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Spatial effects of accessibility to parks on housing prices in Shenzhen, China

Chao Wu [a], Xinyue Ye [e], Qingyun Du [a, b, c, d], Ping Luo [f, *]

[a] School of Resources and Environmental Science, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
[b] Key Laboratory of GIS, Ministry of Education, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
[c] Key Laboratory of Digital Mapping and Land Information Application Engineering, National Administration of Surveying, Mapping and Geoinformation, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
[d] Collaborative Innovation Center of Geospatial Technology, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
[e] Department of Geography, Kent State University, Kent, OH 44242, United States
[f] Shenzhen Research Centre of Digital City Engineering, Shenzhen 518034, China

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ABSTRACT

Accessibility to parks could be an important determinant of housing prices. This article applies the gravity model to calculate accessibility based on park classification in Shenzhen, China. Unlike most traditional studies that use the ratio method and nearest distance (including straight-line distance and network distance) to measure accessibility to given facilities, in this study, we use gravity-based accessibility by park type. Then, we explore the relationships between accessibility to parks and housing prices using a hedonic price model. In addition, we apply a geographical detector method to assess the association between housing price and related factors. The results indicate the following conclusions: (1) compared to traditional methods, the gravity model provides a more effective and objective measure of accessibility to parks because it considers distance decay effects, supply, and demand; (2) it is necessary and important to investigate the effects of the accessibility to different park types on housing prices; and (3) geographical detector models can efficiently detect correlations and interactions among housing prices and related factors.

1. Introduction

The implementation of housing commercialization and housing subsidy monetization policies has resulted in an active and energetic housing market in China (Wei, Lam, Chiang, & Leung, 2014). Buyers tend to pursue high-quality living environments as their living standards improve. A park is an important type of green space with ecological, entertainment, recreational, social, and cultural functionality. Vegetation in parks can absorb atmospheric carbon, maintain a particular degree of humidity in the atmosphere, and moderate temperature. Furthermore, green space can reduce noise by functioning as acoustic screens between roads and residential areas (Morancho, 2003). Therefore, important contributions can be made to control housing prices, analyse spatial equity and guide urban planning by scientifically examining the effects of parks on housing prices.

In recent years, numerous scholars in China and abroad have conducted empirical research regarding the effects of parks on real estate values in different cities. A pioneering study of the impact of parks on real estate was performed by Hammer, Coughlin, and Horn (1974), who found a statistically significant increase in land value with increasing proximity to parks. Many subsequent studies have focused on the valuation of various green spaces. Anderson and Cordell (1988) noted that landscaping with trees can increase sale prices. Furthermore, More, Stevens, and Allen (1988) used three methods to evaluate the value of urban parks and concluded that urban parks had an active influence on housing values. Tyrväinen (1997) indicated that large urban forests had a positive influence on apartment prices, whereas the effect of small forest parks was unclear. Tyrväinen and Miettinen (2000) and Thorsnes (2002) revealed that the price of a house increases with increasing proximity to nearby parks. Morancho (2003) revealed an inverse relationship between housing price and the distance from a green urban area. Jiao and Liu (2010) showed that city-level parks

* Corresponding author.
E-mail address: fsluop@163.com (P. Luo).

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have significant amenity values, whereas district-level parks do not. Panduro and Veie (2013) classified green spaces into different types and investigated the valuation of different types on housing values. Wu, Wang, Li, Peng, and Huang (2015) noted that proximity to a park increases housing prices. Prior studies, however, have primarily relied only on distance as a measure of accessibility and treated all types of parks equal. Thus, these studies did not fully capture the attractions of different parks from the perspective of supply and demand. Simultaneously, related studies that used the hedonic price model (HPM), spatial regression model (SRM), geographical regression model (GWR) and eigenvector spatial filtering (ESF) revealed the effects and relative degrees of importance of influential factors. However, no study to date has focused on the relationships and interactions among factors from a real estate perspective. The geographic detector (GD) is a spatial statistical approach that can be used to explore the relationships and interactions among independent variables but has never been employed in a housing price study (Wang et al., 2010).

According to previous research, the proximity to parks also generates differential effects on nearby real estates. We examine the combined effects of accessibility to parks based on a classification using the gravity model and explore the relationships and interactions between variables using the GD. The remainder of this article is organized as follows. Section 2 provides an overview of the findings from previous studies. Section 3 describes the study area and data sources. Section 4 illustrates the methodology, including the gravity model and geographic detector method used to examine the effects of parks on housing prices. Section 5 presents the research results. Finally, conclusions are presented in Section 6. The data and analysis tools used in this study include ArcGIS 10.2, SPSS 19, and GeoDetector.

2. Literature review

Accessibility to parks can affect the surrounding environment because parks provide entertainment venues to which buyers are attracted. Therefore, the effects of parks on housing prices have been thoroughly studied by scholars. However, previous studies of the effects of parks on housing prices mainly focused on quantitative measures and regression models.

