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Research paper

Understanding active transportation accessibility's impacts on polycentric and monocentric cities' housing price

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A R T I C L E I N F O

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A B S T R A C T

Active transportation (AT) accessibility, specifically walking and cycling accessibility, has a significant impact on housing prices and equity. However, the spatial variation of the impacts of both walking and cycling accessibility and the influence of urban structure on housing submarkets are often overlooked in existing studies. This research aims to fill this gap by investigating the impacts of eight types of AT accessibility, inherent and locational attributes on housing prices in polycentric and monocentric cities. Geographically weighted regression models were estimated using housing price data from 3496 communities in Shanghai (a monocentric city) and 1100 communities in Wuhan (a polycentric city), China. The results illustrate the spatially varying impacts of AT accessibility on housing prices and highlight the existence of housing submarkets within cities due to varying factors such as urban structure, job-housing imbalance, consumer demand, public and private investment, and residential self-selection process. These findings provide valuable insights for investing in residential properties and designing policies and projects to improve AT accessibility in a way that promotes equity.

1. Introduction

Active transportation (AT), also known as "non-motorized transportation", is often defined as transporting people and/or goods through human physical activity. It primarily includes walking and cycling, and can also include modes such as rowing, skateboarding, kick scooters, and roller skates. It serves as a cheap and flexible door-to-door travel option that can be beneficial to both individual travelers and society. From the individual perspective, using AT can potentially promote physical activities, improve travel flexibility, and relieve congestion-related stress compared to using motorized transportation (e.g., cars and transit) (Grabow et al., 2019). This may contribute to the improvement of both physical and mental health, such as reducing the likelihood of having cardiovascular disease and type 2 diabetes and improving happiness and well-being (Celis-Morales et al., 2017; Guo et al., 2021a, 2021b, 2022; Kelly et al., 2014; Mueller et al., 2015). It also improves the accessibility of billions of travelers around the world to various opportunities and services, particularly for those who may find motorized transportation less flexible or affordable (Guo & Peeta, 2020). From the societal perspective, promoting AT-based travel can lead to a mode shift away from motorized modes resulting in decreased greenhouse gas emissions, lowered automobile dependency, decreased traffic congestion, improved air quality, and increased community cohesion (Alfonsin et al., 2019; Maizlish et al., 2013; Mueller et al., 2015). The COVID-19 pandemic further highlights the need for AT in some regions as neighborhood lockdown is becoming the norm in many cities to combat virus spread and various types of restrictions were introduced related to mass transit usage to promote mode shift to AT (Guo et al., 2021a, 2021b). Many people without cars or who cannot afford to use ridesharing services rely on AT to commute and access basic services (Guo et al., 2021a, 2021b). Hence, the quality of AT of a community plays a key role in renters' and potential buyers' residential location decision-making process which is reflected by its positive relationship with the community's housing price in most existing related literature (Espada & Luk, 2011, pp. 55–66; Guo et al., 2016; Litman, 2003; Yang et al., 2018, 2022).

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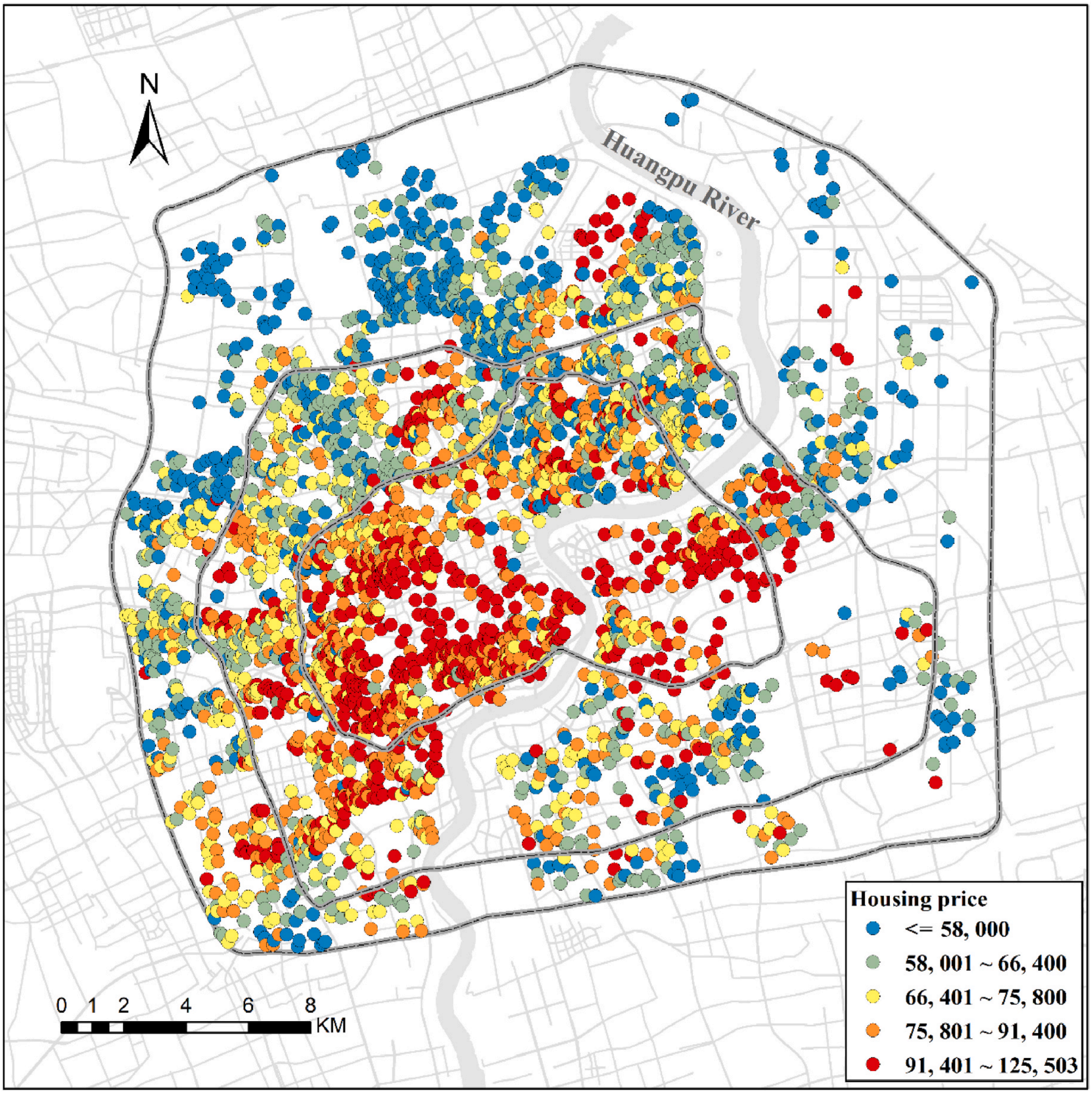

Fig. 1. Housing prices are distributed in Shanghai.

AT accessibility is one of the most widely used measurement to quantify AT of a community as it is a relative term and measures a community's access to the total number of potential opportunities and services using AT compared to other communities in the region. AT accessibility, along with the inherent property attributes (e.g., size, number of bedrooms, and built year), the locational attributes (e.g., the distance to the central business district, transportation hub, and water body), and public taxes and services, collectively determine the housing price (Guo et al., 2018; Redfearn, 2009). The impacts of AT accessibility on property price can be even greater in large cities, particularly in the global south where AT plays a more prominent role in daily travel (Guo et al., 2020; Jamal et al., 2020; Tang et al., 2021). Therefore, various types of strategies have been developed to improve AT accessibility such as constructing AT facilities and improving AT safety, and to uplift the value and attractiveness of the communities. However, most existing studies have focused on car-based, transit-based, and walking-based accessibility, while cycling-based accessibility has often been overlooked. In many developing countries and those with a strong cycling culture, cycling plays a critical role in people's daily travel due to its affordability, convenience, and environmental sustainability (Liu et al., 2022). Additionally, it serves as a complementary mode of transportation to urban public transit as a "first-and-last-mile" option, and the development of bike-sharing services further promotes this integration. A recent study showed that 54% of bike-share users used shared bikes to connect to other modes of transportation, and 91% of rides were used to connect to public transportation (Li, Hu, & Shen, 2019). The emergence of COVID-19 has further highlighted the importance of cycling-based accessibility as many public transportation services experienced a sharp drop in ridership, and many travelers changed their travel behavior towards cycling, even after the pandemic (Guo et al., 2021a, 2021b). Therefore, it is important to consider the impacts of cycling accessibility on housing price.

Despite the aforementioned benefits of the improved community AT accessibility, it can be a double-edged sword for many communities due to its negative impacts on housing affordability and equity, particularly for low-income households (Bouzouina et al., 2021). The increased AT accessibility in a community may lead to the influx of more affluent residents and businesses resulting in an increase in housing price and rent. Many of the low-income families may already be limited in their housing, job, and service options, and suffer from long commute time.

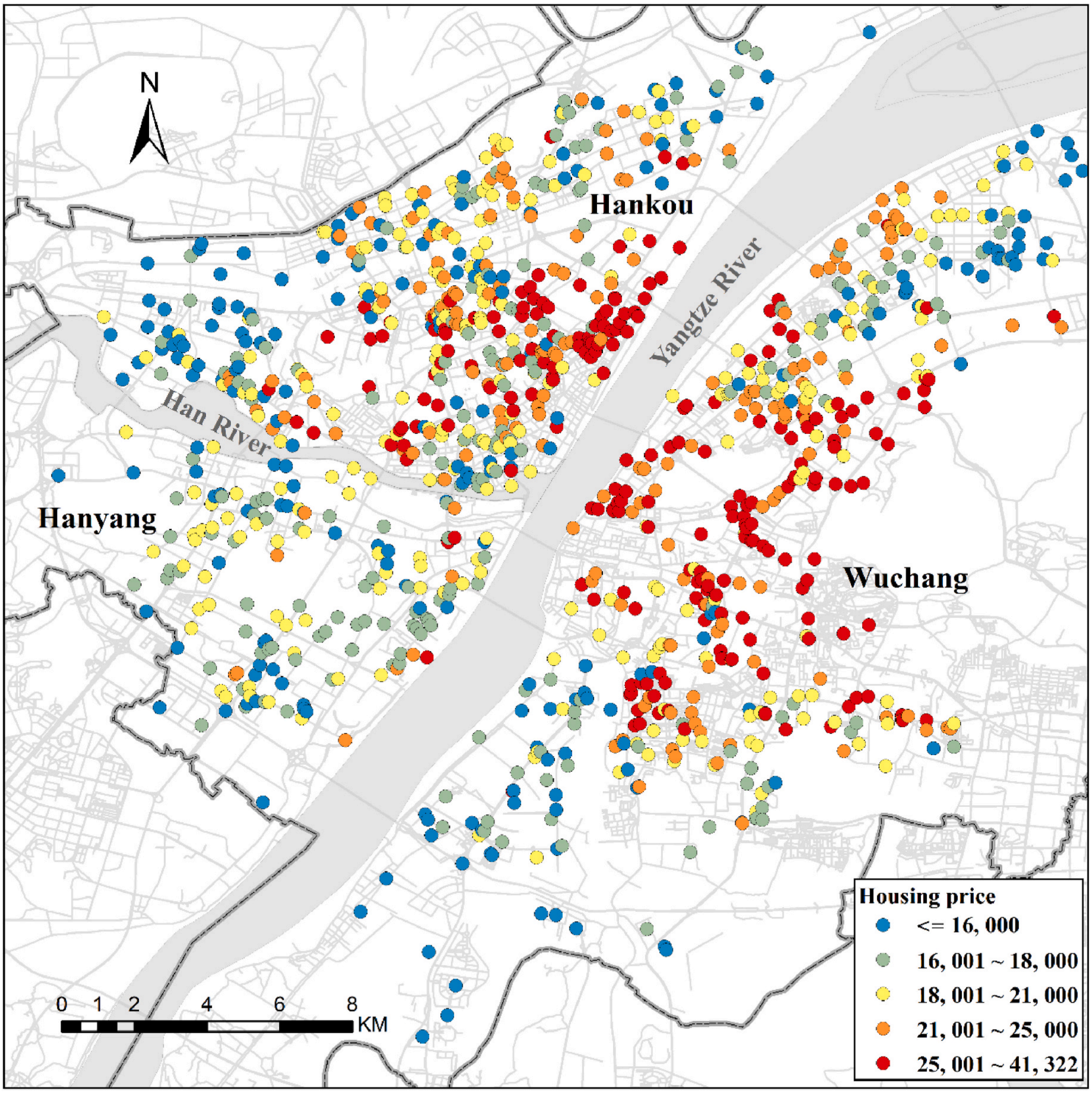

Fig. 2. Housing prices are distributed in Shanghai.

Such improvement projects may drive them further away from these "improved" communities they used to live to locations with lower AT accessibility or force them to spend additional money on housing. This may result in additional daily commute cost and financial burdens which can likely further limit their housing, job, and service options leading to reduced equity (Bohman, 2021; Nilsson & Delmelle, 2018). Such a process, also known as gentrification, was observed in metropolises around the world.

The unique economic and political environment in China may further complicate the already complex impacts of AT accessibility on housing price and equity. The economic boom and the relaxation of the household registration system (as known as "hukou" system) lead to the largest population migration and fastest urbanization process in the past few decades with millions of people migrated from rural villages to coastal cities for higher income and more opportunities (Yusuf & Saich, 2008). The rapid increase in urban population, coupled with resource limitations, has led to an uneven distribution of resources, contributing to spatially varying housing price. In cities with a monocentric spatial structure, such as Shanghai and Beijing, housing price tend to decrease with increasing distance from the CBD, due to the centralization of employment opportunities and public services. These cities exhibit concentric rings of residential differentiation, where the high-income group can afford expensive privatized houses in the urban core with abundant public services, while migrants and low-income groups mostly reside in the peripheral areas (Han & Qin, 2009; Li, Wei, & Wu, 2019). In some Chinese cities, such as Hangzhou and Wuhan, polycentric urban development is emerging during the transitional economy (Wen & Tao, 2015; Yang et al., 2020). The construction of multiple specialized sub-centers or possible natural barriers is driving the formation of several housing submarkets. The organization of economic activity and the structure of urban form between these two types of cities can be very different. As more cities consider making a transition from monocentric to polycentric urban forms, it is important to expand our understanding of the relationship between residential property value and its influencing factors beyond just monocentric cities, which have been extensively studied in the literature. This study represents one of the earliest efforts to study the potential relationships between residential property value and its influencing factors in both monocentric and polycentric cities. By analyzing these relationships in both types of cities, we can gain insights into the unique features of each urban form and the factors

Table 1
Variable definitions and descriptive statistics of Shanghai ($N = 3496$).

