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SPATIAL HETEROGENEITY AND INTERACTION EFFECT OF URBAN BLUE AND GREEN SPACES ON HOUSING PRICES

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Abstract. Rapid urbanization presents policymakers and planners with the challenge of balancing public open spaces design with the conservation and improvement of natural resources. A comprehensive understanding of the land economic value of urban blue-green spaces (UBGS) holds immense significance for urban sustainable development, urban spatial justice and the promotion of human well-being. In this study, the MGWR model is employed to discuss the heterogeneous effects of UBGS on housing prices in Hangzhou. Additionally, the interaction effect between blue space and green space was examined at the district level, and the specific locations and spatial patterns were identified. The results show that (1) different types, features and accessibility of UBGS have different degrees and spatial scale of effect on housing prices, and will be affected by other attributes of UBGS; (2) in 30.92% of the main urban area of Hangzhou, the effect of blue spaces and green spaces on housing prices exhibits an interactive effect. The spatial patterns are divided into blue-green positive synergistic, antagonistic and negative synergistic regions; (3) green space has positive and negative effects on housing prices, while blue space has positive effects on housing prices at the regional level. The existence of water bodies can promote the positive effect of green spaces on housing prices or alleviate the negative effect. The results indicate that planners must transcend the singular focus on blue or green space planning and instead consider both in an integrated manner. This outcome can provide valuable references for UBGS planning.

Keywords: urban blue-green spaces, MGWR, hedonic price model, housing prices, interaction effect, urban planning.

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1. Introduction

Urban blue-green spaces (UBGS), including water bodies such as rivers, lakes, and wetlands, as well as recreational green spaces such as urban parks, natural parks, and green open spaces, are the core elements of the urban landscape pattern (Ghofrani et al., 2017; Lundy & Wade, 2011). UBGS have been proven to have a variety of benefits, including landscaping, preserving biodiversity, ameliorating pollution, mitigating the heat island effect, and promoting the physical and mental health of residents (Ghofrani et al., 2017; Z. Liu et al., 2022; Potter et al., 2023; Wang et al., 2020; Huang et al., 2022). Diverse and high-quality UBGS can increase the resilience of cities as they enhance ecological sustainability and promote social cohesion (Jennings & Bamkole, 2019). In terms of economic value, UBGS can have a positive impact on local residential property prices by improving the living environment (Irwin, 2002; Zhang et al., 2021). This could lead to an increase in revenue, prompting local governments to make further infrastructure investments to promote social well-being. As China implements its urban sustainability strategy, UBGS becomes one of the solutions for building sustainable and resilient cities. In recent years, the integrated construction and balanced distribution of UBGS have been taken into account in the territorial spatial planning of many Chinese cities (China State Council, 2019; Ministry of Natural Resources, 2019). However, the provision of UBGS in high-density urban environments is often expensive. Particularly in the context of housing marketization in China, the inequitable allocation of UBGS may exacerbate unequal access to environmental resources (J. R. Wolch et al., 2014). Therefore, measuring the land economic value of UBGS and understanding the preference of residents in different geographical locations for UBGS are of great practical significance to the urban decision-making of providing social public welfare fairly and realizing the sustainable development of economy and society.

