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The Economic Performance of Urban Sponge Parks Uncovered by an Integrated Evaluation Approach

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Abstract: Climate change and extreme rainfall events pose great pressures on a city's resilience to flooding and waterlogging. Designed as a kind of green infrastructure to manage stormwater, urban sponge parks (USPs) in China have been demonstrated to have ecological and societal benefits, while their landscape economic values lack evaluation. Taking the real-estate choices surrounding six USPs in China as an example, an evaluation framework integrating text mining with housing introduction documents and hedonic price model (HPM) regression with housing prices was constructed to combine the stated preferences and revealed preferences of citizens when purchasing properties. The main findings include the following: (1) USPs do contribute to property appreciation, especially in newer urban areas, although they are not as strong as location and property characteristic factors; (2) the extent of the influence of USPs on houses decreases as the distance increases, with a maximum radius of 3 km; (3) a USP's effects vary according to the urban and environmental context, as HPM with GWR (R^2 ranges from 0.203 to 0.679) outperforms the OLS method (R^2 ranges from 0.149 to 0.491), which evokes the need for more affluent and detailed analyses in the future. This study demonstrates the economic benefits of USPs and provides an evaluation approach based on citizen science data, which could contribute to the policy-making of USPs in China and promote the implementation of Nature-based Solutions.

Keywords: landscape economic value; Nature-based Solutions (NbS); sponge city; housing price; hedonic price model; China

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1. Introduction

Global warming has increased the intensity of urban rainfall and the risk of flood disasters [1], which challenges the capability of a city to cope with climate change and increasingly severe flooding and waterlogging. In response to these problems, China has implemented ecological infrastructure policies [2] and initiated sponge city constructions [3] to promote its cities' resilience and citizens' physical and mental health. As critical components of sponge cities and Nature-based Solutions (NbS), urban sponge parks (USPs) are typically designed under ecological principles of stormwater management, flooding control, and surface water purification [4–6]. Distinct from conventional urban parks that prioritize recreational amenities, USPs integrate more natural elements, such as rivers, wetlands, and native plants, while also providing facilities to meet citizens' basic needs for walks, seating, and lighting [7]. Their objectives encompass restoring damaged habitats and providing ecosystem services.

USPs date back to the late 1990s in China when many urban parks were designed and constructed under ecological principles, such as the Flowing Water Park in Chengdu City [8]

and the Qijiang Park in Zhongshan City [9]. Many parks have been officially constructed under the "sponge" name in the sponge city construction movement since 2015 [10]. Related evaluations of the performance of USPs have focused on ecological dimensions [7], such as recovering contaminated soils [11], reconstructing habitat and species diversity [12], and reducing flood peaks [13], and social dimensions, such as adjusting water environment management objectives to be consistent with users' needs of park services [14], healing citizens' physical and mental disorders, and promoting an inclusive community [15,16]. However, the economic values of USPs do not receive enough attention and are at least not included in the vision of decision-makers [17], which may impair the promotion of USP projects [18].

The economic values of USPs mainly come from two sides, direct and indirect [19,20], as discussed in the theory of landscape economics [21]. A direct value reflects the landscape as a public good for society by improving aesthetic values, while an indirect value is the potential profits from multiple effects of a landscape as an economic asset, such as a landscape triggering other economic activities in a region [19]. Monetary values are the direct values, which are difficult to determine for a landscape, owing to its public good property, whether quantitatively or even qualitatively. In the mid-1970s, landscape architects evaluated economic values from their subjective experiences [22]. After this, more sound quantitative methods developed and could be divided into the behavioural linkage approach and the physical linkage approach [23]. The former uses observations of people's behaviours in actual markets or their survey responses about hypothetical markets, including the stated preference way, such as the political referendum method and the contingent valuation method [24], and the revealed preference way, such as the averting expenditure method, the travel cost method, and the hedonic price method; while the latter is used to estimate benefits based on the relationship between environmental resources and the resource users, such as the damage function method [17,23]. Among these, the hedonic price method reveals people's preferences based on actual market purchasing behaviour using a statistical hedonic price model (HPM) approach; thus, this is considered the most suitable technique to estimate the economic value of environmental attributes [25,26].

Since the 1970s, the hedonic price method has been used to model the housing price determination process [27]. In the 1990s, the spatially explicit model involved tying land values to landscape features so that the value of residential lands was not just affected by specific features of point locations but was also affected by the pattern of surrounding land use [28]. Landscape Ecological Metrics (LEMs) were used to study how urban green spaces realize their ecosystem service value using the price data of developable land transaction records in Beijing [29]. The urban tree cover also influenced housing sale prices, as revealed by a study that found that tree covers within 100 and 250 m increased sale prices to 40–60%, while tree covers beyond 250 m did not contribute significantly [30]. Urban parks have effects on housing prices, such as the value-added coefficients and the influence radius [31,32]. For example, housing prices have been shown to drop by 0.159% as the distance to the West Lake increases by 1% in Hangzhou and exhibit heterogeneities in direction and distance [33]. The value-added effect was shown to be weakened with a slowing down speed as the distance increases from the park to the house in the case of the Olympic Forest Park in Beijing [31]. The maximum influence radius has been shown to be 1.59 km, and the strongest impact location is 0.29 km from the Huangxin Park in Shanghai [34]. Moreover, the gravity model, reflecting accessibility to parks, and a geographical detector method were applied to assess the association between housing prices and related factors [35]. The characteristics of a park also make a difference. The activity facilities in a park have been shown to influence nearby property values, such as skate parks and children's play areas which tended to introduce negative impacts [36].

Whether it is a neighbourhood park, children's park, or waterfront park, the type of park also has different influences [37].

However, the economic value of USPs has not been evaluated systematically. It is more challenging to evaluate USPs for their fewer utilities for human activities. Each evaluation approach cannot accomplish the task alone; thus, human mediation in the evaluation process is necessary [22]. Thus, this study establishes an evaluation framework that combines qualitative and quantitative methods based on open-source data from a home sales website. The economic value of USPs is represented by a rising effect on nearby housing prices [34]. Six sponge parks in China were chosen as the study cases. The rest of this paper is organized as follows: Section 2 illustrates the established evaluation framework, corresponding data, and methods used to investigate the economic value of USPs; Section 3 presents the evaluation results of the six USPs in China; Section 4 discusses the effects of the USPs, the influence of the environmental context, and this study's limitations; and Section 5 highlights the conclusion and implications.

2. Materials and Methods

2.1. An Integrated Evaluation Framework for the Economic Values of USPs

Considering the difficulty of evaluating landscape economic values, an integrated framework is proposed to assess the economic values of USPs, combining qualitative and quantitative methods. The qualitative method analyses the texts describing housing properties, reflecting the stated preferences of citizens, and the quantitative method analyses housing price data and influencing factors, reflecting the revealed preferences of citizens. The stated preferences could help foster factor selection when studying the revealed preferences, and the results of these two methods could be mutually compared and verified.

2.1.1. Qualitative Evaluation of House Descriptions Using Text-Mining Method

Descriptions of houses reflect the salesman's cognitions about the citizen's concerns about houses. If USPs have influenced housing prices, from which they contribute to the city's economy, these descriptions could determine their roles compared to other factors, such as the house's age, surrounding transportation, education, etc.

On the internet, descriptions of houses usually include two types. The first kind is "introduction" texts, which introduce the community's basic information and selling points. These are what sellers want to convey to customers. The second kind is "neighbourhood" texts, which introduce the community's facilities, such as the conditions of schools, hospitals, banks, etc.

After acquiring these texts, a text-mining method may be applied to extract critical information. This analysis process includes three steps [38]: (1) split text sentences into single words and remove irrelevant words, such as punctuations and numbers, (2) sort the words according to their frequencies in these texts, and (3) select the most mentioned words as keywords, which reflect the concerns of the market. The higher the frequency of a keyword, the more critical the corresponding factor is.

The above regressions may be carried out using R 3.63 and the packages "Rwordseg" (https://cran.r-project.org/src/contrib/Archive/Rwordseg/, accessed on 20 December 2024) and "tm" (https://cran.r-project.org/src/contrib/Archive/tm/, accessed on 20 December 2024) in R, which could be used to mine text.

2.1.2. Quantitative Evaluation of Influence Factors of Housing Prices with HPM

(1) Form of HPM with OLS for global relationships

To quantitatively evaluate a park's contribution to housing prices, HPM could be used to estimate coefficients [31,33]. It assumes that the price of a commodity comes from various innate and environmental characteristics; for example, the price of urban real estate consists of three contributions: structural, neighbourhood, and environmental variables [29,39]. HPM normally estimates model parameters using OLS regression to assume that the housing market is stationary [17].

