Geographically Weighted Regression Models to Investigate Urban Infrastructures Impacts

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Abstract. Land transformation, producing effects on the physical and functional system, can generate externalities, modifying the individuals' perception of a given place. These effects, and in particular the changes in terms of urban quality, influence the success and effectiveness of an intervention in social, economic, environmental terms. To understand the perception of urban quality and define the elements that can contribute to its definition, urban infrastructures are increasingly subject to evaluation and quantitative measures and estimation. In the literature, it is possible to identify different types of approaches for assessing the quality of urban environments, both monetary and non-monetary. This study identified the impacts of urban infrastructure on residential property prices in Singapore. Through the application of the Hedonic Prices Method. Once the significance of the model variables was verified through an Ordinary Least Square (OLS) estimator, Geographically Weighted Regression (GWR) and Multi-scale Weighted Regression (MGWR) models were applied to take under control the spatial heterogeneity of the real estate market. Results show how MGWR model explained better the relationship between the selling price and structural and accessibility variables. This application built a bridge between economic valuation and local planning, supporting policy makers to map and identify weak areas in Singapore.

Keywords: Hedonic Prices Method (HPM) · Housing market · Spatial regression models

1 Introduction

The transformations of the territory that arise from the demand for services, connections, the usability of nature, and free time imply the use of monetary resources. Such investments inevitably induce and produce both positive and negative economic impacts on society. Often the results are not at all obvious and require a cost-benefit balance [1, 2]. In this perspective, the quantification of these effects appears to be an increasingly important operation to guide decision-making processes with a view to social equity [3]. The need to estimate and measure the effects of a transformation, and of changes in terms

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of urban quality, seems to have grown more and more over the years [4–6]. In the urban area, estimation methods have been applied over the years which made it possible to quantify the monetary value of the benefits/costs produced by the transformation of the territory. Mainly, these methodologies use the changes induced on the market value of private properties [7–9]. One of the most used techniques is the Hedonic Prices Method (HPM). The basic hypothesis lies in the assumption that the value of a property is linked to the utility attributed to the structural and external characteristics. Starting from this assumption, it is possible to break down the total price of the property into the marginal prices of the characteristics capable of determining its overall value.

Since 1974 when Rosen's first scientific article was published [10], a large literature has been produced on the subject from which the predictive capacity of this method emerges. HPM has been used extensively with real estate market data, primarily to obtain an estimate of the market value of the structural characteristics of real estate, but not only. Some studies have focused their attention on the value of environmental and public externalities. Others have used HPM to assess the effects of neighborhood characteristics on property values. Another branch of econometric research has instead focused on the valuation of the negative impact linked to environmental or noise pollution, considering, for example, the proximity to a certain source of pollution, which can be like an industrial site or a busy road. More recently, the literature has investigated how the construction of urban infrastructures, such as a new train station, a new park or public space, or even a new urban regulation of land use has affected property prices [11].

This research is part of the latter branch and develops ex-post valuations of the impacts of urban planning policies on the multi-family residential market in Singapore (Southeast Asia). In detail, the Geographically Weighted Regression (GWR) and Multi-scale Geographically Weighted Regression (MGWR) models were applied to study the spatial heterogeneity of property characteristics, in terms of structure and accessibility.

The document is structured as follows; after the Introduction, Sect. 2 offers a review of the literature on Spatial Hedonic Prices Methods (SHPM) applied in the study of the effects of urban infrastructures on property prices. Section 3 presents the methodology adopted in this study. The application to the Singapore case study is presented in Sect. 4. The results are presented in Sect. 5. Discussions and conclusions follow in Sect. 6.

2 Research Background

To investigate the determinants of properties prices, many studies have adopted the HPM [12–14]. Despite the many applications, the traditional model based on Ordinary Least Square (OLS) is limited because it cannot explicitly consider geographic location relationships, such as spatial connections. This limit has led scholars to propose new models that consider the dependence and spatial heterogeneity between transactions. To overcome the limitations of OLS-based models, the studies proposed to investigate the real estate market using local regression models such as GWR. Kopczewska and Ćwiakowski [15] filled the gap in the econometric literature by testing the space-time stability of real estate submarkets through the standard GWR estimate of the hedonic

model. Massimo et al. [16] applied a GWR model in the analysis of the real estate market to identify homogeneous areas and to define the marginal contribution that the geographical location gives to the market value of the properties. In detail, the authors focused on identifying possible potential market rewards in the exchange and rental markets for green buildings in Reggio Calabria (Italy). Manganelli et al. [17] applied the GWR model to investigate residential real estate units in the city of Potenza (Italy). The results of the zoning of the territory in homogeneous market areas have provided useful information in terms of taxation, planning of territorial transformations and control of ongoing and ex-post planning.