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The effects of urban landscape on housing price have long been a widely researched topic. As an economic valuation method, hedonic pricing model (HPM) is widely used in real estate valuation (Chin & Chau, 2003). HPM belongs to the revealed preferences method, which considers residential property as a special form of commodity. The total price of residential property is evaluated through a function that incorporates characteristic factors such as structure, location, and neighborhood. Scholars have extensively utilized the HPM to assess the economic value of UBGS across various cities (W. Y. Chen et al., 2019; Panduro & Veie, 2013). Their research consistently demonstrates that accessibility (S. Chen et al., 2022; Tuofu et al., 2021), type (Irwin, 2002; Jiao & Liu, 2010; Peng et al., 2023; Zhang et al., 2021), as well as the scale and quality of UBGS (L. Wu & Rowe, 2022; Ben et al., 2023; X. Li et al., 2021), all exert a significant effect on housing prices. Despite numerous studies, the effect of UBGS on housing prices remains contentious due to the disparities in the classification standard, research scope, and geographical considerations utilized by different scholars (Crompton & Nicholls, 2020). Although studies widely confirmed that proximity to green space positively correlates with housing prices, with prices increasing as the distance to green space decreases (Ben et al., 2023), certain scholars argued for the existence of a distance threshold, beyond which this positive effect diminishes (Kovacs, 2012; Lutzenhiser & Netusil, 2001). Some scholars asserted that diverse types of UBGS exert varying degrees of influence on housing prices. For instance, Jiao and Liu contended that city-level parks exert a more significant positive effect on housing prices compared to district-level parks (L. Jiao & Liu, 2010). A study conducted in Portland, Oregon, revealed that natural parks exert a greater positive effect on housing prices than urban parks (Lutzenhiser & Netusil, 2001), while a study in Beijing yielded contrasting results (L. Wu & Rowe, 2022). Additionally, some studies discovered that the industrial transformation parks and forest parks have a weak positive or even negative effect on housing prices (C. Wu et al., 2017; L. Wu & Rowe, 2022). A comprehensive analysis of blue spaces across eight Chinese cities revealed that lakes and the main rivers consistently have a significant positive effect on housing prices in most cities, while the effect of small rivers on housing prices varies across cities (Peng et al., 2023). Regarding scale, numerous studies corroborated that an increase in the size of green space tends to positively correlate with elevated housing prices (Larson & Perrings, 2013; Lutzenhiser & Netusil, 2001). However, contrary perspectives maintained that larger parks may introduce heightened noise and traffic congestion, resulting in a negative effect on housing prices (Anderson & West, 2006). In terms of research methods, the HPM based on the traditional linear regression function is also prone to resulting in biased outcomes due to its deficiencies. For example, it often suffers from omitted variable bias and endogeneity issues, leading to inaccurate results. Moreover, it fails to capture the spatial autocorrelation of housing prices (Basu & Thibodeau, 1998). Furthermore, it assumes a uniform premium for all UBGS across various locations, overlooking the potential variability in their economic value. However, the effect of UBGS on housing prices has been proved to be spatial non-stationarity (S. Chen et al., 2022; Sander & Zhao, 2015), exhibiting variations in response to changes in direction and distance (Wen et al., 2014; L. Wu & Rowe, 2022). The review of the relevant literature demonstrates the complexity of the effect of UBGS on housing prices, necessitating the adoption of more advanced methods to conduct landscape value studies that account for spatial heterogeneity.

As geographic technology advances, several researchers have adopted spatial statistical techniques to address the limitations of traditional HPM, with the geographically weighted regression (GWR) model standing as a prime example. The GWR model, a local regression approach, has garnered widespread application in examining the effects of various public and landscape facilities on housing prices (Anselin, 1990; Bitter et al., 2007; C. Wu et al., 2016). It possesses the advantage of capturing spatial autocorrelation in the housing market, thereby affording a distinct demonstration of spatial variations in the degree of effect exerted by each variable. The multiscale geographic weighted regression (MGWR) model, an advancement of the GWR model, incorporates the concept of geographical scale, thus generating outcomes that are more aligned with real-world phenomena (Wolf et al., 2018; Yu et al., 2020). In recent years, numerous scholars have applied the MGWR model to the study of China's housing market, yielding findings that demonstrate its superior fit compared to the GWR model (Cao et al., 2019; N. Liu & Strobl, 2023; Lu et al., 2023). MGWR model has advantages in identifying spatial heterogeneity and local regression relationships in the housing market. However, it is also subject to limitations, including elevated computational complexity, stringent requirements for multicollinearity, and its sole applicability to continuous dependent variables (Z. Li & Fotheringham, 2020). But overall, there is a scarcity of research exploring the impact of landscape on property values using the MGWR method. Consequently, within a broader geographical area, there remains a need to evaluate the disparities in landscape economic value according to the MGWR model.