Variables	Description	Mean	Std. Dev.	Unit
Dependent variable				
Price	Thousand yuan per square meters (Source: Fang.com)	74.48	19.20	1000
Independent variable				
Inherent Attributes (Source: Fang.com)				
Size	Gross floor area	89.45	37.24	m^2
Age	The age of buildings in 2021	21.44	7.34	year
Bedroom	Dummy variables; 1 for a property with 4 or more bedrooms, and 0 otherwise	0.55	0.50	—
Elevator	Dummy variables; 1 for yes, 0 otherwise	0.55	0.50	—
Property AT accessibility to (Calculated based on https://lbs.amap.com/api/webservice/guide/api/direction)				
retail	AT accessibility to retail locations (e.g., supermarkets and malls) within the time threshold	0.20	0.15	—
recreation	AT accessibility to recreational locations (e.g., cinemas) within the time threshold	0.36	0.17	—
education	AT accessibility to educational locations (e.g., primary schools) within the time threshold	0.33	0.17	—
social	AT accessibility to social locations (e.g., resorts and clubs) within the time threshold	0.28	0.13	—
healthcare	AT accessibility to healthcare locations (e.g., hospitals and pharmacies) within the time threshold	0.13	0.11	—
leisure	AT accessibility to leisure locations (e.g., parks and wetlands) within the time threshold	0.10	0.11	—
bus	AT accessibility to bus stations within the time threshold	0.37	0.11	—
subway	AT accessibility to subway stations within the time threshold	0.40	0.19	—
Other Locational Attributes (Calculated based on https://lbs.amap.com/api/webservice/guide/api/direction)				
CBD	Transit time to the nearest CBD	21.14	6.78	min
Airport	Transit time to the nearest airport	35.92	12.78	min
Train	Transit time to the nearest train station	25.60	10.04	min
River	Euclidean distance to river	4.83	2.87	km

Table 2
Variable definitions and descriptive statistics of Wuhan ($N = 1100$).

Variables	Description	Mean	Std. Dev.	Unit
Dependent variable				
Price	Thousand yuan per square meters	20.97	6.23	1000
Independent variable				
Inherent Attributes				
Size	Gross floor area	105.60	27.01	m^2
Age	The age of buildings in 2021	10.68	6.35	year
Bedroom	Dummy variables; 1 for a property with 4 or more bedrooms, and 0 otherwise	0.87	0.34	—
Elevator	Dummy variables; 1 for yes, 0 otherwise	0.95	0.22	—
Property AT accessibility to				
retail	AT accessibility to retail locations (e.g., supermarkets and malls) within the time threshold	0.26	0.16	—
recreation	AT accessibility to recreational locations (e.g., cinemas) within the time threshold	0.23	0.17	—
education	AT accessibility to educational locations (e.g., primary schools) within the time threshold	0.14	0.11	—
social	AT accessibility to social locations (e.g., resorts and clubs) within the time threshold	0.23	0.18	—
healthcare	AT accessibility to healthcare locations (e.g., hospitals and pharmacies) within the time threshold	0.26	0.18	—
leisure	AT accessibility to leisure locations (e.g., parks and wetlands) within the time threshold	0.21	0.16	—
bus	AT accessibility to bus stations within the time threshold	0.41	0.19	—
subway	AT accessibility to subway stations within the time threshold	0.17	0.16	—
Other Locational Attributes				
CBD	Transit time to the nearest CBD	20.33	8.81	min
Airport	Transit time to the nearest airport	46.06	11.99	min
Train	Transit time to the nearest train station	21.34	9.17	min
River	Euclidean distance to river	1.48	1.12	km

Table 3
OLS modeling results.

Variable	Shanghai	Wuhan
Inherent Attributes		
Size	0.002	0.001
Age	−0.003	−0.007
Bedroom	−0.070	−0.002
Elevator	0.037	−0.046
Property AT accessibility to		
retail	−0.146	−0.536
recreation	−0.056	0.204
education	0.041	0.461
social	−0.195	−0.085
healthcare	0.232	–
leisure	−0.398	0.905
bus	0.105	0.080
subway	0.198	0.064
Other Locational Attributes		
CBD	−0.004	0.002
Airport	−0.003	0.001
Train	−0.001	−0.002
Waterbody	−0.024	0.000
Constant	11.334	9.672
R^2	0.318	0.332

that contribute to the spatially varying housing price in each type of city. These insights can be used to inform policy decisions and help guide urban development towards more equitable and sustainable outcomes. Hence, city's urban structure may significantly affect AT accessibility distribution and its impacts on housing price as it is directly related to land use distribution. However, most existing studies (i) focused on the impacts of transit and automobile accessibility on housing price but rarely highlight the impacts of AT accessibility, except for some walking accessibility-related studies, (ii) concentrated on studying the impacts in developed countries with limited effort to capture these unique impacts in developing countries such as China, and (iii) have yet to provide a comprehensive understanding on the spatial variation of AT accessibility's impacts on housing price within a city or among cities with different urban structures.

This study seeks to investigate the impacts of AT accessibility to various facilities along with other factors on second-hand housing price and understand their spatial varying nature within and between two cities, Shanghai (a monocentric city) and Wuhan (a polycentric city), China. Through this comparison between cities, this study aims to explore potential influence of urban structure on the formation of housing submarkets. Through this comparison between cities, this study aims to explore potential influence of urban structure on the formation of housing submarkets. 16 possible influencing factors belonging to three categories (houses' inherent attributes, AT accessibility, and other locational attributes) of over 3000 communities in Shanghai and 1000 communities in Wuhan were collected. These communities represent all the communities within these cities having at least 1 s-hand house available for sale throughout December 2021. Geographically weighted

Table 4
GWR model estimates of Shanghai ($N = 3496$).

Variable	25%	50%	75%
Inherent Attributes			
Size	0.000	0.001	0.002
Age	−0.007	−0.004	−0.002
Bedroom	−0.085	−0.033	0.017
Elevator	−0.011	0.013	0.040
Property AT accessibility to			
retail	−0.237	−0.002	0.185
recreation	−0.312	−0.167	−0.025
education	0.015	0.168	0.367
social	−0.281	−0.052	0.188
healthcare	−0.335	−0.048	0.268
leisure	−0.212	0.479	0.903
bus	−0.179	0.053	0.311
subway	−0.025	0.064	0.150
Other Locational Attributes			
CBD	−0.006	−0.001	0.003
Airport	−0.003	0.000	0.002
Train	−0.001	0.002	0.005
Waterbody	−0.038	−0.020	0.002
Constant	10.943	11.278	11.597
Performance statistics			
R^2	0.591		
AICc	−2104.914		
−2 Log-likelihood	−2755.379		
ANOVA	Sum of residuals	df	*F*-value
Global residuals	155.177	3479.000	N/A
GWR improvement	62.107	392.425	N/A
GWR residuals	93.069	3086.575	5.249

Note: The values under 25%, 50%, and 75% columns the coefficient values at the 25th, 50th, and 75th percentiles, respectively.

Table 5
GWR model estimates of Wuhan ($N = 1100$).

Variable	25%	50%	75%
Inherent Attributes			
Size	0.000	0.001	0.001
Age	−0.015	−0.011	−0.007
Bedroom	−0.033	0.005	0.058
Elevator	−0.114	0.027	0.080
Property AT accessibility to			
retail	−0.598	−0.279	−0.001
recreation	−0.071	0.029	0.165
education	−0.095	0.107	0.272
social	−0.083	0.154	0.329
leisure	0.425	0.573	0.694
bus	−0.090	0.028	0.194
subway	−0.279	0.019	0.235
Other Locational Attributes			
CBD	−0.001	0.002	0.004
Airport	0.000	0.002	0.004
Train	−0.006	0.000	0.004
Waterbody	−0.033	−0.016	0.004
Constant	9.638	9.739	10.022
Performance statistics			
R^2	0.566		
AICc	−467.490		
−2 Log-likelihood	−686.185		
ANOVA	Sum of residuals	df	*F*-value
Global residuals	53.135	1084.000	N/A
GWR improvement	18.621	116.434	N/A
GWR residuals	34.515	967.566	4.483

Note: The values under 25%, 50%, and 75% columns the coefficient values at the 25th, 50th, and 75th percentiles, respectively.

regression (GWR) models were estimated for each city to capture the impacts of these influencing factors on housing price and the possible spatial correlations among them. Statistical analysis and model estimation results highlight the spatial varying impacts of these factors on housing price and their potential differences between polycentric and monocentric cities. The study insights can be used to design future AT accessibility improvement projects and policies and facilitate effective resource and investment allocation to promote equitable AT transportation.

The remainder of this paper is organized as follows. Section 2 describes the previous studies related to AT accessibility quantification and influencing factors of housing price. After that, the methodology used for AT accessibility quantification and GWR models is presented in Section 3, followed with discussion of the study region and data collection process in Section 4. Next, the results and discussions are presented in Sections 5 and 6, respectively. Section 7 concludes with some concluding comments, limitations, and future research directions.

2. Literature review

There is an ample number of studies related to quantifying accessibility and its spatial varying impacts on housing price (Boyle et al., 2014; Condon et al., 2009; Gilderbloom et al., 2015; Li et al., 2015; Pivo & Fisher, 2009). Most studies focused on understanding the impacts of motorized accessibility on housing price and have reached a consensus that these impacts vary spatially. The rest of the studies focus on quantifying the impacts of walking accessibility on housing price (Adair et al., 2000; Du & Mulley, 2006; Guo et al., 2016; Ingvardson & Nielsen, 2018). Gravity-based method, cumulative opportunity, and utility-based measures are the three most used methods to quantify walking accessibility. The floating catchment method (FCM) and its extended families, a special form of the gravity-based method, were developed later and is often considered more intuitive to quantify walking accessibility (Guo et al., 2017; Song et al., 2013). Despite these efforts, little is known related to the impacts of other AT accessibility, particularly cycling accessibility on housing price. It is important to separate cycling accessibility from walking accessibility and understand its impacts on housing price for two key reasons. On one hand, using a bike can greatly extend people's access to opportunities and services compared to walking due to their relatively high speed, less physically taxing, and better travel experience. On the other, cycling represents one of the most important travel modes in many developing countries. For example, in 2020, cycling accounts for over 15% of all the trips made in Shanghai (SURCTDRI, 2020). This percentage may be even higher considering the development of cycling infrastructure (e.g., bike lane) and pandemic induced mode shift from public transportation (Guo et al., 2021a, 2021b; Li et al., 2022; Guo et al., 2023; Hwang & Guhathakurta, 2023). However, to the best of the authors' knowledge, Espada and Luk (2011, pp. 55–66) remains the one of the few studies that has attempted to understand these impacts. They developed a property price model and found that walking and cycling accessibility has a positive impact on the sale price of both houses and apartments in Melbourne, Australia.

In terms of types of accessibility, some studies only focused on understanding the impacts of AT accessibility to one or a few types of opportunities and services such as accessibility to healthcare (Li et al., 2016), educational (Wen et al., 2014), and leisure facilities (Guo et al., 2016; Yang et al., 2018). Yet, housing price may depend on its accessibility to multiple types of opportunities and services instead of one as people's need for access may vary, and selectively excluding some of them may yield mixed results (Feng & Lu, 2013; Yuan et al., 2020). For example, Guo et al. (2017) used an extension to FCM to quantify walking accessibility (Guo et al., 2017). They quantified the positive impacts of walking accessibility and other walkable environment-related factors on single-family residential property value. Similar results were also found in other recent studies (Yang et al., 2018, 2019).

