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Multiscale Effects of Multimodal Public Facilities Accessibility on Housing Prices Based on MGWR: A Case Study of Wuhan, China

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Abstract: The layout of public service facilities and their accessibility are important factors affecting spatial justice. Previous studies have verified the positive influence of public facilities accessibility on house prices; however, the spatial scale of the impact of various public facilities accessibility on house prices is not yet clear. This study takes transportation analysis zone of Wuhan city as the spatial unit, measure the public facilities accessibility of schools, hospitals, green space, and public transit stations with four kinds of accessibility models such as the nearest distance, real time travel cost, kernel density, and two step floating catchment area (2SFCA), and explores the multiscale effect of public services accessibility on house prices with multiscale geographically weighted regression model. The results show that the differentiated scale effect not only exists among different public facility accessibilities, but also exists in different accessibility models of the same sort of facility. The article also suggests that different facilities should adopt its appropriate accessibility model. This study provides insights into spatial heterogeneity of urban public service facilities accessibility, which will benefit decision making in equal accessibility planning and policy formulation for the layout of urban service facilities.

Keywords: multiscale effect; public facilities; accessibility; MGWR; housing prices; 2SFCA

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1. Introduction

Along with the ongoing planetary urbanization, the surging in urban population poses a major challenge for global cities to provide residents with safe, healthy, and sustainable public services [1]. Especially in developing countries, public facilities such as education [2–4], transportation [5–8], green spaces [9,10], and medical care [11,12], are becoming the core public policies and methods to bridge the growing gap in economic inequality. Wherein, the accessibility of public facilities is considered to play an important role in urban planning and management in terms of public service [13–15]. As housing prices may reflect the quality of nearby public services, it is important to understand the accessibility of various public service facilities through housing prices [16–18].

The hedonic model proposes the classic correlations between price and structural, locational, and neighborhood attributes of properties [19]. The spatial accessibility and scarcity of facilities distributed in urban space such as commercial districts, schools, bus stations, subway stations and parks, are critical factors that affect housing prices [20]. Furthermore, housing prices are also affected by spatial correlation [21] and spatial heterogeneity [22], for instance, there exist distance decay effect of facilities on urban housing prices, and different kinds of stations will have different impact on housing price [23]. Such a dilemma could be partly explained by the scale effect of spatial accessibility [23,24].

Although a large number of studies have analyzed the impact of the accessibility of different public facilities such as healthcare [25,26], education [16], transportation [15], and public green space [27] on housing prices, there still remains uncertainty in measuring accessibility in terms of travel costs and model selection [28].

In terms of travel costs in accessibility models, traditional models often use nearest Euclidean distance, nearest street network distances as spatial barriers, recent studies assume using real time cost or distance as a spatial cost based on open map services such as Google Map API [29,30]. However, while map API provides multimode models via driving, walking or public transit [31], it is not clear which kind of distance should be chosen according to the various kinds of public facilities.

Furthermore, there are also a variety of models for measuring accessibility, such as the supply-oriented model (SOM), the cumulative opportunity model (COM), and the supply-demand ratio model (SDRM) [32]. Various nearest distance models are commonly used in SOM to assign a single supply point to each demand area, while Kernel density model, gravity-based potential model can be categorized as COM that considers multiple supply sources [33]. SDRM is also popular in urban planning or policy making, using ratio between the amount of demand and supply in a certain spatial unit. Such methods may underestimate the distance decay effect and the capacity of both supply and demand, the Two-Step Floating Catchment Area (2SFCA) were proposed and widely used in health care accessibility research [34,35]. Similarly, which model should be selected for a particular type of public facilities may need more exploration. In fact, more and more studies have shown that the accessibility measurement should be adopted according to the daily use mode and available data of public service facilities [36,37].

In addition, current research rarely considers the multiscale spatial effect of the multimodal accessibility on housing prices [38]. Although there have been studies integrating spatial statistical models (SSM) and Geographic Weighted Regression model (GWR) into the classic hedonic model to enhance the spatial effects [39,40], recent studies have pointed out that Multiscale Geographic Weighted Regression model (MGWR) can better reflect the scale difference of spatial effects [41,42]. The knowledge of scale differences help to better capture the coexisting features of spatial heterogeneity and spatial autocorrelation [43].

This study thus takes Wuhan as the case study to explore the multi-scale effects on housing prices impacted by the multimodal accessibility of public service facilities. Based on measuring the public facilities accessibility of schools, hospitals, green space, and public transit stations with four kinds of accessibility models such as the nearest distance, real time travel cost, kernel density, and 2SFCA, MGWR is used to explores the multiscale effect of public services accessibility on house prices. The result verified the differentiated scale effect of public facility accessibilities and the coexistence of heterogeneity and homogeneity in space, which may benefit the policymaking of public facility layout planning and improve spatial justice in providing urban public services for local governments.

2. Data and Methods

2.1. Study Area

This study area is set as the main urban area (MUA) of Wuhan, the leading city in the middle reaches of the Yangtze River Economic Belt. The Yangtze River and the Han River converge in the center of Wuhan city, dividing the city into three major areas: Wuchang, Hankou and Hanyang (Figure 1). Wuchang is dominant on educational functions and has many well-known universities and Hankou focuses on commercial functions, and it has been a historical concession area before 1949, while the economics of Hanyang are driven by the automobile industry. In terms of environment, the abundant water and mountains in the city form a good ecological background, such various geographic context could impose potential scale effect on accessibility.

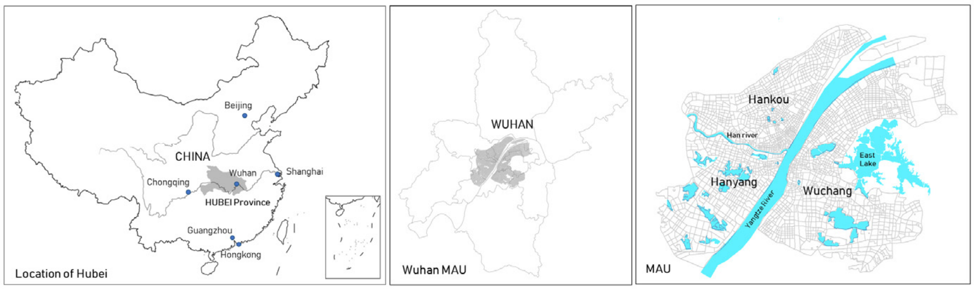


Figure 1. Location of Wuhan and its Main Urban Area (MUA).