An OLS regression analysis can be conducted on each park. Each model is formed as follows:

$$P = \alpha + \beta_i S_i + \gamma_j N_j + \eta_k L_k + \varepsilon \quad (1)$$

where α, β_i, γ_j, η_k are the coefficients to be estimated; S_i is the structural properties of communities; N_j is the neighbourhood properties of communities; L_k is the location properties of communities; and ε is the random error term.

(2) Form of HPM with GWR for local relationships

For the sake of spatial heterogeneity, global OLS regression may be biased for parameter estimations. Spatial heterogeneities of housing prices and other attribute variables exist, leading to an estimated parameter bias. To overcome this problem, spatial nonstationary analysis techniques, such as the spatial autoregressive model (SAR), spatial error model (SEM), and spatial lag model (SLM), are introduced [33]. Geographically weighted regression (GWR) is such a technique that considers the spatial location of variables and addresses nonstationary relationships [40].

Hence, a local model that extends the hedonic price model's form using GWR technology may be supplemented to investigate these nonstationary effects [40]. The form of HPM with GWR is as below:

$$P(u_i, v_i) = \alpha(u_i, v_i) + \beta_i(u_i, v_i) S_i + \gamma_j(u_i, v_i) N_j + \eta_k(u_i, v_i) L_k + \varepsilon(u_i, v_i) \quad (2)$$

where (u_i, v_i) is the coordinate representing the house's location, which means the coefficients may present variations depending on the location, and the other variables are the same as above.

(3) Average estimations of the influence radius and degree

Although the relationships may vary in different locations, an average estimation of the influence radius and degree of a park to its surrounding housing prices is meaningful. The semi-logarithmic model with a dummy variable reflecting the distance to the park is used to determine the influence radius and degree [31]. The dummy variable D has an interval of 500 m from 0–4500 m and thus has nine levels in total. This model is formed as follows:

$$\ln P = \alpha + \beta_i S_i + \gamma_j N_j + \eta_k L_{k+} + \theta_n D_n + \varepsilon \ (i = 1, 2; j = 1, 2, 3; k = 1, 2; n = 1, 2, \ldots, 9) \quad (3)$$

where ln P is the natural logarithm of the housing price, θ_n is a coefficient to be estimated, D_n is the distance interval, and the other variables are the same as above.

The influence radius is distinguished by the significant levels of D_n. The value-added coefficient, which reflects the increased degree of housing prices to each D_n, is calculated as follows:

$$\rho_n = e^{\theta_n} - 1 \quad (4)$$

where ρ_n is the value-added coefficient of D_n, and n is the order of the significant regression coefficients of D_n.

The above regressions may be carried out using R 3.63, and the package "spgwr" (https://cran.r-project.org/src/contrib/Archive/spgwr/, accessed on 20 December 2024) may be used for GWR analysis.

2.2. Data Sources and Model Specifications

2.2.1. Data Sources and Selected Cases

The housing price data are as of May 2019. This is because the COVID-19 outbreak in 2020 influenced housing prices and changed the preferences of residents for properties [41,42]. The descriptions of houses and corresponding housing prices may be acquired from online home sales websites. In this study, we collected data from Fang.com (https://jh.fang.com/?s=BDPZ-BL, accessed on 1 December 2024), an online showing/purchasing platform for houses with detailed real-estate information and housing prices of major cities in China. Other information in the collected dataset includes names, cities, addresses, introductions to neighbourhoods, properties, areas, green ratios, plot ratios, longitudes, latitudes, etc. In addition, Point-of-Interest (POI) data as of 30 September 2018 were downloaded from Peking University Open Research Data to reflect the neighbourhood properties of these houses [43]. A POI can be a bank, a shop, a park, etc. Moreover, this study focused solely on spatial concerns and thus avoided time series problems by only considering housing price data in 2019.

The selection criteria of the studied park cases were as follows: (1) parks with typical USP elements, such as ponds collecting rainwater, wetlands purifying wastewater, banks adapting floods, etc.; (2) parks from the same design institute with similar styles and design ideas, such as low impact development (LID), stormwater management, and low maintenance; (3) parks of roughly similar sizes to ensure their effects are comparable. Six parks in China were selected according to the above criteria (Figure 1), and the number was determined by the balance of data processing workloads and sample representativeness for illustrating the evaluation methods. Detailed descriptions of these parks' building year, size, and design characteristics are listed in Table A1.

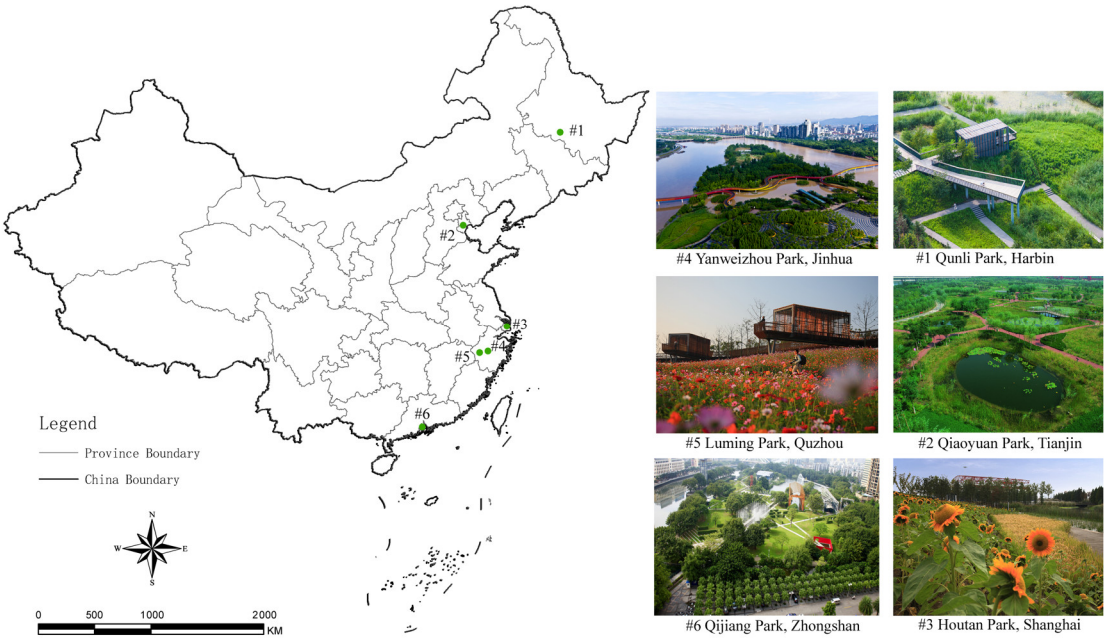

Figure 1. Locations and photographs of the six USPs. (Source: photographs are from Turenscape; www.turenscape.com, accessed on 20 December 2024).

2.2.2. Specification of HPM

To specify HPM, we finally selected eight variables based on previous research [31,33], and the text-mining results derived in Section 2.1. These variables were categorized into structure, neighbourhood, and location dimensions. As shown in Table 1, the building age (S_1) and greening condition inside the community (S_2) reflect the structure properties of the community; education facilities (N_1), traffic facilities (N_2), and living facilities (N_3) represent neighbourhood properties; the distance to downtown (L_1) reflects the community's location in the city; the distance to water (L_2) reflects the proximity of a house to water; and the distance to a park (L_3) reflects the community's location relative to parks.

Table 1. Housing characteristic variables and measuring methods.

Variables	Variable Definition and Measuring Methods
Building age (S_1)	Building age (year; the age of houses built in 2019 is 1)
Greening condition (S_2)	Greening condition inside the community (percentage; from 0 to 1)
Education facility (N_1)	Kindergartens, elementary schools, middle schools, and universities within 1000 m from the community (each item is scored as 1, and the total is 4)
Traffic facility (N_2)	Metro stations, bus stations, railway stations, and coach stations within 1000 m from the community (each item is scored as 1, and the total is 4)
Living facility (N_3)	Supermarkets, banks, post offices, and hospitals within 1000 m from the community (each item is scored as 1, and the total is 4)
Distance to downtown (L_1)	Euclidean distance from the community to downtown (m)
Distance to water (L_2)	Euclidean distance from the community to the nearest body of water (m)
Distance to park (L_3)	Euclidean distance from the community to parks (m)

The scope of the analysis was limited, as the influence of a park cannot be expanded to the whole city. In previous studies, the influence radius of an urban park was usually less than 3 km [31,34], and the average spatial effect distance of a big park, such as the West Lake in Hangzhou, was 3.98 km [33]. Hence, a 5 km threshold distance is enough to capture influence effects, with another 1 km buffer ring zone outside the 5 km ring area to include other factors, such as hospitals, supermarkets, and banks. Moreover, a 500 m distance interval was used to capture the heterogeneity in the distance from a park, which represents differences in urban spaces and was convenient for calculating. In the regression process, outlier points of housing price data were deleted from the samples.