In terms of modeling housing price, the hedonic price method, proposed by Rosen, 1974, has replaced simpler comparison methods and is now the most commonly used method for explaining the influencing factors of residential properties, due to its ability to better reflect market complexities (Malpezzi, 2003). Recent studies suggest that the housing pricing may be spatially correlated which cannot be captured by hedonic

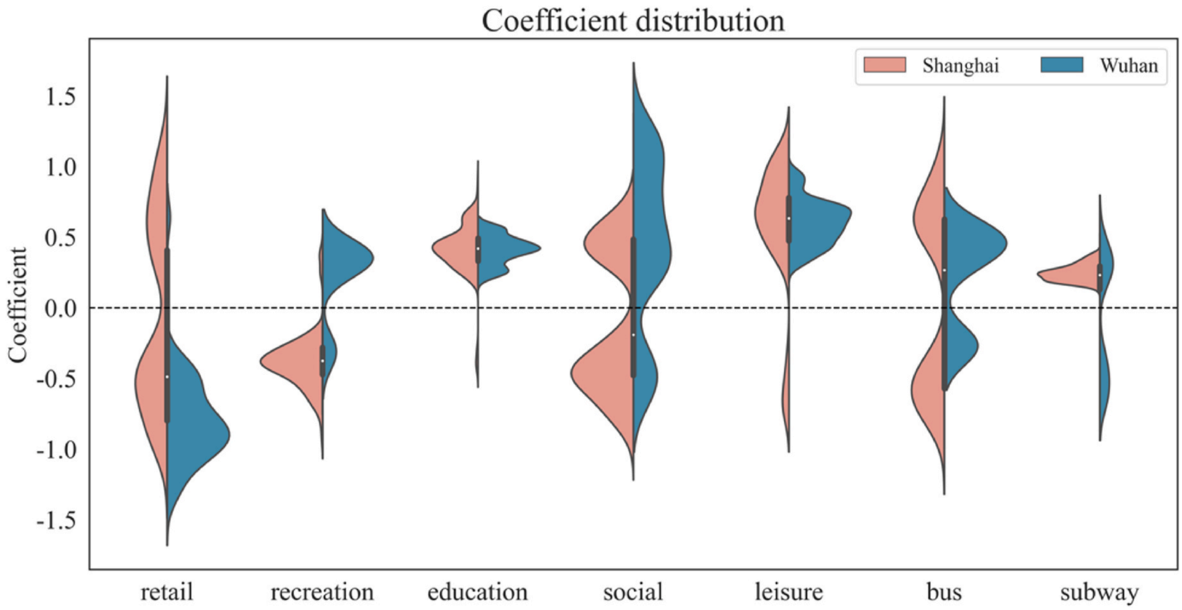

Fig. 3. Coefficient distribution.

price method (Anselin, 1988; Brunsdon et al., 1996; Fingleton, 2006; Hui & Liang, 2016). Spatial econometric models, such as the spatial lag model, spatial error model, and GWR model, were later introduced to address this issue. Among them, the GWR model incorporates the importance of the spatial location of the observations into its calculation. Empirical evidence suggests that the GWR model outperforms the hedonic price method in terms of model goodness-of-fit and robustness (Bitter et al., 2007; Fotheringham et al., 2002; Hanink et al., 2012; Long et al., 2009; Wen et al., 2018). Moreover, compared to the spatial lag model and the spatial error model, which both use one equation to predict housing price, the GWR model has the ability to capture space-varying relationships and provide regression results that are specific to a particular location or area. The GWR model also enables the presentation of results in a visual manner, which can be particularly useful for spatial analysis and decision-making (Yang et al., 2019; Zhao et al., 2020). The above-mentioned studies highlight the potential spatially varying benefits of the increased AT on equity, particularly for house owners and their beneficiaries. It can raise their personal or even generational wealth through increased housing price, promote an increase in physical and mental health, and decrease automobile dependency (Doling & Ronald, 2010).

Some studies focused on the negative impacts of improving AT accessibility on housing price which can lead to housing inequity and AT inequity among renters and would-be house owners (Bohman, 2021; Lemanski, 2014). Renters whose communities experience improved AT accessibility may witness the influx of wealthier relocating families and businesses seeking communities with good AT accessibility. They may choose to either stay and experience additional financial burdens (e.g., the increased rent and service costs in the neighborhood) or move further away to other communities with lower AT accessibility. For would-be house owners, they may need to make trade-offs between longer commute time and lower AT accessibility. For example, the construction of new subway stations in poor neighborhoods can attract high-income families to move in resulting in the displacement of many low-income families (Mayer & Trevien, 2017). Similar processes, also known as gentrification, has been observed across metropolises around the world (Carlucci et al., 2018; Coulombel, 2018; Lemanski, 2014; Mayer & Trevien, 2017). Such phenomenon may be further complicated by the unique regional and national policies in China such as complex housing regulations and household registration system that prevent homeownership of most migrants, particularly for newly developed houses (Wu & Wang, 2017). Most migrants are experiencing long commute time and unfavorable policies despite that they are the backbones of the economic miracles in China (Guo et al., 2018, 2020; Li, Wei, et al., 2019; Wu, 2002).

Apart from the aforementioned limitations, most studies were restricted to one city or one region. Little is known if the impacts of AT accessibility and other factors on housing price are different among cities with different urban structures. Most studies made the monocentric urban structure assumption or focus on cities with such urban structure when analyzing the influencing factors of housing price by introducing factors such as distance to and travel time to the city center (Alonso, 2013; Wang & Huang, 2007). In recent years, with the rapid urbanization, many planners and researchers proposed plans to transform the city from a monocentric urban structure to a polycentric one (Wen & Tao, 2015; Yu et al., 2008). However, only a handful of studies attempted to understand the possible influencing factors of housing price in cities within polycentric urban structure (Wen & Tao, 2015). None of the existing studies have compared the potential differences between the impacts of AT accessibility on housing price in cities with different urban structures.

3. Methodology

The community AT accessibility quantification method and the models used to study its impacts on housing price are presented.

3.1. AT accessibility quantification

A modified FCM method is developed to quantify the AT accessibility. It is a special form of the gravity-based method that combines the "regional available method" (Xiao, Wei, & Wan, 2021). Eight types of facilities (retail, recreation, education, social, healthcare, leisure, bus, and subway) were considered to be potential destinations for communities based on a recent residence preference survey (Beike Research Institute, 2021). Taking AT accessibility to the hospital as an example, a community's AT accessibility to the hospital can be written as follows:

$$A_i = a \sum_{j \in \left(t_{ijw} \le t_{w0}\right)} S_j f\left(t_{ijw}, t_{w0}\right) + b \sum_{j \in \left(t_{ijc} \le t_{c0}\right)} S_j k\left(t_{ijc}, t_{c0}\right) \tag{1}$$

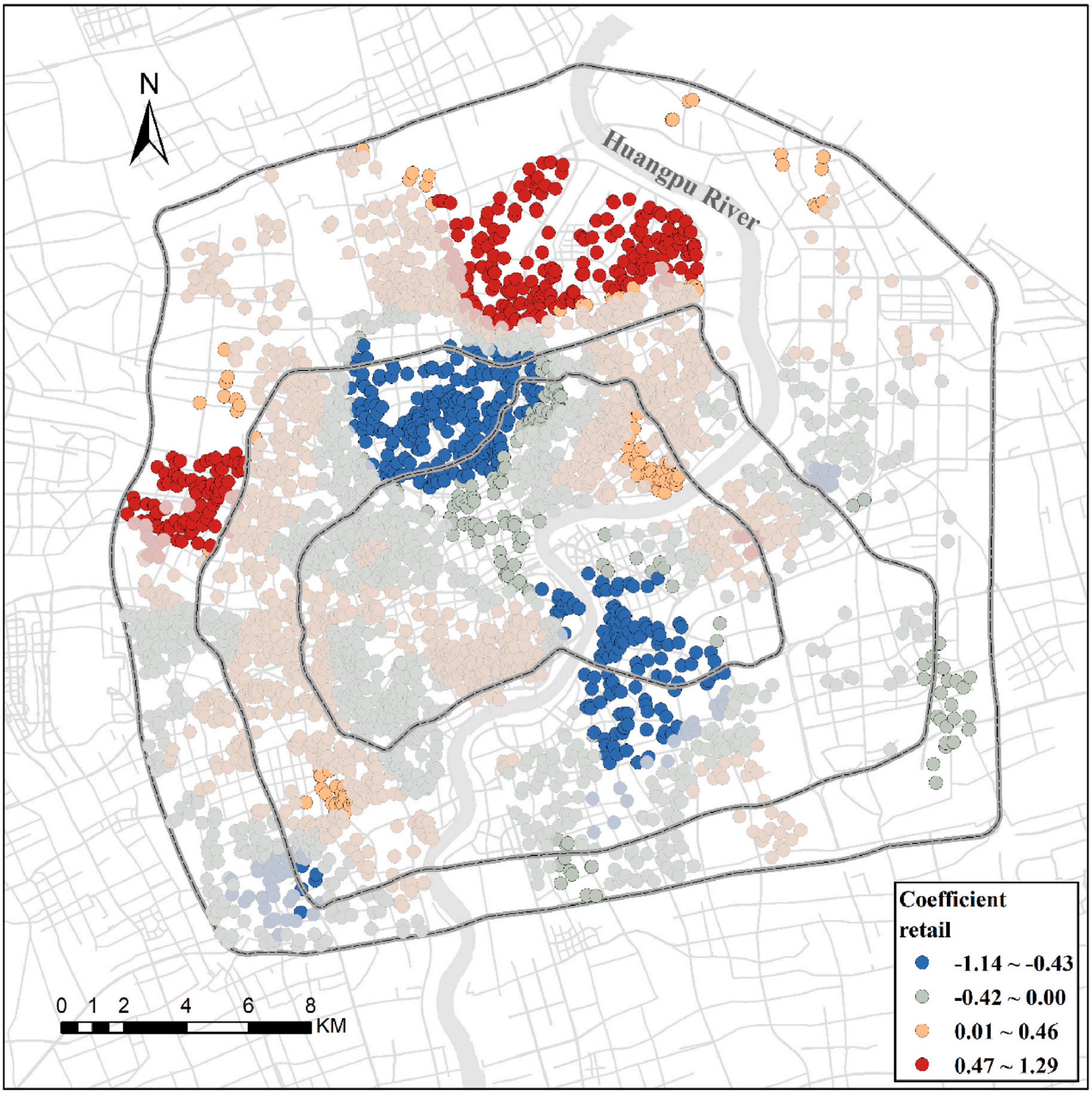

Fig. 4. GWR results of "retail" in Shanghai.

$$f(t_{ijw}, t_{w0}) = \begin{cases} \frac{3}{4}\left[1 - \left(\frac{t_{ijw}}{t_{w0}}\right)^2\right], t_{ijw} \le t_{w0} \\ 0, t_{ijw} > t_{w0} \end{cases} \tag{2}$$

$$k(t_{ijc}, t_{c0}) = \begin{cases} \frac{3}{4}\left[1 - \left(\frac{t_{ijc}}{t_{c0}}\right)^2\right], t_{ijc} \le t_{c0} \\ 0, t_{ijc} > t_{c0} \end{cases} \tag{3}$$

where t_{ijw} and t_{ijc} are the travel time between community i and destination j by walking and cycling, respectively. The maximum walking and cycling time from a community to a hospital that is considered accessible are set as 15 min (t_{w0}) and 20 min (t_{c0}), respectively based on previous studies that measures people's preferred walking and cycling time for access (Yang et al., 2019). $f(t_{ijw}, t_{w0})$ and $k(t_{ijc}, t_{c0})$ represent the distance decay function for walking and cycling, respectively. a and b are constants that present the importance of walking and cycling accessibility to a community. The weight of walking accessibility and bike accessibility were assigned the same value (0.5), based on the assumption that potential buyers equally weigh both accessibilities.

3.2. Geographically weighted regression models

GWR can provide a more localized and accurate understanding of the data, with greater flexibility in model specification, improved model fit, better outlier detection, and enhanced visual representation (Brunsdon et al., 1998; Fotheringham et al., 2002; Griffith, 2003; Nakaya & Yano, 2010). These benefits, supported by empirical and theoretical evidence, make GWR particularly useful for analyzing spatial data, where the relationships between the variables (property price and influencing factors) may vary across space. The GWR model was first introduced by Fotheringham et al. (2002) can be written as follows:

$$\log y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{4}$$

where y_i is the price of property i, (u_i, v_i) is the coordinates of community i, $\beta_0(u_i, v_i)$ is a constant for property i, $\beta_k(u_i, v_i)$ is the regression coefficient of x_{ik}, and x_{ik} is the k_{th} attribute of property i, and ε_i is a residual.

The principle of the GWR model is to generate the geographical weight for each observation considering the influence of nearby observations. The weights of nearby observations are calculated by kernel

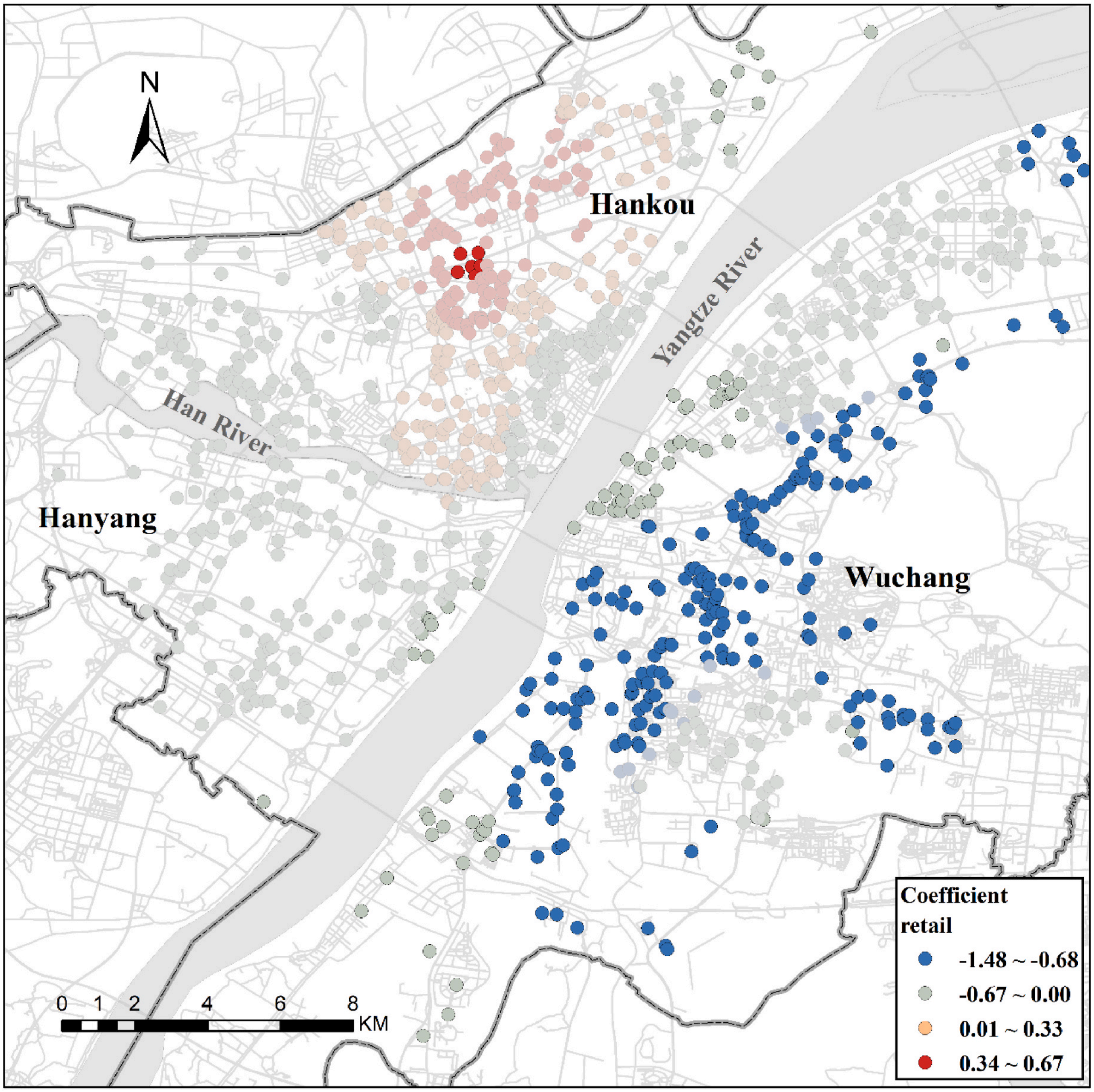

Fig. 5. GWR results of "retail" in Wuhan.

functions which can be Gaussian or bi-square kernel functions (Xu & Huang, 2015). The number of regression points included in the weight matrix is determined by the bandwidth, which can be fixed or adaptive (Efthymiou & Antoniou, 2013). The former considers regression points within a certain distance range, and the latter uses the same number of nearby regression points as the observation point. Considering the unevenly spatially distribution of property locations, the adaptive Gaussian kernel function was used, and the bandwidth was determined by Akaike Information Criteria (AICc) minimization. Additionally, when applying GWR to specific sites, it is important to consider the spatial heterogeneity of the data and the limitations of the method in capturing complex spatial relationships. Moran's I test used to conduct spatial autocorrelation analysis is always recommended to complement the GWR analysis to obtain a more comprehensive understanding of the spatial patterns and relationships in the data.