From the price trend chart from 2013 to 2020 (Figure 2), it can be seen that the housing prices in Hanyang are relatively lower compared to the other two districts. From 2015 to 2018, housing prices in Wuhan rose rapidly, with an average increase of 95%, and then shower a relatively stable trend. Housing price in Wuchang has been rising strongly, surpassing Hankou in 2016, and it leads a slightly upward trend in 2020 when the overall average price decline.

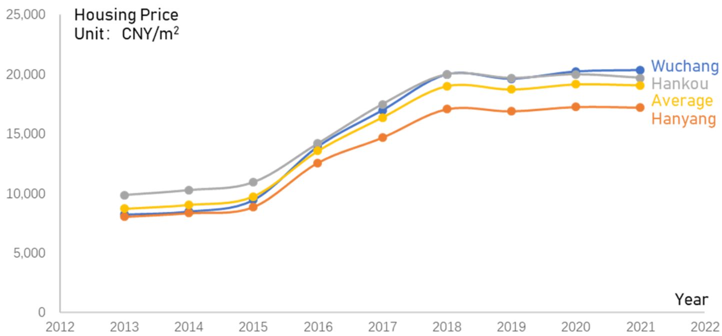


Figure 2. Housing price of Wuhan from 2013 to 2021 (MUA). Data source: https://www.anjuke.com/ (accessed on 1 January 2022).

2.2. Data Preprocessing

Three kinds of variables were adopted to explore the multiscale effect of accessibility on housing prices. Wherein, housing prices were set as the dependent variable with the accessibility of various public facilities taken as explanatory variables, beyond which several additional parameters were also included as control variables, such as population density, location centrality, and average building age (Figure 3).

(1) Housing prices and average house age: the data were grasped from an online housing platform (Lianjia.com, accessed on 8 August 2021) in 2020, the mean value of all point-based housing price within the boundary of the TAZ was generated as the average value of each TAZ. In order to increase the comparability, the data set only retains the apartment type, the most mainstream residential form in China, and the villa is not included because of the scarcity and the extremely high price.

(2) Public facilities: the data were extracted from the POI data of Baidu Maps, among which, only the public facilities often invested by the government was kept; education (kindergarten, elementary school, middle school), transportation (bus station, subway station), green space, hospital. Business and commercial spaces (stores, markets, offices) were also used for representing the employment centers. The hospitals have been further screened and only the general hospitals were retained. The corresponding accessibility of TAZ in the subsequent models were calculated based on the centroid of TAZ (n = 2383).

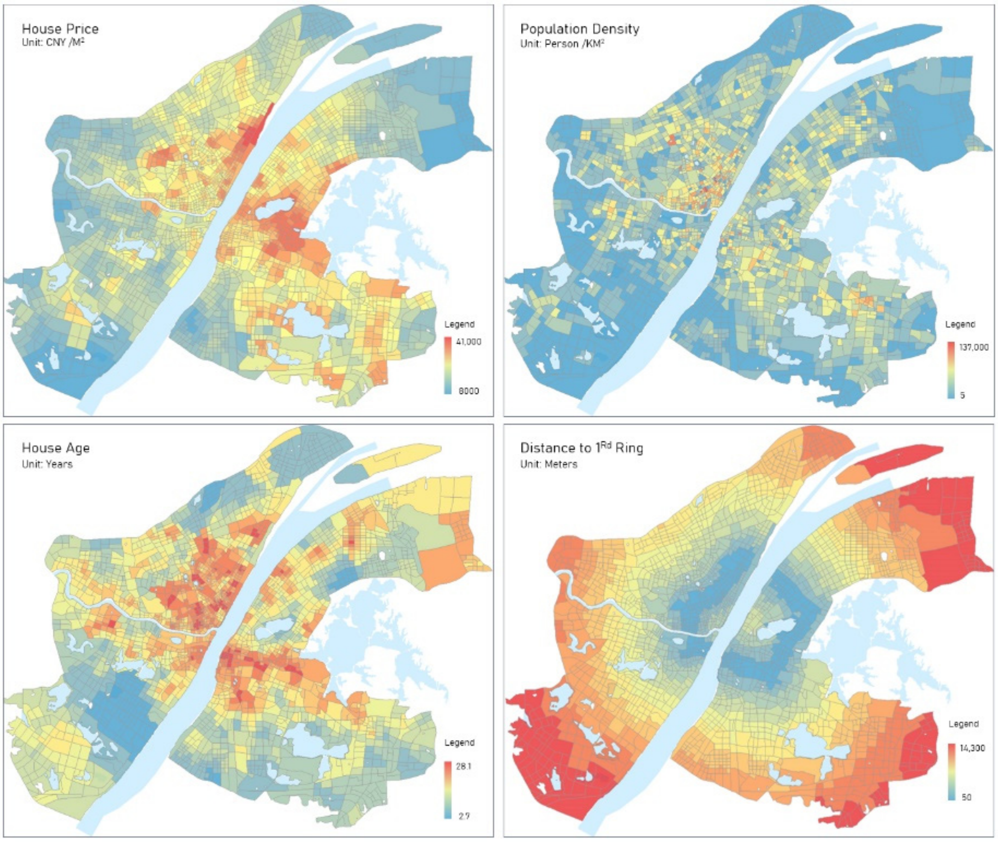


Figure 3. Mapping Variables of Housing prices and other control variables.

2.3. Methods

2.3.1. Multimodal Accessibility

This study takes four popular models to calculate the accessibility of various public facilities, nearest Euclidean distance, minimum multimodal travel time, Kernel density, and 2SFCA (Figure 4). The first two models could be seen as simple supply models, while the other two models could be taken as multiple supply models; in particular 2SFCA further considers the spatial threshold effect of both supply and demand.