First, accessibility is an important topic in various fields, and it refers to the quantitative ease associated with overcoming an obstacle to reach a destination, such as the distance, travel time, or travel cost to a location or service facility (Comber, Brunsdon, & Green, 2008). Land use and location theory suggests that accessibility is an important determinant of residential land values and changes in those values. In previous studies, the most commonly used method to measure accessibility to parks was based on the shortest distance, including straight-line distance (Ardeshiri, Ardeshiri, Radfar, & Shormasty, 2016; Poudyal, Hodges, & Merrett, 2009), network distance (Lu, Charlton, Harris, & Fotheringham, 2014), and cost-weighted distance (Kong, Yin, & Nakagoshi, 2007). Most studies focused on the distance to urban parks or the proportion of open space within a real estate buffer to measure their effects on housing prices. However, measuring accessibility not only involves determining the shortest OD (origin to destination) distance but also the attractiveness of the destination and the demand of an origin. Therefore, scholars have not been limited to simple measures of accessibility but rather tend to use more suitable calculation methods, such as the cumulative opportunities measure (Cordera, Coppola, dell'Olio, & Ibeas, 2016; Handy & Niemeier, 1997), locational profile approach (Sohn, Choi, Lewis, & Knaap, 2012), kernel density method (Guagliardo, 2004) and gravity model (Hansen, 1959). Gravity models, or potential models, are widely used to study socioeconomic spatial interactions and are based on Newton's law of universal gravitation. Hansen (1959) was the first to use a gravity model to measure accessibility. Guagliardo (2004) argued that gravity models provide the most reliable measure of spatial access, whether potential or actual. Geurs and Van Wee (2004) identified four types of accessibility: land use, transportation, temporal and individual. They concluded that the gravity model can be easily computed using existing land-use and transport data and/or models that are traditionally employed as input for estimating infrastructure-based measurements. Gravity-based accessibility has important advantages in capturing supply and demand features while considering distance decay effects, which have previously been studied most often in the medical field (Schuurman, Bérubé, & Crooks, 2010) and have rarely been used to measure accessibility to forests or urban and community parks in real estate studies.

Second, planners and park managers often use HPM to examine whether and how (positively or negatively) park proximity is incorporated into housing values while holding other housing factors and neighbourhood attributes constant (Payton & Ottensmann, 2015). HPM is a popular and effective quantitative method used to precisely estimate the marginal prices (as defined by Cropper, Deck, & McConnell, 1988) of various factors. The HPM was first used in the field of real estate and urban economics by Rosen (1974). Thereafter, an increasing number of researchers began to use HPM to measure and evaluate the impact of various factors on housing prices in China (Jim & Chen, 2007, 2009a, 2009b; Wen & Jia, 2004; Wen, Jia, & Guo, 2005; Wu, Deng, & Liu, 2014) and in other countries (Ali, Bashir, & Ali, 2015; Benson, Hansen, Schwartz, & Smersh, 1998; Gibbons, Mourato, & Resende, 2014; Kassie, Abdulai, & Wollny, 2011; Selim, 2011; Seo, Golub, & Kuby, 2014; Wheeler, Páez, Spinney, & Waller, 2014). Previous studies using HPM to examine housing prices typically classify the influential variables into different categories—such as structural variables, neighbourhood characteristics, and market and environmental variables—and use them as independent variables (Ali et al., 2015; Poudyal et al., 2009; Wen & Jia, 2004; Wu et al., 2015). In this model, the market values of various factors are inferred by estimating the sales price of a property as a function of various attributes (such as accessibility to green space and the central business district (CBD)) in association with other characteristics (Jim & Chen, 2006). Overall, different studies have roughly similar categories for their particular area of emphasis, providing a reference for our work to classify the variables according to our focus. Although HPM is widely used in housing price studies, it can only be applied to explore the quantitative relationships between factors and housing prices. Clarifying the relative degrees of importance of various factors and the interactions between these factors and housing prices is also very important. The GD is a spatial statistical method that can be used to analyse the effects of geographical spatial factors on human health (Wang et al., 2010), land use (Liang & Yang, 2016), and socioeconomics (Yansui & Ren, 2012). The GD has been widely used in many fields because it is based on simple assumptions and can identify the relative importance of various factors and the interactions among these factors.

Based on the above discussion, few studies have focused on the access to different types of parks by applying an HPM and GD simultaneously from the perspective of supply and demand. Therefore, this study assesses the relationships between residential property sale prices and parks by type using a gravity-based model. In addition to common traditional regression models, we use the GD to extract the interrelationships among accessibility to parks by type and the relative importance of factors to housing prices. By exploring the premiums associated with different types of parks based on spatial equity and identifying the interactions between different factors, we comprehensively explore the links between parks and housing prices. Moreover, the distribution of park accessibility can be used to explore the spatial equity of public facilities in urban planning and management.

3. Study area and data sources

Shenzhen (22°27′–22°52′N, 113°46′–114°37′E) is a rapidly developing city in southern Guangdong Province, China. It covers an area of 1996.85 km^2 and had a residential population of 10.7789 million as of 2014 (Shenzhen Statistics and Information Bureau, 2014). Originally a county, Shenzhen is now a special economic zone (SEZ) with 10 districts (eight administrative regions and two functional zones), 57 sub-districts, and 726 communities. Shenzhen was the first SEZ established since China's reform and 'expansion' (Hao, Sliuzas, & Geertman, 2011), and it has experienced rapid urbanization since the mid-1980s, the so-called window of economic reform (Quan, 2006; Sui & Zeng, 2001). Shenzhen was the first city in China selected for promotion of the real estate market. Currently, "hot real estate" has become a trend in Shenzhen and has attracted considerable attention from the government, business enterprises, and other entities (Wu et al., 2016). As such, Shenzhen was chosen as the study area in the present study.