4. Study region and data collection

4.1. Study region

Shanghai and Wuhan, two metropolises along the Yangzi River, are chosen as the study region. Shanghai, located in the Yangzi River Delta, is the economic hub of China with the second highest GDP per capita in Mainland China (Berliant & Konishi, 2000). Its population doubled since the 1980s to over 24 million people among whom over 40% of the city's residents are from other regions of China (i.e., migrants). Its urban core expanded rapidly from the original Inner Ring Road (the first elevated expressway loop) in the early 1990s, to Middle Ring Road and Outer Ring Expressway in the early 2000s. Several studies suggested that Shanghai has a monocentric spatial structure with its main urban core within the Inner Ring Road surrounded by suburban areas (Li et al., 2016; Qiu & Xu, 2017; Sun et al., 2017). Most resources, opportunities, and services are concentrated in the urban pole resulting in higher AT accessibility and higher housing price. To combat the rising housing price, Shanghai introduced a polycentric planning strategy in 2021 by creating five new sub-centers outside of the Outer Ring Expressway and

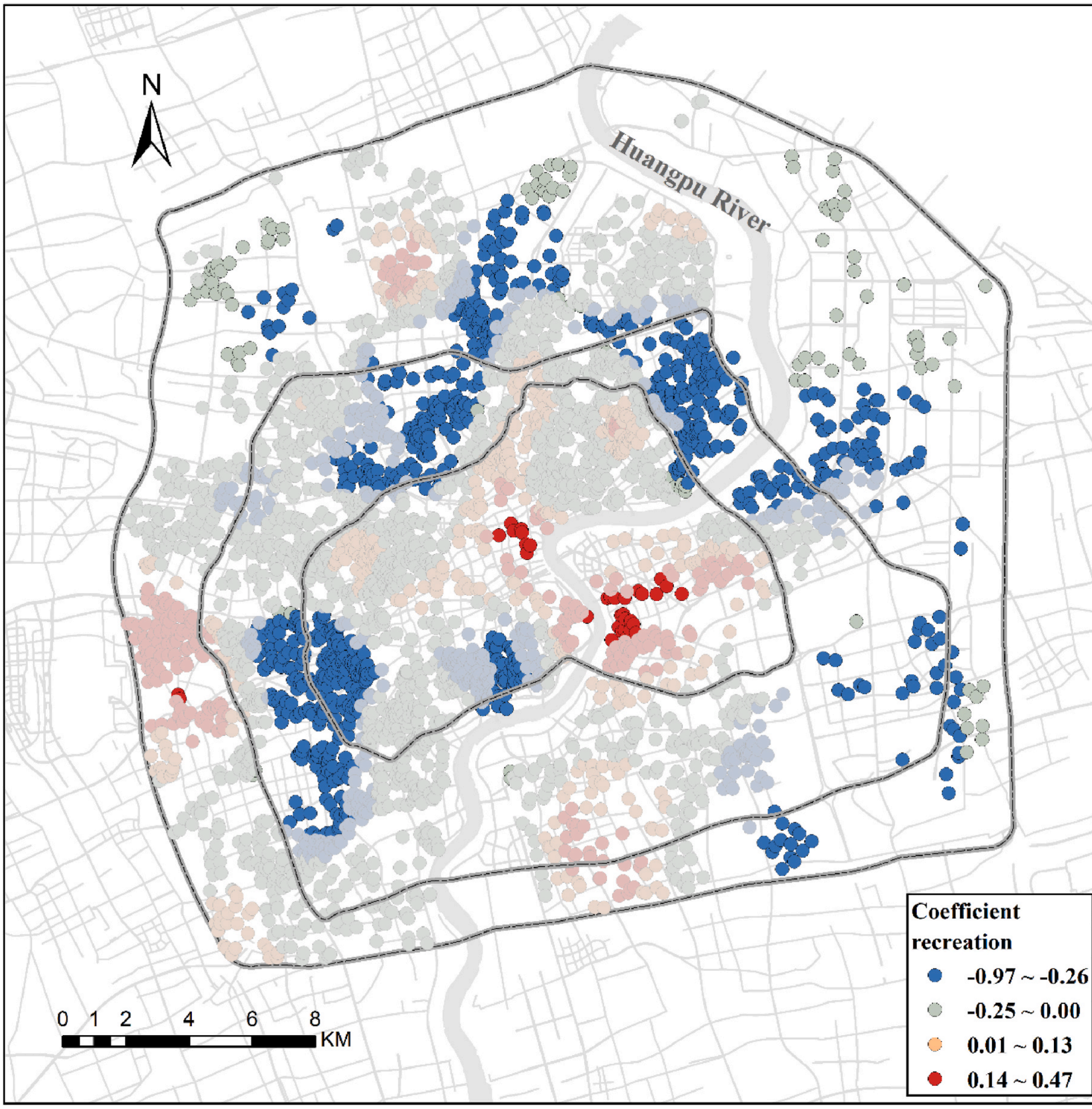

Fig. 6. GWR results of "recreation" in Shanghai.

introducing tougher regulations to limit people's ability to own a house. It means that nearly 8 million migrants are less likely to be allowed to become house owners unless they paid years of income taxes or are highly sought talents. Hence, most migrants have to choose to either spend a large portion of their income on rent and spend a shorter commute time or live further away from the city centers with longer commute time and living in communities with worse AT accessibility. The urban center of Shanghai (inside the Outer Ring Expressway) is chosen as the study region with an area of 664 km^2 and a population of 12 million in 2020 (SSB, 2020).

Unlike Shanghai, Wuhan, the capital city of Hubei province, is the largest city in the central region of China with the nickname "China's crossroad". It is developed along two major rivers, Yangzi River and Han River, and formed three city centers (Wuchang, Hankou, and Hanyang) that are separated by the two rivers. It means that Wuhan is a polycentric city with an area of 671.5 km^2 and a population of 6.4 million in 2020 (WSB, 2020). Each center serves a unique function with specialized industries and unevenly distributed resources, including Wuchang as the technology and education center, Hankou as the commerce and trade center, and Hanyang as the tourism and manufacturing center (Liu & Wang, 2016; Yang et al., 2020). Therefore, Wuhan has a typical polycentric urban structure.

4.2. Data collection and descriptive statistics

All the communities with at least 1 s-hand house for sale in the urban centers of Shanghai and Wuhan are selected as the study samples. The reason to choose only second-hand houses is that the two cities have different restrictions related to the newly developed house purchase and most of these houses may not be purchasable for migrants. In addition, most newer developments are located in suburban areas and their prices are highly regulated which may not reflect their true market value, whereas second-hand houses have often been considered as a form of investment. Hence, only second-hand houses were included. 3496 and 1100 communities with at least 1 s-hand house for sale in the urban centers of Shanghai and Wuhan, respectively throughout December 2021 were identified using Fang.com (one of the largest real estate agency's websites) as the study sample after data clean up. The data was collected before the emergence of the Omicron variant, and due to China's strict epidemic-containing measures, large COVID-19 outbreaks

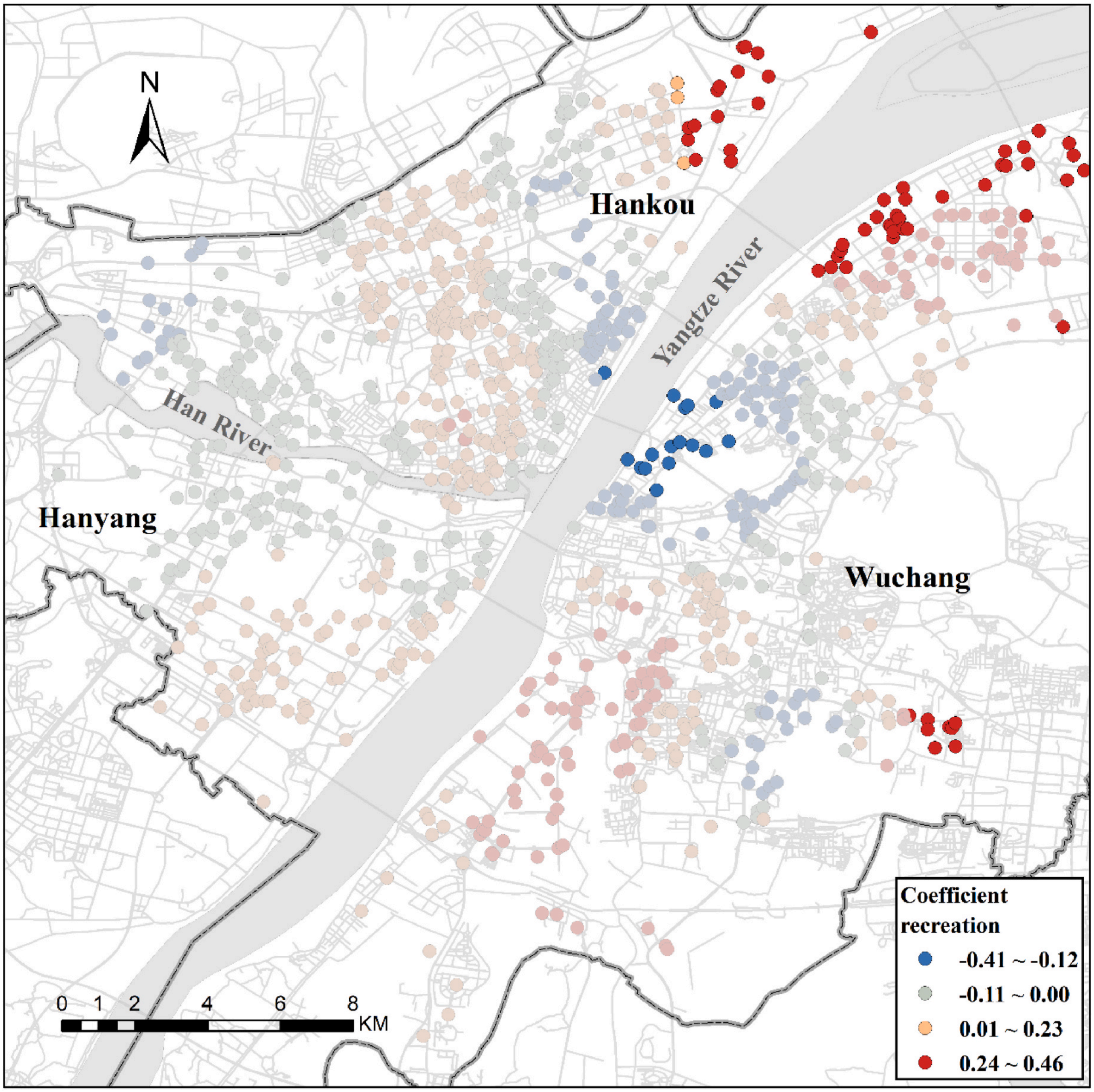

Fig. 7. GWR results of "recreation" in Wuhan.

were prevented in the two cities. As a result, the housing market remained largely intact during this period. None of the included second-hand properties are located in ungated communities. Future studies can explore such differences in small-to-medium-sized cities, as most properties in large cities are gated.

Fig. 1 shows the housing price (in yuan per square meters) of second-hand houses in Shanghai and Wuhan communities, respectively. It is also important to note that these are the listing price which can be different from the final transaction price, but they are very similar most of the time, except for some highly competitive bidding markets (Salon et al., 2014) (see Fig. 2).