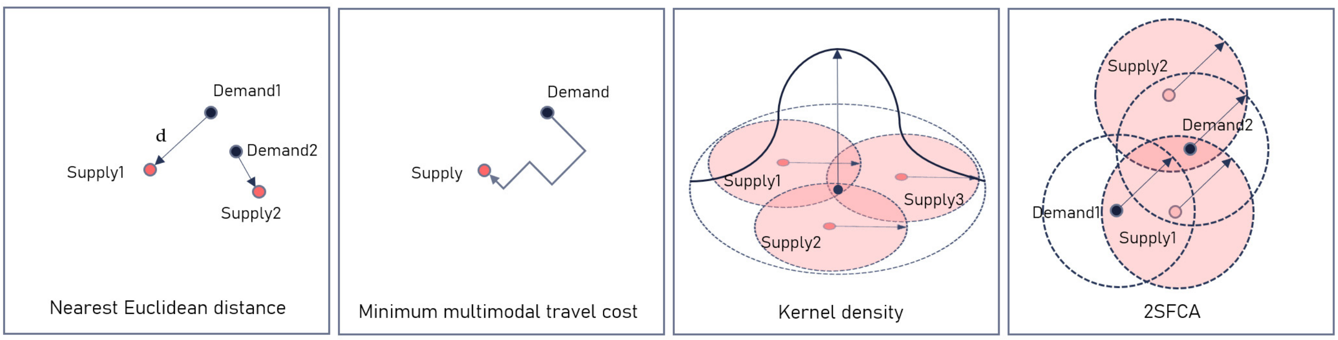


Figure 4. Multimodal accessibilities of public facilities.

(1) Nearest Euclidean distance (NED)

It was calculated based on the distance between the centroid of TAZ and all other public facilities under the projected geographic coordinates system. Such distance is the primary way for accessibility calculation. NED was used for TAZ as the distance to the urban center (the 1st ring road of Wuhan), rivers, employment centers, bus stops, metro stations, and parks.

(2) Minimum multimodal travel cost (MMTC)

Such parameter was acquired by Python programming with Baidu Map API, a similar web map service as Google Map API, to calculate the minimum travel time or distance via optimal multiple ways combining walking, driving, and public transit. MMTC was mainly applied in the accessibility of metro stations and hospitals, and for hospitals, all three kinds of travel modes were combined to generate the optimal cost, while only waking and public transit were used for metro stations.

(3) Kernel density (KD)

The accessibility computed by Kernel density (A_i^K) is affected by two parameters in the process, weight, and searching distance, wherein, appropriate weights should be assigned to various points representing the importance or capacity of public facilities, the search distance could be seen as the radius of service area in terms of specific facilities. Such equation could be written as:

$$A_i^K = \frac{1}{r^2} \sum_{i=1}^{n} \left(\frac{3}{\pi} w_i \left(1 - \left(\frac{d_i}{r} \right)^2 \right)^2 \right) \tag{1}$$

where d_i is the distance from demand point to supply point i, r is the searching radius, and w_i is the assigned weights of facilities. The calculation was executed in the ArcGIS platform which would use a default bandwidth for searching radius.

For bus station and bus lines, equal weight was used, while the ranking weights were assigned to schools according to their quality reports.

(4) 2SFCA

The whole calculation could be divided into two steps, firstly an average supply value was assigned from every single supply point to nearby demand points (k) within its service radius, then the assigned value from all nearby supply points (j) to every single demand point will be sum up based on the demand point as the result of accessibility (A_i^K). The accessibility for demand point i by 2SFCA is expressed as

$$A_i^F = \sum_{j \epsilon \{d_{ij} \leq d\}} \left(\frac{S_j}{\sum_{k \epsilon \{d_{kj} \leq d\}} D_k} \right) \tag{2}$$

where d_{ij} represents the distance between demand point i and each surrounding supply point with the threshold distance of d, d_{kj} is the distance between supply point i and each nearby demand point k, D_k is the total population of demand point k, and S_j is the supply capacity of j.

Due to the data lack of hospitals, 2SFCA is only implemented on green space with the demand and supply paraments set as the population of TAZ and the area of parks, respectively. According to related accessibility research on green space [44], 3 km was used as the threshold distance d.

2.3.2. Multiscale Geographical Weighted Regression

In this study, OLS regression was first applied for a preliminary test of the correlation between housing prices and explanatory variables and selection for further regression in GWR and MGWR.

(1) OLS Regression

The traditional hedonic model could be expressed as OLS regression, which means, for each observation of housing price y_i,

$$y_i = \beta_0 + \Sigma\beta_i x_i + \varepsilon_i \quad (3)$$

where β_0 is the intercept, x_i represents the independent variable, β_i is the corresponding coefficient and ε as the error.

(2) Geographical Weighted Regression

Comparing to OLS regression model, GWR model strengthen the expression of spatial heterogeneity by adding space-varying parameters according to the coordinates of each observation (u_i, v_i). The GWR equation for housing price y_i could be written as

$$y_i = \beta_{0(u_i,u_i)} + \sum_k \beta_{k(u_i,u_i)} x_{ik} + \varepsilon_i \quad (4)$$

where and are the intercept and the coefficient of local variable k at location i, respectively; x_{ik} is the kth variable at location i.

(3) Multiscale Geographical Weighted Regression:

Different sorts of public facilities may have various service areas which may result in a spatial effect on housing prices on changeable scales, which means spatial heterogeneity and spatial homogeneity may coexist. GWR using single bandwidth is not capable to express such features, while MGWR could alleviate such problems by assigning specific bandwidths for each variable based on iteration. The MGWR is as

$$y_i = \beta_{bw_0(u_i,u_i)} + \sum_k \beta_{bw_k(u_i,u_i)} x_{ik} + \varepsilon_i \quad (5)$$

The parameters are nearly the same as GWR, except the denoted label of *bw*, which represent the different bandwidth of each variable.

The models of OLS, GRW, and MGWR could be applied directly via the software MGWR [42].

3. Results

3.1. Preliminary Statistical Description and Correlation Test

There were 19 independent variables included for OLS regression, the statistical description was shown in Table 1. Wherein, the housing prices ranges from 7994 to 40,663, and Figure 3 also showed that the apartments with higher price were clustered in Hankou and Wuchang. The building age ranged from 2.7 to 28.1, the maximum population density is 137,014 persons per square kilometers. In terms of hospitals, the maximum distance calculated by Realtime Map API is 14,639 m which is 55% larger than the Euclidean distance, showing obvious differences among the various models of accessibility. Such a gap could also be found in the comparison of accessibility of metro stations, the maximum API distance is 118% larger than Euclidean distance.