GWR model has seen a limited application in the estimation of the externalities associated with urban infrastructures. Some researchers have recognized the importance of analyzing the housing market at local level rather than considering global impacts applying GWR calibration. The construction of spatial maps is a useful tool to represent additional information on phenomena occurring in the real estate market, providing more detailed local information. In this perspective, Cellmer and Trojanek [18] used a hedonic regression model in the form of OLS, Quantile Regression (QR) and GWR to analyze 12,219 apartment transactions in Poznan in the years 2013–2017. The maps created allowed to define and visualize the dynamics of the real estate market, demonstrating the increasing or decreasing attractiveness of the areas.

Despite the potential of the GWR method to represent the dynamics of the market in space, the literature has highlighted a non-negligible limit [19–22]. The GWR method uses a single bandwidth to calibrate the model and define the rate at which the location weights decline based on the distance for each observation to neighboring ones. The model, therefore, assumes that the bandwidth is constant for all covariates implying that the relationships vary at the same geographical scale. In GWR models, the presence of outliers, multicollinearity and spatial autocorrelation cause instability in its estimates [23–26]. The lack of diagnostic tools to measure multicollinearity could be a strong weakness for the model. To overcome this limitation, Fotheringham et al. [27] proposed a more generalized MGWR model than GWR, which assumes that each covariate varies differently in space.

3 Geographically Weighted Regression Models

The presence of spatial dependence of the characteristics of the neighborhood and accessibility on the location implies the inefficiency of the models based on the OLS estimator, as they can determine an incorrect determination of the coefficients. The implication of this spatial dependence is closely linked to spatial heterogeneity and autocorrelation issues. Many researchers have investigated these effects by proposing spatial regression models. GWR is a spatial statistical technique that recognizes that traditional "global" regression models can be limited when the elements that affect the dependent variable vary by context [28–30]. In the real estate sector, the GWR model can capture the spatial heterogeneity of the housing market, inevitably influenced by urban elements that are not uniformly distributed in the space. The GWR model is based on a set of local linear

models which is calibrated considering the data of a number of nearby observations. The result is an estimate of the position characteristics for each observation in the model, as well as a single bandwidth parameter that provides insights into the geographic scale of the effects. A GWR model is specified as Eq. 1;

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i \, i = 1, \ldots, n, \tag{1}$$

where y_i is the dependent variable at location i, β_{i0} is the intercept coefficient at location i, x_{ik} is the k-th explanatory variable at location i, β_{ik} is the k-th local regression coefficient for the k-th explanatory variable at location i, and ε_i represents the random error term associated with location i. Location i indicates the regression point, indexed by geographic coordinates (u_i, v_i). GWR estimator for local parameter estimates become in matrix form as Eq. 2;

$$\widehat{\beta}(i) = \left[X' W(i) X\right]^{-1} X' W(i) y \tag{2}$$

where X is a n by k matrix of explanatory variables, $W(i)$ is the n by n diagonal weights matrix that weights each observation according to its distance from the position i, $\widehat{\beta}(i)$ is a k by 1 vector of coefficients, and y is a k by 1 vector of observations of the dependent variable.

To calculate the weight matrix W, a kernel function is applied to the distances between the observations and the calibration points. This kernel places more emphasis on observations that are closer than those farther away. The three most used kernel functions are the Gaussian, exponential, and bi-square functions. Generally, the function is chosen based on the distribution of the dependent variable. In the real estate sector, the Continuous (Gaussian) Model Type since the dependent variable (sales price or rent) can take on a wide range of values is mainly selected. Bandwidth selection is done by optimizing a model fit criterion or by specifying it manually. Optimal selection (golden search) is preferable when there is no theoretical guide to manually specify bandwidth. The optimal bandwidth is that which minimizes the Akaike information criterion (AICc).