Shenzhen serves as one of China's emerging cities. In its pursuit of economic development, Shenzhen has sought to incorporate green construction and has received the titles of "International Garden City" and "National Garden City," among others. Moreover, Shenzhen's liveable index is ranked ninth of the 40 cities in China released by the Chinese Academy (Zhang, Yin, Zhang, Meng, & Gao, 2016). Shenzhen is planning a comprehensive tertiary park system that includes forest parks, city parks, and community parks (Fig. 1). Table 1 summarizes the types and descriptions of these parks. Different park sizes and types have different subjectivity functions and service radii for residents. Thus, it is reasonable to investigate the effects of accessibility to different types of parks.

Transaction price data for 3047 dwelling units (72 real estate properties) from September 2014 to December 2014 were collected from the Shenzhen Research Centre of Digital City Engineering, and attributes such as apartment size, floor height, number of bedrooms, number of bathrooms, property fee, floor area ratio and landscaping ratio were collected from the SOFANG website (SOFANG, 1999). Geographic information system (GIS) was used to measure other characteristic variables, such as distance to the CBD (the CBD of Shenzhen is enclosed by four main urban roads, namely, Riverside Avenue, Lianhua Road, Caitian Road, and Xinzhou Road) and to the nearest metro station, bus station, hospital, school, and supermarket. The market for housing sales varies dramatically, and housing prices fluctuate considerably. To minimize the effect of parameter instability, this study utilizes a short time period for the analysis, and the period of trading data is short. Thus, it is reasonable to ignore the influence of time on price. To avoid potential biases, the scope of the study is limited to ordinary commercial housing, and duplex apartments and cottages are excluded.

Before model estimation, the data were pre-processed (data cleaning and collinear data processing) to remove any abnormal values. We obtained 3007 complete records representative of the housing in Shenzhen. Based on previous studies and the conditions in Shenzhen, 18 independent variables were chosen. They were divided into three categories: structural attributes, locational attributes, and accessibility variables relevant to our study focus. Structural attributes describe the internal properties of a house. In this study, the size of the house (APARTSIZE), floor level (FLOOR), number of bedrooms (NBEDROOM), number of bathrooms (NBATHROOM), property management fee (FEE), plot ratio of the real estate (RPLOT), and green space ratio of the real estate (RLANDSCAPE) are considered structural attributes. Locational attributes include variables associated with the distance to services, such as the distance to the CBD (DCBD) and to the nearest metro station (DMETRO), bus station (DBUS), hospital (DHOSPITAL), nursery school (NSCHOOL), primary school (PSCHOOL), middle schools (MSCHOOL), and supermarket (SUPERMARKET). Accessibility attributes can be divided based on accessibility to different

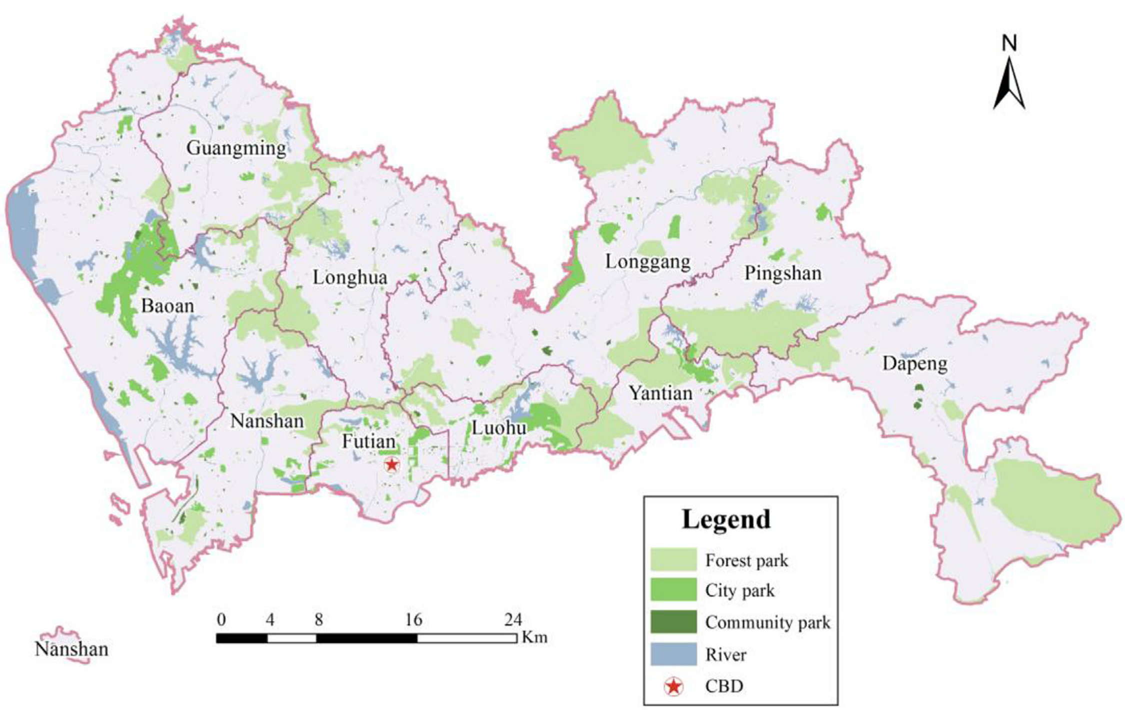

Fig. 1. Study area and distribution of parks in Shenzhen.

Table 1
Types and descriptions of parks in Shenzhen.