As for educational facilities and parks, the minimum of accessibility by kernel density and 2SFCA could be zero, due to the distance between such TAZ units and facilities being beyond the service radius of public facilities.

The Pearson Correlation test indicated that housing price is highly related to most of the explanatory variables (Figure 5). Wherein, housing price showed obvious positive correlation to population density, building age, kernel density of bus stops and lines, kindergarten and primary school, negative relative to the distance to the 1st ring road, hospitals, metro stations and parks, which means the closer the distance, the higher the housing price. The extra high correlation in the various kinds of accessibility measurements in terms of hospitals and metro stations could be observed, and the collinearity between the distance to the ring road and employ centers is obvious as well.

Table 1. Statistical description of variables.

Variables	Method	Min	Max	Mean	Std.	Units	Explanation
HousePrice		0.7	4.0663	1.7847	0.4014	10,000 CNY/m^2	Average housing prices
BuildAge		2.69	28.07	15.32	4.71	Years	Average age of residential units
Popu		1	14,709.00	1030.67	1215.99	Person	Total population
PopuDen		4.00	137,014.00	7565.85	10,092.27	Person	Population density
BCenterD	NED	87.00	14,531.00	4075.87	3158.61	Meters	Nearest distance to employment centers
RingD	NED	56.00	14,344.00	4485.25	3500.91	Meters	Nearest distance to the 1st ring road
MarketNum		0	103	18.23	17.05		Total number of commercial POI
RiverD	NED	0.00	16,226.00	3153.78	3043.41	Meters	Nearest distance to rivers
HosD	NED	23.00	9432.00	2267.75	1794.89	Meters	Nearest distance to hospitals
HosApiT	MMTC	0.03	31.05	10.96	5.05	Minutes	Minimum time cost to hospitals via API
HosApiD	MMTC	2.00	14,639.00	3868.28	2907.81	Meters	Minimum distance to hospitals via API
MetroD	NED	64.00	7727.00	1299.20	1196.83	Meters	Nearest distance to metro stations
MetroApiD	MMTC	0.00	16,834.00	2226.84	2729.52	Meters	Minimum time cost to metro stations via API
MetroApiT	MMTC	0.00	75.00	19.97	15.11	Minutes	Minimum distance to metro stations via API
Busline	KD	0.00	35.41	10.39	7.42		Kernel density of bus lines
Busstop	KD	0.02	48.25	14.85	9.87		Kernel density of bus stops
BustopD	NED	32.00	1237.00	278.24	160.66	Meters	Nearest distance to bus stops
Kdg	KD	0.00	6.82	0.45	0.77		Kernel density of kindergartens
Psch	KD	0.00	4.43	0.72	0.87		Kernel density of primary schools
Msch	KD	0.00	3.25	0.68	0.75		Kernel density of high schools
GreenD	NED	27.00	7488.00	903.69	806.30	Meters	Nearest distance to parks
G2SFCA	2SFCA	0.00	3,281,352.00	46,857.27	305,939.43		Green space accessibility by 2SFCA

3.2. OLS Regression

The stepwise OLS regression was utilized to reduce the collinearity between variables, and 12 variables were retained in the last step (Table 2). The results indicate that variables such as building age, population density, the distance to the ring and green space are highly negatively correlation with housing prices. Such a result may imply that location and environmental factors play the most important roles, consist with the common sense that the closer to city center and green space, the higher the housing price.

Table 2. Step OLS regression result.

Variables	Coefficient	Std. Err.	t-Value	*p*-Value		VIF
	Estimate	Std. Error	t value	Pr (>|t|)		
(Intercept)	21,183.943	363.936	58.208	0.000	***	
BuildAge	−114.761	17.805	−6.445	0.000	***	2.011
PopuDen	−0.014	0.007	−2.059	0.040	*	1.368
RingD	−0.550	0.025	−22.190	0.000	***	2.158
HosD	−0.952	0.112	−8.501	0.000	***	11.560
HosApiD	0.163	0.072	2.256	0.024	*	12.663
HosApiT	283.289	28.895	9.804	0.000	***	6.083
MetroApiT	−23.272	5.501	−4.230	0.000	***	1.977
BusStop	36.481	9.396	3.883	0.000	***	2.462
Psch	−369.599	104.301	−3.544	0.000	***	2.339
Msch	828.863	122.381	6.773	0.000	***	2.423
GreenD	−1.044	0.095	−10.977	0.000	***	1.685
G2SFCA	0.000	0.000	−1.440	0.150		1.096
Adjusted R^2	0.559					

Note: ***, * represent significant at the level of 0.001, 0.05, respective.