If GWR limits the relationships within each model to vary at the same local spatial scale, MGWR allows it to vary at different spatial scales [31], according to the Eq. 3;

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{iwk} x_{ik} + \varepsilon_i \tag{3}$$

where β_{iwk} is the k-th local regression coefficient for the k-th explanatory variable at location i according to the bandwidth used for calibration of the j-th conditional relationship.

4 Singapore Case Application

4.1 Dataset Reference

As public housing in Singapore accounts for about 80% of total residential housing, the private sector was chosen to develop the study. This ensured that the coefficient estimates were not biased due to the different nature of transaction prices. In addition, dwellings in multi-storey buildings (condominium and apartment) were selected as they represent the largest portion of the housing stock. Moreover, the multi-family stock is efficient for the analysis of the urban context and infrastructure as it is uniformly distributed over the urban territory. The real estate transaction data was obtained from the Real Estate Information System (REALIS) database of the Urban Redevelopment Authority in Singapore [32]. The period covered was from January 2015 to December 2017. The initial dataset included approximately 45,000 georeferenced transactions of dwellings. To avoid having more than one observation per geographical point, it was decided to reduce the sample by eliminating duplicates. In detail, it was decided to order the observations in ascending temporal order and to eliminate the observations in the same geographical position. After eliminating the transactions with the same geographic coordinates, the final dataset had 3,444 transactions.

4.2 Variables Description

The literature in the real estate valuation industry has identified characteristics that affect the value of buildings. The characteristics can be classified into two different types: intrinsic characteristics, such as the surface, the presence of a lift, apartment level, quality of the property in which the apartment is located; extrinsic characteristics that characterize the urban area in which it is located, the quality of the neighborhood, including the quality of the environment and accessibility.

Table 1 presents the variables considered in the OLS, GWR, and MGWR models. The dependent variable considered refers to the total log-transformed amount of the transaction in local currency (Singapore dollars - SGD). The intrinsic characteristics included the surface area of the property in square meters, the floor on which the apartment is located within the multi-story building (Floor level), and the age of the property at time of sale (Age). As previously mentioned, the study will focus mainly on estimating the impacts of urban infrastructures, precisely because the positional characteristics group those properties that represent how the property relates to the external environment. The extrinsic characteristics investigated refer to the presence of urban green infrastructures (UGIs), understood both as an equipped public green area and as proximity to urban parks, accessibility to public transport (Mass Rapid Transit – MRT, bus stops), expressway network. Moreover, the proximity to the Central Business District (CBD) is investigated. As suggested by previous studies, distance from Orchard Road could be an effective proxy variable for distance from CBD [33, 34]. To consider accessibility to urban infrastructure, the QGIS tool was used to calculate the Euclidean distance in meters. In particular, the distance to each nearest urban infrastructure was considered for each flat.

Table 1. Variable included in the models.

Variable	Description
Market price	Natural logarithm of the price, SGD, Singapore dollars
Surface	Gross dwelling area expressed in square meters
Floor level	Floor level where the apartment is in the block
Age	Age of the property at the time of sale, calculating the difference between the year the apartment was sold and the year the building was constructed
Orchard Road	Euclidian distance expressed in meters from the apartment unit to the Orchard Road (where the CBD is located)
MRT	Euclidian distance expressed in meters from the apartment unit to the nearest MRT station
Bus stop	Euclidian distance expressed in meters from the apartment unit to the nearest bus stop
Expressway	Euclidian distance expressed in meters from the apartment unit to the nearest expressway
Natural Park	Euclidian distance expressed in meters from the apartment unit to the nearest natural park
Regional Park	Euclidian distance expressed in meters from the apartment unit to the nearest regional park

The functional form chosen for the regression analysis is the semi-logarithmic one, where only the dependent variable is log-transformed. In this case, the coefficient can be interpreted as the percentage change in the property price following an extra-unity of the independent characteristic.