Type	Description	Number
Forest park	An important part of the ecological resource protection system in which construction prioritizes protection	50
City park	An important part of the urban landscape that can provide rest, travel, exercise, and communication services	88
Community park	The nearest open space that provides public services for community residents	758

types of parks (AFORESR, ACITY, and ACOMMUNITY) to support the focus of this study. The descriptive statistics, variable definitions, and expected effect signs are presented in Table 2. Notably, the expected effect signs of variables are "+" or "-" based on previous studies. This article uses "unknown" for variables that had inconsistent effects in previous studies or were not previously considered.

4. Methodology

4.1. Accessibility to parks

Accessibility to parks in this article is defined as the level of difficulty associated with residents accessing parks. We use a gravity model to calculate the accessibility to parks by type in Shenzhen based on the distance decay effect and supply and demand. Hansen (1959) introduced the gravity model as a measure of accessibility, and the model has been widely used in housing price studies, for example, to measure accessibility to transportation, jobs and retail stores (Ibeas, Cordera, dell'Olio, Coppola, & Dominguez, 2012; Jang & Kang, 2015; Kok, Monkkonen, & Quigley, 2014; Martínez & Viegas, 2009). However, it has not been applied to a case study that focuses on forest, urban and community parks from a real estate perspective. Like the subjects of previous studies, parks have many attributes, such as area, landscape layout, and facilities that attract residents. Therefore, it is reasonable to use a gravity model to measure park accessibility. To establish a unified index to express park attraction by type, we use the area of parks to represent the attractiveness of parks based on the results of Troy and Grove (2008) and Poudyal et al. (2009), who found that large parks appeal to more people. This demand factor is calculated based on the population of each community census tract. Because a community is the smallest census tract in Shenzhen, community-level information is used to analyse the accessibility to parks, produce accurate results, analyse spatial equality, and guide urban planning. The equations used to calculate the accessibility index of the community are as follows:

$$A_i^G = \sum_{j=1}^{n} \frac{S_j}{D_j d_{ij}^{\beta}} \tag{1}$$

$$D_j = \sum_{k=1}^{m} \frac{P_k}{d_{jk}^{\beta}} \tag{2}$$

where A_i^G is the accessibility of the i th community, j is the corresponding park, and n is the total number of each type of park. S_j represents the area of park j, d_{ij} is the network distance between the i th grid and j th park, D_j is the demand for the j th park, m is the total number of communities in Shenzhen, P_k is the population of the k th community, d_{jk} is the network distance between the j th park and k th community, and β is the decay distance parameter. In this study, the coefficient β is set to 2 based on previous studies (Arbia & Petrarca, 2013; Luo & Wang, 2003; Peeters & Thomas, 2000). Fig. 2 illustrates the accessibility to parks by type for each community.

4.2. HPM and GD

The determination of the value of non-market-priced recreational resources to society is not a new concept to economists (Cho, Lambert, Kim, Roberts, & Park, 2011; Price, 2000). HPM has been widely used to study the marginal prices of housing factors and is based on actual transactions (Hidano, 2002; Ready, Berger, & Blomquist, 1997). The values of the influential factors are inferred by estimating the sales price or the value of a property as a function

Table 2
Measurement methods and housing characteristic variables.

Variable	Variable definition and measurement method	Mean	Std.	Expected sign
Structural attributes				
APARTSIZE	Square footage of the living area (m2)	93.04	23.44	+
FLOOR	Floor on which the unit is situated (floor)	17.14	8.73	+
NBEDROOM	Number of bedrooms in unit	3.11	0.85	+
NBATHROOM	Number of bathrooms in unit	1.63	0.56	Unknown
FEE	Property management fees (RMB/Mon·m2)	3.32	0.49	+
RPLOT	Ratio of the floor area of the real estate	3.92	1.10	−
RLANDSCAPE	Ratio of the green space area of the real estate	0.34	0.91	+
Locational attributes				
DCBD	Distance to the CBD (km)	25.04	10.29	−
DMETRO	Distance to the nearest metro station (km)	2.33	1.87	−
DBUS	Distance to the nearest bus station (km)	0.21	0.16	−
DHOSPITAL	Distance to the nearest hospital (km)	1.38	0.64	Unknown
NSCHOOL	Distance to the nearest nursery school (km)	0.93	0.56	−
PSCHOOL	Distance to the nearest primary school (km)	1.01	0.32	−
MSCHOOL	Distance to the nearest middle school (km)	0.96	0.45	−
SUPERMARKET	Distance to the nearest supermarket (km)	1.08	0.65	−
Accessibility attributes				
AFOREST	Accessibility to forest parks	2.15	0.52	+
ACITY	Accessibility to city parks	0.48	0.32	+
ACOMMUNITY	Accessibility to community parks	0.004	0.003	+

