of inequities with informal housing, only notified slum categories that are listed by the government through their agencies are used since no information on the other categories, including recognized and identified slums, exist in forms of shapefile or other data formats.

In terms of processing limitations, the proximity component used in objective b is calculated through the geodesic method and for the listings using the planar method due to the usage of the tool in different software implementation packages. Since the study area is only taken as a city, no significant differences in the calculation methods are assumed. Also, for objective c. the standard GWR implementation considered for analysis as opposed to other implementation such as Multiscale Geographically Weighted Regression (A. S. Fotheringham, Yang, & Kang, 2017), Geographically Temporally Weighted Regression (A. S. Fotheringham, Crespo, & Yao, 2015; Shim & Hwang, 2018), due to the lack of consistent temporal data and very high convergence time of the model due to the high dimensionality of the dataset. The feature of urban green spaces was extracted using the intersect topology, which produces a few outlier values, but since the model works on analyzing the nearest neighbors and using a large number of permutations to produce pseudo p values and False Discovery Rate correction, the effects of outliers on the model would not be significant. Using other techniques of clipping a vector feature (UGS) with another vector feature (tiles/subzone polygons) also presented the issues of containing outliers and multiple values since there were multi polygons present in the layer being clipped. Even after the imputation of outliers and then analyzing the results were not different from the original results as the tool works by generating permutations-based estimation. An improved version of the extraction tool exists in the ArcGIS suite, which extracts unique features which have their geometrical center in another feature, but the problems of not being able to iterate make it impossible to implement on a large number of features.

With reference to the methodological limitations, the analysis was only conducted using the vector data of urban green spaces, by their types and no other landscape indices (Du et al., 2018) or tree cover (W. Li & Saphores, 2012), which have been occasionally used by researchers to quantify the environmental amenities. In terms of ownership of urban green spaces, only public urban green spaces falling with the jurisdiction of the Municipal Corporation of Mumbai (BMC) are considered for analysis and not the private urban green spaces. Also, the individual components of managed and unmanaged urban green spaces are not accounted for in the analysis. The property listing prices were used for the analysis as opposed to the property transaction prices (due to non -availability). The property listings prices are in general 5-10 percent inflated than the real transaction prices. Also, in the case of sale property listings analysis, the model suffers omitted variable bias and does not produce satisfactory results due to the macroeconomic factors that affect the prices of sale property listings.

6. CONCLUSION

There is a vast literature present about environmental inequities and valuation in the Global South, but unfortunately, only a few instances of qualitative studies and valuation studies in some Indian cities have been conducted. The case area for the study is taken as Mumbai, which has seen a drastic depletion in the green spaces of the city over the past 30 years (D'souza & Gupta, 2016; Rahaman, Jahangir, Haque, Chen, & Kumar, 2021), due to overcrowding and rapid densification of the city. The Municipal Corporation of Greater Mumbai aims to increase the per capita green spaces from 0.12 sq.m. to 4 sq.m. by 2034. The approach of the municipality is still restricted to the theory of supply and demand in each ward, with little emphasis on the spatial aspects of provision. Therefore, the study aimed at quantifying the inequities and relationships related to the managed and unmanaged urban green spaces with indicators of SES and Real Estate property listings. This study also focused on the usage of models that capture local variations over the study area and which are not subject to only modeling the mean of the phenomenon. The major findings from the analysis are as follows:

- The relationships between managed and unmanaged UGS with land values (market values of open land + residential built-up) were found to be insignificant over the study area due to the imposed aggregation scheme. However, the analysis revealed significant relationships when the land values were disaggregated. Both the market values of open land and residential built-up were significant in the southern part of the city (Mumbai Central), which is the Central Business district (higher land value districts) due to having higher proportions of managed UGS as it was hypothesized. In the case of unmanaged UGS, the relationship was only significant with the market values of open land and not residential built-up. The location of unmanaged UGS played a vital role as the wards closer to the CBD (higher land value sub-zones) had a positive relationship with values of open land, and the ward situated in the suburbs (lower land value sub-zones) negatively affected the market values of open land.
- For checking the inequities in the provision of urban green spaces with the low SES areas, both managed and unmanaged UGS showed no significant relationship locally with the informal residential land use, which was contrary to the original hypothesis that informal residential land uses are subject to lesser availability of managed UGS and more availability of unmanaged UGS. In terms of Inequities in terms of access to managed and unmanaged UGS, the differences between formal and informal residential land uses were as expected, i.e., managed UGS were farther from informal residential land uses, and unmanaged UGS was closer to informal residential land use when compared to formal residential land use on average. However, the results were not found statistically significant through the application of t-tests. The results indicate insufficient evidence for concluding that the inequities in provision and access exist in the low SES areas.
- Finally, the results from the regression model for the rent category explain 96% of the local variation of rent prices over the study area and the role of proximity to both managed and unmanaged urban green spaces. The results are significant in both Central and Suburban areas, whereas the regression model for sale does not explain the relationships between urban green space and sale prices over the study area. The reasons for the poor performance of the sale model are credited to the influence of multiple macroeconomic factors affecting the sale prices over the city and the inapplicability of the basic microeconomic principles. These factors indicate that real estate has turned into an investment market.

