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Which types of shopping malls affect housing prices? From the perspective of spatial accessibility

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ABSTRACT

The shopping mall plays an important role in the daily life of a city's residents, as well as the economic development of the city, especially in neighboring areas. However, the mechanisms that shape the impact of shopping malls on housing prices remain unclear, particularly in the context of urban China. Considering both the location and quality of shopping malls, this study investigates two questions: 1) Which types of shopping malls impact housing prices, and 2) does this impact change with location? Using Hangzhou, China as an example, data for shopping malls built in Hangzhou prior to 2014 and second-hand housing transaction data from 2014 were collected and analyzed. Based on these data, shopping malls were further divided into several types, according to scale, grade, and tenant mix. Then, spatial accessibility to shopping malls was characterized using two gravity-based models. A geographically weighted model was also used to further analyze the spatial heterogeneity of the accessibility effects of shopping malls on housing prices, especially between the city center and the non-core areas. The study finds that the gravity-based model performed well, and that spatial accessibility to shopping malls had a significant positive impact on housing prices on a whole-city level, but this impact changed with the type of shopping mall and the urban area. Large-scale and high-end shopping malls only had a significant positive impact in the non-core areas of the city. In contrast, high-leisure shopping malls had a significant positive effect on most areas, including the city center.

1. Introduction

Shopping malls are an important form of retail outlets around the world. Although offline retailing is now seriously impacted by the Internet, shopping malls still have a profound impact on urban retail formats and urban economic development. In China, the number of shopping malls has grown rapidly over the past two decades. The number of shopping malls in Shanghai alone reached 148 in 2015, with a construction area of over 16 million square meters.[1] Shopping malls have become an integral part of urban residential life in China.

In general, there are two aspects of shopping malls that influence residential shopping convenience: location and quality. Residential shopping convenience is the biggest and most prominent feature of shopping malls. This is reflected in one-stop shopping, large parking lots, and especially a good location. In the U.S, private cars are the main means of transportation. This leads to a prevalence of out-of-town shopping malls. However, this does not apply to other countries. Because of land market barriers and authorities' attitudes, the out-of-town shopping mall is not popular in the U.K. (Guy, 1994; Lowe, 2000). Beiró et al. (2018) argue that many developing countries have different socio-economic characteristics, compared to the U.S. These include an extensive public transportation system, leading to the close integration of malls with pedestrian and city life.

In China, public transportation dominates many large cities. In Beijing, 35.6% of residents can reach a shopping mall within 10 min using public transportation; 90.4% of residents can arrive within 20 min (Jiang, Zhang, & Wei, 2017). Shi, Wu, and Wang (2015) found that shopping malls in Shanghai remain concentrated in the urban area, with no trend toward suburbanization. As a result, location is a very important factor in how shopping malls provide residents with shopping convenience (Reimers & Clulow, 2009). The most direct way to increase convenience is to reduce the distance from shopping malls to residents

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[1] The data come from the SHANGHAI COUNCIL OF SHOPPING CENTERS (SCSC), which is a professional association dedicated to shopping center research.

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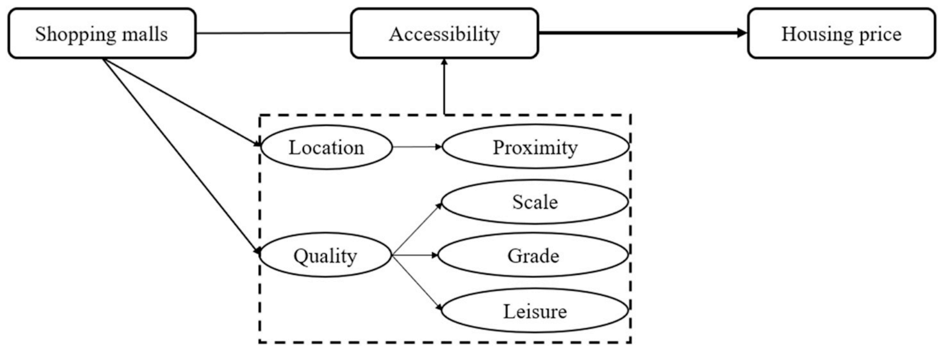

Fig. 1. Impact path of shopping malls on housing prices.

(i.e. proximity). Nevertheless, studies about shopping mall choices have found that the nearest shopping mall may not be the only choice for residents, due to heterogeneity in preference (Kamakura, Kim, & Lee, 1996; Suárez, del Bosque, Rodríguez-Poo, & Moral, 2004). To address this problem, accessibility theory provides a new perspective to measure the convenience offered by shopping malls. This is because the theory considers all shopping malls that are likely to be convenient to the residents. However, the topic of spatial accessibility to shopping malls has only been studied by a limited number of scholars.

In addition to location, the quality of shopping malls also plays an important role in shopping convenience (Léo & Philippe, 2002). Many studies have discussed the factors that influence the attractiveness of shopping malls to residents. In addition to the scale of store agglomeration created by mall size, retail marketing scholars have identified the importance of many other factors, including: parking (Mingardo & Van Meerkerk, 2012), anchor tenants (Finn & Louviere, 1996), shopping mall atmosphere (Hoffman & Turley, 2002; Ruiz, Chebat, & Hansen, 2004), and store allocation (Brueckner, 1993). According to Teller and Reutterer (2008), the factors that influence attractiveness include site-related factors, tenant-related factors, environment-related factors, and buying situation factors. The leisure function provided by a shopping mall plays a particularly increasingly important role (Howard, 2007\). A survey by Erkip (2005) found that the proportion of customers who go to malls to shop is only 42.6%; many other customers come to participate in other activities or just to relax. As a result, most shopping malls are now adding tenants who provide catering and entertainment; some have even introduced public service outlets, such as places that provide medical care, community services, etc. In contrast, the retail functions offered by shopping malls have steadily weakened. Therefore, the way shopping malls affect the lives of urban residents has changed. In addition, consumers also have preference heterogeneity, due to different income levels, culture, and aesthetic preferences. El-Adly (2007) divided shoppers into three types, based on mall attractiveness attributes including relaxed shoppers, demanding shoppers, and pragmatic shoppers.

In summary, shopping malls can provide significant conveniences for residents, which are reflected in the quality and location of the malls. As such, people are willing to spend more money to invest in residential properties that have good accessibility to shopping malls. For example, in real estate advertising, the presence of shopping malls around a residential area is important information for prospective home buyers. Previous studies have found that shopping malls significantly impact housing prices (Colwell, Gujral, & Coley, 1985; Des Rosiers, Lagana, Thériault, & Beaudoin, 1996; Sirpal, 1994; Yu, Cho, & Kim, 2012). However, these studies only focus on the proximity and scale of the shopping malls. There are several open questions involved in identifying the mechanism driving the relationship between shopping malls and housing prices. First, we need to assess the question of whether spatial accessibility is a better way to measure the convenience offered by the shopping mall than proximity alone. Further, improvements are needed in the methods used to measure spatial accessibility to shopping malls. Next, there are also questions about how to quantify and aggregate the quality of shopping malls. Based on this, how do shopping malls with different quality levels influence housing prices? Third, because of the uneven distribution of shopping malls in the city, especially between the main city area and peripheral areas, the demand for shopping malls and their different types varies across different regions. As a result, the role of spatial heterogeneity on housing prices remains a problem requiring additional study.

To address these research gaps, this study completes the following steps: First, the shopping convenience of the shopping mall is measured using spatial accessibility. The gravity-based model is applied in different ways to make it an accurate measure of accessibility to shopping malls. In addition to comparing the functional form of the model and transportation costs, this study further discusses supply calculations to introduce shopping mall quality into the accessibility model. Second, given the number of factors impacting shopping mall quality, classification is applied as the most effective method to quantify quality levels. Scale, grade, and tenant mix are the indicators used to divide shopping malls into several types. Then, the impact of different types of shopping malls on housing prices are discussed in detail, reflecting the preference of home buyers for shopping mall types. Considering the residents' close attention to the functions of the shopping mall in addition to retail, this study assumes that shopping malls with more leisure, entertainment, and other life service functions may more significantly impact housing prices and may be deemed more favorable by residents. The impact path is shown in Fig. 1. Third, this study applies a geographically weighted model (GWR) to analyze the spatial heterogeneity of shopping mall effects. As a result, residential preferences in disparate areas for different shopping mall types can be seen intuitively, which can provide guiding implications for urban planning and mixed land use policy.

The structure of this paper is as follows: The literature review is presented below. Section 3 introduces the construction process of the shopping mall accessibility index. Section 4 presents the research data and models used in this study. Sections 5 and 6 discuss the regression results of hedonic price model (HPM) and GWR, separately and in detail. Conclusions and the limitations to this research are summarized in the last section.