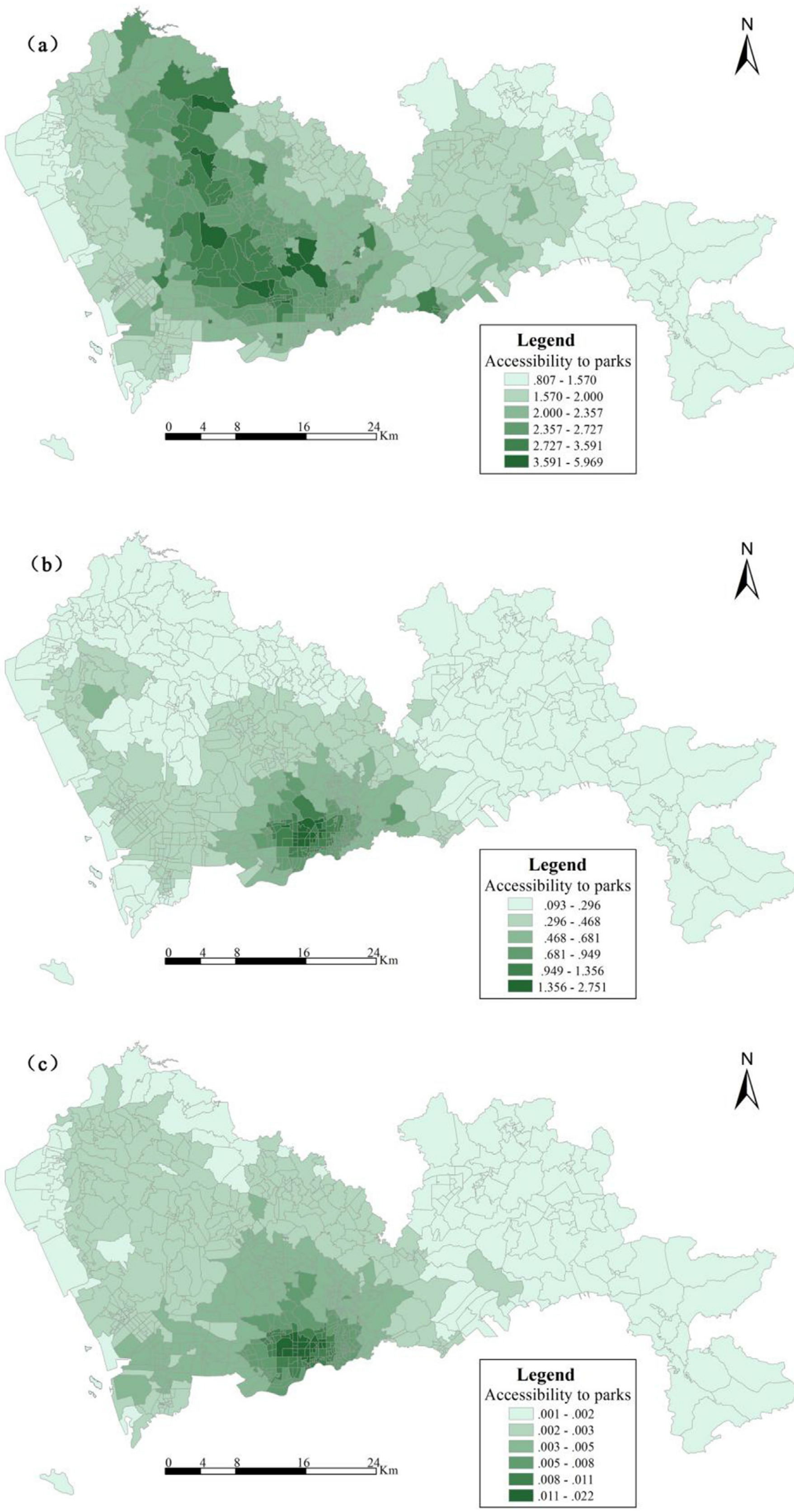

Fig. 2. Spatial accessibility to parks in Shenzhen: (a) forest parks, (b) city parks, and (c) community parks.

of the attributes, such as accessibility to parks, in association with other characteristics (Jim & Chen, 2006). Since the HPM was first proposed by Rosen (1974), the model has become a classic method for studying the economic value of local public goods. HPM can reveal the implicit prices of the attributes of a house, the total of which is the hedonic price (Rosen, 1974). We use a semi-logarithmic function in this study. Malpezzi (2003) highlighted the following advantages of the semi-logarithmic functional form: (1) the implicit price of a housing attribute is related to the quantity of the other housing attributes; (2) the estimated coefficients can be interpreted in terms of semi-elasticity; (3) this form can address and mitigate heteroskedasticity problems; and (4) it can be computed easily. Thus, we use a typical hedonic equation of housing price in a semi-logarithmic form, as shown in Equation (3):

$$\ln P_i = \beta_0 + \sum \beta_j S_{ij} + \sum \beta_k L_{ik} + \sum \beta_l A_{il} + \varepsilon_i \tag{3}$$

where P_i is the market price of the housing, S_{ij} represents the structural attributes, L_{il} represents the locational attributes, and A_{ik} represents the accessibility attributes. β_0 is the intercept value, and β_j, β_k, and β_l are estimated coefficients for the structural, locational, and accessibility attributes, respectively. β_j, β_k, and β_l also indicate the semi-elasticity of corresponding variables. For example, under the condition of other variables being invariable, the estimated coefficient represents the percentage of residential price variations that corresponds to the united attribute changes in the semi-log model.