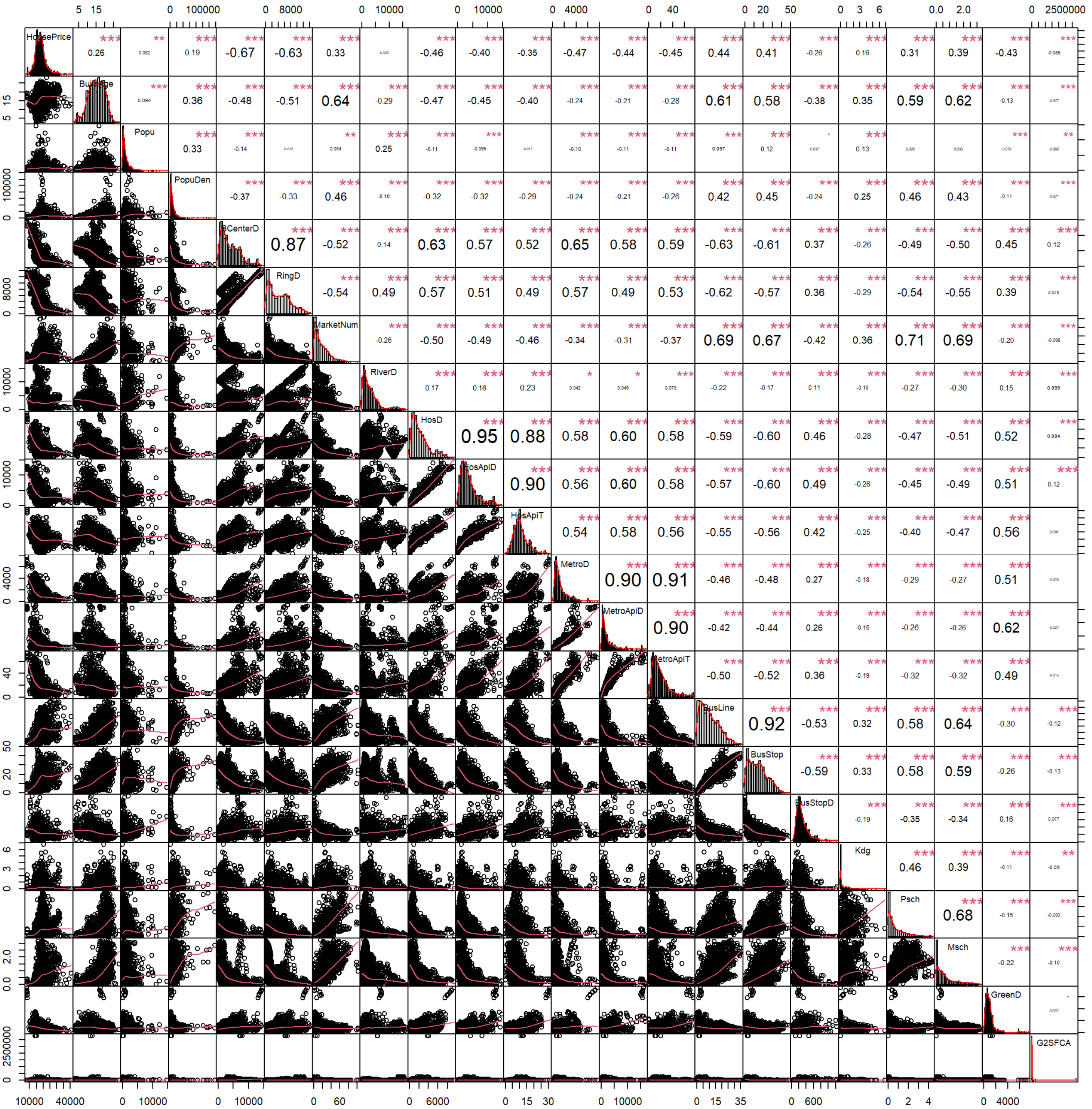


Figure 5. Multimodal accessibility of public facilities. Note: ***, **, * represent significant at the level of 0.001, 0.01, 0.05, respective.

It is still noteworthy that there are opposite effects among different accessibilities of hospitals and schools. In terms of green space, the influence of nearest distance outweighed that of 2SFCA, implying that spatial proximity may be more important than the spatial capacity. The variance inflation factors (VIF) were also reported here, showing that the collinearity among hospital accessibilities remains.

Based on the OLS result, the house price in Wuhan will decrease by 114 CNY for every year the house age increases, decrease by 23 CNY for every minute the time from the subway station increases, and decrease by 1 CNY for every meter increase in the distance to the green space.

3.3. MGWR

3.3.1. Model Comparison

During the application of MGWR, the result of GWR and MGWR were both generated by the software MGWR with interval bandwidth searching method (Table 3). The results show that although both GWR and MGWR can greatly improve the result of OLS, the latter shows a higher degree of fitness.

Table 3. Comparison of Regression Diagnostic Information.

	R^2	Adj. R^2	AIC	AICc	BIC
OLS	0.563	0.559	4830.614	4832.969	
GWR	0.936	0.926	891.129	1007.728	2879.145
MGWR	0.983	0.983	−1357.427	−831.346	2515.29

3.3.2. MGWR Parameter Estimates

Comparing with the bandwidth value 81 displayed by the GWR model, MGWR suppose that the bandwidth ranges from 20 to 2300 (Table 4). The results show that, with the exception of bus stops and metro stations, most variables show local or global scale except, wherein, all local variables showed changing correlation from negative to positive. In terms of global variables, Kdg, Msch, HosApiT, and Busline showed positive influence on housing prices, while Psch, G2SFCA, MetroApiT, MetroD, HosD and HosApiD were negatively related to housing prices.

Table 4. Summary statistics for MGWR parameter estimates.

	Bandwidth	Coefficients				
		Mean	STD	Min	Median	Max
Intercept	20	2.311	0.125	1.968	2.290	2.663
BuildAge	20	−0.228	0.223	−1.238	−0.195	0.430
PopuDen	20	−0.013	0.221	−1.896	−0.006	0.960
RingD	20	−0.562	0.313	−1.917	−0.557	0.607
Kdg	2300	0.014	0.000	0.013	0.014	0.016
Psch	2300	−0.064	0.000	−0.065	−0.064	−0.063
Msch	2300	0.109	0.000	0.108	0.108	0.110
GreenD	20	−0.196	0.302	−1.692	−0.179	1.020
G2SFCA	2300	−0.016	0.001	−0.017	−0.017	−0.011
Busstop	365	0.041	0.038	−0.061	0.034	0.100
BusstopD	20	−0.004	0.135	−0.671	0.000	0.505
MetroApiT [a]	1045	−0.056	0.003	−0.061	−0.056	−0.050
HosApiT [a]	2160	0.034	0.010	0.016	0.031	0.057
MetroD [b]	1985	−0.090	0.008	−0.099	−0.094	−0.073
HosD [b]	2300	−0.088	0.000	−0.089	−0.088	−0.087
MetroApiD [c]	295	−0.081	0.054	−0.197	−0.065	0.016
HosApiD [c]	2300	−0.010	0.002	−0.012	−0.010	−0.006

Note: [a, b, c] represents 3 independent regressions which share the same variables without labels and add another two labeled variables.

From the perspective of various public facilities, the impacts of educational and medical facilities are global, while the impacts of public transportation and green space are cross-scale.

Calculations based on MGWR and standardized results show that for every 1 year increase in house age, housing prices will drop by an average of 194 CNY; for every increase in the Euclidean distance to green spaces or bus station by 1 m, housing prices will decrease by an average of 2 CNY. In terms of metro stations, for every additional meter of European distance and travel distance, house prices will fall by 4 CNY and 533 CNY, respectively. For every minute of travel time to metro stations, house prices will decrease by 5954 CNY.

3.3.3. Multiscale Effect of Multimodal Accessibilities

The results of MGWR show the scale characteristics of all variables coefficients changing with space, and provide their statistical p-value, which can support more accurate information about the cooccurrences of spatial heterogeneity and homogeneity.