2. Literature review

According to hedonic price theory, the price of the commodity can be decomposed into the characteristic price or the implied price corresponding to each characteristic. Previous scholars have conducted significant research on the characteristic prices of housing prices, including education (Bae & Chung, 2013; Clark & Herrin, 2000), landscape (Cassel & Mendelsohn, 1985; Hui, Chau, Pun, & Law, 2007; Jim & Chen, 2010), transportation (So, Tse, & Ganesan, 1997; Golub, Guhathakurta, & Sollapuram, 2012; Yang, Zhou, & Shyr, 2019) and others. The shopping mall is a convenience for residents, and as such, consistently plays an important role in residential characteristics. Colwell et al. (1985) first studied the externalities of a shopping mall's effect on housing prices. The results show that shopping malls do have a positive effect on housing prices at a certain distance from the mall, but the effect turns negative at closer distances, owing to the noise, pollution and traffic congestion associated with shopping malls. Later, some scholars reached similar conclusions when using even more shopping mall samples, different transportation cost calculations or different function forms (Des Rosiers et al., 1996; Kholdy, Muhtaseb, & Yu, 2014; Sale, 2017; Sirpal, 1994; Yu et al., 2012; Zhang, Zhou, Hui, & Wen, 2019). In addition to the distance from the shopping mall, the scale of the shopping mall can also have an impact on housing prices. Sirpal (1994) initially introduced the interaction between a shopping mall's area and distance from houses to investigate the effects of shopping malls on housing prices. It turned out that larger shopping malls did have a positive effect on housing prices. A study by Des Rosiers et al. (1996) divides shopping malls into three categories, according to the number of shops: neighborhood (1–42 shops), community (44–90 shops) and regional (101–476 shops). The results demonstrate that the three types of shopping malls have different effects on housing prices; the optimal distances are 0.215 km, 0.310 km and 0.532 km, respectively. Previous studies have discussed the impact of shopping malls on residential prices. However, the proximity and scale of shopping malls are the only factors considered, leaving the impact mechanism still ambiguous.

The hedonic price model is a global model with some potential disadvantages. Spatial heterogeneity is an important consideration; it refers to changes in processes and relationships over space (Bailey & Gatrell, 1995). For example, the shopping convenience provided by retail facilities is not evenly distributed throughout the city; residential demand also differs, because of uneven population distribution. As a result, the effects of shopping malls on housing prices change over space, such as across city center and non-center areas. This distinction has not been addressed by previous studies. Scholars have historically proposed several methods to address this, including the dummy variable method (Goodman & Thibodeau, 1998), spatial expansion model (Casetti, 1972; Thériault, Des Rosiers, Villeneuve, & Kestens, 2003), multilevel model (Aitkin & Longford, 1986; Goldstein, 1991) and geographically weighted regression model (GWR) (Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Brunsdon, & Charlton, 2003). Of these, the first three models all have a flaw: they all require the nature of the spatial structure to be pre-defined. In contrast, GWR uses weights calculated from geographic locations to adjust the extent of the impact between samples. The closer the distance of the sample points, the greater the influence they have on each other. GWR very effectively solves the problem of spatial heterogeneity; it is considered to be the most important of these models (Anselin, 2010). The GWR model has been widely used in the field of housing price research (Hanink, Cromley, & Ebenstein, 2012; Helbich, Brunauer, Vaz, & Nijkamp, 2014; Lan, Wu, Zhou, & Da, 2018; Wen, Xiao, Hui, & Zhang, 2018).

The accessibility measurement has been being developed for decades. Originally, accessibility was simply characterized by the transportation cost from the point of origin to the destination (O'Sullivan, Morrison, & Shearer, 2000; Yang et al., 2019). However, this method ignores the supply of the destination and the demand of an origin. Therefore, many scholars have developed a number of more complicated measures to better measure accessibility, including cumulative opportunities measures (Páez, Gertes Mercado, Farber, Morency, & Roorda, 2010; Wachs & Kumagai, 1973), gravity-based measures (Hansen, 1959; Shen, 1998; Xu, Ding, Zhou, & Li, 2015), utility-based measures (Ben-Akiva & Lerman, 1977) etc. In recent years, scholars have begun to pay closer attention to the relationship between accessibility and housing prices. Adair, McGreal, Smyth, Cooper, and Ryley (2000) measures an accessibility index for each of 182 traffic zones and uses transaction data for a sample of 2648 residential properties sold in 1996, in the Belfast urban area. The study concludes that accessibility has little impact on housing prices on a city-wide scale, but illustrates a significant impact on the submarket, particularly in lower-income areas. Yang et al. (2019) discusses the effects of bus accessibility on property prices. The results demonstrate that access to bus stops and bus travel times to essential destinations significantly influences housing prices.

The relationship between retail accessibility and housing prices was first investigated by Song and Sohn (2007). They used a gravity-based model to take retail supply and demand into consideration when calculating the retail accessibility index. The results support the hypothesis that greater spatial accessibility to retailing is capitalized into residential property values. On this basis, Jang and Kang (2015) further improved the gravity-based model and began to consider the impact of retail types and residential submarkets. The multilevel hedonic price model was adopted, and the results show that the effect of accessibility by retail type (e.g. convenience store, supermarket, etc.) varies across housing submarkets. Notably, this research considers the shopping mall as being a retail type and develops its accessibility index accordingly. However, the study only considered shopping mall scale as the supply factor. This did not account for the complexity of the mechanism of shopping mall impact, e.g., the quality of shopping malls. Therefore, more work is needed to calculate shopping mall supply.

In summary, previous studies have focused on the impact of shopping malls on house prices; however, research gaps remain. First, spatial accessibility provides a new perspective to rethink shopping mall convenience. However, few studies have engaged in this work. In particular, methods for investigating shopping mall supply need to be more deeply investigated. Second, the quality of shopping malls also plays an important role, in addition to location; this variable also needs further research. Third, the spatial heterogeneity of the impact of shopping malls on housing prices remains unclear. To address these problems, this study first develops two accessibility models to measure the spatial accessibility to shopping malls. Then, shopping malls are divided into several types, according to their scale, grade and tenant mix. Lastly, the HPM and GWR are adopted to discuss the impact of spatial accessibility to shopping malls on housing prices.

3. Spatial accessibility to shopping malls

3.1. Developing the accessibility index

Several accessibility measures have been developed in previous literature, and cumulative opportunities measures and gravity-based measures are most widely applied among them. However, cumulative opportunities measures are too simple to properly characterize shopping mall accessibility. Gravity-based measures were first proposed by Hansen (1959); these measures use the distance decay function to adjust the influence. Subsequently, Shen (1998) made improvements on this basis, which account for supply and demand. This new model has been applied by many scholars (Jang & Kang, 2015; Wu, Ye, Du, & Luo, 2017) and performs well. This study builds on these two ideas and develops two models. The formulae are as follows:

$$GM : A(i) = \sum_{j=1}^{n} S_j d_{ij}^{-\beta} \tag{1}$$

$$DGM : A(i) = \sum_{j=1}^{n} \frac{S_j d_{ij}^{-\beta}}{V_j}, V_j = \sum_{k=1}^{m} D_k d_{kj}^{-\beta} \tag{2}$$

where: A(i) is the accessibility index of community i, and n and m are the number of shopping malls and communities, respectively. In addition, S_j is the supply of the shopping mall, that is, shopping mall attractiveness; d_{ij} is the road distance from community i to shopping mall j, calculated by ArcGIS; β is the distance decay parameter ($\beta > 0$), and D_k is the demand for the destination, that is, the number of households at community k. In the gravity-based model (GM), the impact scope of the shopping mall is adjusted by the distance decay parameter β. The greater