The GD is used to quantify the driving mechanisms of housing prices. It is a creative integration of various dominant factors combined with logical reasoning and existing statistical techniques (Wang et al., 2010). The GD has been widely used in the fields of health science (Wang et al., 2010), disaster assessment (Hu, Wang, Li, Ren, & Zhu, 2011), land use (Liang & Yang, 2016), and socio-economics (Yansui & Ren, 2012) but is only rarely used in housing price studies. In this study, we use the GD to address the spatial effects of housing factors and to reveal the interactions among accessibility variables. Unlike the traditional regression model, the GD does not rely on any hypotheses, such as the homogeneity of variances or independent error (Wang et al., 2010). The mechanism of the GD is measured by the Power of Determinant (PD) (also called the q-statistic) (Wang, Zhang, & Fu, 2016), as shown in Equation (4):

$$P_{D,H} = 1 - \frac{1}{N'\sigma_H^2} \sum_{w=1}^{m} n_{D,w} \sigma_{H_{D,w}}^2 \tag{4}$$

where $P_{D,H}$ is the power of determinant of factor D associated with the housing price, σ_H^2 is the variance of the housing price in Shenzhen, and $\sigma_{H_{D,w}}^2$ is the variance of the housing price in a parcel. N' represents the total number of samples in this study, and $N' = 3007$. $n_{D,w}$ denotes the sample number of the w th parcel. The value of PD lies within $[0, 1]$, which reflects the impact of a factor on the housing price. The larger the value of PD is, the greater the impact of factor D on the housing price. The GD includes four functions:

(1) The risk detector (RD) is used to determine whether the housing price in a parcel is significantly different when the study area is stratified by various factors. If the result of two stratums is "Y", then there are significant differences between these two stratums that influence housing prices. In contrast, if the result of two stratums is "N", then the difference may be caused by system error.

(2) The factor detector (FD) quantifies the effects of housing variables based on the q-statistic, i.e., PD in Equation (4), and can be written as Equation (5):

$$q = 1 - \frac{\sigma_{D,p}^2}{\sigma_{D,z}^2} \tag{5}$$

where $\sigma_{D,z}^2 = \frac{1}{n_{D,p}} \sum_{z=1}^{n_{D,z}} \sum_{p=1}^{n_{z,p}} (y_{z,p} - \overline{y_z})^2$ is the stratified global dispersion variation; $\sigma_{D,p}^2 = \frac{1}{n_{D,p}} \sum_{p=1}^{n_{D,p}} (y_{D,p} - \overline{y_D})^2$ represents the observed spatial housing price using dispersion variation, and $\overline{y_z}$ and $\overline{y_D}$ are average housing prices within the coverage of factor D and a specific zone stratified by factor D, respectively.

(3) The ecological detector (ED) reveals the difference between the impacts of two housing variables based on the F-value. The F test for the different factors C and D is shown in Equation (6):

$$F = \frac{n_{C,p}(n_{C,p} - 1)\sigma_{c,z}^2}{n_{D,p}(n_{D,p} - 1)\sigma_{D,z}^2} \tag{6}$$

where $n_{C,p}$ and $n_{D,p}$ denote the number of sample units p within the coverage of factors C and D, respectively. If factor C is more likely than factor D to influence housing prices in Shenzhen, then $\sigma_{c,z}^2$ would be larger than $\sigma_{D,z}^2$.

(4) The interaction detector (ID) identifies whether two or more housing variables have an interactive effect on the housing price. The relationship can be defined in a coordinate axis that has 5 intervals, including "$(-\infty, q(x_1))$", "$(min\ q(x_1), q(x_2)), (\ max\ q(x_1), q(x_2))$", "$(min\ q(x_1), q(x_2)), (\ q(x_1) + q(x_2))$", "$q(x_1) + q(x_2)$", and "$(q(x_1) + q(x_2), +\infty)$". The descriptions and interaction relationships are presented in Table 3.

In this article, we focus on the accessibility to different types of parks and the associated effect on housing price. Therefore, we use the GD results to analyse the relationships and interactions among ACOMMUNITY, ACITY, and AFOREST in Section 5.

5. Results

5.1. Effects of park accessibility based on HPM

We present the HPM results estimated using the OLS model in Table 4. Then, we check the sign and statistical significance of the coefficients by referring to existing studies. The explanatory variables account for 80.2% of the housing variance in the HPM. The computed VIF values do not exceed the threshold value of 10, indicating the absence of multicollinearity between the variables in the model. CBD, FEE, NSCHOOL, SUPERMARKET, ACOMMUNITY, ACITY, NBEDROOM DMETRO, APARTSIZE, PSCHOOL, FLOOR, RPLOT, DBUS, DHOSPITAL, MSCHOOL, and AFOREST all have statistically significant effects on housing value at the 1% level.

Notably, the various factors listed in Table 4 all have significant influences on housing prices in Shenzhen at the 1% level. The marginal effects of accessibility to parks based on the gravity model are derived from the coefficients of the HPM. As noted in the previous section, the effects of park accessibility are compared among different park types.

The accessibility to community parks has a positive significant effect on the surrounding real estate and results in a 54% premium.

Table 3
Descriptions and interaction relationships.

Description	Result representation	Interaction relationship
$q(x_1 \cap x_2) < \min(q(x_1), q(x_2))$		Weakened, nonlinear
$\min(q(x_1), q(x_2)) < (x_1 \cap x_2) < \max(q(x_1), q(x_2))$		Weakened, uni-
$q(x_1 \cap x_2) > \max(q(x_1), q(x_2))$		Enhanced, bi-
$q(x_1 \cap x_2) = q(x_1) + q(x_2)$		Independent
$q(x_1 \cap x_2) > q(x_1) + q(x_2)$		Enhanced, nonlinear

Note:

$\min(q(x_1), q(x_2))$; $\max(q(x_1), q(x_2))$; $q(x_1)+q(x_2)$

Table 4
Results of the hedonic price model.