(1) Intercept and control variables

Figure 6 shows the coefficients of intercept and all three control variables. Based on the mapping of intercept coefficients, the spatial distribution of housing prices displayed an obvious difference among three districts in Wuhan. The overall housing prices in Wuchang are generally higher than those in the other two districts, and there are only two small spatial clusters in Hanyang and Hankou with higher prices. This may be because Wuchang has seven universities and is known as the Optics Valley Industrial Park, which has advantages in educational functions, economic vitality and scientific research.

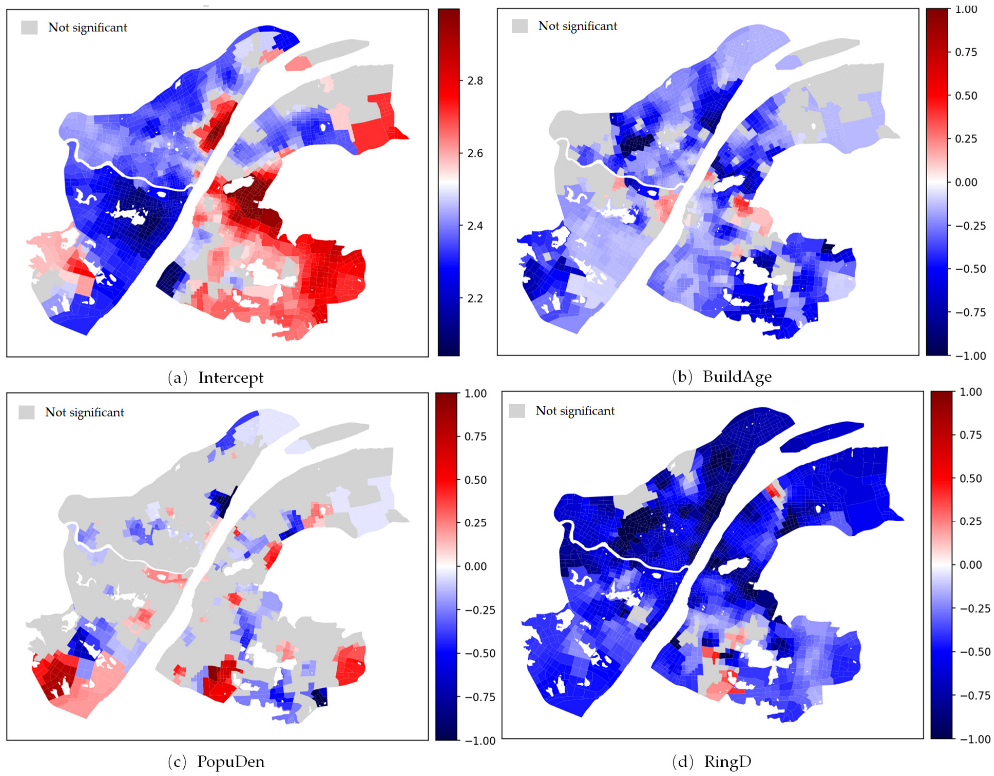


Figure 6. Variables of housing prices and other control variables. (**a**) Intercept of the MGWR indicates the spatial variation in housing price, (**b**) Age of resident apartments, (**c**) Population density, (**d**) Distance to 1st Ring road.

In terms of control variables, BuildAge and RingD show more robust results than PopuDen, as PopuDen is not statistically significant in most of units. Such results may indicate that the location and building age play dominant roles in housing price.

The coefficient of BuildAge is negative in most areas, which is consist with the commonsense that the newer the property, the higher the price. However, MGWR still reveals two interesting phenomena. One is the different between TAZs with significant varying coefficients or relative stable coefficients, for instance, most of the property value in the central Hanyang does not decline with time. The other is there are positive related clusters in Hanyang and Wuchang, it might be explained by the features of such location. The cluster in Wuchang is closer to government agencies and commercial centers. A possible alternative reason might be the difference in residences, as most of the newly developed real estate is restricted by high floor area ratio (FAR), preferring super high-rise buildings with nearly 30 floors, the communities of low or middle-rise buildings in urban center may be also attractive.

(2) Educational facilities

The Kernel density accessibility of educational facilities shows that in the southeast part of the city, middle schools and kindergartens have positive impacts on surrounding housing prices and are more sensitive to such resources (Figure 7). It is might due to that such area is located in the expanding area of Optics Valley and its high-tech industry parks, new residents may show a higher preference for educational facilities. However, elementary schools show a negative correlation, which could be related to the school zoning system adopted in Wuhan where each community have been assigned to a certain primary school and could not be captured by Kernel density algorithm.

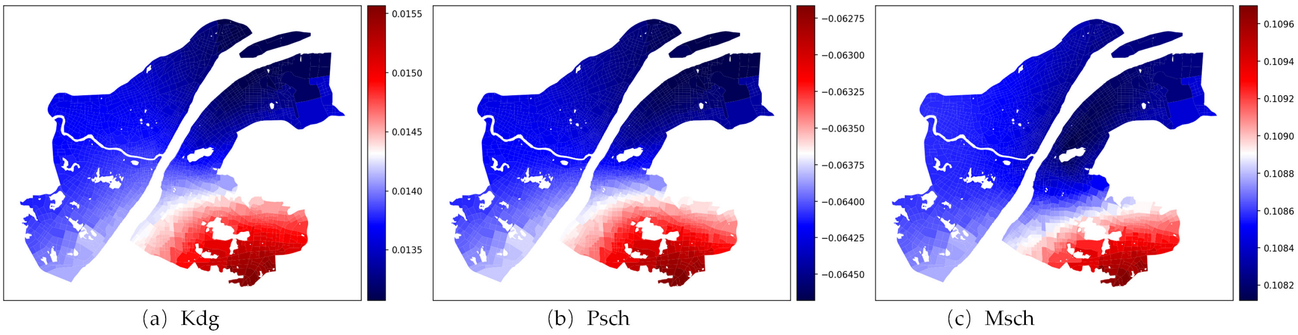


Figure 7. Global effect of educational facility accessibility. (**a**) Kernel density of Kindergartens, (**b**) Kernel density of primary schools, (**c**) Kernel density of Middle schools.