2.2.3. Influence of Site Background

USPs are located in different sites and have different environmental and developmental backgrounds. For example, a park may belong to a new town development project, while another is an old town renovation project. Although other factors, like the park type, size, and construction year, might also be influenced, this study focused on the site background and left others to future statistical studies with large samples.

To determine the site's influence, the six parks were categorized into four types according to two dimensions: (1) whether the park belongs to a new town development project or an old town renovation project, and (2) whether the park is waterfront or non-waterfront (Figure 2). For an intuitive impression of these, satellite images before, during, and after the park's construction, which reflect these parks' site backgrounds, are shown in Figure A1.

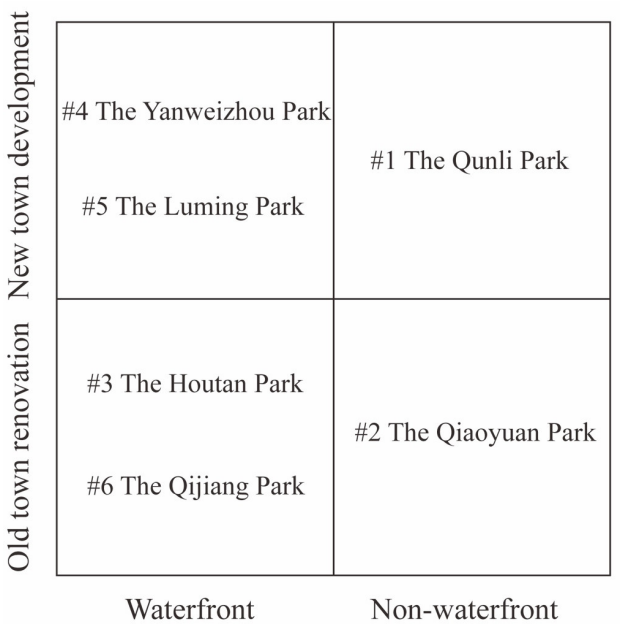

Figure 2. Four quadrants of the six USPs.

3. Results

3.1. Qualitative Evaluation Results

Many factors influence a citizen's decision to buy a house, such as its location, transportation, education, living convenience, and surrounding environment. If citizens pay more attention to USPs as an essential concern, the economic values of USPs would be higher in terms of their contribution to housing prices. The text-mining results reveal the relative importance of the ecological landscape in this process, as shown in the number distribution of the keywords (Figure 3).

In the introduction texts, "business", "living", "architecture", "planning", "community", "park", and "square" are the most mentioned words. However, in the neighbourhood texts, the most mentioned words are "kindergarten", "university", "hospital", "bank", "market", "supermarket", and "post office"; "park", "square", "landscape", and "ecology" are not necessary, as they are in the introduction texts. This difference reveals that ecological landscapes and parks are attractive to customers, as emphasized in the introduction texts, but they are not a "rigid demand", like the demands for schools, banks, and markets in the actual market. As reflected in the above keyword frequencies, citizens may consider parks when buying a house, but they may pay more attention to the location, transportation, and other facilities, which could be compared with the quantitative analysis results in the following section.

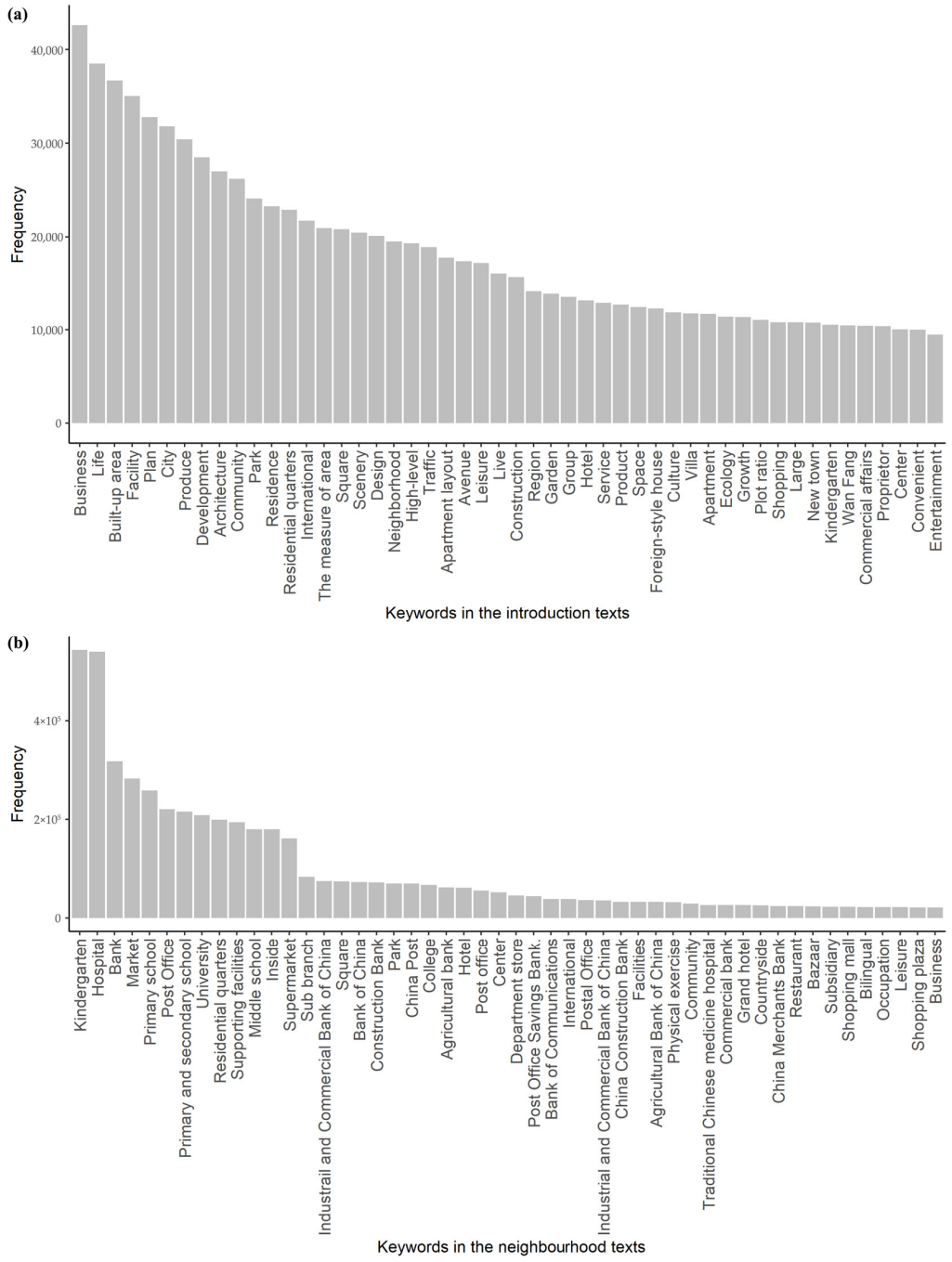

Figure 3. Frequencies of keywords in the online introduction (**a**) and neighbourhood texts (**b**).

3.2. Quantitative Evaluation Results

The study area characteristics of each park are listed in Figure 4. Four parks are near rivers, while two parks are at a certain distance from rivers or lakes. Due to the city-scale nature of this study and the degree of development, the number of communities in each case varies a lot, such that developed areas tend to have more communities, as is the case for parks 2, 3, and 6, while newly developing areas have fewer communities, as is the case for parks 1, 4, and 5.