Sixteen variables belonging to three categories (including 4 inherent attributes, 8 AT accessibility, and 4 locational variables) were selected for the subsequent modeling. The variable definitions and descriptive statistics are provided in Tables 1 and 2. The four inherent attributes were collected from Fang.com. As for the parameter choices, they were selected based on the current practices and latest advancements in the related field. Apart from AT accessibility, most of the variables that were included have been identified in literature as affecting residential properties to varying degrees. The original value of a variable was used for modeling process, except for the number of bedrooms. A dummy variable was used instead of an integer variable to capture the effect of the number of bedrooms more accurately. This is because if a variable that is skewed towards the lower end is treated as an integer variable in the modeling process, the regression will treat it as continuous, leading to biased estimates. By creating dummy variables, we are able to control for the effect of the categorical variable and obtain unbiased estimates (Agresti, 2002). Hence, the number of bedrooms is used as a dummy variable and properties with four or more are considered "large" properties as they are commonly classified as large houses by practitioners when conducting market analysis. A travel time-based measure was used instead of the network distance-based one to account for terrain, bike lane availability, congestion levels, and other factors that may affect actual travel time. The map application programming interface (API) provided by Amap, a Chinese alternative to Google Maps, was used to measure travel time. Locational attributes include transit time to the nearest CBD, airport, train station, and Euclidean distance to the nearest water body. The first three variables reflect the ease of access to major transportation and service hubs and may affect people's residential location decision-making process (Yang et al., 2019). Some potential

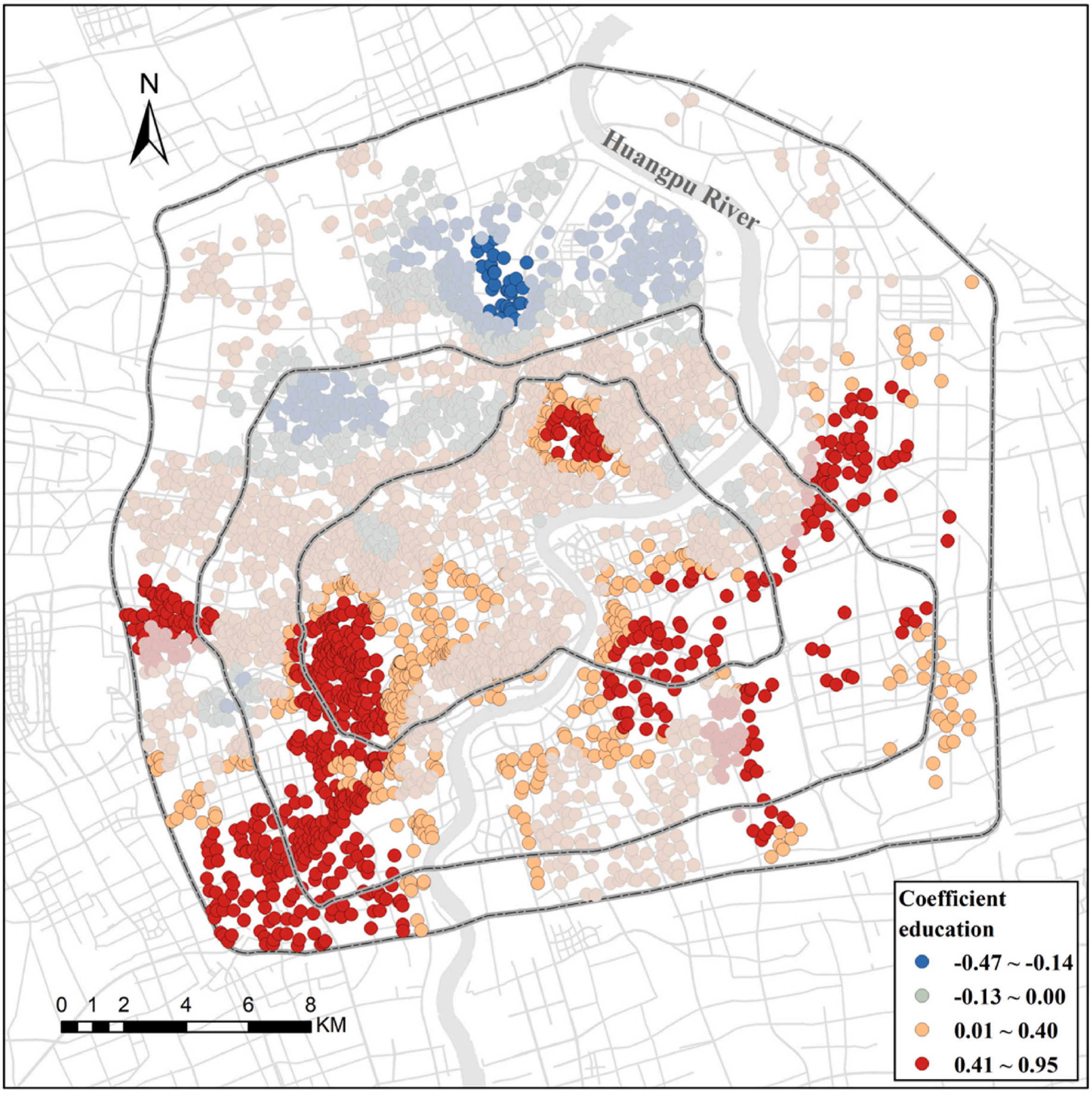

Fig. 8. GWR results of “education” in Shanghai.

buyers and renters may also prefer to stay close to water body.

A few key observations can be identified. First, the average age of the second-hand houses in Shanghai is much older than the average in Wuhan. This suggests that Shanghai has a more mature urban core compared to Wuhan. Second, the average transit time to the nearest airport is much shorter in Shanghai compared to Wuhan which may reflect that transit service to the airport is better in Shanghai. Third, the Euclidean distance to the nearest water body in Wuhan is shorter as Wuhan has a large number of water bodies within the city compared to Shanghai.

5. Results

Initially, both car-based and transit-based accessibility were considered for this study. However, doing so would require collecting travel time information for over 5000 properties and numerous potential destinations using an API (approximately 500 travel times per mode), which would take a significant amount of time (around 1.5 months per mode). To assess multicollinearity, we included eight car-based accessibility variables (one for each type of access) in our model, and found that six of them displayed severe multicollinearity (VIF>5). These results suggest that including these car-based accessibility variables could lead to unreliable estimates of the coefficients and affect the accuracy of the predictions. We suspected that transit-based accessibility would also face similar problems. Moreover, adding more variables increases the likelihood of overfitting, where the model becomes too complex and fits random noise instead of the underlying relationship. This can lead to misleading results and poor predictive power. Additionally, adding more variables increases the computational complexity and time required to estimate the model, which can make the model difficult to interpret and may not be practical in real-world applications. Thus, we made a judgment call to focus solely on active transportation (AT) accessibility, which is an underexplored area in the literature. Moreover, Pearson correlation tests were conducted on each type of walking and cycling accessibility, and no coefficient higher than 0.5 was found, indicating that walking and cycling are not strongly correlated. Three separate models were estimated for Shanghai and Wuhan, respectively, including a model using only walking accessibility, a model using only cycling accessibility, and a model using AT accessibility with equal weights assigned to walking and cycling (0.5 each). The AT accessibility

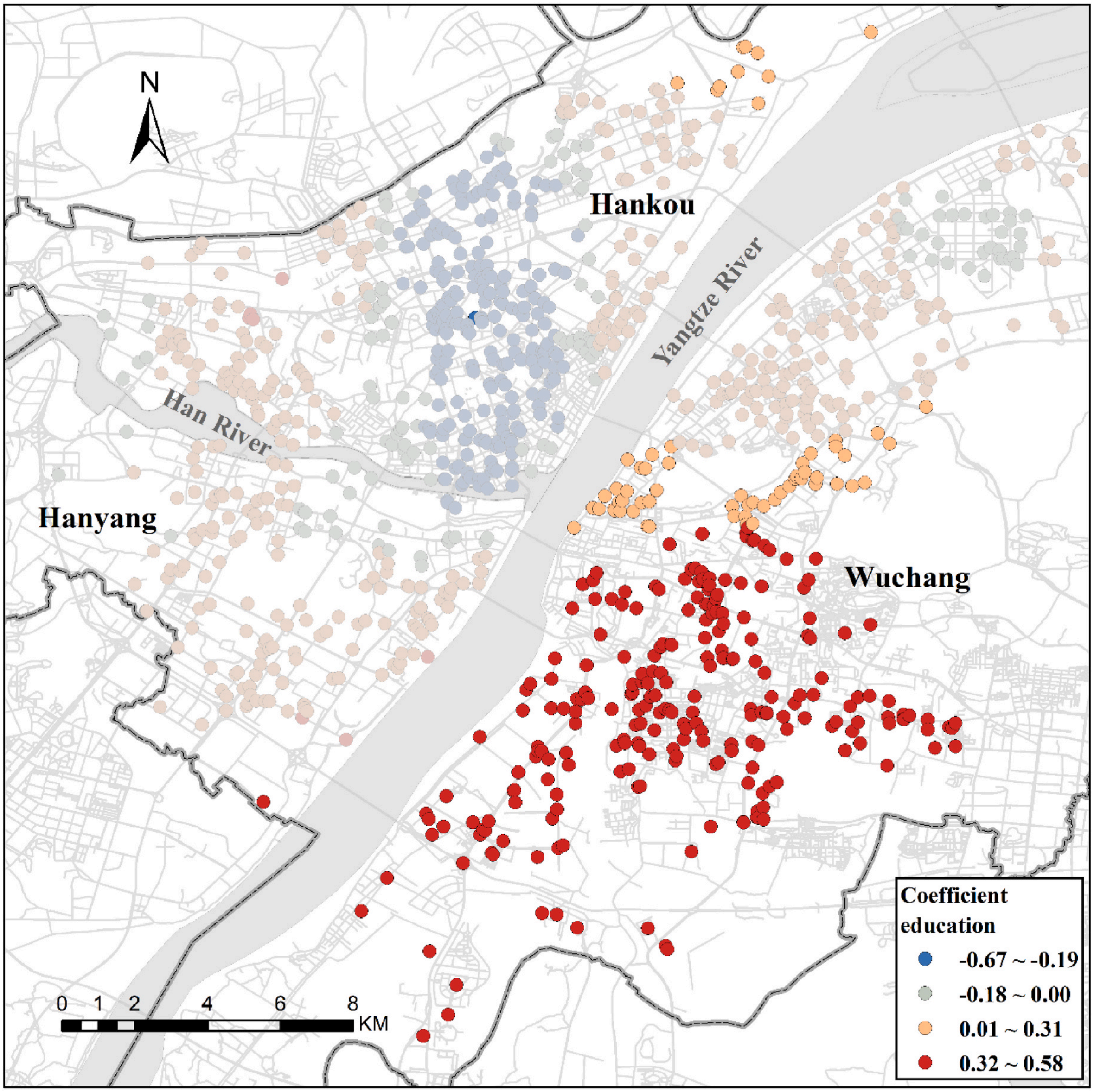

Fig. 9. GWR results of "education" in Wuhan.

model had the highest R^2 value in both Shanghai and Wuhan, indicating that it provided the best explanation for the variance in property price.

Specifically, multicollinearity analysis was first performed to remove possible multicollinearity among potential independent variables. AT accessibility to healthcare facilities in the Wuhan sample was removed as its VIF is larger than 10. A global model was first created to estimate the average impacts of potential factors on the housing price. Moran's I test, Durbin-Watson test, Shapiro-Wilk test, spatial variance test, and multicollinearity test were conducted to validate five GWR assumptions: stationarity, independence, normality, homoscedasticity, and no multicollinearity. The final model passed all five tests. **Appendix** Table A1 presents the results of Moran's I test and the details of other tests can be made available to readers upon reasonable request. The golden section search algorithm was used to find the bandwidth that provides the best goodness-of-fit for a given set of data in GWR, using AICc as the measurement. A bandwidth of 74 surrounding data points was used to calibrate the GWR model for Shanghai, while a bandwidth of 72 surrounding data points was used for Wuhan.

The R^2 of global models for Shanghai and Wuhan are 0.318 and 0.332 (Table 3), respectively, and the GWR models outperformed the corresponding global models in terms of the model's goodness-of-fit based as shown in Tables 4 and 5. The coefficient distributions of AT accessibility are presented in Fig. 3. As depicted in Figs. 4–17, blue and green colors suggest a negative correlation between AT accessibility and housing price, while red and orange represent a positive correlation. The gray color indicates that AT accessibility does not have a statistically significant relationship with housing price at the 95% confidence level.

Five key observations can be identified based on the distributions of AT accessibility's impacts on housing price (Fig. 3). First, AT accessibility to education (e.g., schools and training facilities) and leisure (e.g., parks and playgrounds) have statistically significant positive impacts on housing price of most communities in both cities. Second, AT accessibility to bus stations and social places (e.g., country clubs and vocational homes) have mixed impacts on housing price in both cities. Third, in terms of AT accessibility to retail locations (e.g., supermarkets and convenience stores), almost all the communities with good access to retail locations are valued lower in Wuhan, while its impacts on housing price are complex in Shanghai. Fourth, the impacts of AT accessibility to recreation locations (e.g., KTV and movie theaters) on housing price in Wuhan are mostly positive, while its impacts on the housing price in