Variable	Coefficient	p-value	VIF
Constant	0.0000	1.000	
APARTSIZE	0.0617***	0.000	1.75
FLOOR	0.0516***	0.000	1.04
NBEDROOM	0.0596***	0.000	2.14
FEE	0.4435***	0.000	1.52
RPLOT	−0.0661***	0.000	1.86
DCBD	−0.3353***	0.000	4.66
DMETRO	−0.1502***	0.000	2.64
DBUS	−0.0510***	0.000	1.61
DHOSPITAL	−0.0563***	0.000	1.71
NSCHOOL	−0.2326***	0.000	2.38
PSCHOOL	0.1225***	0.000	1.75
MSCHOOL	0.0369***	0.000	1.42
SUPERMARKET	0.1273***	0.000	1.54
AFOREST	−0.0404 ***	0.006	3.27
ACITY	0.3223***	0.000	5.17
ACOMMUNITY	0.5400***	0.000	3.48
	$R^2 = 0.802$	SE = 0.44	

***indicates significance at the 1% level.

Thus, high accessibility to community parks generally increases the housing price. The main function of community parks is providing people with a place for entertainment and exercise. Therefore, community parks directly improve the daily living standard.

The distance from a house to the nearest city park is positively related to housing price. The coefficient of regression suggests that a one-degree increase in accessibility from an address to the nearest city park is associated with a 32.23% increase in housing price, ceteris paribus. This result demonstrates that homebuyers place considerable importance on the proximity to city parks. Most city parks not only function as community parks but also have positive and unique qualities. For example, Lotus Hill Park and Wutong Mountain Park are two of the most popular city parks in Shenzhen. Lotus Hill Park has Deng Xiaoping's statue in the square at the top of the mountain, and Wutong Mountain Park is the highest peak in Shenzhen, which attracts many residents and boosts the surrounding housing prices.

Unlike the trends associated with community and city parks, the accessibility to forest parks has a negative effect on the housing price. With each 1-degree increase in the accessibility to a forest park, the housing price decreases by 4.04%, as shown in Table 4. Forest parks are an important part of the city environment and urban development. However, most forest parks are distributed in the suburbs of Shenzhen, often in areas with limited transportation and convenience. The proportion of forest parks (area of forest parks/area of the district) in Shenzhen is the largest of all the Yantian districts. Yantian is the only district in Shenzhen with no subway stations. Additionally, if too many people visit forest parks, it can create traffic congestion, which decreases housing prices. Meanwhile, forest parks with large areas may lead to poor public order and sanitary conditions (Troy & Grove, 2008).

5.2. Effects of park accessibility based on GD

According to the GD results, there are four GD indexes that measure the interaction relationships among the variables, as follows.

5.2.1. Factor detector

The FD quantifies the impact of housing variable D based on the *q*-statistic. We use the FD to determine which geographic parameter among ACOMMUNITY, ACITY, and AFOREST is the most important factor associated with housing prices. Table 5 shows the effects of variables based on the *q*-statistic (FD) in sequence. From Table 5, we can conclude that the three factors all significantly affect housing prices, although the extents of these effects vary. The influences of the three accessibilities can be ranked as follows: accessibility to community parks (90.48%)>accessibility to city parks (90.36%)> accessibility to forest parks (90.31%). Accessibility to community parks has the greatest influence on housing prices because it has the highest FD among the three. Accessibility to city parks is the second most important factor, which means that city parks also have obvious effects on housing prices. Accessibility to forest parks has the least influence of the three factors, which is consistent with the cognitive perceptions.

5.2.2. Interaction detector

The ID is used to detect the influence of interactions between two factors and to determine whether two influential factors work independently. In this article, the interaction relationship between the two factors is bivariate enhanced or nonlinear enhanced. Table 6 shows the interaction relationships among AFOREST, ACITY and ACOMMUNITY, which are the focus of our work. The interactive effect between ACOMMUNITY and ACITY (0.904893) is stronger than those between ACOMMUNITY and AFOREST (0.904877) and ACITY and AFOREST (0.903823). Tables 5 and 6 also show that the relationship between two accessibilities is bivariate enhanced (shown in the results as “enhanced, bi-”). The combinations of accessibility to different parks have enhanced effects on housing prices: (ACOMMUNITY∩ACITY)(0.904893)>Max(ACOMMUNITY, ACITY)(0.904861), (ACOMMUNITY∩AFOREST)(0.904877)

Table 5
Results of the factor detector analysis between housing prices and impact factors.

Variable	*q*-statistic	p-value
NSCHOOL	0.933604	0.000
MSCHOOL	0.933295	0.000
PSCHOOL	0.931149	0.000
DCBD	0.928028	0.000
SUPERMARKET	0.926043	0.000
DBUS	0.908197	0.000
DHOSPITAL	0.905742	0.000
ACOMMUNITY	0.904861	0.000
ACITY	0.903642	0.000
AFOREST	0.903060	0.000
DMETRO	0.896521	0.000
APARTSIZE	0.861375	0.000
FEE	0.719427	0.000
RLANDSCAPE	0.572903	0.000
RPLOT	0.544492	0.000
NBEDROOM	0.070723	0.000
NBATHROOM	0.06387	0.000
FLOOR	0.061023	0.9947

Table 6
The results of ID.