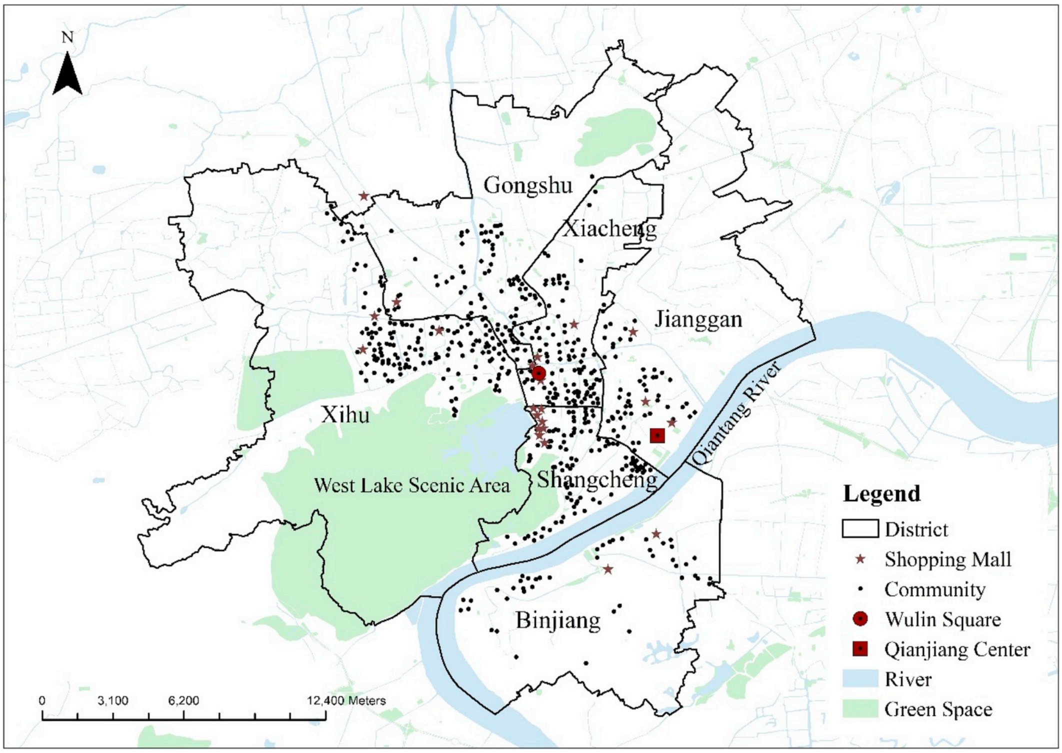

Fig. 2. Spatial distribution of shopping malls and communities in Hangzhou.

the distance between the shopping mall and the community is, the smaller the $d_{ij}^{-\beta}$ and the smaller the impact will be. The supply of shopping malls is also considered, but the model does not consider community demand. This question can be addressed using the new gravity-based model (DGM), which adds V_j to the denominator. Similarly, community demand will decrease as distance increases, so V_j is also adjusted by the distance decay parameter β. However, the distance decay parameter will also vary with the shopping mall. Some scholars (Jang & Kang, 2015; Kwan, 1998) have compared the distance decay parameters, and the empirical results of different types and regions are different. Therefore, this study sets multiple distance decay parameters for comparison: $\beta = 1.0$, 1.2, 1.4, 1.6, 1.8, and 2.0.

3.2. The supply of shopping malls

In the above two models, the supply of services (S_j) is often characterized by the scale of that supply in previous studies (Jang & Kang, 2015; Song & Sohn, 2007). However, many other factors affect the supply of shopping malls, including shopping atmosphere, tenant mix, and spatial layout. To systematically consider the influencing factors of shopping mall supply, this study uses two approaches to address this problem. The first one is to adjust the way in which S_j is calculated. The second approach is to classify shopping malls into the types discussed in section 3.3.

The weighted sum is a better way to calculate the supply. Dony, Delmelle, and Delmelle (2015) uses the weighted sum of park acreage and on-site amenities to represent the S_j, and tested different weight values. Similarly, Lin et al. (2016) measures the attractiveness of train stations by calculating the weighted sum of several factors and calibrates weights using the multiple-criteria decision analysis model. Consistent with this approach, this study proposes a new method to calculate the supply (attractiveness) of shopping malls. It is difficult to quantify the many influencing factors mentioned above for each single shopping mall. As such, this study measures shopping mall quality along three dimensions: scale, grade, and tenant mix. In fact, large-scale shopping malls often have conditions that allow for the set-up of indoor and outdoor pedestrian streets and the introduction of large-scale anchor stores. High-end shopping malls have advantages in terms of product and service uniqueness, and shopping atmosphere. Finally, the tenant mix refers to the direct proportion of life and leisure formats. The new calculation method is shown in Equation (3).

$$S_j^w = w_1 S_j^s + w_2 S_j^g + w_3 S_j^t \tag{3}$$

$$S_j^{s,g,t} = \frac{S_j^{s,g,t} - minS_j^{s,g,t}}{maxS_j^{s,g,t} - minS_j^{s,g,t}} \tag{4}$$

where, the supply of shopping malls (S_j^w) is calculated using the weighted sum approach; w_1, w_2 and w_3 represent the importance of shopping malls' scale (S_j^s), grade (S_j^g) and tenant mix (S_j^t), respectively; and $w_1 + w_2 + w_3 = 1$. The values of the three factors are discussed below. Because the units of these factors are not uniform, the score range method is used to standardize all factors, as shown in Equation (4). This study compares multiple weight combinations to optimize the weights. In addition, the study also adopts the method where S_j is equal to the total floor area of shopping mall j (unit: 10000 m^2) for purposes of better comparison.

3.3. Shopping mall classification

In addition to adjusting how S_j is calculated, it is also useful to classify shopping malls in a way that considers the factors that influence shopping mall quality. This study classifies shopping malls into several types according to three factors, including traditional classification (i.e. scale and grade) and new classification (i.e. tenant mix). Thus, the differences in accessibility to different types of shopping malls can be compared and analyzed. The quantitative criteria for classification are based on the distribution of shopping mall data that will be discussed in Section 4.1.

Scale. The scale of a shopping mall is an important indicator of the classification of that shopping mall, because the scale determines the

Table 1
Descriptive statistics of shopping malls.

	Min	Max	Mean	Std. dev.
Total floor area (m^2)	18,000	289,000	76996.318	60680.479
Proportion of retail (%)	40	95	66.409	15.546
Proportion of catering (%)	5	25	14.636	4.914
Proportion of entertainment (%)	0	40	12.955	10.196
Proportion of services (%)	0	20	6.000	6.407

Table 2
Descriptions of residential characterization variables.

Characteristics	Characterization variable	Quantitative basis	Min	Max	Mean	Std. dev.
	Sale price	Second-hand transaction price data of housing communities from January 2014, to December 2014 (¥/m^2)	11,844	47,515	21,091	5112
Structure	1. Building's age	Years (calculated until 2014)	4	36	15.239	6.983
Location	2. Distance to Wulin Square	Euclidean distance from the community to Wulin Square (km)	0.350	111.250	4.691	5.304
	3. Distance to West Lake	Euclidean distance from the community to West Lake (km)	0.210	10.800	3.909	2.011
	4. Distance to Qianjiang Center	Euclidean distance from the community to Qianjiang Center (km)	0.940	16.457	7.109	3.454
Neighborhood	5. External environment	Environmental quality around the community is divided into five degrees: quite poor (scored 1), poor (scored 2), average (scored 3), good (scored 4), and very good (scored 5).	1	5	3.149	0.805
	6. Inner environment	Environmental quality inside the community is divided into five degrees: quite poor (scored 1), poor (scored 2), average (scored 3), good (scored 4), and very good (scored 5).	1	5	3.210	0.950
	7. Bus route	Total number of bus routes within 1 km of the community	2	74	31.893	14.999
	8. Living facilities	Supermarket, community store, bank, post office, and hospital within 1 km of the community. Each item adds 1 point to the score (maximum possible total is 5 points).	0	5	4.294	1.047
	9. University nearby	This dummy variable is equal to 1 if a college or university is located within 1 km from a community and 0 if otherwise.	0	1	0.606	0.489
	10. Educational facilities	Kindergarten, primary, secondary, and high schools located within 1 km from the community; each item adds 1 point to the score, and the maximum total score is 4.	1	4	3.151	0.762
	11. Sports facilities	General quality of community sports facilities inside the community is divided into five degrees: quite poor (scored 1), poor (scored 2), average (scored 3), good (scored 4), and very good (scored 5).	0	6	1.786	1.256
	12. Property management	Community property management service quality is divided into five degrees: quite poor (scored 1), poor (scored 2), average (scored 3), good (scored 4), and very good (scored 5).	1	5	2.516	1.258

quality and quantity of services that the shopping mall can provide. This study uses the total floor area to characterize the scale, and shopping malls are divided into three types: small-scale shopping mall (area $<50000\,m^2$), mid-scale shopping mall ($50000\,m^2 \leq$ area $<100000\,m^2$), and large-scale shopping mall ($100000\,m^2 \leq$ area).

Grade. To a certain extent, the grade of a shopping mall determines the attractiveness of that shopping mall, given the fact that a high-end shopping mall definitely has better operations, a better shopping atmosphere and a superior spatial layout than lower-end malls. Therefore, the grade of the shopping mall is considered to be one of the classification criteria, and shopping malls are divided into three types, according to the available shopping mall data: high-end shopping mall, mid-end shopping mall and low-end shopping mall.