5 Results

5.1 Global Regression Model

Global regression analysis was obtained through the OLS estimator. All variables achieved a significant influence of the dependent variable of 5%, as shown in Table 2. The value of R^2 and adjusted R^2 are 0.823 and 0.822 respectively. The examination of multicollinearity was performed by considering the Variance Inflation Factor (VIF) value. The results show that variables had no strong correlation (VIF < 2).

Table 2. OLS model results

Variable	Estimates	SE	t-value	p-value	VIF
Intercept	13.742781	0.016	834.962	0.000	n/a
Surface	0.006206	0.000	90.308	0.000	1.264
Level floor	0.006826	0.001	11.001	0.000	1.106
Age	−0.007087	0.000	−17.435	0.000	1.199
Orchard Road	−0.000039	0.000	−36.669	0.000	1.620
Expressway	0.000053	0.000	10.476	0.000	1.199
MRT	−0.000040	0.000	−3.765	0.000	1.166
Bus stop	0.000251	0.000	7.003	0.000	1.072
Natural Area	−0.000024	0.000	−16.360	0.000	1.217
Regional Park	−0.000021	0.000	−6.924	0.000	1.467
RSS	159.134	Log-likelihood	407.713	AICc	−793.349
R^2	0.823	Adj. R^2	0.822	DW	1.962
Number of observations: 3,444		Mean dependent variable: 14.10			
VIF = Variance inflation factor SE = Standard Error		RSS = Residual Sum of Square DW = Durbin-Watson statistic			

Focusing on accessibility variables, all coefficients obtained the expected sign. Having considered the distance between dwelling and the urban infrastructures as accessibility variables, the coefficients assume positive value for urban infrastructures that negatively impact property price; as the effect of the impact (distance) increases, the value increases. While the coefficients are negative if the urban infrastructures' proximity impact positively prices. As shown by the coefficient estimates, the distance from Orchard Road (−0.000039), nearest MRT station (−0.00004), Natural Area (−0.00024) and Regional Park (−0.00021) negatively affected property prices. Conversely, bus stops' distance had an unexpected positive effect (0.000251).

The study area is large and urban infrastructures are heterogeneously distributed over the territory. In the same way, the housing market is also heterogeneous. The results would be problematic if homebuyers' preferences for different urban infrastructures are heterogeneous. Starting from this, the local approach was needed to model and overcome the local variation of homebuyers' preferences.

5.2 Local Regression Models

The first step of GWR determined the value of optimum bandwidth with iterations to get minimum AICc. The weighted matrix was formed using the adaptive bisquare function since the observations were not spatially uniformly distributed. To calculate parameter estimates of local regressions, MGWR® software was used [31]. Table 3 summarizes the variation of the coefficient estimates from the GWR. The result of iteration yielded AICc was −2879 with a bandwidth value of 69. This bandwidth value described the number of neighbors giving the greatest influence. GWR improved the fit as expected (GWR adjusted $R^2 = 0.931$) compared to OLS (adjusted $R^2 = 0.822$).

Table 3. GWR model results

Variable	1Q	Med	3Q	IQR
Intercept	11.10075	14.33742	18.30478	7.20403
Surface	0.00577	0.00643	0.00727	0.00150
Level floor	−0.00241	0.00395	0.00863	0.01105
Age	−0.01400	−0.01048	−0.00579	0.00820
Orchard Road	−0.00064	−0.00010	0.00036	0.00100
Expressway	−0.00035	0.00008	0.00053	0.00088
MRT	−0.00047	−0.00013	0.00022	0.00068
Bus stop	−0.00027	0.00010	0.00047	0.00074
Natural Area	−0.00063	0.00003	0.00064	0.00127
Regional Park	−0.00054	0.00001	0.00067	0.00121
RSS	47.735	AICc	−2879.544	
R^2	0.947	Adj. R^2	0.931	
Number of observations: 3,444		Mean Dependent variable: 14.10		
1Q = 1st quartile, Med = median, 3Q = 3rd quartile, IQR = interquartile range				

Subsequently, the MGWR model was implemented, and an individual bandwidth was determined for each predictor variable. MGWR model defined a non-stationarity relationship for each predictor. The AICc was equal to −2,804. Both local regression models improved (decreased) the AICc than that found using OLS (AICc = −793). As the GWR model, MGWR one improved the fit between observed and predicted values (adjusted $R^2 = 0.91$) compared to the OLS model (Table 4).