Moreover, in the present study, the economic value of blue or green spaces was evaluated independently. Despite the inclusion of blue spaces and green spaces indicators concurrently on a large geographical scale by some scholars, the categorization of these indicators was relatively rough (i.e., forestland or water body) (Gibbons et al., 2014), which has limited effect on guiding practical planning policies. Currently, there is still a lack of comprehensive and systematic research in response to the context of integrated planning of UBGS. The objective of this study on the Hangzhou housing market is to integrate blue space and green space in order to provide an in-depth estimation of the economic value of UBGS.

More importantly, the interaction effect between blue spaces and green spaces in terms of economic value has been neglected. As ecological infrastructures, these spaces interact with each other in landscape value, with strong correlation and coherence (Yuan et al., 2023). The interrelationship between the two has gained increasing attention and consideration in ecological, social, and health research. Some scholars have gone beyond estimating the value of single blue or green spaces to discuss them jointly. And it has been found that there is a mutually reinforcing synergistic effect between blue and green spaces. That is, the co-configuration of urban blue and green spaces may achieve multiple overlapping effects beyond the original function of a single water body or green space, which has been proved in the fields of climate, physical and mental health (Voskamp & Van de Ven, 2015; Shi et al., 2020; X. Jiao et al., 2023; Hu & Li, 2020; Liang et al., 2024). But when it comes to the economy and land values, there is little discussion about the huge benefits of the combination of the two, especially for housing prices.

In particular, there may be spatial variations in such interaction effects (G. Liu et al., 2019). It is essential to take into account subtle spatial variations. Because the effect of UBGS on housing price may vary considerably in different geographical locations, depending on the type of land, socio-cultural and natural resource qualities, as well as the positioning of the city's development. For example, Anderson and West have discovered that the effect of open space accessibility on housing prices varies contingent upon factors such as population density, income, and other factors (Anderson & West, 2006). Additionally, crime rates have been empirically shown to influence the premium for green spaces (Troy & Grove, 2008). The existence of spatial autocorrelation in housing prices is another factor that has to be considered. The root causes for the autocorrelation of housing prices are social segregation and income disparity, which leads to geographic differentiation between high-value and low-value residential communities (Musterd et al., 2016; Owens, 2019). In the current literature, the examination of interaction effect predominantly relies on global regression techniques applied to interaction terms in the ordinary least squares (OLS) models (X. Li et al., 2021; G. Liu et al., 2019) and it is essential to take into account subtle spatial variations in diverse interaction effect at the urban scale. Considering the above factors, the second objective of this study is to reveal the interaction effect of blue and green spaces and their spatial pattern at the scale of smaller spatial units (grid units), employing spatial regression methods. In the context of promoting refined urban management in China, the study results can help planners and decision makers to accurately identify specific geographical locations requiring improvement and intervention in the process of UBGS planning. Furthermore, they can aid in evaluating the differentiated improvement strategies for different regions, which can provide a more comprehensive and scientific reference for UBGS planning decisions of Hangzhou city.

This study used a multiscale geographically weighted regression (MGWR) model to improve the traditional HPM. MGWR model can solve the spatial heterogeneity problem that traditional linear regression models cannot deal with. Our contributions are as follows: Firstly, previous studies on the landscapes economic value rarely included various elaborate characteristics of UBGS on a larger geographic scale, which limited the effectiveness of guidance for practical planning policies. In this study, four models were established from the housing level to discuss the heterogeneous effects of various attributes (accessibility, features and quality) of UBGS on housing prices. Secondly, previous studies rarely focused on the interaction effect between blue spaces and green spaces in terms of economic value. On the scale of 1 km*1 km grids, the study explored the interaction effects between blue spaces and green spaces on housing prices at the district level, as well as the different spatial patterns of the interaction effects. Finally, the study put forward some policy recommendations for UBGS planning in different urban environments.

The research questions can be summarized as follows:

(1) How do different types, features, and accessibility of UBGS effect housing prices?

(2) When urban blue spaces and green spaces collaborate to affect the housing prices, are there interaction effects between them?

(3) If so, are there different spatial patterns for this interaction effects? What suggestions do the study results provide for UBGS planning in China?