Tenant mix. Given that residents pay close attention to the versatility of shopping malls, this study accounts for tenant mix. A good tenant mix, especially the combination of retail tenants and non-retail tenants, has a positive effect on the attractiveness of a shopping mall. The proportion of non-retail tenants is the most intuitive indicator of this factor, as more and more people are paying attention to the leisure functions of shopping malls. A shopping mall with a high non-retail proportion indicates that the more other leisure functions the shopping mall has, the more types of services it offers. Similarly, shopping malls are divided into three types: high-leisure shopping mall ($60\% \geq$ proportion $> 40\%$), mid-leisure shopping mall ($40\% \geq$ proportion $> 20\%$), and low-leisure shopping mall ($20\% \geq$ proportion $> 0\%$). The proportion refers to the proportion of non-retail tenants.

Consequently, spatial accessibility to shopping malls is measured using two models, which changes as the distance decay parameter or the way S_j is calculated. To consider the differences between different shopping malls, this study further classifies shopping malls by three criteria. Hence, in addition to calculating the composite accessibility index, it is also necessary to calculate nine types of accessibility index.

4. Data and models

4.1. Study area and data sources

Hangzhou is the capital of Zhejiang Province and one of the most developed cities in the Yangtze River Delta. It is surrounded by mountains on three sides, and the Qiantang River passes through the southeast. The West Lake and numerous historical sites make Hangzhou a tourist city, while the rise of the IT industry in Hangzhou has led to its rapid economic development. The main urban area of Hangzhou is composed of six districts, namely Shangcheng District, Xiacheng District, Gongshu District, Jianggan District, Binjiang District, and Xihu District. The traditional city center is located in the Wulin Square area, northeast of the West Lake. In recent years, the rapid development of the Qianjiang Center has made it the new city center.

The spatial distribution of shopping malls and communities in Hangzhou is shown in Fig. 2. The shopping malls in Hangzhou are distributed throughout all six districts; the concentration of malls near Wulin Square is the densest. To obtain more detailed data about the shopping malls, this study mined the shopping mall data from the CRIC database.[2] A total of 22 shopping malls, all of which opened before January 2014, are taken into consideration. The smallest shopping mall has a building area of $18{,}000\,m^2$, and the largest has a maximum area of $289{,}000\,m^2$. The database divides the shopping malls into five grades, according to their market positioning, anchor tenants and other related information. The five grades are high-end, mid-to-high-end, mid-end, low-to-mid-end and low-end. To simplify matters, this paper combines the high-end and mid-to-high-end into the high-end grade, and

[2] The China Real Estate Information Corporation's (CRIC) database is one of the largest real estate information databases in China.

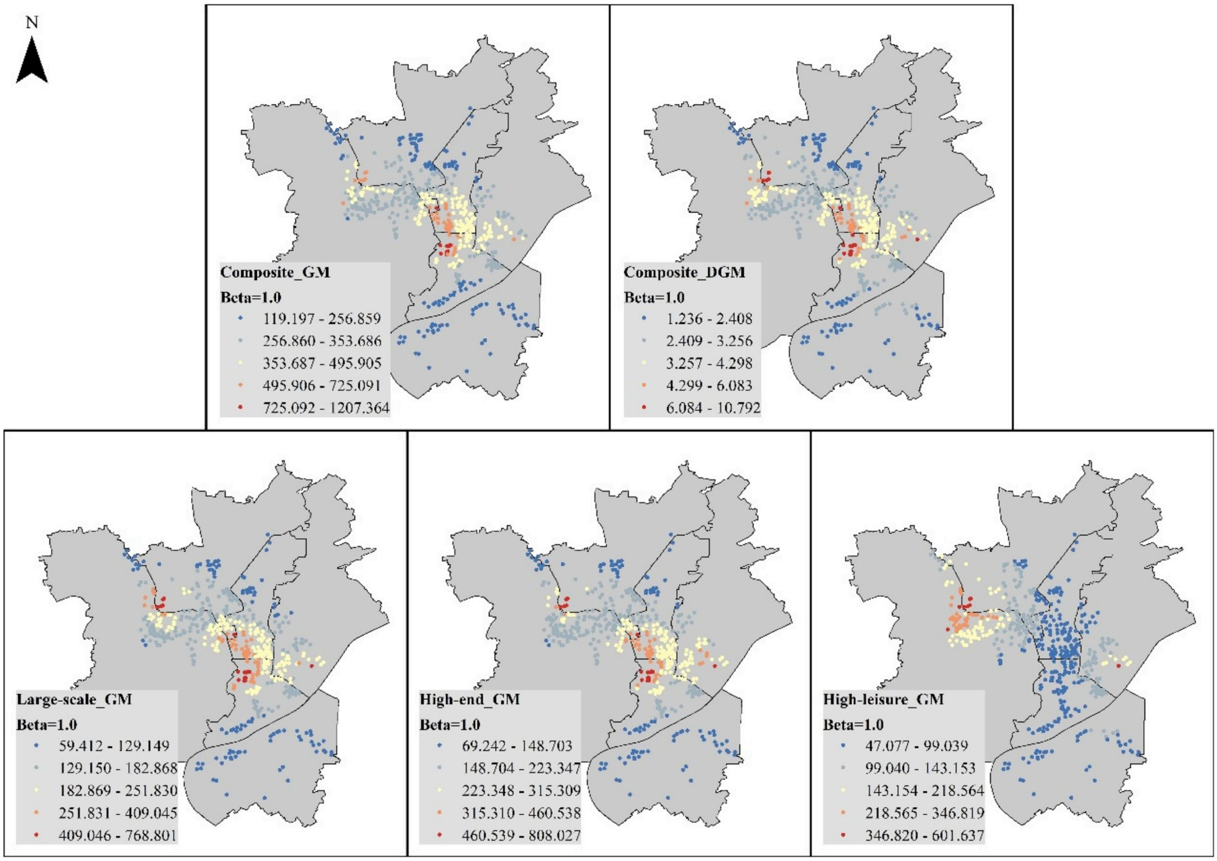

Fig. 3. Spatial accessibility to shopping malls in Hangzhou.

Table 3
Regression results of independent variables.

Independent variables	HPM				GWR				
	Coef.	T	Coef.	T	Min	Lwr Quartile	Median	Upr Quartile	Max
Constant	9.528***	47.108	9.962***	92.326	2.705	9.357	10.369	11.142	31.313
Ln distance to Wulin Square	−0.082***	−4.298	−0.088***	−4.678	−2.176	−0.183	−0.126	−0.017	0.191
Ln distance to West Lake	−0.170***	−10.017	−0.173***	−10.289	−0.702	−0.303	−0.211	−0.152	1.071
Ln distance to Qianjiang Center	−0.048***	−3.769	−0.047***	−3.625	−2.759	−0.166	−0.019	0.097	2.897
Ln building's age	−0.003	−0.164	−0.003	−0.125	−0.137	−0.075	−0.045	−0.024	0.070
External environment	0.004	0.379	0.004	0.387	−0.067	−0.019	0.000	0.021	0.134
Inner environment	−0.008	−0.710	−0.007	−0.616	−0.127	0.006	0.013	0.025	0.096
Bus route	−0.003***	−4.661	−0.003***	−4.589	−0.011	−0.004	−0.002	−0.001	0.022
Living facilities	0.017**	1.999	0.018**	2.105	−0.049	−0.006	0.010	0.039	0.142
University nearby	0.066***	4.394	0.068***	4.510	−0.219	0.008	0.040	0.062	0.132
Education facilities	0.035***	3.507	0.035***	3.540	−0.074	−0.007	0.019	0.044	0.092
Sports facilities	0.023***	3.458	0.023***	3.390	−0.065	0.008	0.021	0.037	0.064
Property management	0.058***	7.023	0.058***	7	−0.056	0.020	0.032	0.040	0.129
Ln GM_acc (β = 1.0)	0.092***	3.150			−2.974	−0.164	−0.004	0.114	0.872
Ln DGM_acc (β = 1.0)			0.082***	2.783					
AICc	−504.103		−501.827		−651.995				
adj R^2	0.580		0.578		0.743				

Notes: ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. The dependent variable is lnP.

combines the low-end and low-to-mid-end into the low-end grade. The proportions of the four types of tenants in the mall are also counted by the database: retail, catering, entertainment and services. There are almost no shopping malls with a purely retail format, while the proportion of restaurants and entertainment tenants is on the rise. This is in line with the trend of residents being more interested in entertainment and dining, given the improvement in living standards. Table 1 presents the descriptive statistics of shopping malls.