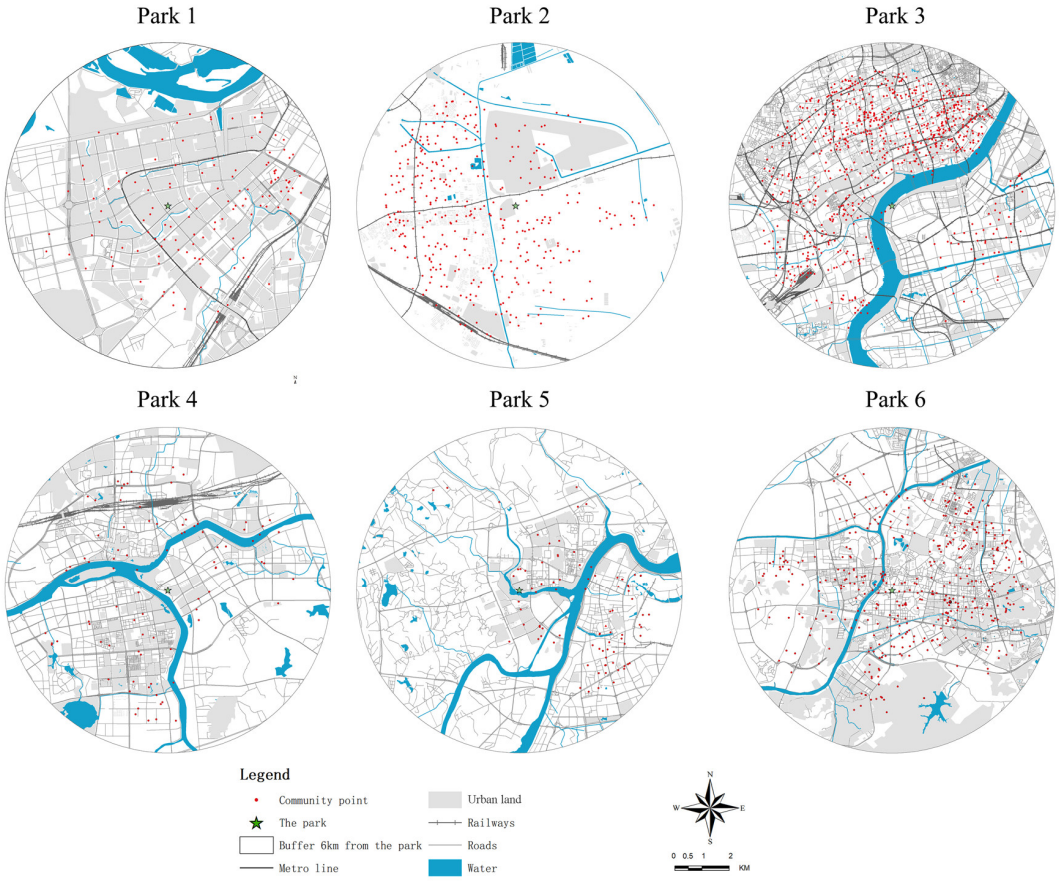

Figure 4. The community points, park locations, and other urban characteristics within a 6 km buffer zone of each park.

3.2.1. Global Model: OLS

The global regression results are listed in Table 2. The range of R^2 in five parks is from 30% to 50%, while the Qijiang Park only has 14.9%. Of all the six parks, the building age and greening conditions nearly all have a significant influence on housing prices, which means more greenery inside the community and younger building ages will increase housing prices, and these results are consistent with previous studies that found that the influence of house structural attributes is significant [44]. The influence of neighbourhood properties is not as significant as the building age and greening conditions inside the community. Education facilities even introduce a negative impact, which may come from the similarity of the 6 km buffer zone neighbourhood. Furthermore, the influence of the distance to downtown is nearly significantly negative, revealing that the economic location is the most influential factor. The influence of the distance to parks is significantly negative in four parks, while it is significantly positive in two parks, indicating spatial heterogeneity of the relationship between parks and housing prices even within the 5 km range area. This situation also applies to the variable of the distance to water.

Table 2. Regression results of six parks using OLS.

	#1 Qunli Park			#2 Qiaoyuan Park			#3 Houtan Park		
Variables	**Coef.**	**St Coef.**	***p*-Value**	**Coef.**	**St Coef.**	***p*-Value**	**Coef.**	**St Coef.**	***p*-Value**
Constant	35,751.413 ***	0.000	0.000	39,474.352 ***	0.000	0.000	139,200 ***	0.000	0.000
Building age	−261.772 ***	−0.417	0.000	−104.663 ***	−0.191	0.001	359.6 ***	0.228	0.000
Greening condition	6879.279 *	0.131	0.059	12,168.019 ***	0.304	0.000	47,000 ***	0.154	0.000
Education facility	−637.910	−0.183	0.158	−349.288	−0.074	0.134	5483 *	0.063	0.079
Traffic facility	730.457	0.1112	0.123	−315.376	−0.035	0.450	−11,410 ***	−0.116	0.001

Table 2. *Cont.*

	#1 Qunli Park			#2 Qiaoyuan Park			#3 Houtan Park		
Variables	**Coef.**	**St Coef.**	***p*-Value**	**Coef.**	**St Coef.**	***p*-Value**	**Coef.**	**St Coef.**	***p*-Value**
Living facility	−922.494 **	−0.276	0.038	126.601	0.018	0.720	−15,650 ***	−0.109	0.002
Distance to park	−1.242 ***	−0.332	0.001	−0.651 ***	−0.162	0.000	5.133 ***	0.183	0.000
Distance to downtown	−1.028 ***	−0.551	0.000	−1.696 ***	−0.720	0.000	−5.794 ***	−0.491	0.000
Distance to water	0.207	0.023	0.781	0.759 **	0.117	0.011	−9.576 ***	−0.132	0.000
R^2 (adj)	0.491			0.464			0.336		
N	128			348			631		
	#4 Yanweizhou Park			**#5 Luming Park**			**#6 Qijiang Park**		
Variables	**Coef.**	**St coef.**	***p*-Value**	**Coef.**	**St coef.**	***p*-Value**	**Coef.**	**St coef.**	***p*-value**
Constant	21,733.845 ***	0.000	0.000	9784.219 **	0.000	0.048	9520.969 ***	0.000	0.000
Building age	−266.838 ***	−0.597	0.000	−231.528 **	−0.253	0.023	−89.584 ***	−0.269	0.000
Greening condition	9065.506	0.158	0.148	33,656.404 ***	0.397	0.000	7675.931 ***	0.239	0.000
Education facility	−104.306	−0.031	0.804	74.695	0.020	0.887	−315.060	−0.086	0.218
Traffic facility	1911.636 ***	0.284	0.005	1284.573	0.119	0.329	479.614	0.049	0.307
Living facility	−174.810	−0.042	0.705	899.657	0.203	0.331	301.852	0.069	0.228
Distance to park	−1.061 ***	−0.338	0.008	−1.378 ***	−0.429	0.001	0.482 ***	0.146	0.004
Distance to downtown	−0.597 ***	−0.266	0.098	−0.363	−0.113	0.562	−0.397 ***	−0.152	0.008
Distance to water	1.149	0.128	0.207	−2.707 *	−0.211	0.054	0.381	0.034	0.464
R^2 (adj)	0.397			0.509			0.149		
N	74			57			470		

Note: Coef. represents the regression coefficient; St coef. represents the standardized coefficient of the regression; and ***, **, and * represent the significance level of 0.01, 0.05, and 0.1, respectively.

3.2.2. Local Model: GWR

A local model using GWR could reveal different relationships depending on the location, i.e., the spatial heterogeneity. The Quasi-global R^2, reflecting the fitting effect of GWR, is higher than the OLS R^2, as shown in Table 3, indicating that GWR performs better than OLS in addressing spatial heterogeneity, which is consistent with previous findings [17,40]. This spatial heterogeneity is reflected in the spatial distribution of the local R^2 of the GWR (Figure 5). On the one hand, the values of local R^2 in the analysed area are different along a certain direction from the parks, indicating that heterogeneity is distributed along with the distance to the parks; on the other hand, the values are different in different directions from the parks, indicating that heterogeneity is also distributed in different directions, which is also consistent with previous findings [33].

Table 3. GWR results of the six parks.

Park	Min	Lower Quantile	Med	Up Quantile	Max	Quasi-Global R^2	OLS R^2
Park 1	0.5104	0.6154	0.6479	0.6723	0.7496	0.679	0.491
Park 2	0.4734	0.4838	0.4885	0.4908	0.4964	0.491	0.464
Park 3	0.1717	0.3247	0.4328	0.5647	0.7236	0.684	0.336
Park 4	0.5194	0.5432	0.5745	0.5827	0.6016	0.553	0.397
Park 5	0.5617	0.564	0.5716	0.5813	0.6093	0.584	0.509
Park 6	0.1806	0.2429	0.2475	0.2522	0.2542	0.203	0.149

Other than the overall fitting effect, heterogeneity also exists in each explainable variable. Taking the critical variable, the distance to parks, as an example (Figure 6), the sign of a regression coefficient may be different in different locations. In park 1, the values on the west side are usually higher than those on the east side, but higher or even positive values exist on the easternmost side. The distribution in park six has a similar situation as park 1, but all values are positive. Hence, the influence of a park on its nearby housing price is complicated and heavily depends on the location.