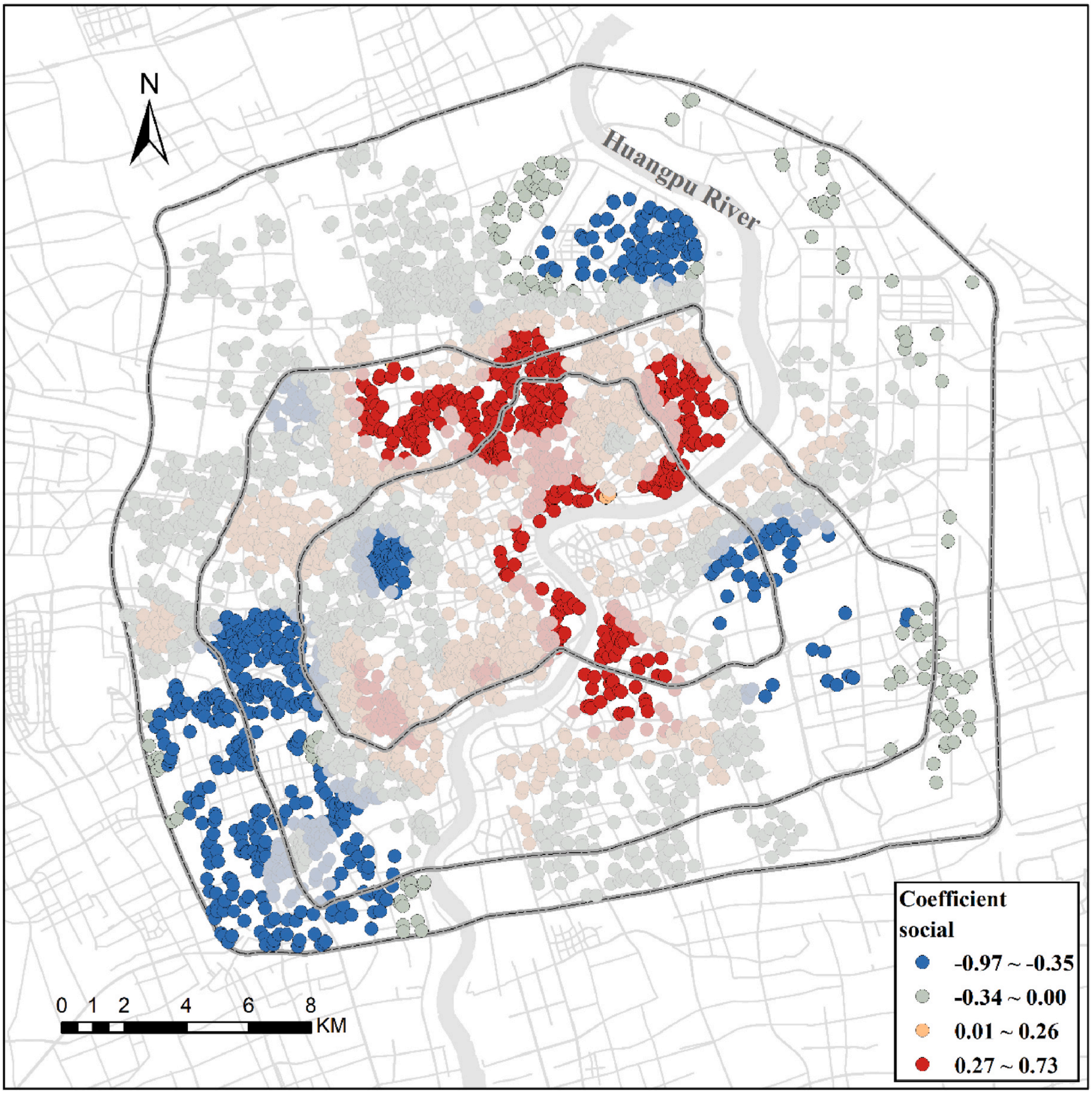

Fig. 10. GWR results of "social" in Shanghai.

Shanghai are mostly negative. Fifth, the impacts of AT accessibility to subway stations on housing price in Wuhan are mixed, while its impacts on the housing price in Shanghai are mostly positive. These several interesting observations in Fig. 3, such as AT accessibility to bus stations in Shanghai and Wuhan, where a bimodal distribution in the violin plot suggests the possibility of two distinct groups within the data that may reflect two different types of housing needs. Although there are relatively minor sociocultural differences within the city, factors such as the presence of the Yangzi River may contribute to this phenomenon. This further illustrates the existence of housing submarkets and emphasizes the significance of using a GWR model to better identify spatial variation as compared to global models.

These results highlight the spatially varying impacts of AT accessibility on housing price. Three distinct housing submarkets can be identified based on spatially varying variable impacts in each of the two cities. The existence of these differences in housing submarkets may likely be due to their unique sociodemographic, economic, and cultural characteristics. Specifically, Shanghai is a major city that has developed into a megacity with three ring-shaped expressways within its urban core. The densely populated inner ring regions are more mature and offer better access to opportunities and services, which has resulted in higher housing price. Most of the current house owners are Shanghai natives, while most potential buyers are likely to come from wealthier families. As the urban core of Shanghai has expanded, migrants and younger residents have settled in the middle and outer ring regions. However, most opportunities and services are still concentrated in the inner ring, which means that local residents must rely on the subway to commute to access them. Wuhan is a city with three urban cores, divided by the Yangzi River and the Han River. Hankou is the commercial center and has experienced the fastest development in recent years, and most of the needs of the residents living here can be met locally. Wuchang is the political and cultural center, with many universities, startups, and high-tech companies, and the proportion of young people is relatively high here. Hanyang is known for its tourism industry and has many beautiful natural landscapes. Table 6 summarizes the differences of these varying impacts of housing submarkets in two cities. If a variable has a plus sign (+), a negative sign (−), mixed, or an NS sign, it means that this variable has a statistically significant positive, negative, mixed, or no impact on the dependent variable, respectively.

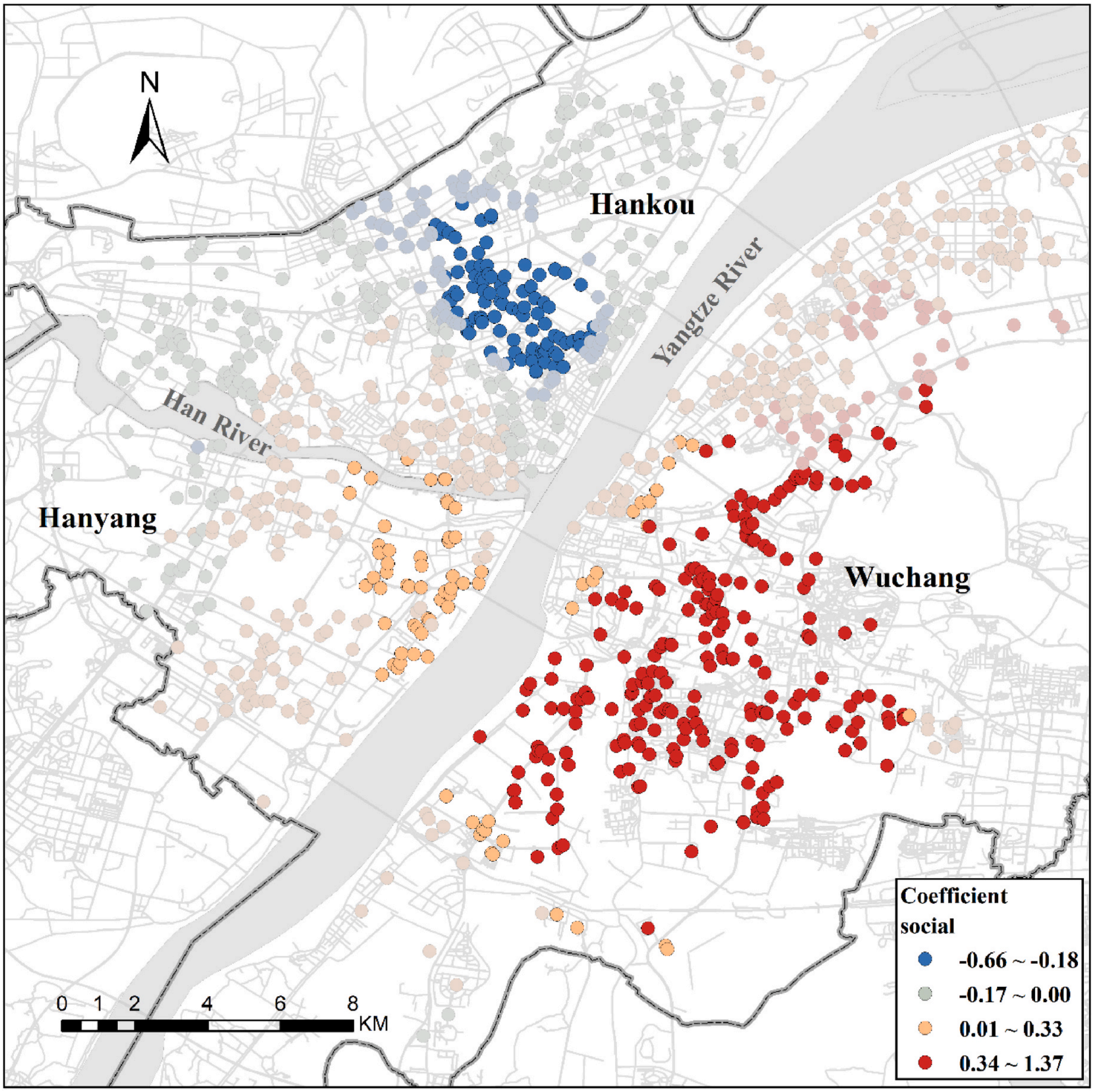

Fig. 11. GWR results of “social” in Wuhan.

6. Discussions

The spatially varying impacts of AT accessibility on housing price are highly correlated with their urban structures which are collectively shaped by years (even hundreds of years) of geographical, historical, cultural, and economic factors.

Shanghai, a monocentric city, has gradually developed from a small city along the west bank of the Huangpu River into a mega-city with three ring-shaped expressways inside its urban core. Communities located in the densely populated inner ring region (i.e., inside Inner Ring Expressway) are much more mature and have good access to abundant opportunities and services leading to a higher housing price. Most of its current house owners are mostly Shanghai residents and its would-be house owners are more likely to be from wealthier families. Hence, they may value more about AT access to social and leisure locations but prefer to avoid retail locations due to their negative externalities. In addition, as they are already located near their likely destinations and most of its residents are older, AT accessibility to bus stations is considered much more important than AT accessibility to the subway as most trips are shorter and most older generations prefer to use a bus instead of using the subway.

As Shanghai’s urban core expanded, many migrants and younger generation of residents located into the middle (between Middle and Inner Ring Expressways) and outer (between Middle and Inner Ring Expressways) ring regions, while most opportunities and services remain in the inner ring region (Wu et al., 2022). Its middle ring region was original served as the manufacturing hub of the Shanghai (Li, Wei, et al., 2019). After early 2000s, most of these manufacturing factories moved out of Shanghai’s urban core and even to other cities due to tightened environmental restrictions and raising labor cost. Majorities of the remaining residents are more likely to be retirees or lay off employees of these factories living in communities that were original designed to maximize the number of residents instead of their quantify of living (Sun & Chen, 2021). These communities which are already less attractive can be further penalized in terms of housing price if they are located near retail and recreational locations.

Shanghai’s outer region remains as the ideal locations for migrants and many younger generation residents due to its cheaper and more modernized communities (Xiao, Wei, & Li, 2021). Most of its would-be residents are more concerned about have AT access to retail locations as

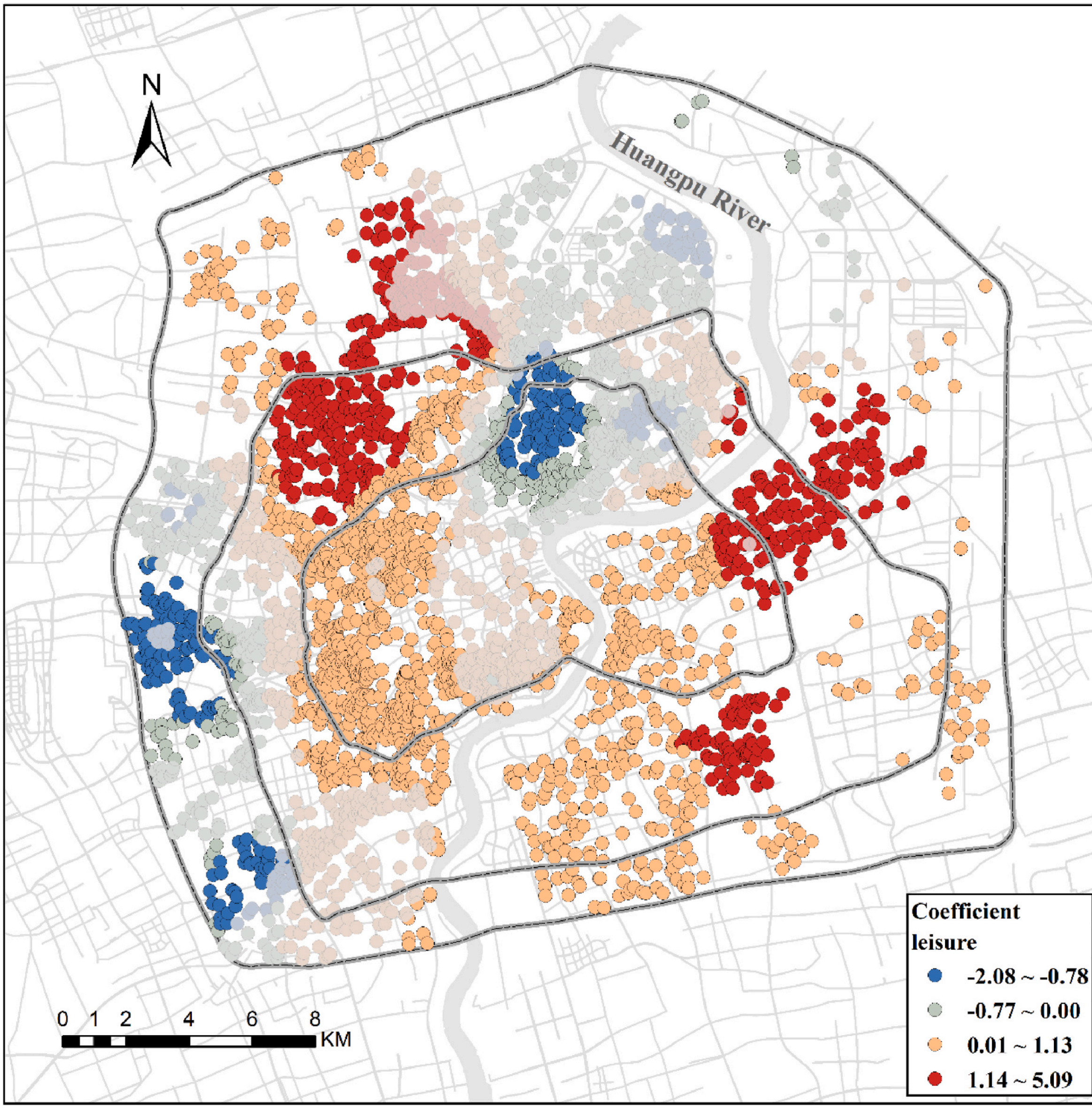

Fig. 12. GWR results of “leisure” in Shanghai.

they are sparsely located there. They also need reliable and fast access to Shanghai’s inner ring region and having good AT access to subway stations can potentially significantly reduce their travel time and cost to work and other opportunities and services, which is in line with Li, Wei, et al. (2019).