(3) Green space

The coefficients of GreenD varies from negative to positive, showing an obvious local spatial effect. Wherein, there was global negative connection between G2SFCA and housing price (Figure 8). Generally, the closer to green space, the higher housing price, but there are also positive effects in some clusters, most of which are close to water bodies, and there may be more green space nearby. As the value of 2SFCA represents the potential green space for each resident, it should be positively related to housing price. The negative effect may be caused by the threshold radius of 3000 m used in the 2SFCA, so that excessive green space might be included in the calculation of accessibility, and then affect tis correlation to housing prices.

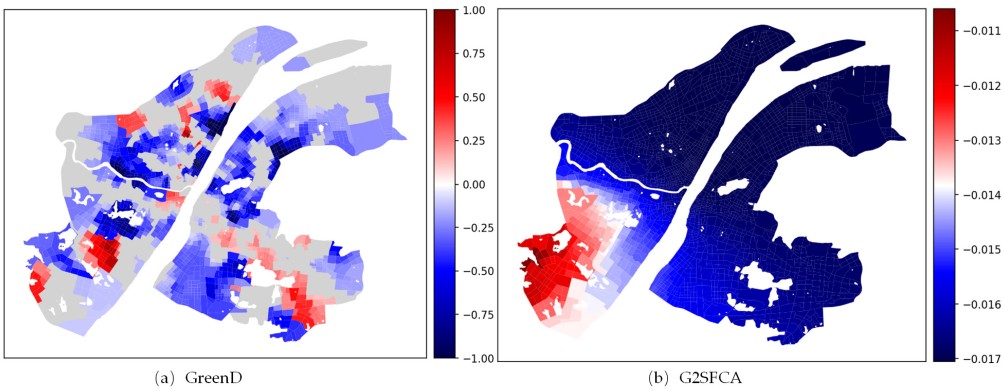


Figure 8. Multiscale effect of green space accessibility. (**a**) Distance to nearest green space, (**b**) Green space accessibility calculated by 2SFCA.

(4) Public transportation

In terms of bus stops, the accessibilities of Kernel density and shortest distance show opposite scales, and the distance parameter is not significant in many TAZ units (Figure 9). The Kernel density is not significant in Hanyang, but positive correlated in most areas of Wuchang and Hankou, and negatively correlated in the old town area in Wuchang.

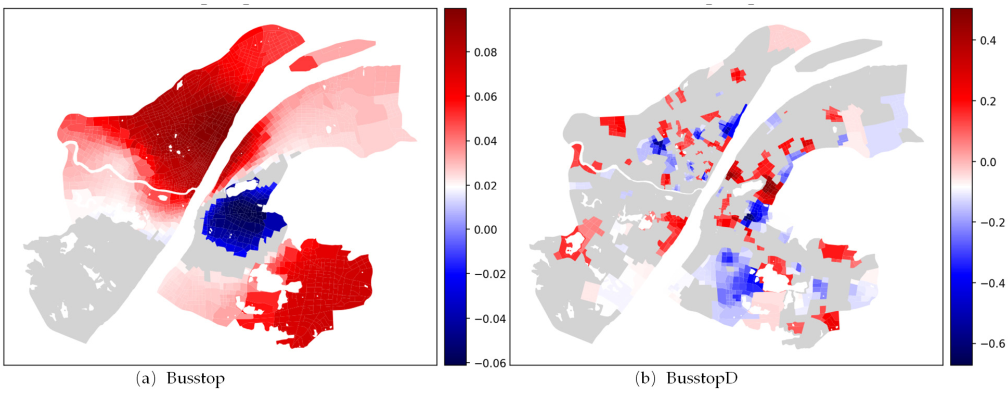


Figure 9. Multiscale effect of the accessibility of bus stops. (**a**) Kernel density of bus stops, (**b**) Distance to nearest bus stop.

The three different accessibilities of metro stations have a strong correlation, and share a negative connection with housing prices, that is, the closer the distance, the higher the house price, but the scales are different (Figure 10). Comparing with the global effect of the other two variables, the real-time travel distance via API presents a meso effect, and it is more sensitive to housing prices in the central urban areas.

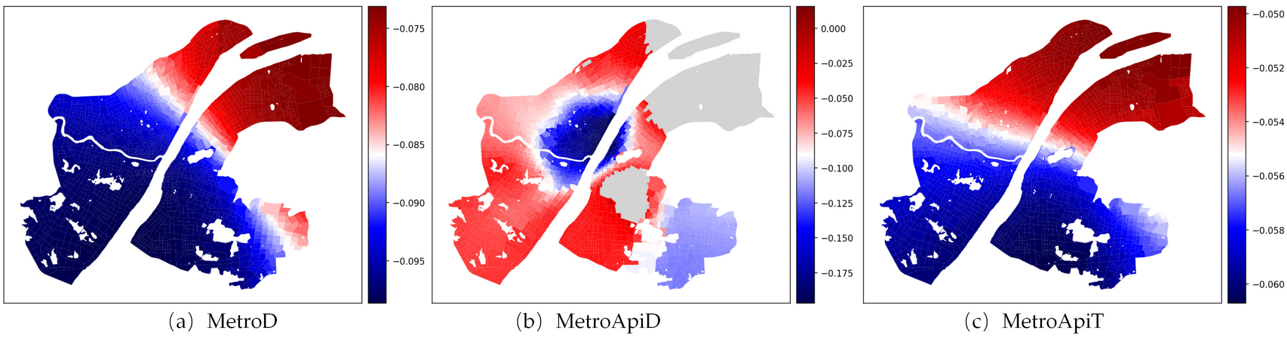
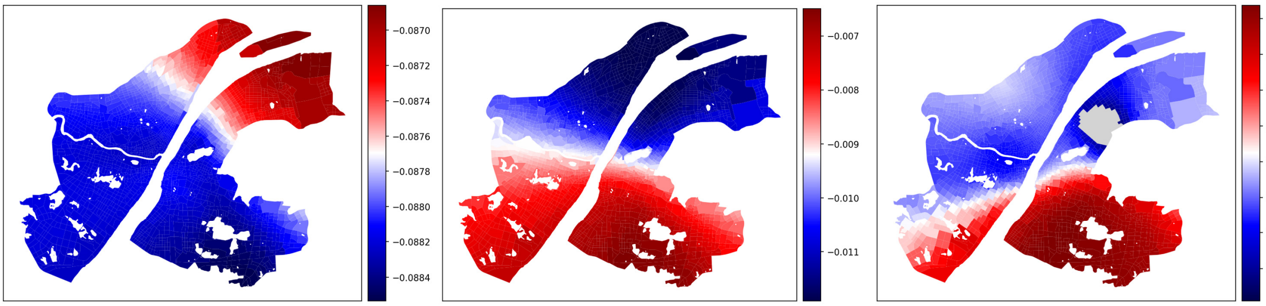


Figure 10. Multiscale effect of metro station accessibility. (**a**) Distance to nearest metro station, (**b**) Travel distance to metro stations calculated by Baidu Map API, (**c**) Travel time to metro stations calculated by Baidu Map API.