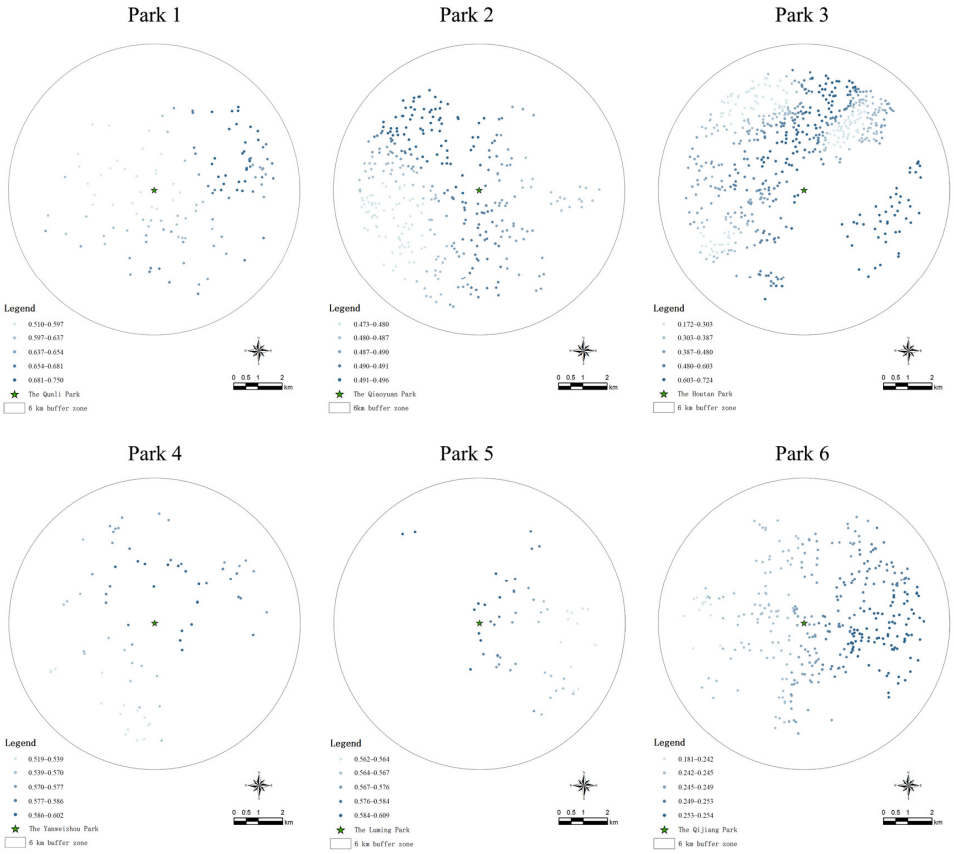

Figure 5. Local R^2 of GWR for six parks.

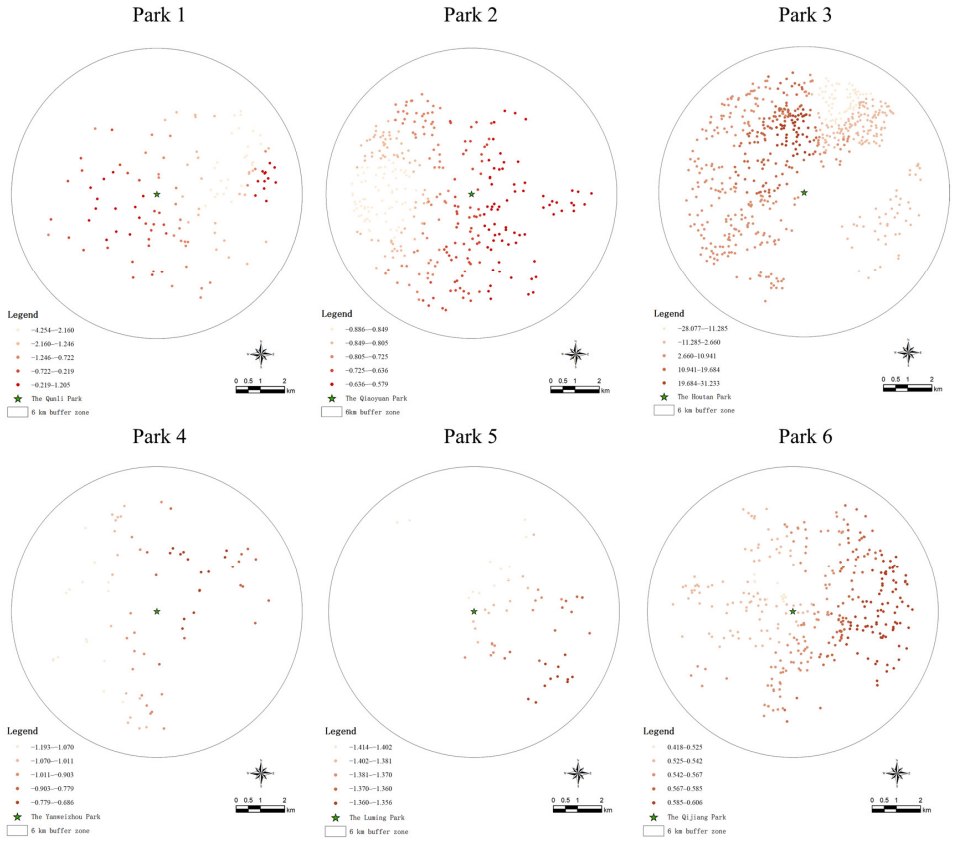

Figure 6. Regression coefficients of the distance to parks of GWR for six parks.

3.2.3. Influence Radius and Degree

Although spatial heterogeneity and other local factors are influencing effects, an average estimate is necessary in practice. Going back to the OLS model, the regression results for the single variable, the distance to parks, are all significant at the 0.05 level, although the R^2 of parks 2, 3, and 6 are nearly zero (Figure 7a). A boxplot with a 500 m interval helps to understand the heterogeneity in the distance from the parks (Figure 7b).

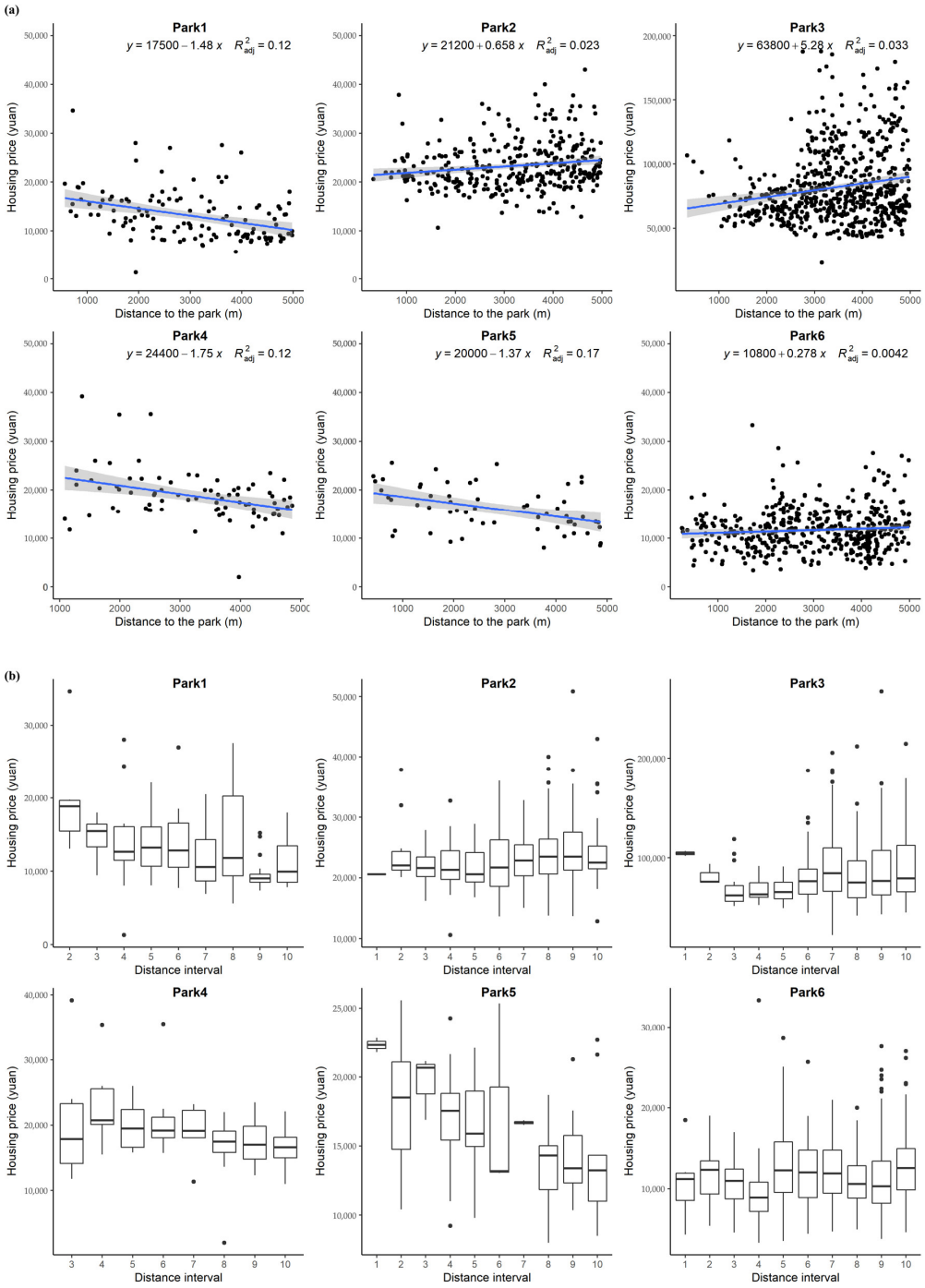

Figure 7. The relationship between housing prices and the distance to parks: (**a**) regressions between housing prices and the distance to parks; (**b**) boxplots of housing prices in different distance levels.