Table 4. MGWR model results

Variable	1Q	Med	3Q	IQR	Bandwidth
Intercept	13.69379	13.79743	13.89224	0.19845	44
Surface	0.00569	0.00638	0.00702	0.00133	44
Level floor	0.00296	0.00498	0.00638	0.00342	334
Age	−0.00857	−0.00770	−0.00702	0.00155	1241
Orchard Road	−0.00004	−0.00004	−0.00004	0.00000	2499
Expressway	0.00006	0.00007	0.00008	0.00002	1943
MRT	−0.00004	−0.00004	−0.00004	0.00000	3442
Bus stop	0.00015	0.00015	0.00016	0.00001	3442
Natural Area	−0.00003	−0.00003	−0.00003	0.00000	3442
Regional Park	−0.00003	−0.00003	−0.00003	0.00000	3442
RSS	73.076	AICc	−2804.461		
R^2	0.919	Adj R^2	0.910		
Number of observations: 3,444		Mean Dependent variable: 14.10			
1Q = 1st quartile, Med = median, 3Q = 3rd quartile, IQR = interquartile range					

As indicated by the interquartile range (IQR), the GWR coefficient estimated show a higher variation than the MGWR ones. Comparing coefficients, some marked differences between the standard GWR and MGWR models can be summarized. First and foremost, all the covariate coefficient estimated in the GWR model inflect from negative to positive, indicating both negative and positive associations with Level floor and all accessibility variables. All the coefficients maintain the same sign in MGWR. The identification of specific bandwidth for each of the variables considered highlighted the limitations of the GWR model. The MGWR bandwidths for structural characteristics considered apartments very close; 44 for Surface, 334 for Level floor. Otherwise, the accessibility variables extended the analysis to more distant observations, sometimes referring to almost the entire sample; 2,499 for Orchard Road, 1,943 for Expressway, 3,442 for MRT, bus stop, Nature Area, and Regional Park. The MGWR outputs for Orchard Road, MRT, Natural Area, and Regional Park showed limited variation, indicating largely stationary processes. This stationary quality was reflected by their wide bandwidths.

The MGWR bandwidths for the intercept and other covariates indicated the relationship with real estate prices at different spatial scales. Structural variables in the model had impacts on prices that vary over relatively short distances. The intercept was distributed on a highly localized scale of 44 neighbors, with a spatial pattern similar to that observed in the OLS residual map (Fig. 1). This suggested that much of the residual autocorrelation could be captured by interceptions of variables via spatial models.

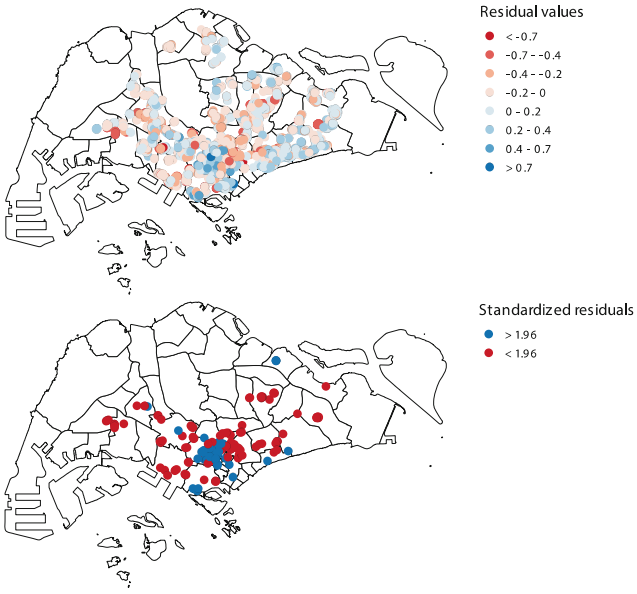


Fig. 1. Spatial distribution of OLS model residuals.