(5) Medical care facilities

The impacts of all three types of hospital accessibility on housing prices was not high, as the absolute values are below 0.1 (Figure 11). Among them, the Euclidean distance and the actual travel distance calculated by the API have weak negative correlations with the housing price, that is, the closer the distance, the higher the housing price. Moreover, the coefficients also change from north to south, where the south is sensitive to the Euclidean distance, and the north is more sensitive to the API based distance. This could be explained by the spatial structure in Wuhan, where there are more newly developed industry parks and residential districts in the south. What is unusual is that travel time is positively correlated. To a certain extent, this reflects people's ambivalence about living near the hospital, hoping to be closer to the hospital to facilitate medical treatment, but not too close to avoid potential sources of transmissible diseases.



(a) HosD (b) HosApiD (c) HosApiT

Figure 11. Global effect of hospital accessibility. (**a**) Distance to nearest hospital, (**b**) Travel distance to nearest hospital calculated by Baidu Map API, (**c**) Travel time to nearest hospital calculated by Baidu Map API.

4. Discussion

The main purpose of this study is to explore the multiscale effect of the impact of multimodal accessibility of different types of public facilities such as public transportation, schools, green space, and medical facilities on housing prices. The result verifies that the multi-scale effect not only exists among the accessibilities of different facilities, but also among the multimodal accessibility of the same facility. In addition, the MGWR model is supposed to be more suitable for capturing the impact of accessibility parameters at various spatial scales.

The results of MGWR reflect the sensitivity of housing price to location in the traditional hedonic model [19], but well reflect the multi-scale feature of the impact of public service facilities, distinguishing the spatial correlation on the global scale, and the spatial heterogeneity on the local scale [24]. As public facilities were supposed to impose positive influence on housing price [20,21], the results of MGWR only verify those in public transportation and green space, but the correlation of schools and hospitals needs to be further classified and analyzed. As there exists collinearity between commercial factors and the urban centrality which is reflected by the variable of the distance to 1st ring road, RingD.

In terms of control variables, urban centrality has a dominant influence on housing price, the closer to the center, the higher the housing price, which is consistent with previous studies [17]. There is also similarity on population density and house age with a related study based on GWR, which suggests that those two variables show both positive and negative connections with housing prices [45], but this study further shows that population density is of local spatial effect and not significant in most regions. Moreover, the model also captured the overall negative correlation of house age, which was challenged by previous GWR models but supported by most hedonic models [25]. Such an improvement implies that flexible bandwidth can bring more accurate results than fixed bandwidth used in GWR.

The result of Kernel density accessibility shows that only middle schools and kindergartens are positively correlated, and primary schools are negatively correlated. It does not support the general idea that all kinds of schools would boost the housing price of surrounding communities in previous studies [45]. It is also different from a similar case study in Hangzhou, which suggests that only primary and middle schools are related [16]. The results of MGWR are suggested to be more credible, as it may better reflect the influence of China's primary school zoning policy, which will make the density of primary schools show a non-positive correlation to housing prices.

Although the negative correlation between the distance to green spaces and housing price has been verified [46], the results of MGWR show that three is indeed a negative correlation in most areas, but positive correlation also cooccurs. Such observation of spatial heterogeneity is consistent with a recent related study in South Korea, which suggests that residents in the city center and the suburbs may value different spatial characteristics [15].

More importantly, the accessibility models based on nearest distance and 2SFCA are found to influence housing prices at different spatial scales.

Similarly, although the distance to bus station is generally negatively correlated to housing price, which may be supported by most studies [6], it also changes over space. Such a phenomenon is consistent with a recent case study in Melbourne [47], which verifies the spatial varying relationship between housing price and transportation facilities. However, the result here further indicates that it has a local spatial effect and is insignificant in most regions. The result of Kernel density is basically consistent with recent study which suggest a positive relation between bus stops density and housing price [46], and it also points out that there may be clusters with negative correlation, showing an impact of meso spatial scale.

As for subway stations and hospitals, all three types of accessibilities are of global spatial scale, indicating heterogeneous spatial effects between the urban center and the newly developing area [19]. Interestingly, all coefficients of subway stations are negative, while those for hospitals differs. The accessibility based on travel time are totally opposite from the other two. This result may support the conclusion of a recent case study in Shenzhen that the shortest distance is more important than the accessibility of time-based distances on housing prices [48].

MGWR can not only reflect the multi-scale spatial effects of factors affecting house prices, but also identify statistically insignificant spatial units, helping better understand the coexistence of homogeneity and heterogeneity in urban space. This conclusion also provides a certain reference for the comparison of accessibility models of public service facility, which suggest that in terms of bus station accessibility models, Kernel density model may be more suitable than the shortest distance model. For the green space accessibility model, the shortest distance model is better than 2SFCA which needs to be used after sensitivity analysis of the threshold distance. Although both the shortest distance, real time travel cost can be used for subways and hospitals, the mechanism of travel time on housing prices still needs further analysis. In general, the spatial effect of various accessibility varies from global to local, depending on the corresponding calculation method.

5. Conclusions

This study compares the multiscale effects of various accessibility of different facilities on housing prices and provides insights into spatial scale for understanding housing prices and accessibility. It may benefit decision-making for the evaluation and layout planning of public facilities in urban planning process. However, there are still shortcomings in this study. First, due to the data limitations, not all accessibility models are applied to all types of facilities. Second, the API travel time only used the optimal value based on combination of multiple travel modes such as walking, driving and public transportation, which should be calculated and compared separately. In addition, the threshold distance and distance decay model used in 2SFCA should be explored with more parameters. Future research can extend the study by adding more data to test more accessibly models and corresponding parameters.

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