To acquire the influence radius and degree of parks on housing prices, a distance interval was used to represent the directional heterogeneity. The regression results and the calculated value-added coefficients are listed in Table 4.

Table 4. The regression results using distance intervals and calculated value-added coefficients.

	#1 Qunli Park			#2 Qiaoyuan Park			#3 Houtan Park		
Variables	**Coefficient**	***p*-Value**	**ρ**	**Coefficient**	***p*-Value**	**ρ**	**Coefficient**	***p*-Value**	**ρ**
D_1	-	-	-	0.173	0.239	18.9%	0.346 *	0.100	41.4%
D_2	0.3417 ***	0.006	40.7%	0.191 ***	0.000	21.0%	0.052	0.736	5.4%
D_3	0.351 ***	0.005	42.0%	0.100 **	0.013	10.5%	−0.208 ***	0.001	−18.8%
D_4	0.266 ***	0.007	30.5%	0.096 ***	0.006	10.1%	−0.209 ***	0.000	−18.9%
D_5	0.1959 **	0.040	21.6%	0.068 **	0.046	7.1%	−0.190 ***	0.000	−17.3%
D_6	0.1973 *	0.063	21.8%	0.039	0.240	3.9%	−0.084 **	0.031	−8.1%
D_7	0.05027	0.601	5.2%	0.067 **	0.023	7.0%	−0.030	0.395	−2.9%
D_8	0.1221	0.145	13.0%	0.058 **	0.046	5.9%	−0.076 **	0.030	−7.3%
D_9	−0.007796	0.922	−0.8%	0.055 **	0.047	5.7%	−0.048	0.160	−4.7%
R^2 (adj)	0.567				0.466			0.365	
N	128				348			631	
	#4 Yanweizhou Park			**#5 Luming Park**			**#6 Qijiang Park**		
Variables	**Coefficient**	***p*-Value**	**ρ**	**Coefficient**	***p*-Value**	**ρ**	**Coefficient**	***p*-value**	**ρ**
D_1	-	-	-	0.5578 ***	0.005	74.7%	−0.2309 *	0.064	−20.6%
D_2	-	-	-	0.5058 ***	0.003	65.8%	−0.1349	0.113	−12.6%
D_3	0.166	0.116	18.1%	0.2988 **	0.048	34.8%	−0.1949	0.018	−17.7%
D_4	0.192 **	0.027	21.1%	0.1476	0.179	15.9%	−0.3457	0.000	−29.2%
D_5	0.336 ***	0.001	40.0%	0.1221	0.266	13.0%	−0.1008	0.142	−9.6%
D_6	0.183 **	0.023	20.1%	0.2146	0.185	23.9%	−0.1397	0.054	−13.0%
D_7	0.120	0.174	12.8%	0.08174	0.632	8.5%	−0.0825	0.242	−7.9%
D_8	0.110	0.134	11.6%	−0.09443	0.441	−9.0%	−0.1535	0.023	−14.2%
	0.075	0.269	7.8%	−0.03248	0.743	−3.2%	−0.1708	0.006	−15.7%
R^2 (adj)	0.386				0.527			0.160	
N	74				57			470	

Note: ***, **, and * represent the significance level of 0.01, 0.05, and 0.1, respectively.

For the influence radius, the furthest range of influence is park 1, Qunli Park, with a distance of up to 3 km, while park 3, Houtan Park, only increases the price of houses within a 500 m area. For the degree of influence, the general trend is the closest to a park, the greater the influence (Figure 8). The value-added coefficient is up to 70% in park 5, Luming Park, within a 500 m buffer zone, and approximately 40% in the case of park 1, Qunli Park, within a 1 km buffer zone. It is noted that some parks have no houses near their 500 m or 1 km range area; thus, the dummy variables are absent. Typically, the influence mode of a park on housing prices exponentially decreases as the distance to the park increases, which is most evident in the cases of parks 1 and 5. The maximum value-added effect with a value up to 70% appears close to the park's edge, while the minimum effect value should be zero, but some negative values are observed in the cases of park 3, Houtan Park, and park 6, Qijiang Park. This may come from other influence factors not included in the regression. Moreover, the site background of these parks also matters, which will be discussed later.

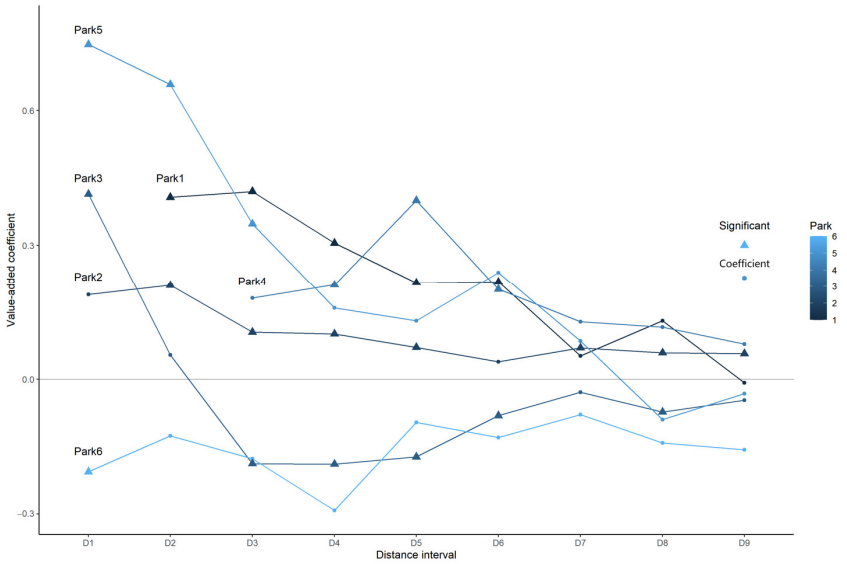

Figure 8. The relationship between the value-added coefficient and the distance level.

4. Discussion

4.1. The Role of USPs in Determining Housing Prices

The standardized coefficients of the variables in Table 2 can be used to compare the contributions of different influence factors (Table 5). The structural variables, including the building age and greening condition, are significant and present the highest robustness. The neighbourhood variables are not very significant in general, which may come from the similar, limited analysing scope in each case. The environmental variables present two kinds of influence forms, i.e., long-range and short-range. For the former, this indicates that the variable's effect is long and even across the city, like the stable and significant relationship of the distance to downtown with housing prices; for the latter, this indicates that the variable's effect is short and local, like the regression coefficient signs that vary within the 5 km buffer zone in the variables of the distance to parks and water.

Table 5. The significant signs and standardized coefficients of the selected variables for the six parks.

Variables	Park 1	Park 2	Park 3	Park 4	Park 5	Park 6
Building age	−0.417 (2)	−0.191 (3)	+0.228 (2)	−0.597 (1)	−0.253 (3)	−0.269 (1)
Greening condition	+0.131 (5)	+0.304 (2)	+0.154 (4)		+0.397 (2)	+0.239 (2)
Education facility			+0.063 (8)			
Traffic facility			−0.116 (6)	+0.284 (3)		
Living facility	−0.276 (4)		−0.109 (7)			
Distance to park	−0.332 (3)	−0.162 (4)	+0.183 (3)	−0.338 (2)	−0.429 (1)	+0.146 (4)
Distance to downtown	−0.551 (1)	−0.72 (1)	−0.491 (1)	−0.266 (4)		−0.152 (3)
Distance to water		+0.117 (5)	−0.132 (5)		−0.211 (4)	

Note: only significant coefficients are listed, and their ranks in each model are listed in parentheses.

It may be inferred that the role of USPs as analysed in this study is not as essential as the economic location and the properties of houses when citizens buy houses. As reflected in Table 4, the distance to downtown ranks first in parks 1, 2, and 3; the building age ranks first in parks 4 and 6; and the distance to parks ranks first only in park 5. Notably, the influence of parks is stronger than that of water, for a park's coefficient is more significant than that of water.