Wuhan has a polycentric structure with three urban cores that are naturally divided by the Yangzi River and the Han River. Hankou, the commercial center of Wuhan, is the youngest center among them but enjoys the fastest development in recent years. The majority of the subway stations are located at the mouth of the Han River and the proximity to these locations may be considered less advantageous in terms of housing price (Song et al., 2023). It is also possible that most people in each core generally do not travel to other urban cores which makes access to bus stations more important for its convenience to travel within the urban core. In addition, most people who live in these commercial centers are more likely to be the employers or employees of these businesses. Hence, the housing price of communities with higher AT accessibility to retail are valued higher.

Wuchang is the oldest urban core and the political and cultural center of the city. It has all the departments of the provincial government and city government. It also has more than 80 universities with approximately 1 million students. Many companies, particularly startups and high-tech companies, relocated to the city in recent years in order to have better access to these young talents. Most younger generations prefer to use the subway and have more desire to socialize after work (Ellem et al., 2019). This is shown as AT accessibility to social facilities and subway stations have significantly positive impacts on housing price.

Unlike the other two urban cores in Wuhan, Hanyang is known for its tourism industry with many beautiful natural landscapes. Therefore, AT accessibility to leisure and social are the only two AT accessibility factor that has statistically positive impacts on housing price in Hanyang, which is in line with Liu et al. (2020).

Although the impacts of AT accessibility on housing price vary between Shanghai and Wuhan, AT accessibility to education has statistically significant positive impacts on housing price of most communities in both cities. These results suggest that most people in both cities value the importance of education (a long hold traditional for most Chinese families) when they make residential location decisions. It is also important to note that children whose families own a house within a

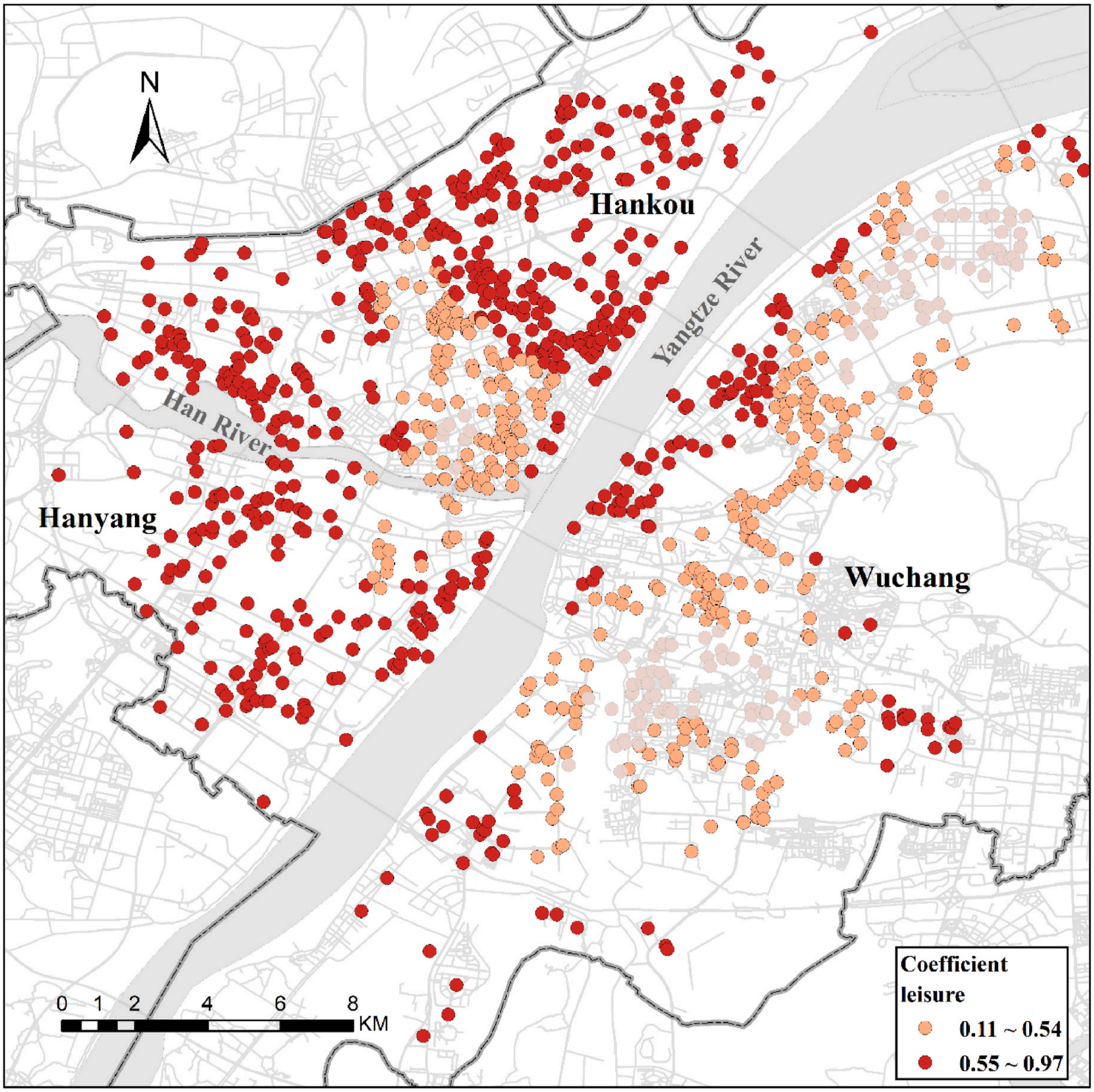

Fig. 13. GWR results of "leisure" in Wuhan.

school district can attend the school which is different from most other countries in which the family can rent a house instead (Wen et al., 2018). It is also important to note that most people who live in or want to live in these communities may also consider proximity to retail locations as possible distraction.

In summary, this study examines the development of three different housing submarkets in Shanghai and Wuhan, which are influenced by the respective monocentric and polycentric urban structures of the cities. The distribution of public and private services, which is affected by uneven public and private investment and natural barriers, plays a crucial role in shaping these submarkets. While this study provides valuable insights into the impact of urban structure on housing submarkets, it is important to note that the results may not be generalizable to other cities without further investigation. Therefore, more research is needed in this area to produce more reliable and broadly applicable results. The empirical findings of this study can serve as valuable information for future studies that examine the relationship between urban structure and housing submarkets. By analyzing the relationship between urban structure and housing submarkets, we can gain insights into the factors that contribute to spatially varying housing price and how they can be addressed through policy and planning efforts. These insights can be used to inform decisions about urban development and to promote more equitable and sustainable outcomes. We hope that our study will contribute to the growing body of research in this field and encourage further investigation into this important topic.

7. Concluding comments

This study investigates the spatially varying impacts of AT accessibility to eight types of facilities, inherent attributes, and other locational factors on housing price, and explore potential influence of polycentric and monocentric urban structure on the formation of housing submarkets. It addresses previous studies' limitations by expanding the types of accessibility considered and analyzing the potential differences among cities with different urban structures. A modified FCM was proposed to quantify AT accessibility by incorporating both walking and cycling accessibility. GWR models were estimated to illustrate the spatially varying impacts of AT accessibility by analyzing the housing price of 3496 communities in Shanghai (a monocentric city) and 1100 communities in Wuhan (a polycentric city).

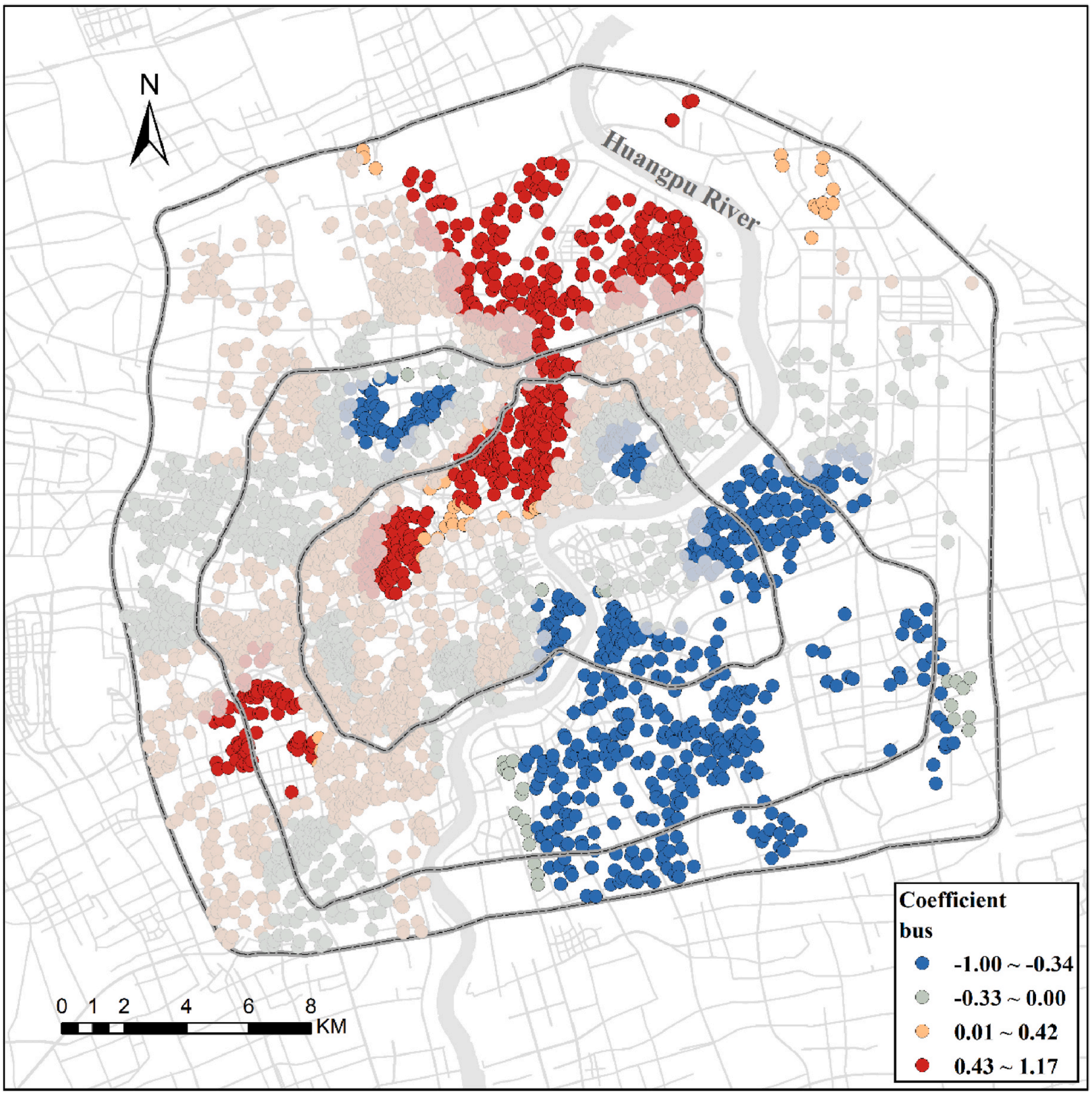

Fig. 14. GWR results of "bus" in Shanghai.

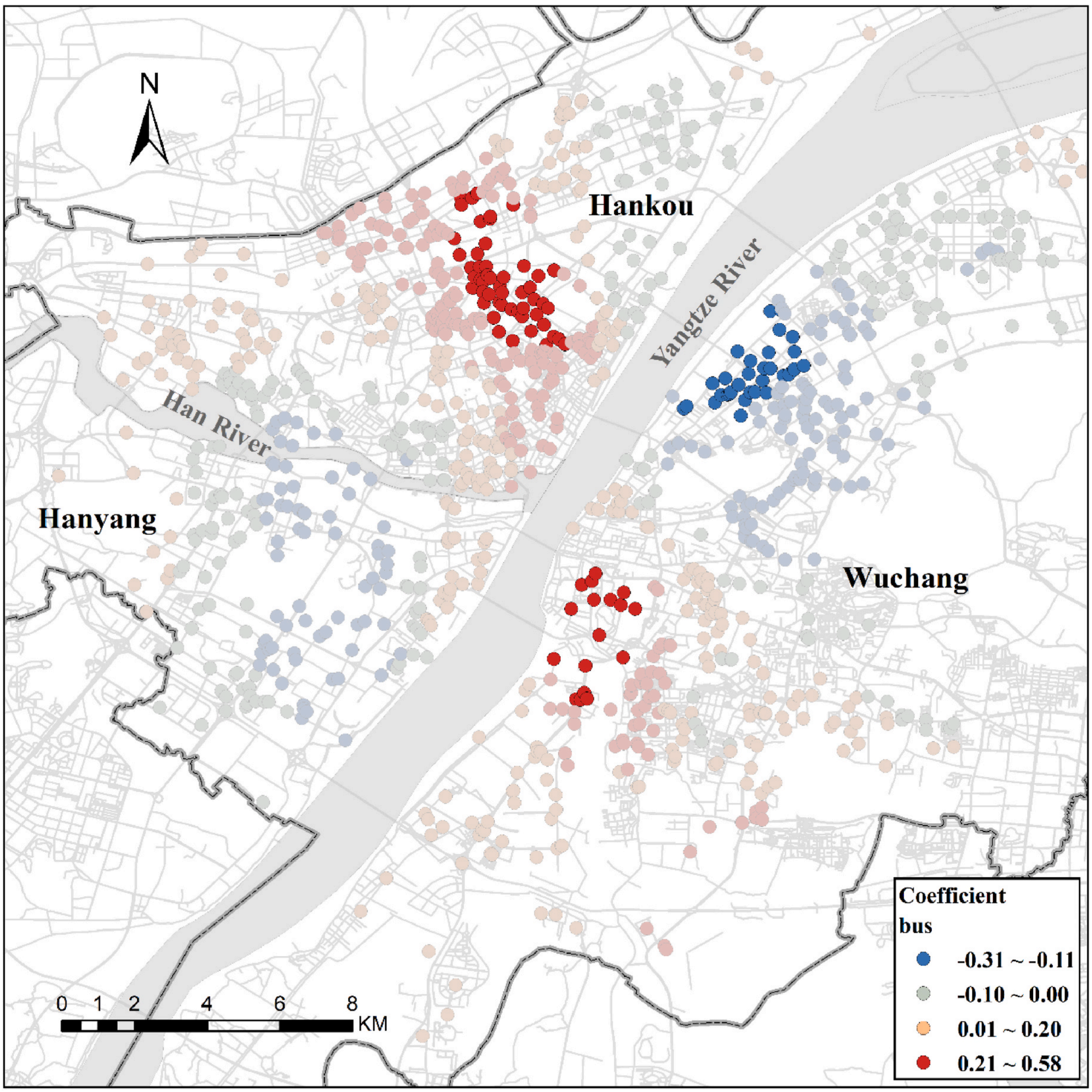

Fig. 15. GWR results of "bus" in Wuhan.