	ACOMMUNITY	ACITY	AFOREST
ACOMMUNITY			
ACITY	0.904893		
AFOREST	0.904877	0.903823	

Description	Result representation	Interaction relationship
AFOREST ∩ ACITY		Enhanced, bi-
AFOREST ∩ ACOMMUNITY		Enhanced, bi-
ACITY ∩ ACOMMUNITY		Enhanced, bi-

>Max(ACOMMUNITY, AFOREST)(0.904861), and (ACITY∩AFOREST)(0.903823)>Max(ACITY, AFOREST)(0.903642). Compared to the effects of individual accessibility, the interaction among accessibilities to different parks plays a more important role in housing prices. Thus, it is necessary to measure accessibility to parks by type, which is a unique finding of our work.

5.2.3. Ecological detector

The ED (Table 7) shows that differences in PD among ACOMMUNITY, ACITY and AFOREST are statistically significant. By combining the results of FD (Table 5) and ED (Table 7), we find that ACOMMUNITY, ACITY and AFOREST have substantial effects on housing prices and that the fine distinctions among their effects are statistically significant.

5.2.4. Risk detector

Based on the RD results, we can conclude that most stratums of original factors have significant effects on housing prices. RD can be used to test the statistical significance of the spatial consistency of housing price distribution with suspect geographical strata. The results of RD can be used to guide the division of an area into submarkets by accounting for significant differentiation among the factors.

5.3. Structural and locational variables

FEE, NBEDROOM, FLOOR, RPLOT and APARTSIZE have similar effects and all increase housing prices significantly. However, house prices are not significantly affected by NBATHROOM and RPLOT. We cannot exclude multicollinearity between NBATHROOM and

Table 7
Statistical significance of the PD between two accessibility types based on the ED.

Stat. Sig. Diff	ACOMMUNITY	ACITY	AFOREST
ACOMMUNITY			
ACITY	Y		
AFOREST	Y	Y	

Y indicates the difference between two accessibilities (statistically significant at the 0.05 level).

APARTSIZE. In terms of the greening rate, Shenzhen is well constructed and has a low level of pollution. The residents may not consider the forestation rate given the large environment.

This article selects the Citizen Centre as the CBD of Shenzhen. The overall housing price gradually decreases with increasing distance from the CBD. This result is in accordance with the results of many previous studies (Jim & Chen, 2006; Morancho, 2003). The distance to a metro station has a negative effect on housing price. With each 1-km increase in the distance to a metro and bus station, the housing price decreases by 15.02% and 5.1%, respectively. The distances to public facilities, such as business facilities (e.g., supermarkets), education facilities, and medical facilities (e.g., above-third-level, grade-A hospitals), have varying degrees of influence on housing prices. Distance to the nearest supermarket has a positive effect on the housing price in accordance with previous studies (Jang & Kang, 2015). The results show an inverse relationship between housing price and the distance from the nearest hospital. Additionally, the proximity to a primary school and middle school can decrease the housing price; however, these factors are affected by the school district structure, in which residents value the quality of a school more so than distance. Pre-primary education is not included in compulsory education and residents tend to go to neighbourhood schools. Therefore, proximity to a nursery school can promote housing values.

6. Conclusions

This article analyses the relationship between housing prices and accessibility to parks by type using the HPM and GD. We focus on an innovative method of assessing accessibility to parks called the gravity model. Unlike previous studies that only considered distance or cost-related measures, we measure accessibility to parks based on the distance decay effect, supply, and demand. Additionally, we creatively use the GD to identify the different interactions and impacts of various factors on the accessibility to different types of parks. Different models are used to analyse the influential factors from different perspectives that have not been previously investigated in real estate research. The HPM can explore the overall effects of factors on housing prices based on hedonic theory. The GD evaluates the spatial effects of housing factors and reveals the interactions among all types of variables. The key findings can be summarized as follows.

First, the effect of parks on the housing price is statistically significant in Shenzhen based on the results of the HPM, which are consistent with those of previous studies (Anderson & West, 2006; Brander & Koetse, 2011). Second, the accessibility to community parks and accessibility to city parks have positive effects on housing prices, while accessibility to forest parks has a negative effect. The effects of parks are heterogeneous, and this article has important significance for measuring accessibility based on the gravity model. Finally, the GD reveals the relationships and interactions among factors. This approach has never been used in housing price studies and provides a new perspective for such analyses. The results reveal the need to measure the accessibility to parks by type.

The results have important implications for government departments regarding the development and evaluation of policy. Gravity-based accessibility can reflect the distribution of park resources. This study can guide park planning in the future to better satisfy the fundamental demands associated with enjoying the green and recreational benefits of parks. Considering the household demand and park supply contributes to social equality and promotes the goal of "residents can see green space at the door, and the nearest park is no more than 500 m" In addition to using an HPM, as in previous studies, this article uses a GD to explore the relationships between housing variables and housing prices. Compared to the HPM, the GD requires fewer assumptions and constraints, can identify correlations and interactions among factors, and provides an intuitional scientific basis for controlling and regulating housing prices.

However, our study framework has some limitations. It considers only parks and does not consider other types of facilities, such as schools and hospitals, or other types of green space, such as lakes and green belts (Wen, Zhang, & Zhang, 2014b). In addition, we do not consider the spatial effects of factors on housing values (Li, Ye, Lee, Gong, & Qin, 2016; Wen, Bu, & Qin, 2014a). In follow-up studies, we will address the aforementioned limitations to offer more realistic indications of people's willingness to buy.

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