The MGWR coefficient estimates for Surface were like the GWR ones because the bandwidths of both models were similar. The difference between the GWR and MGWR was in the significance of those relationships; however, a greater number of apartments have significant coefficient estimates obtained from the MGWR calibration. The MGWR demonstrated that the building Age had a relatively strong relationship with transaction price (a median coefficient estimates of −0.00857). However, this relationship was somewhat localized following the urbanization phase of the city (bandwidth equal to 1,241). On the other hand, the parameter estimated associated with the accessibility variables were global. To see more clearly the variations in the spatial scales at which different processes operated, in Figs. 2–3 we present the local parameter estimates both from GWR and MGWR associated with the variables "Floor level" (district area variation), "Regional Park" and "MRT".

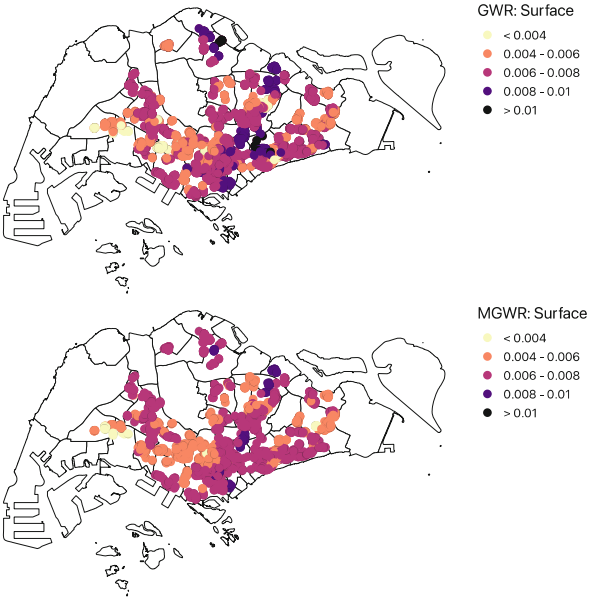


Fig. 2. GWR and MGWR coefficients for Surface covariate

In Fig. 2, the local parameter estimates for the "Surface" variable were broadly similar from both the GWR and the MGWR calibrations because the bandwidth for the relationship between housing prices and "Surface" in the MGWR (44 neighbors) calibration was fairly close to that of the single bandwidth obtained in GWR (69 neighbors). The MGWR results, however, suggested a slightly more local trend in the relationship with many of the local estimates with lower values. There was some evidence that "Surface" had a stronger influence on prices in the Central Area of Singapore (Orchard, Potong Pasir, Tanjong Katong), along the southwest coast, and west of the Catchment Central Area.

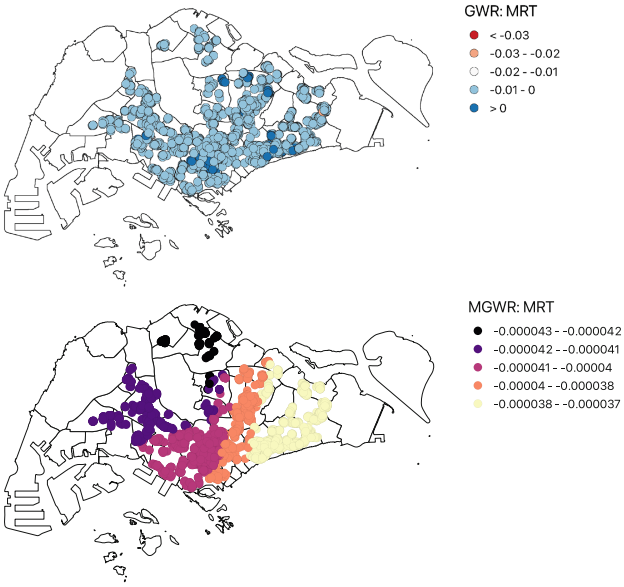


Fig. 3. GWR and MGWR coefficients for MRT covariate

Figure 3 shows that the local parameter estimates for the variable "MRT" derived from the MGWR model were uniformly negative across the country, varying from −0.00004313 to −0.00003793, indicating that proximity to the MRT had little spatial variation. However, some interesting conclusions were drawn. From the map, it appeared that the properties most affected by the distance from the MRT were in the north and west of the city, where the network was not widely developed, and the stations were limited [19]. GWR calibration suggested a local effect and a weaker trend with many of the local estimates being close to zero.