This study uses second-hand transaction price data of 541 housing communities from January 2014, to December 2014. High-priced housing (such as villas and townhouses) and urban fringe communities are removed, in order to make the data comparable. A total of 523 housing communities, which mainly consist of multi-layer and high-rise housing, are retained, and these price data are further converted into community average price data. The characterization variables that influence housing prices are mainly summarized as structure characteristics, location characteristics, and neighborhood characteristics, as shown in Table 2. Data of housing prices and *Building's age* are obtained from a real estate agency in Hangzhou. *Bus route* and the three location characteristics are measured directly through a digital map, while other

Table 4
Hedonic regression results of two types of accessibility index.

Model	GM						DGM					
l_0/β	1.0	1.2	1.4	1.6	1.8	2.0	1.0	1.2	1.4	1.6	1.8	2.0
Coef.	0.092***	0.065***	0.049***	0.038***	0.030***	0.024**	0.082***	0.054**	0.036**	0.024	0.015	0.009
T	3.150	2.990	2.853	2.727	2.612	2.506	2.783	2.396	2.006	1.622	1.251	0.903
VIF	2.562	2.305	2.117	1.978	1.875	1.797	2.139	1.933	1.797	1.706	1.646	1.603
Adj R^2	0.580	0.579	0.578	0.578	0.577	0.577	0.578	0.576	0.575	0.574	0.573	0.572

Note: ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 5
Hedonic regression results of different S_j calculation methods.

S_j ($w_1 : w_2 : w_3$)	S_j^w (0.50 : 0.25 : 0.25)		S_j^w (0.25 : 0.50 : 0.25)		S_j^w (0.25 : 0.25 : 0.50)		S_j^w (0.33 : 0.33 : 0.33)		S_j^s	
Model	GM (β = 1.0)	DGM (β = 1.0)	GM (β = 1.0)	DGM (β = 1.0)	GM (β = 1.0)	DGM (β = 1.0)	GM (β = 1.0)	DGM (β = 1.0)	GM (β = 1.0)	DGM (β = 1.0)
Coef.	0.091***	0.076**	0.086***	0.072**	0.091***	0.076**	0.090***	0.075**	0.092***	0.082***
T	2.948	2.432	2.730	2.268	3.067	2.460	2.923	2.388	3.150	2.783
VIF	3.003	2.510	3.323	2.753	2.649	2.234	2.970	2.482	2.562	2.139
Adj R^2	0.577	0.575	0.576	0.574	0.578	0.575	0.577	0.575	0.580	0.578

Note: ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

variables that cannot be directly measured are obtained through a field survey conducted in 2014. Table 2 presents the descriptive statistics of the variables.

4.2. Housing price models

This study first uses the commonly used hedonic price model to investigate the impact of shopping malls on housing prices. The model is shown in Equation (5).

$$LnP = \alpha_1 + \alpha_2 LnS + \alpha_3 LnL + \alpha_4 LnN + \alpha_5 LnA + \varepsilon \tag{5}$$

where: P is the average transaction price of a community; S, L and N are the structure characteristic variables, the location characteristic variables and the neighborhood characteristic variables, respectively; A is the accessibility index, and α_1 represents the intercept. The variables $\alpha_1$to α_5 are the coefficients to be estimated; ε is the error term, and α_5 can directly capture the impact of spatial accessibility to shopping malls on housing prices. A positive α_5 indicates that spatial accessibility to shopping malls has a premium effect on housing prices, while a negative α_5 reveals the opposite.

The hedonic price model measures the average of the entire data pool. In other words, the model shows whether the influence of accessibility on the housing prices of the whole city is significant. However, this effect has characteristics of spatial heterogeneity, which is due to various factors, such as differences in the supply and demand of shopping malls, transportation, residents, and city planning. To solve this question, a geographically weighted model is adopted, as shown in Equation (6).

$$LnP_i = \alpha_1(u_i, v_i) + \alpha_2(u_i, v_i)LnS_i + \alpha_3(u_i, v_i)LnL_i + \alpha_4(u_i, v_i)LnN_i + \alpha_5(u_i, v_i)LnA_i + \varepsilon_i \tag{6}$$

where: P_i represents the average transaction price of community i; u_i and v_i are the coordinates of community i, and $\alpha_k(u_i, v_i)$ is the coefficient for variable j at regression point i (i.e. community i). Similarly, $\alpha_5(u_i, v_i)$ reflects the effect of spatial accessibility to shopping malls on the housing prices of community i.

A GWR model allows different relationships to exist at different points in space (Brunsdon et al., 1996; Fotheringham et al., 2003). In other words, the regression coefficient at one location is an estimate of local regression that is obtained by using the observations of that location's neighboring data, so each point has its own regression coefficients. In the application of the GWR model, a spatial weight matrix needs to be introduced. The means to determine the spatial weight function include the threshold distance, inverse distance, bi-square function and Gaussian function. In addition, the choice of bandwidth also has a large impact on the results of the model. Gaussian function and an adaptive bandwidth have been proven to be highly suitable in practice (McMillen & Redfearn, 2010; Wen, Jin, & Zhang, 2017). Hence, the Gaussian function was chosen as the adaptive spatial kernel in this study, which allows the bandwidth to vary with the density of communities around each regression point.

5. The results of the hedonic price model

5.1. Characteristic variables

In this paper, 10 types of accessibility indices calculated by two models are analyzed, some of which are shown in Fig. 3. To support a better analysis, two representative regression results were selected for the characteristic variables analysis. Their accessibility indices are calculated using GM (β = 1.0) and DGM (β = 1.0), respectively, as shown in Table 3. The Adjust R^2 of all two regressions reach 0.570, indicating that this model has explained more than 57% of housing prices. In terms of characteristic variables, almost all variables are significant at the 1% level, with just a few exceptions. The coefficients of *Distance to Wulin Square*, *Distance to West Lake* and *Distance to Qianjiang Center* are large and negative, indicating that the farther the community is from those three locations, the lower the housing price will be. It is noticeable that the Wulin Square and West Lake are still considered to be in the center of Hangzhou, while the Qianjiang Center has gradually developed into another city center.

5.2. Comparison of accessibility models

The accessibility models differ because of the differences in definitions. Two models are compared in this study, through the accessibility index results of a hedonic price model, as shown in Table 4.

In the GM regression results, almost all coefficients are positive and significant, at a significance level of 1%. This finding demonstrates that the accessibility index has a significant positive impact on housing

Table 6
Regression results of accessibility index by different shopping mall type.

Shopping mall type		Hedonic price model								GWR model							
		GM ($\beta = 1.0$)				DGM ($\beta = 1.0$)				GM ($\beta = 1.0$)							
		Coef.	T	VIF	Adj R^2	Coef.	T	VIF	Adj R^2	Min	Lwr Quartile	Median	Upr Quartile	Max	Proportion	AICc	Adj R^2
Composite		0.092***	3.150	2.562	0.580	0.082***	2.783	2.139	0.578	−2.974	−0.164	−0.004	0.114	0.872	39.6%	−651.995	0.743
Scale	Large	0.078***	3.487	2.088	0.582	0.081***	3.780	1.836	0.584	−2.734	−0.078	0.014	0.066	0.716	18.9%	−647.011	0.742
	Medium	0.101***	3.151	2.130	0.581	0.062*	1.867	1.621	0.575	−1.623	−0.160	0.025	0.156	1.020	45.1%	−664.933	0.751
	Small	−0.002	−0.056	5.319	0.572	−0.019	−0.590	5.696	0.573	−1.997	−0.120	−0.078	−0.002	0.904	24.7%	−640.931	0.739
Grade	High-end	0.086***	3.599	2.409	0.583	0.088***	3.855	2.096	0.585	−2.756	−0.059	0.027	0.080	0.778	16.8%	−646.804	0.742
	Mid-end	0.036	1.224	2.238	0.574	0.018	0.609	1.761	0.573	−3.743	−0.221	−0.106	0.045	0.837	60.4%	−660.081	0.746
	Low-end	0.004	0.177	1.921	0.572	−0.044*	−1.835	1.711	0.575	−0.839	−0.094	−0.007	0.043	1.126	28.1%	−649.992	0.742
Tenant mix	High-leisure	0.141***	8.031	1.398	0.621	0.143***	7.503	1.355	0.616	−3.284	−0.003	0.126	0.265	0.689	54.7%	−652.333	0.736
	Mid-leisure	−0.217***	−6.019	9.557	0.601	−0.245***	−6.966	8.828	0.610	−2.082	−0.305	−0.168	−0.054	1.206	49.1%	−637.745	0.731
	Low-leisure									−2.011	−0.337	−0.097	0.007	1.204	22.9%	−633.503	0.729

Notes: 1. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively. 2. The hedonic price model results of low-leisure shopping malls are removed, because of multicollinearity. 3. The *Proportion* means the proportion of significant sample points at a 5% level.

prices. At the same time, the smaller the β is, the more significant the coefficient is, and the higher the Adjusted R^2 of the model is. When $\beta = 1.0$, the GM model measures the accessibility to shopping malls most accurately. Also, the housing prices increase by 0.092% when the accessibility index increases by 1%, while other characteristic variables remain the same. The DGM regression results are similar to those of GM. The smaller β is, the more significant the coefficient is, and the higher the Adjusted R^2 of the model is. However, the coefficient is less significant, which is significant only when $\beta \leq 1.4$. The T statistic is also significantly lower than that of the GM of the same β.