From the results of this study, the departments in the urban local body concerning the provision and maintenance of green spaces should very carefully reconsider their provision scheme in the wards which are subject to positive relationships between land value/listing prices of rent and sale prices of properties with managed urban green spaces to avoid further inequity and cases of green gentrification. The goal of providing at least four sq.m. per capita may be achieved by 2034, but if the approach continues to remain non-spatial as usual, then there are strong chances of cascading effects of green gentrification to take place. The areas with non-significant relationships between these variables should not cause any problems if regular alterations are made as planned. Special attention needs to be paid towards the provision/up-gradation of managed urban green spaces as they have been considered as the primary source of green gentrification in the literature. On the other hand, the preserving and increasing accessibility to the unmanaged urban green spaces of the city, which account for 84% of the total green spaces, should be the main point of focus for avoiding further encroachments (Zérah, 2007) and depletion (D'souza & Gupta, 2016). Ultimately, this study should cater as a starting point to the urban local body to realize the relationships and economic value of urban green spaces so that it does not become a cause of future inequalities and green gentrification as observed in the past decade (Doshi, 2019).

There are a number of ways through which the methodology of this study can be improved. For the analysis on inequity, the temporal dimension of the market values of the properties can be analyzed to reveal different trends of change in values of open land and residential built over a period of time. Also, socio-economic/socio-cultural data from the upcoming census could be used w.r.t to avoid systematic bias, as, in many studies, there are results that reveal inequities in access and provision of UGS between different ethnic groups**.** The qualitative variables for urban green spaces could also be analyzed apart from the quantitative vector data, for example, as in the research conducted by (Czembrowski, Łaszkiewicz, Kronenberg, Engström, & Andersson, 2019). Also, landscape pattern metrics can be calculated to analyze the patterns of urban green spaces.

For the analysis of the variation in property listing prices, actual transaction data could be used, which would present more accurate results. The transaction data can be analyzed using a more novel method such as GTWR (Geographically Temporally Weighted Regression), which would also assist in proving the recent cases of green gentrification along with the socio-economic variables. Also, the UGS variables explaining the areas and shape of the nearest UGS could be analyzed using MGWR (Multiscale GWR), which would provide more reliable bandwidths for the variables' influence areas. The analysis of the property listings where the prices are significantly affected by green spaces needs to be further analyzed w.r.t to the position of slum clusters and hotspots of property prices before the provision of new green spaces or modification/up-gradation of existing green spaces. Finally, the analysis can be further extended by selecting more environmental variables such as hillslopes, beaches (coastline), and inventory of water bodies which may provide better insights into the existing model. Most importantly, the analysis in future studies should make use of methods that operate at varying spatial scales and resolutions to analyze the zones of the significant influence of each variable more accurately.

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8. Appendix

This section contains results from the Global OLS and local GWR model for the economic valuation of urban green spaces.

Table 18: Coefficient estimate of the independent variables for the rent category.

RENT		OLS	GWR				
S.No.	Variable	Estimate	Mean	STD	Min	Median	Max
1	Intercept	0	-0.035	0.663	-2.534	-0.111	17.813
2	Built-up area	0.191	0.147	0.125	-0.129	0.118	0.741
3	bedroom	-0.028	0.054	0.065	-0.169	0.05	0.469
4	parking	-0.01	-0.004	0.032	-0.186	0	0.132
5	balcony	0.018	0.006	0.032	-0.253	0.002	0.235
6	age	-0.002	-0.013	0.029	-0.193	-0.006	0.073
7	security	0.356	0.288	0.154	-0.059	0.276	1.027
8	brokerage	0.503	0.288	0.229	-0.391	0.243	0.999
9	total_floor	-0.005	0.01	0.053	-0.317	0.01	0.239
10	furnishing	-0.017	-0.005	0.027	-0.16	-0.007	0.123

11	society_amenities	-0.047	-0.012	0.042	-0.172	-0.013	0.36
12	closest_airport	0.001	-0.015	0.449	-3.848	-0.013	3.438
13	closest_busstop	-0.026	0.002	0.091	-0.494	-0.001	0.538
14	closest_railways	0.001	-0.004	0.159	-0.991	-0.002	0.742

Table 19: Coefficient estimate of the independent variables for the sale category.