This result is also consistent with the findings in Section 3.1. The economic location and structural properties of houses and various kinds of facilities nearby influence citizens' house-buying decisions, thus contributing more to the city's economy than USPs. However,

the economic contribution of USPs is still positive, and its degree of influence is huge within most proximity areas.

4.2. Influence of Site Background of USPs

As reflected in Figure 8, the influence forms of the six parks are different, which may correlate with their site backgrounds. The forms of parks 1 and 5 are closest to the ideal model, and these two parks both belong to the new town development project category, as illustrated in Figure 2. The forms of parks 3 and park 6 most deviate from the ideal mode, and these two parks both belong to the old town renovation project category. In particular, park 6, Qijang Park, before renovations, was a shipyard located in the built city district in the past [9]. So, its economic value may be covered by dense buildings. In contrast, the influence is more evident and typical in the new town development background, and we see that the construction of USPs promoted the development of nearby real estate.

Water may be another critical site background. It is a source of spatial heterogeneity, as seen from the cases of parks 1, 3, 5, and 6, which are all near a big river. As illustrated in Figure 6, these four parks have more influence on their own houses than those on the other side of the river. It seems that the river replaces the effect of parks. The detailed mechanism of this phenomenon and more environmental factors should be thoroughly discussed in future studies.

4.3. Limitations and Future Work

Compared to similar studies in which R^2 may be up to 60% [31,34], the OLS R^2 in this study ranges from 14.9% to 49.1%, which is not very high. Because this study selected the same variables in different parks for the convenience of conducting a comparative study, the ignored locally related factors impaired the R^2. An extreme case found in this study is the effect of the building age in the case of Houtan Park, where houses with a building age of more than 50 years positively impact housing prices. This phenomenon may come from the fact that these buildings are historical sites, thus causing the opposite effect of the building age variable, which was also detected in previous studies [45].

Other than the localized factor issue, the sample size of the cases selected in this study is relatively small, although these cases are distributed from the south to the north of China and cover different site backgrounds. More cases and more data sources should be included in the future and analysed using the integrated evaluation framework established in this study to generalize the findings and find more common rules about the economic values of USPs. In addition, this study focuses on the spatial effects of USPs on housing prices, lacking a temporal analysis of the evolution of economic values over time. Supplementing a temporal perspective could promote a better understanding of the return on long-term investments related to NbS and would benefit future policy-making.

5. Conclusions

Urban sponge parks (USPs) are one of the critical green infrastructures in China's high-speed urbanization process to ensure its cities' resilience and citizens' welfare. As a type of Nature-based Solutions, USPs play a more critical role and attract more investments in facing climate change and future sustainable development challenges. Although an evaluation of the economic value of USPs is based on management and decision-making, there is a lack of standard methods to measure their economic performance by considering the public-good property of USPs. Therefore, this study established an integrated evaluation framework, combining qualitative and quantitative evaluations based on open-source data from an online home sales website. A text-mining analysis of the texts about the houses was conducted to determine the role of USPs in citizens' house-buying decisions, reflecting their

stated preferences when purchasing a house. Six USPs in China were selected, and their impacts on nearby housing prices were quantitatively evaluated to reflect citizens' revealed preferences. These two evaluations confirm each other and jointly reveal that USPs do contribute to property appreciation, especially in newer urban areas, but not as strongly as location and property characteristic factors. Moreover, the extent of the influence of USPs on houses decreases as distance increases, with a maximum radius of 3 km. A USP's effects vary according to the urban and environmental context, as HPM with GWR outperforms the OLS method, which evokes the need for more affluent and detailed analyses in the future.

This study demonstrates the economic benefits of USPs and provides an evaluation approach with scientific data on citizens, which could be a benchmark for future national-scale evaluations using the same framework. With a deepened understanding of the economic values of USPs, the government and public sectors could make better decisions to promote the construction of USPs and broader Nature-based Solutions, thus advancing stormwater management, adapting to climate change, and moving towards more sustainable cities. Last but not least, the social impacts of rising property prices near USPs may risk gentrification or the displacement of low-income communities, which we should be aware of in the process of public investments.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Basic information of six case parks.

Number	English Name	Chinese Name	Building Year	Region	Size (ha)	Design Characteristics
1	Qunli Park	群力雨洪湿地公园	2009	Harbin, Heilongjiang Province	30	Designed to solve urban waterlogging, restore multi-type habitats, and use trestles in the air to create recreational spaces [46].
2	Qiaoyuan Park	天津桥园	2005	Tianjin	22	Use cut–fill technology to collect acid rainwater, neutralize alkaline soil, and repair brownfields to create a recreational space [11].
3	Houtan Park	上海世博后滩公园	2007	Shanghai	14	Improve the ecological water quality of polluted river water by constructed wetlands to provide a space for recreation and conference [47].
4	Yanweizhou Park	金华燕尾洲公园	2014	Jinhua, Zhejiang Province	26	Adopt adaptive flood banks, adaptive plants, and permeable pavements to adjust to floods [48].
5	Luming Park	衢州鹿鸣公园	2015	Quzhou, Zhejiang Province	32	Utilize natural surface runoff system on this site, multiple ponds to collect rainwater, and low-maintenance native plants, and this park has a resilient design to adapt to floods [49].

Table A1. *Cont.*

Number	English Name	Chinese Name	Building Year	Region	Size (ha)	Design Characteristics
6	Qijiang Park	广东中山岐江公园	2001	Zhongshan, Guangdong Province	11	This park exhibits a standard flood solution, has changeable water levels, collects rainwater, and uses native plants to reflect the "beauty of weeds" [9].

Appendix B



Figure A1. Satellite images before, during, and after the parks' construction. A dashed line highlights the park boundary in each image. Older satellite images of Qijiang Park could not be obtained.