The above results illustrate that the accessibility index calculated by GM is the more stable, and the index also explains housing prices well. In previous studies, DGM performed better in terms of examining the influence of public services, such as employment (Grengs, 2010; Shen, 1998), health care (Luo & Wang, 2003) and parks (Wu et al., 2017). In the DGM model, the introduction of both supply and demand can accurately and effectively reflect the influence of competitive public services. In other words, an excessive flow of people can make these public services less attractive, because of crowding or a reduction in job opportunities or medical resources. However, this mechanism changes when we measure the spatial accessibility to shopping malls, because the general popularity of shopping malls can have a positive impact on the attractiveness of shopping malls (El-Adly, 2007; Wong & Yu, 2003). Thus, the gravity and accessibility of a shopping mall will not decrease with large passenger flows.

5.3. Comparison of different S_j calculation methods

Table 5 shows the hedonic regression results of different S_j calculation methods. All coefficients are positive and significant. The results using GM are still slightly better than the result using DGM. The results by different weight combinations are all significant at the level of 1%. This means that the combination of weights has little effect on S_j and the accessibility index. This study argues that there may be correlations between the three influencing factors, because a large-scale shopping mall tends to have a higher grade and a more reasonable tenant mix. The Pearson test further demonstrates that the scale of shopping malls (S_j^s) correlates significantly with the grade of shopping malls (S_j^g) but is not correlated with the proportion of leisure tenants (S_j^s). Therefore, the scale can generally correctly characterize the shopping mall supply. However, the tenant mix of shopping malls requires further discussion.

5.4. Comparison of shopping mall types

To further compare the differences of the impacts from accessibility to shopping malls of different types, the regression results of the nine types of accessibility index calculated by GM ($\beta = 1.0$) and DGM ($\beta = 1.0$) are shown in Table 6. In the table, S_j is equal to the total floor area of shopping mall j.

In the case of classification by scale, the results show that the coefficients of the large and mid-scale shopping mall accessibility index are significant and positive. The coefficient of the small-scale shopping mall accessibility index is not significant, indicating that both the large and mid-scale shopping mall accessibility indexes have a significant positive impact on housing prices. This result is in line with expectations, as large and mid-scale shopping malls are accompanied by more retail stores and are therefore more attractive to consumers. The regression results of the shopping mall accessibility index classified by grade show similarity. The coefficient of the high-end shopping mall accessibility index is significantly positive, while the coefficients of the mid and low-end shopping mall accessibility indices are not significant. Even the low-end shopping mall accessibility index is significantly negative, at a significance level of 10% in the DGM results ($\beta = 1.0$). High-end shopping malls tend to have better infrastructural facilities, better tenants and a better shopping atmosphere, so these malls are more attractive to

Table 7
Hedonic regression results of two types of accessibility index (driving time).

Model	GM						DGM					
T_0/β	1	1.2	1.4	1.6	1.8	2	1	1.2	1.4	1.6	1.8	2
Coef.	0.102***	0.077***	0.060***	0.048***	0.002***	0.033***	0.092***	0.065**	0.045**	0.0311*	0.020	0.012
T	3.175	3.189	3.172	3.132	3.078	3.015	2.761	2.564	2.246	1.828	1.377	0.961
VIF	1.360	1.286	1.237	1.204	1.182	1.167	1.373	1.306	1.263	1.238	1.232	1.235
Adj R^2	0.578	0.578	0.578	0.578	0.578	0.578	0.576	0.576	0.574	0.573	0.572	0.571

Note: ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 8
Hedonic regression results of accessibility index by different shopping mall type (driving time).

Shopping mall type		GM (β = 1.0)				DGM (β = 1.0)			
		Coef.	T	VIF	Adj R^2	Coef.	T	VIF	Adj R^2
Composite		0.102***	3.175	1.360	0.578	0.092***	2.761	1.373	0.576
Scale	Large	0.090***	3.710	1.258	0.581	0.090***	3.723	1.251	0.581
	Medium	0.049	1.072	1.404	0.571	0.000	0.002	1.424	0.570
	Small	−0.026	−0.742	3.285	0.571	−0.053	−1.478	3.599	0.572
Grade	High-end	0.097***	3.690	1.424	0.581	0.097***	3.694	1.430	0.581
	Mid-end	0.041	0.995	1.322	0.571	0.009	0.228	1.253	0.570
	Low-end	−0.058**	−2.111	1.367	0.574	−0.092***	−3.446	1.434	0.580
Tenant mix	High-leisure	0.142***	7.250	1.351	0.610	0.142***	6.882	1.352	0.607
	Mid-leisure	−0.211***	−6.518	4.722	0.603	−0.216***	−6.690	4.626	0.605
	Low-leisure	−0.067**	−1.988	3.924	0.573	−0.075**	−2.195	3.957	0.574

Note: ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

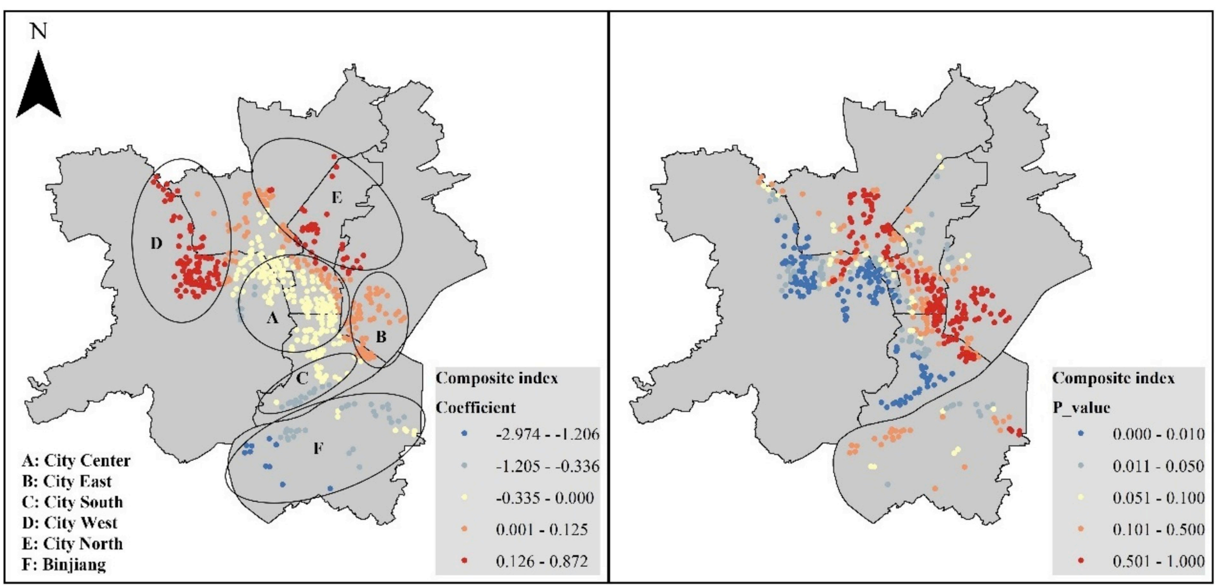

Fig. 4. GWR regression results of composite accessibility index.

residents.

In the case of tenant mix classification, the coefficients of the high and mid-leisure shopping mall accessibility indices are significant at a 1% level. However, the coefficient of high-leisure malls is positive, indicating that the index has a positive effect on housing prices. In contrast, the mid-leisure coefficient is negative, representing the opposite effect. This result verifies residents' preference for high-leisure shopping malls, because these malls tend to have more catering and entertainment facilities. This finding is consistent with the field survey implemented by Erkip (2005). Therefore, residents will also be willing to pay a higher price when buying a house in such areas, in order to get access to this level of convenience. The results of the low-leisure shopping mall accessibility index are removed, as its Variance Inflation Factor (VIF) is greater than 10.0, indicating the existence of a serious variable collinearity problem. The spatial distribution of shopping malls is further assessed. The results show that most of the city's mid and low-leisure shopping malls are concentrated in the Wulin Square area. Thus, the accessibility index is highly correlated with *Distance to Wulin Square*, which in turn leads to the model being unable to correctly estimate the true impact of the accessibility index.