SALE		OLS	GWR				
S.No.	Variable	Estimate	Mean	STD	Min	Median	Max
1	Intercept	0	0.004	0.381	-1.846	-0.045	1.475
2	Built-up area	0.31	0.185	0.119	-0.182	0.172	0.627
3	bedroom	-0.109	-0.065	0.105	-0.455	-0.036	0.237
4	parking	-0.053	-0.069	0.082	-0.556	-0.049	0.033
5	balcony	-0.002	-0.006	0.026	-0.081	-0.003	0.135
6	age	0.023	0.022	0.08	-0.125	0.008	0.536
7	brokerage	0.063	0.032	0.148	-0.476	0.021	0.348
8	society-amenities	0.052	0.057	0.053	-0.043	0.052	0.327
9	total_floors	-0.035	-0.048	0.082	-0.364	-0.044	0.19
10	closest_airport	0.02	0.026	0.329	-1.438	0.045	1.271
11	closest_busstop	0.02	0.025	0.122	-0.483	0.021	0.388
12	closest_railway	0.002	0.018	0.106	-0.297	0.024	0.638

Table 20: Ward wise assessment of urban green spaces for Development Plan 2034

Wards	**Population 2011**	**Population 2034**	**Demand For 2034***	**RDP 2034 Designation**	**RDP 2034 Reservation**	**Total Provision**	**Existing Per Capita Land area**	**Propo-sed Per Capita Land area**	**Surplus {+)/ Deficit {-)**
A	1,85,000	1,67,750	67.10	149.99	8.38	158.37	8.94	9.44	91.27
B	1,27,000	1,12,159	44.86	2.07	3.40	5.46	0.18	0.49	-39.40
c	1,66,000	1,52,146	60.86	13.50	3.31	16.81	0.89	1.10	-44.05
D	3,47,000	3,35,501	134.20	105.27	35.19	140.46	3.14	4.19	6.26
E	3,93,000	3,60,859	144.34	44.08	25.79	69.87	1.22	1.94	-74.47
F/N	5,29,000	4,81,795	192.72	61.83	80.63	142.46	1.28	2.96	-50 .25

F/S	3,61,000	3,51,106	140.44	37.05	34.45	71.51	1.06	2.04	-68.94
G/N	5,99,000	5,80,300	232.12	39.33	15.09	54.42	0.68	0.94	-177.70
G/S	3,78,000	3,44,279	137.71	140.62	47.68	188.31	4.08	5.47	50.60
City Total	3085000	2885894	1154.36	593.75	253.92	847.68	2.06	2.94	-306.68
H/E	5,57,000	5,56,893	222.76	37.54	22.51	60.05	0.67	1.08	-162.71
H/W	3,08,000	2,87,712	115.08	45.11	35.40	80.51	1.57	2.80	-34 .58
K/E	8,24,000	8,34,851	333.94	61.41	134.65	196.06	0.74	2.35	-137.88
K/W	7,49,000	7,82,185	312.87	146.27	89.22	235.49	1.87	3.01	-77.39
P/N	9,41,000	10,35,762	414.30	105.12	118.29	223.41	1.01	2.16	-190.90
P/S	4,64,000	4,83,746	193.50	54.71	128.59	183.30	1.13	3.79	-10.20
R/C	5,62,000	5,75,580	230.23	66.26	101.57	167.83	1.15	2.92	-62.40
R/N	4,32,000	5,10,420	204.17	33.52	74.99	108.52	0.66	2.13	-95.65
R/S	6,91,000	7,82,185	312 .87	78.28	67.15	145.43	1.00	1.86	-167.44
Western Total	5528000	5849334	2339.73	628.22	772.36	1400.58	1.07	2.39	-939.16
L	9,02,000	9,81,145	392.46	51.90	212.11	264.00	0.53	2.69	-128.46
M/E	8,08,000	9,02,147	360.86	51.97	129.91	181.88	0.58	2.02	-178.98
M/W	4,12,000	4,13,524	165.41	101.38	62.72	164.11	2.45	3.97	-1.30
N	6,23,000	6,31,990	252.80	58.07	85.70	143.77	0.92	2.27	-109.02
s	7,44,000	7,79,260	311.70	95.61	257.25	352.87	1.23	4.53	41.16
T	3,41,000	3,47,205	138.88	52.78	118.24	171.02	1.52	4.93	32.14
Eastern Total	3830000	40,55,271	1,622.11	411.70	865.94	1,277.64	1.02	3.15	-344.47
Suburb Total	9358000	99,04,605	3,961.84	1,039.92	1,638.30	2,678.22	1.05	2.70	-1,283.62
Mumbai Total	12443000	1,27,90,498	5,116.20	1,633.67	1,892.22	3,525.89	1.28	2.76	-1,590.30
Others Proposed {Refer Table No. 20.1 of Chapter 20)						4308.52	-	3.37	-
Grand Total						7834.41	-	6.13	2718.21