References

1. Stocker, T.F.; Qin, D.; Plattner, G.-K.; Tignor, M.; Allen, S.K.; Boschung, J.; Nauels, A.; Xia, Y.; Bex, V.; Midgley, P.M. (Eds.) IPCC Climate Change 2013: The Physical Science Basis. In *Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2013.
2. Liu, H.L.; Li, D.H.; Han, X.L. Review of Ecological Infrastructure: Concept and Development. *City Plan. Rev.* **2005**, *29*, 70–75.
3. Ma, Y.; Ning, X.; and Jiang, Y. China's Sponge City Development: Global Position, Governance, and Potential Enhancement with Ecosystem Services. *J. Urban Technol.* **2024**, *31*, 83–106. [CrossRef]
4. Dobkowitz, S.; Bronstert, A.; and Heistermann, M. Water Retention by Green Infrastructure to Mitigate Urban Flooding: A Meta-Analysis. *Urban Water J.* **2025**, 1–16. [CrossRef]
5. Xue, R.; Zhang, K.; Liu, X.; Jiang, B.; Luo, H.; Li, M.; Mo, Y.; Liu, C.; Li, L.; Fan, L.; et al. Variations of Methane Fluxes and Methane Microbial Community Composition with Soil Depth in the Riparian Buffer Zone of a Sponge City Park. *J. Environ. Manag.* **2023**, *339*, 117823. [CrossRef] [PubMed]
6. Tong, P.; Yin, H.; Wang, Z.; Trivers, I. Combining Stormwater Management and Park Services to Mitigate Climate Change and Improve Human Well-Being: A Case Study of Sponge City Parks in Shanghai. *Land* **2022**, *11*, 1589. [CrossRef]
7. Liu, J.; Guo, Y.; Han, J.; Yang, F.; Shen, N.; Sun, F.; Wei, Y.; Yuan, P.; Wang, J. Nature-Based Solutions for Landscape Performance Evaluation—Handan Garden Expo Park's "Clear as a Drain" Artificial Wetland as an Example. *Land* **2024**, *13*, 973. [CrossRef]
8. He, J.F. A Blending of Ecology and Culture: A Review of Flowing Water Park in Funan River, Chengdu. *Time Archit.* **1999**, *3*, 58–60.
9. Yu, K.J. The Culture That Has Been Ignored, the Beauty of Weeds—Qijaing Park in Zhongshan City. *New Archit.* **2001**, *5*, 17–20.
10. Gohd, C. China Is Building 30 "Sponge Cities" to Soften the Blow of Climate Change. Available online: https://futurism.com/china-sponge-cities-climate-change (accessed on 20 December 2024).
11. Liu, J. Empirical Research on the Landscape Performance of Designed Ecologies through a Field Observation of Saline-Alkali Soil Improvement in Qiaoyuan Park of Tianjin. *Landsc. Archit. Front.* **2019**, *7*, 68–81. [CrossRef]
12. Hao, S.; Wang, C.L.; Lin, H.W. Design and Assessment of Biodiversity in Urban Wetland Parks: Take Liupanshui Minghu National Wetland Park as an Example. *Acta Ecol. Sin.* **2019**, *39*, 5967–5977.
13. Wu, Y.J.; Lin, H.W.; Wang, Z.Y. Performance of Water Quality and Water Quantity Control and Operational Experiences of a Multi-Pond Urban Green Space of Yichang Canal Park. *Acta Ecol. Sin.* **2019**, *39*, 5978–5987.
14. Deng, Y.Y.; Wang, C.L. Research of the Evaluations and the Behavioural Preferences of Park Users in Urban Wetland Park: A Case Study of Yichang Canal Park. *Acta Ecol. Sin.* **2019**, *39*, 5988–6000.
15. Liu, H.X.; Hu, Y.H.; Li, F.; Yuan, L.X. Associations of Multiple Ecosystem Services and Disservices of Urban Park Ecological Infrastructure and the Linkages with Socioeconomic Factors. *J. Clean. Prod.* **2018**, *174*, 868–879. [CrossRef]
16. Peters, K.; Elands, B.; Arjen, B. Social Interactions in Urban Parks: Stimulating Social Cohesion? *Urban For. Urban Green.* **2010**, *9*, 93–100. [CrossRef]
17. Samad, A.; Abdul-Rahim, A.S.; Yusof, M.J.M.; Tanaka, K. Assessing the Economic Value of Urban Green Spaces in Kuala Lumpur. *Environ. Sci. Pollut. Res.* **2020**, *27*, 10367–10390. [CrossRef]
18. Tagliafierro, C.; Longo, A.; Van Eetvelde, V.; Antrop, M.; Hutchinson, W.G. Landscape Economic Valuation by Integrating Landscape Ecology into Landscape Economics. *Environ. Sci. Policy* **2013**, *32*, 26–36. [CrossRef]
19. Rodríguez-Entrena, M.; Colombo, S.; Arriaza, M. The Landscape of Olive Groves as a Driver of the Rural Economy. *Land Use Policy* **2017**, *65*, 164–175. [CrossRef]
20. Cooper, T.; Hart, K.; Baldock, D. *The Provision of Public Goods Through Agriculture in the European Union*; Institute for European Environmental Policy: London, UK, 2009.
21. Price, C. *Landscape Economics*; Palgrave Macmillan: London, UK, 2017.
22. Price, C. Landscape Economics at Dawn: An Eye-Witness Account. *Landsc. Res.* **2008**, *33*, 263–280. [CrossRef]
23. Smith, V.K.; Krutilla, J.V. *Explorations in Natural-Resource Economics*; John Hopkins University Press: Baltimore, MD, USA, 1982.
24. Tyrvainen, L.; Vaananen, H. The Economic Value of Urban Forest Amenities: An Application of the Contingent Valuation Method. *Landsc. Urban Plan.* **1998**, *43*, 105–118. [CrossRef]
25. Tyrvainen, L.; Miettinen, A. Property Prices and Urban Forest Amenities. *J. Environ. Econ. Manag.* **2000**, *39*, 205–223. [CrossRef]
26. Kong, F.; Yin, H.; Nakagoshi, N. Using GIS and Landscape Metrics in the Hedonic Price Modelling of the Amenity Value of Urban Green Space: A Case Study in Jinan City, China. *Landsc. Urban Plan.* **2007**, *79*, 240–252. [CrossRef]
27. Rosen, S. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *J. Political Econ.* **1974**, *82*, 34–55. [CrossRef]
28. Geoghegan, J.; Wainger, L.A.; Bockstael, N.E. Spatial Landscape Indices in a Hedonic Framework: An Ecological Economics Analysis Using GIS. *Ecol. Econ.* **1997**, *23*, 251–264. [CrossRef]
29. Xu, L.Y.; You, H.; Li, D.H.; Yu, K.J. Urban Green Spaces, Their Spatial Pattern, and Ecosystem Service Value: The Case of Beijing. *Habitat Int.* **2016**, *56*, 84–95. [CrossRef]

30. Sander, H.; Polasky, S.; Haight, R.G. The Value of Urban Tree Cover: A Hedonic Property Price Model in Ramsey and Dakota Counties, Minnesota, USA. *Ecol. Econ.* **2010**, *69*, 1646–1656. [CrossRef]
31. Chen, G.; Zhu, D.L.; Su, Y.Y.; Zhang, L.X. The Impact of Green Space in Large Urban Parks on Housing Prices: Taking Beijing Olympic Forest Park as an Example. *Resour. Sci.* **2015**, *237*, 2202–2210.
32. Fang, X.; Shi, C.Y.; Shen, Y.; Zhao, T.T.; Wu, R.Y.; Kuai, B.Q. Evaluation of the Effect of Green Park Space on Housing Price in the Main Urban Area of Xuzhou City. *J. Jiangsu Norm. Univ.* **2018**, *36*, 13–18.
33. Wen, H.; Bu, X.; Qin, Z. Spatial Effect of Lake Landscape on Housing Price: A Case Study of the West Lake in Hangzhou, China. *Habitat Int.* **2014**, *44*, 31–40. [CrossRef]
34. Shi, Y.S.; Zhang, R. Temporal-Spatial Impact Effects of Large-Scale Parks on Housing Price: Exemplified by the Huangxing Park in Shanghai. *Geogr. Res.* **2010**, *29*, 510–520.
35. Wu, C.; Ye, X.; Du, Q.; Luo, P. Spatial Effects of Accessibility to Parks on Housing Prices in Shenzhen, China. *Habitat Int.* **2017**, *63*, 45–54. [CrossRef]
36. Lin, I.H.; Wu, C.; De Sousa, C. Examining the Economic Impact of Park Facilities on Neighbouring Residential Property Values. *Appl. Geogr.* **2013**, *45*, 322–331. [CrossRef]
37. Kim, H.-S.; Lee, G.-E.; Lee, J.-S.; Choi, Y. Understanding the Local Impact of Urban Park Plans and Park Typology on Housing Price: A Case Study of the Busan Metropolitan Region, Korea. *Landsc. Urban Plan.* **2019**, *184*, 1–11. [CrossRef]
38. Wang, F.; Peng, X.; Qin, Y.L.; Wang, C.S. What Can the News Tell Us about the Environmental Performance of Tourist Areas? A Text Mining Approach to China's National 5A Tourist Areas. *Sustain. Cities Soc.* **2020**, *52*, 101818. [CrossRef]
39. Poudyal, N.C.; Hodges, D.G.; Merrett, C.D. A Hedonic Analysis of the Demand for and Benefits of Urban Recreation Parks. *Land Use Policy* **2009**, *26*, 975–983. [CrossRef]
40. Jaimes, N.B.P.; Sendra, J.B.; Delgado, M.G.; Plata, R.F. Exploring the Driving Forces behind Deforestation in the State of Mexico (Mexico) Using Geographically Weighted Regression. *Appl. Geogr.* **2010**, *30*, 576–591. [CrossRef]
41. Qian, X.; Qiu, S.; Zhang, G. The Impact of COVID-19 on Housing Price: Evidence from China. *Financ. Res. Lett.* **2021**, *43*, 101944. [CrossRef] [PubMed]
42. Huang, N.; Pang, J.; Yang, Y. JUE Insight: COVID-19 and Household Preference for Urban Density in China. *J. Urban Econ.* **2023**, *133*, 103487. [CrossRef]
43. State Information Center MAP POI (Point of Interest) Data 2018. Available online: https://opendata.pku.edu.cn/dataset.xhtml?persistentId=doi:10.18170/DVN/WSXCNM (accessed on 1 December 2024).
44. Clark, D.E.; Herrin, W.E. The Impact of Public School Attributes on Home Sale Prices in California. *Growth Change* **2000**, *31*, 385–407. [CrossRef]
45. Li, M.M.; Brown, H.J. Micro-Neighbourhood Externalities and Hedonic Housing Prices. *Land Econ.* **1980**, *56*, 125–141. [CrossRef]
46. Yu, K.J. Symbiosis of Architecture and Waterlogging: Harbin Qunli Stormwater Park. *Archit. J.* **2012**, *10*, 68–69.
47. Yu, K.J. Low Carbon and Water Purification Landscape: Houtan Park of Shanghai World Expo. *Beijing Plan. Rev.* **2011**, *2*, 139–149.
48. Yu, K.J.; Yu, H.Q.; Song, Y.; Zhou, S.M. Landscape of Resilience: On the Design of Yanweizhou Park in Jinhua City. *Archit. J.* **2015**, *4*, 68–70.
49. Yu, K.J. Terrain and Water as Canvas: Luming Park in Quzhou. *Landsc. Archit. Front.* **2016**, *4*, 102–115.

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