5.5. Comparison of transportation cost

According to models, the accessibility index is also affected by the method used to calculate traffic costs. A robust test is applied to verify the validity of the road distance approach used above. The driving time from houses to shopping malls is determined using a Baidu map. Then, all accessibility indices are recalculated and entered into the regression

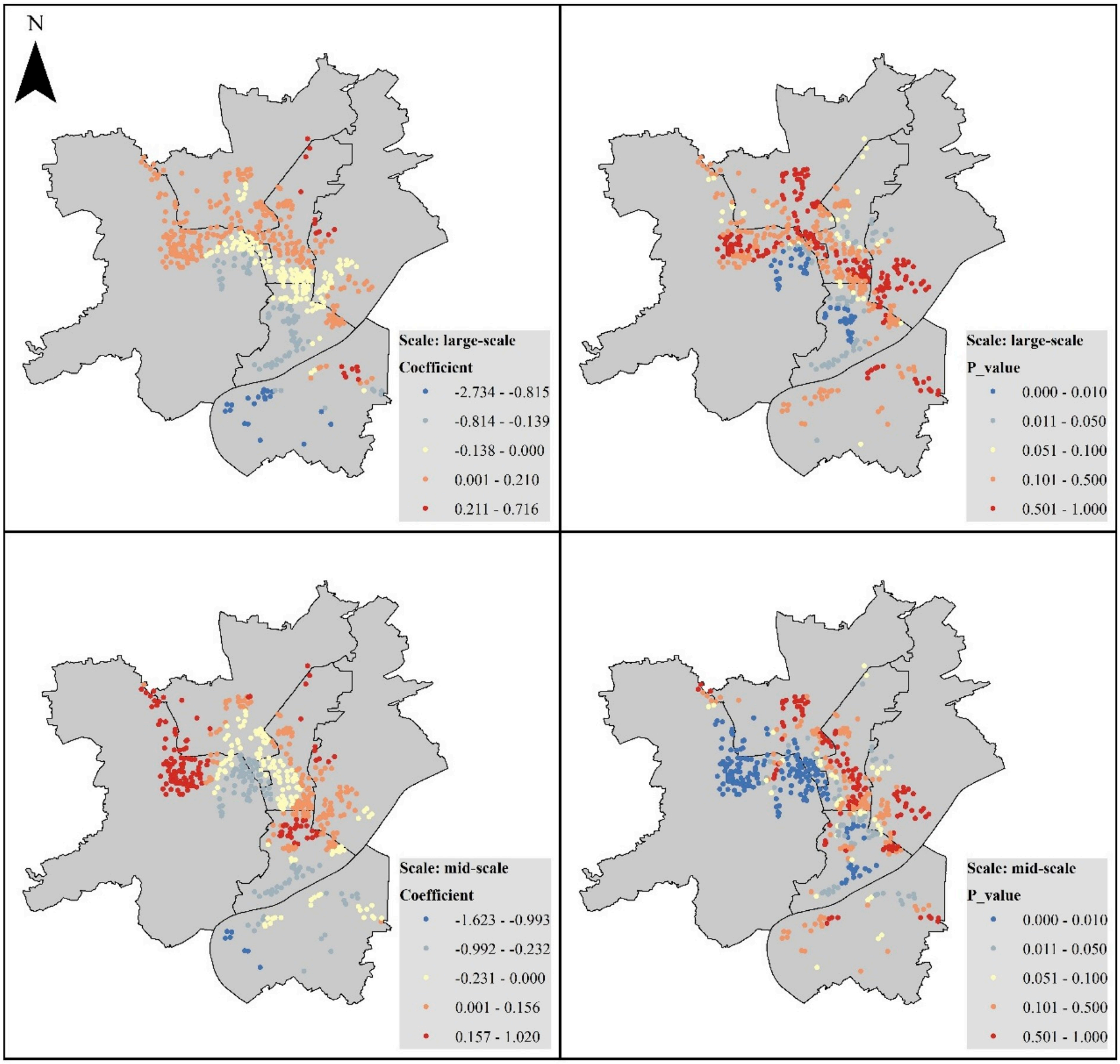

Fig. 5. GWR regression results of accessibility index by scale.
Note: Only results with better significance are shown; the figures below are the same.

equations. The results of the hedonic price model are shown in Tables 7 and 8. The results of the two transportation costs are almost the same. These results show that the road distance calculated by ArcGIS can accurately measure the transportation cost. In addition, the results of both transportation cost calculations show that mid- and low-leisure shopping malls negatively impact housing prices, which is counter-intuitive. Further tests indicate that the negative impact disappears when *Distance to Wulin Square* is removed from the regression. Therefore, the possible reason is that mid- and low-leisure shopping malls are highly concentrated in the city center, resulting in a correlation between *Distance to Wulin Square* and mid- or low-leisure shopping malls accessibility indices. This leads to a certain degree of bias in the variable estimates.

6. The GWR model results

6.1. Characteristic variables

To further discuss the spatial heterogeneity of the impact of accessibility to shopping malls on housing prices, a GWR model is introduced in this section. The accessibility index is calculated using the GM ($\beta = 1.0$), due to its better performance in Section 5. The variable S_j is equal to the total floor area of shopping mall j. The accessibility composite index's regression results of all characteristic variables are shown in Table 3. The adjusted R^2 reaches 0.743, and the AICc reached −651.995, both of which are superior to the hedonic price model. Therefore, compared with the hedonic price model, the GWR model can better explain the relationship between housing prices and characteristic variables.

6.2. Spatial heterogeneity of accessibility index by type

The regression results of all accessibility indices are shown in Table 6. This study further graphically expresses the regression results of the accessibility index through ArcGIS, as shown in Figs. 4–7. To more intuitively and accurately discuss the impact of different types of shopping mall accessibility indices on housing prices in the different areas of Hangzhou, this study divides the main city area into six parts, according to their orientation. The six parts are the city center, city east, city south, city west, city north and Binjiang District.

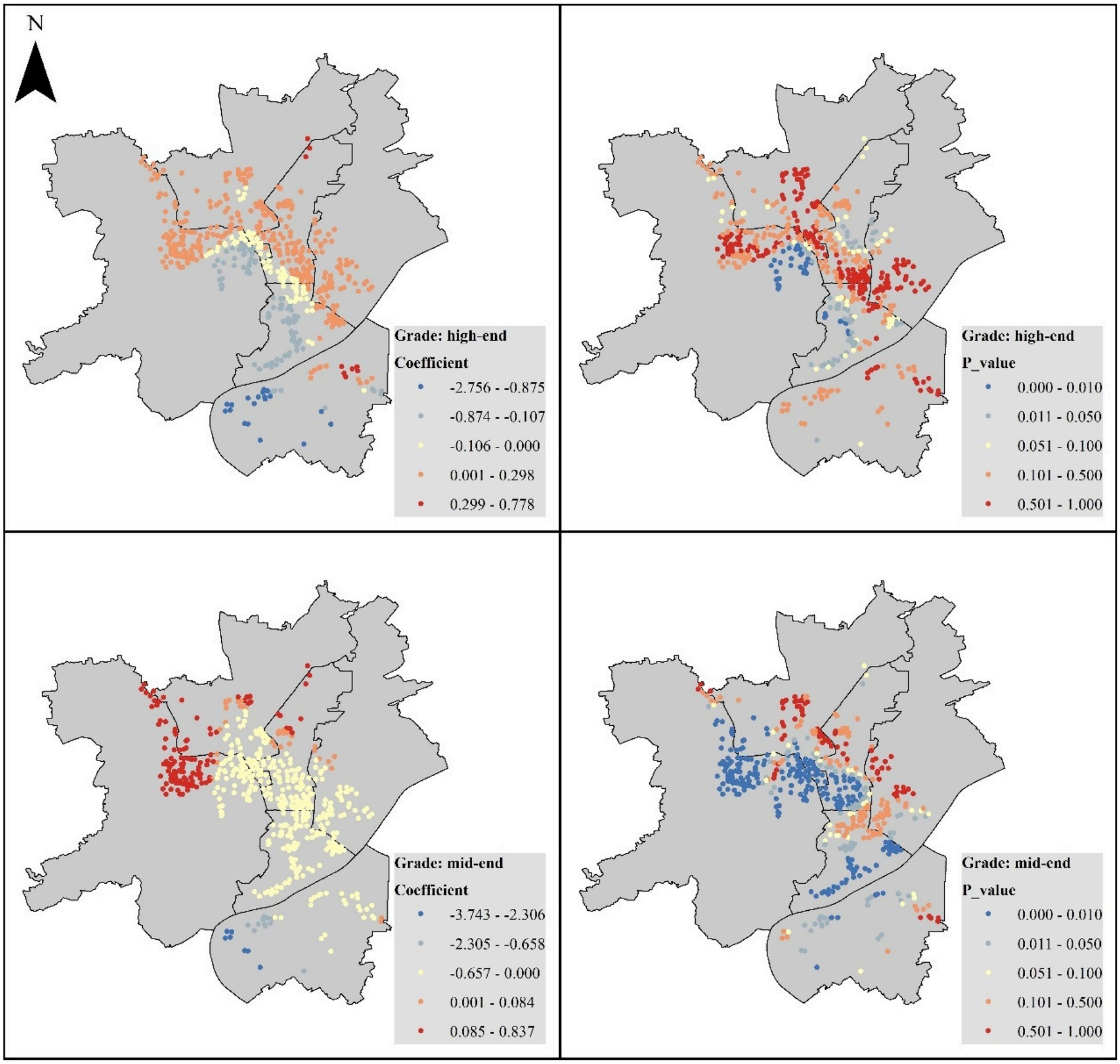

Fig. 6. GWR regression results of accessibility index by grade.