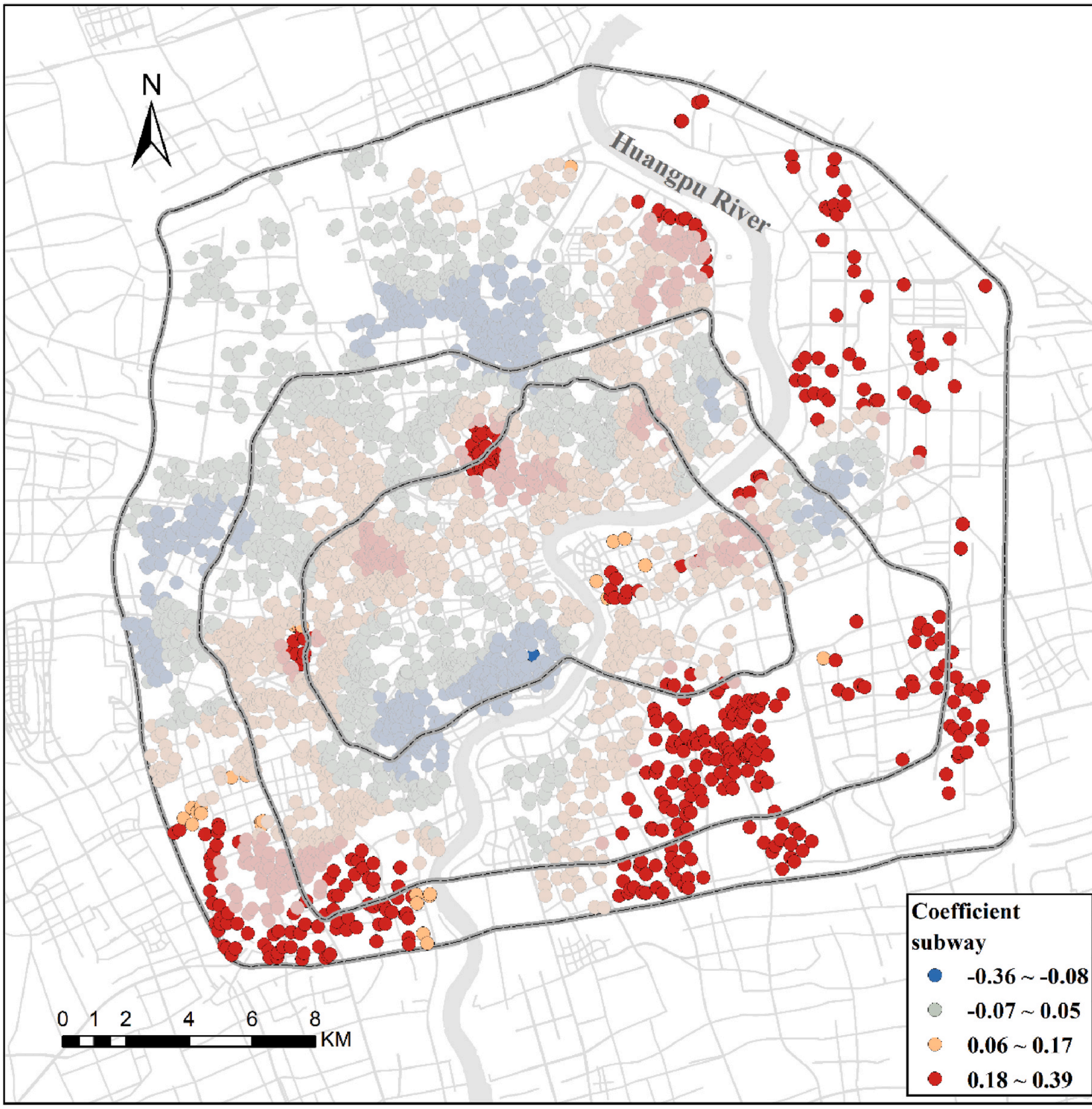

Fig. 16. GWR results of "subway" in Shanghai.

The model estimation results and descriptive statistics show that a city's urban structure, along with job-housing imbalance, varying consumer demand, unevenly distributed public and private investment, and residential self-selection process, may collectively shape its housing market into submarkets with residents' diverse sociodemographic and housing need. A city with a monocentric urban structure such as Shanghai is expanding rapidly throughout the years with most of its opportunities and services remaining at its original urban core. Taking Shanghai as an example, three ring-shaped expressways were constructed to address the travel needs within its expanding urban areas resulting in three unique submarkets: a glittering inner ring region with wealthier residents, high paying jobs, good services, and great AT accessibility; a middle ring region with older residents, older communities, the remains of legacy industries, and good AT accessibility; and a young and energetic outer ring region with many young migrants but having limited opportunities, poor services, and bad AT accessibility. If such an urban expansion persists, many migrants may be pushed further away from urban cores, which further limit their opportunities and services, and AT accessibility. Despite the AT accessibility improvement projects, most migrants may be unable to enjoy its benefits due to its subsequent raising housing price.

Unlike its monocentric urban structure counterparts, a city with a polycentric urban structure such as Wuhan has multiple specialized subcenters. Most residents may choose to live in the center that satisfies their needs most and rarely travel between centers, particularly in cities like Wuhan with natural barriers separating city centers. These centers may become more specialized to better address their resident's needs. However, some major life-changing events (e.g., getting married, having kids, or changing jobs) may alter people's needs making the original subcenter unsuitable for living. They may need to relocate or spend long commute time resulting in heavy financial and social burdens.

The study insights can potentially be used by planners, policymakers, and investors. It may be important to be mindful of both the positive and negative impacts of community AT accessibility improvement projects. Their potential returns may depend on the improved AT accessibility types and their locations. In addition, improving AT accessibility without providing affordable housing and other supporting policies may lead to neighborhood gentrification in some communities which may further widen the social inequity. Planners and policymakers may need to rethink the "one-size-fits-all" approach for AT accessibility

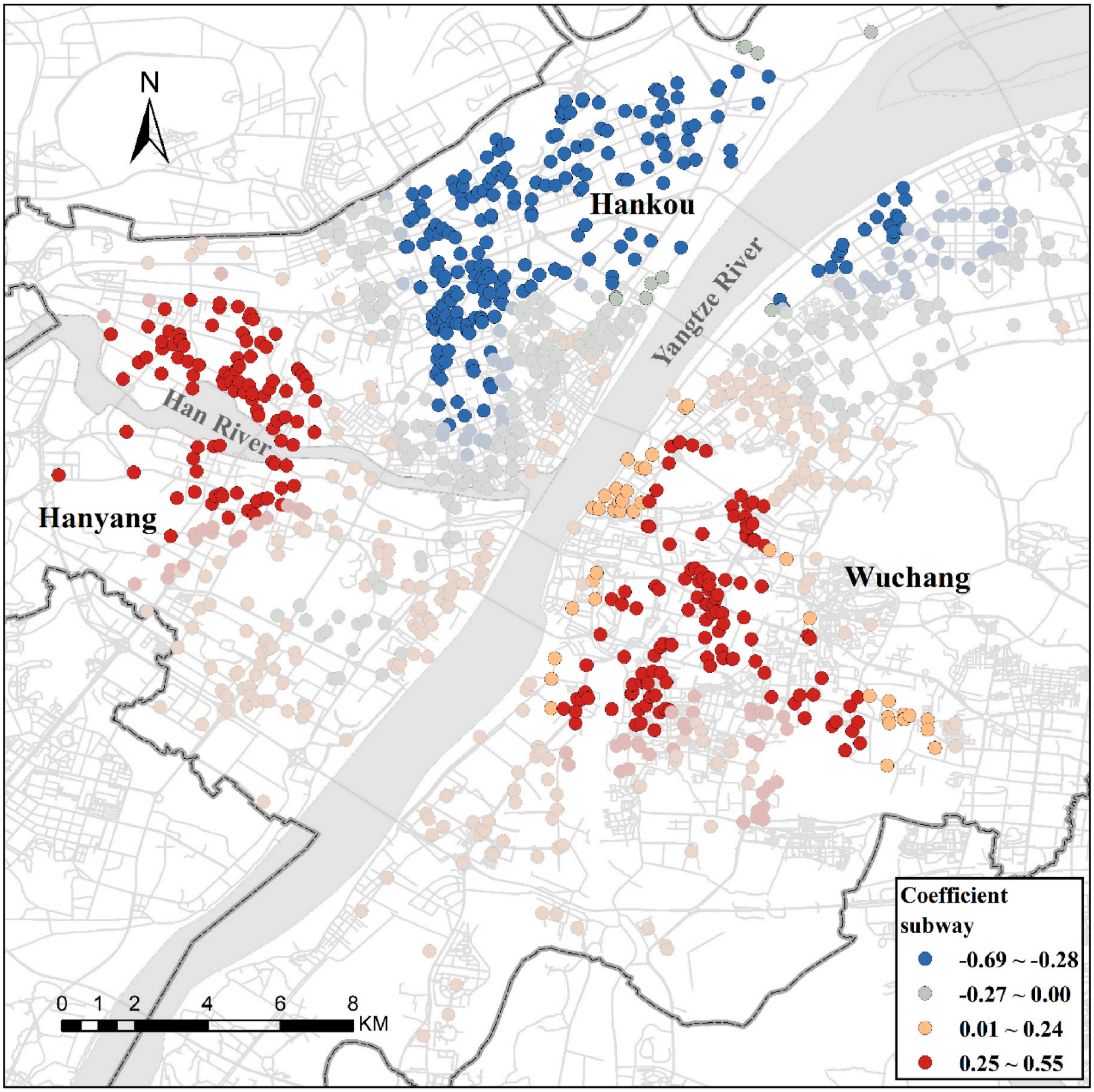

Fig. 17. GWR results of "subway" in Wuhan.

Table 6
Summary of results.

		Retail	Recreation	Education	Social	Leisure	Bus	Subway
Shanghai	Inner ring	–	Mixed	+	+	+	+	NS
	Middle ring	–	–	+	–	+	–	+
	Outer ring	+	–	Mixed	–	–	Mixed	+
Wuhan	Hankou	+	+	NS	–	+	+	Mixed
	Wuchang	–	Mixed	+	+	+	–	+
	Hanyang	NS	NS	NS	+	+	NS	NS

Note:+ statistically significant positive; - statistically significant negative; NS not statistically significant; Mixed contained both positive and negative.

improvement. More customized and transparent approaches can be used such as identifying the AT accessibility needs of the communities by holding public outreach programs and using more advanced methods such as cooperative governance or community self-governance approach when it comes to improving AT accessibility.

This study has three limitations and can be addressed in future studies. Firstly, the measurement of AT accessibility can be further improved by measuring spatially varying travel time thresholds, as well as the weights assigned to walking and cycling accessibility. Survey questionnaires and structured interviews can be useful methods for obtaining these values. Another important direction for future research is to examine the relationship between housing price and accessibility to multiple modes of transportation. Secondly, cities with other urban structures can be studied in the future to improve the understanding related to the impacts of AT accessibility on housing price. Thirdly, natural barriers such as rivers may affect the accuracy of estimation in the GWR modeling, as some observations across the river may contribute to the estimation of regression coefficients. Additional studies are needed to investigate the impacts of COVID-19 on property market in China as many markets are experiencing a post-pandemic market boom.

Credit author statement

Ziqi Yang: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization. Xinghua Li: Conceptualization, Methodology, Resources, Writing – original draft, Supervision, Project administration. Yuntao Guo: Conceptualization, Methodology, Formal analysis, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. Xinwu Qian: Methodology, Writing – review & editing.

Data availability

Data will be made available on request.

Acknowledgements

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Appendix

Table A1
Moran's I test results for significant explanatory variables.

Variables	Shanghai			Wuhan		
	Moran's	*Z-score*	*P-score*	Moran's	*Z-score*	*P-score*
Inherent Attributes						
Size	0.058	26.255	0.000	0.026	5.108	0.000
Age	0.064	28.610	0.000	0.165	31.633	0.000
Bedroom	0.036	16.382	0.000	0.033	6.473	0.000
Elevator	0.156	70.146	0.000	0.048	9.421	0.000
Property AT accessibility to						
retail	0.814	365.093	0.000	0.880	167.985	0.000
recreation	0.717	321.633	0.000	0.732	139.587	0.000
education	0.701	314.483	0.000	0.393	75.328	0.000
social	0.677	303.796	0.000	0.975	185.978	0.000
healthcare	0.761	341.297	0.000			0.000
leisure	0.747	335.519	0.000	0.738	140.750	0.000
bus	0.525	235.520	0.000	0.719	137.114	0.000
subway	0.647	290.257	0.000	0.794	151.714	0.000
Other Locational Attributes						
CBD	0.742	332.730	0.000	0.722	137.722	0.000
Airport	0.683	306.186	0.000	0.896	170.782	0.000
Train	0.605	271.318	0.000	0.704	134.374	0.000
River	0.734	328.924	0.000	0.450	85.889	0.000

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