As for MRT, parameter estimates associated with Regional Park were global with the optimal bandwidth as larger as it could be. Considering the MWGR model, estimates of local parameters varied very little over the territory of the city (−0.000026185 to −0.000025408). However, the MGWR calibration allowed to highlight the spatial variation of regional park influence. As shown in Fig. 4, regional parks had a great influence on the North and Northeast regions, where these green infrastructures are limited or absent [35, 36]. However, in this part of the city, there is an abundance of green spaces, pristine forests, and even agricultural land, which are now a rarity in Singapore, perhaps constituting important drivers in the choice of real estate. Furthermore, given the industrial vocation of the area, proximity to the workplace can be a determining factor in choosing the location of the home.

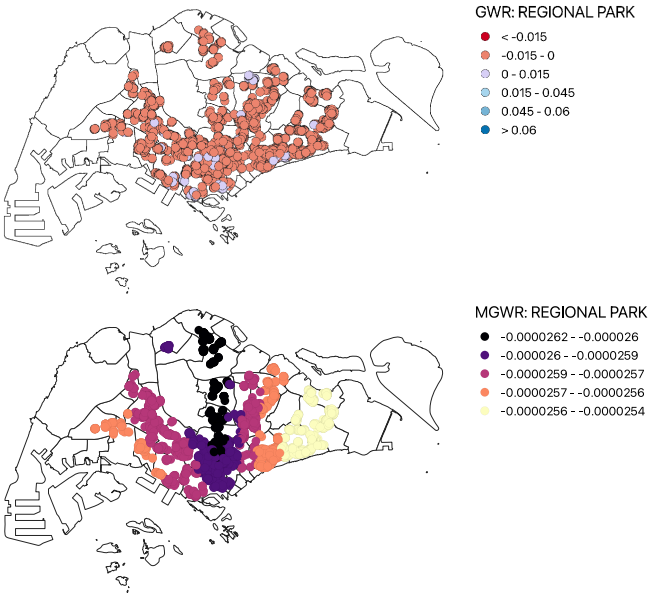


Fig. 4. GWR and MGWR coefficients for Regional Park covariate

6 Discussion and Conclusions

This study estimated the local effects of structural and accessibility characteristics on the real property prices of multi-family homes in Singapore. To estimate the economic effects of these infrastructures, the HPM was employed on a georeferenced dataset of 3,444 transactions of apartments sold between 2015 and 2017. To estimate the local coefficients, two local regression models were applied: GWR and MGWR.

Calibration by GWR allowed to investigate of the spatial variation of the variables introduced in the model by relaxing the assumption that the parameters are constant in space. Furthermore, the GWR model foreseen to calculate an optimal bandwidth that describes the spatial scale of the investigated phenomenon. The bandwidth is unique and is used to calibrate relationships between dependent variable and predictors. When several independent variables come into play, the GWR model appeared unable to represent the relationships, as they are not uniformly distributed in space. Therefore, an extension of the GWR model, called MGWR, was proposed which provides for relaxing the assumption that all relations operate at the same scale by calculating optimal bandwidth for each investigated variable. The model thus set up allowed to generate intuitive interpretations in terms of geographical scale; local, regional, or global.

The MGWR calibration highlighted the local spatial distribution (local variation) of the structural characteristics, such as Surface, Level floor, and Age. This makes sense because real estate developments often follow urbanization processes, resulting in buildings with the same structural and temporal characteristics. Compared to the GWR model,

the MGWR one offered the possibility to improve the understanding of the local relationships between the selling prices of multi-family residential properties in Singapore and the structural and quality characteristics of the neighborhood.

The outcomes of the local models can help policy makers to map and identify vulnerable areas in Singapore that are affected negatively by urban infrastructures not planned correctly. By focusing on the variables of accessibility to important urban infrastructures, it is however possible to confirm that the results show that the distance from MRTs, urban parks, had a significant and positive effect on housing values, with the effect of decaying prices in relation to the increase in distance. On the other hand, heavily trafficked road infrastructure, such as the expressway, negatively impact property prices. These results demonstrated the ability of these SHPMs to consider the spatial heterogeneity of the real estate market, identifying the various positive and negative impacts provided by urban infrastructures.

As future perspectives, the walking distance could be tested as a better indicator when compared with Euclidian distance to investigate urban infrastructure heterogeneity through local regression models.

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