In the city center, the high-leisure accessibility index has a significant positive impact on housing prices. In contrast, many other types of accessibility indices have either no significant impact or even a significant negative impact. The commercial facilities in the city center are largely developed within a concentration of shopping malls, which leads to high accessibility indices and high supply levels for residents living in close proximity to shopping malls. In addition, the shopping malls in the city center are predominantly retail-oriented, underlining the fact that nearly all shopping malls in this area are mid- and low-leisure shopping malls. These results indicate that the high-leisure shopping malls have a greater appeal to the residents of this area, because of the diversity of services and facilities such malls provide.

In the city west and city north areas, the accessibility index of some types of shopping malls has a significant positive impact on housing prices. These areas were developed later than the city center, so commercial facilities are not yet as developed as they are in the city center. Simultaneously, the impact of city center commercial facilities on these areas is relatively weak, due to the excessive distances from these areas to the city center. Therefore, shopping malls in these areas can bring a great level of convenience to residents. In city west, the accessibility of mid-scale and mid-end malls, as well as high-leisure malls, can generate a significant house price appreciation effect. The composite index is also significant in this area, showing that residents in city west are willing to pay more for houses that are conveniently located near shopping and leisure facilities. The number of shopping malls in city north is even less than in city west. Therefore, the residents in the city north area need to travel to other areas to shop. Large-scale, high-end and high-leisure shopping malls are currently better able to meet their shopping needs, which in turn leads to the positive impact of accessibility to these types of shopping malls on housing prices in the city north area.

In city east, city south and the Binjiang District, the impact of various types of shopping mall accessibility indices on housing prices is either not significant or is significantly negative. The southeast part of the city east area that is near the Qiantang River is the Qianjiang Center area. This is a sub-center of Hangzhou that is dominated by office buildings, while the city south area is close to the West Lake scenic area and the Qiantang River. Residents in these areas are more concerned with the area's development potential or the local scenic resources. Therefore, they pay less attention to shopping malls when buying a house. The Binjiang District is separated from other areas of Hangzhou by the Qiantang River. Although several bridges connect this district to other areas, there are still obvious geographical barriers that make it

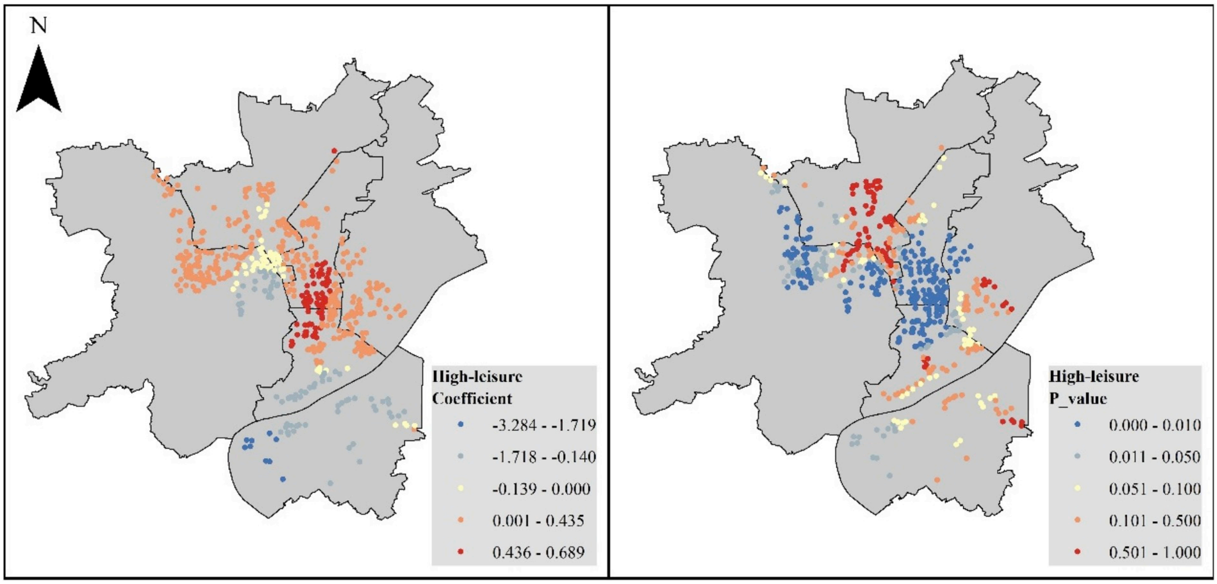

Fig. 7. GWR regression results of accessibility index by tenant mix.

inconvenient for residents to go shopping outside the Binjiang District. Therefore, the accessibility index calculated by road distance rather than time cost may be overestimated, resulting in insignificant or even negative impacts on housing prices.

7. Conclusions

Shopping malls have always been an important topic in the field of real estate economy. However, previous studies have not sufficiently addressed the impact of shopping malls on housing prices. These studies do not consider the diverse impact of shopping malls with different types or locations. This study addresses these gaps, analyzing the different influences of different shopping mall types, and examining the heterogeneity impact on housing prices. First, the study processes shopping mall data in two ways, as follows: 1) This paper uses two gravity-based models to build the shopping mall accessibility index. 2) Shopping malls are classified by scale, grade, and tenant mix. Second, this study uses the hedonic price model to explore the different impacts of different types of shopping mall accessibility on housing prices on a whole-city level. Finally, the geographically weighted model is used to analyze the spatial heterogeneity of the impact of spatial accessibility to shopping malls on housing prices.

This research led to three main results: 1) The original gravity-based model (GM) is more accurate in characterizing the accessibility to shopping malls, compared to the developed one. This is because the GM model is more stable, is less affected by the distance decay parameter β and has a high degree of interpretation of housing prices. 2) There are significant differences in the impact of different types of shopping mall accessibility indices on housing prices. This study finds that accessibility to large-scale, high-end, and high-leisure shopping malls positively impacts housing prices, while accessibility to small and mid-scale, low and mid-end, mid and low-leisure shopping malls exert either no impact or even a negative impact. 3) The impact of accessibility to shopping malls on housing prices is spatially heterogeneous, because of different degrees of urban development, geographical features, etc.

This study provides important implications for those involved in urban economic development and urban planning. The accessibility index makes it possible to visually discover the optimum distribution of shopping malls in the city. The empirical research on the residential market further reflects the interaction between shopping malls and housing prices. According to these findings, the government can rationally map out commercial land and residential land in the city, thereby helping make the convenience provided by shopping malls to be more evenly and reasonably distributed. When urban resident preferences are known, residential property developers can intuitively obtain the shopping mall accessibility index of the developing plots, allowing for better market positioning and pricing. Commercial property developers and shopping mall managers can better analyze the needs of residents in some urban plots, and optimize the tenant mix and market positioning of shopping malls accordingly. In addition, these conclusions also provide very important reference points for home buyers in terms of surrounding shopping malls and other related facilities.

This study also has some limitations. First, because of a lack of data and the difficulties associated with measurement, shopping mall quality cannot be completely considered (such as atmosphere, infrastructural facilities and so on). Second, this paper only studies the real estate market in 2014, and does not consider the change in the impact of spatial accessibility to shopping malls on housing prices over time. In particular, the paper does not address whether newly-built shopping malls significantly impact the accessibility index and housing prices of local areas. These issues will be further studied in the future by establishing a spatial-temporal model. The results of this paper on the type of shopping malls and spatial heterogeneity provide a basis for further research.

CRediT authorship contribution statement

Ling Zhang: Conceptualization, Methodology, Formal analysis, Supervision. **Jiantao Zhou:** Conceptualization, Methodology, Formal analysis. **Eddie Chi-man Hui:** Conceptualization, Supervision.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.habitatint.2020.102118.

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