2. Data and methodology

2.1. Overall research frame

The sequence of this study is shown in Figure 1, which is divided into three steps. (1) Housing level: Based on 1,461 housing transaction data, four MGWR models were employed to improve the traditional HPM model, and the heterogeneous effect of various attributes of UBGS on housing price, including accessibility, features and quality, was comprehensively explored. (2) District level: Based on 676 1 km*1 km grids data, the heterogeneous effects of blue and green spaces and their interaction on housing prices at district level, and different spatial patterns of interaction effects were summarized. (3) UBGS planning strategies and suggestions for different urban areas are proposed. The objective of this study is to conduct a comprehensive investigation into the interrelationship between UBGS and housing prices, with the aim of providing valuable insights for the sustainable and coordinated development of the UBGS.

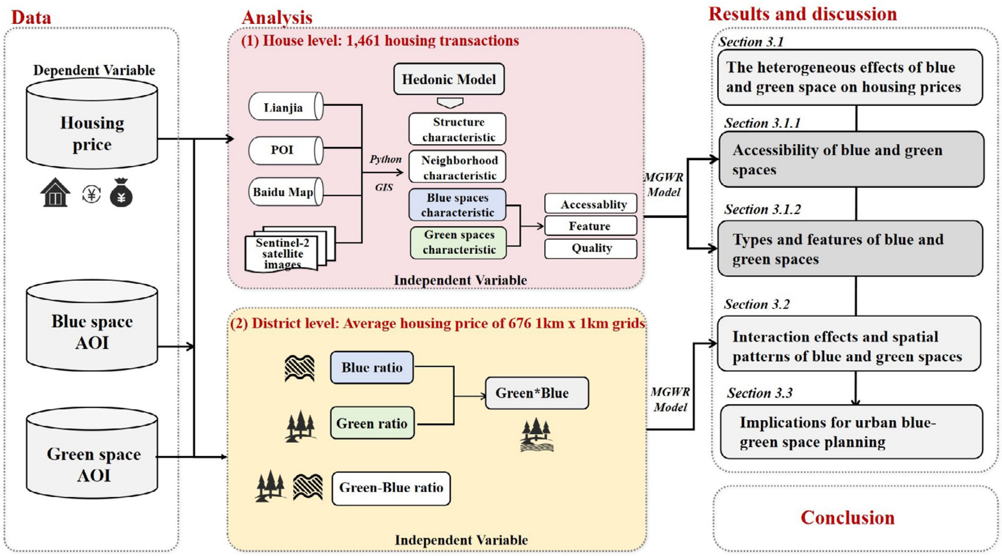

Figure 1. Research process overview

2.2. Study area

Hangzhou is the capital of Zhejiang Province, China. It is an important city in the Yangtze River Delta, located in the northern part of Zhejiang Province. This historic and cultural city is known for its picturesque natural landscape and environment, with rolling hills and a complex diversity of lakes and rivers. The city-lake integrated spatial pattern of "cloud mountains on three sides and city on one side" makes this city unique. The West Lake, a large natural lake in the center of the city, was listed as a World Heritage Site by UNESCO in 2002. The Grand Canal, the world's longest man-made canal, and the Qiantang River, with its spectacular tidal landscape, also pass through the city. Meanwhile, Hangzhou is rich in natural green space resources. The per capita public green space area in the urban area is 12.27 m^2, and the greening rate in built-up areas is 39.40% (Hangzhou Bureau of Statistics, 2021).

As the host city of the G20 Summit, Hangzhou had carried out a number of large-scale urban construction and landscape renovation projects in the past two decades. These projects are all carried out around urban blue spaces, including the Xixi Wetland Comprehensive Protection Project, the Grand Canal Protection and Development Project, the Five Waters Co-management Project. These urban construction projects have greatly improved the quality of urban blue spaces and also promoted the development and transformation of urban green space. For example, in the protection and development of the Grand Canal, the government has created linear waterfront green spaces on both sides. Industrial factories in urban built-up areas have been transformed into parks to provide space for residents' growing needs for outdoor leisure activities. In the suburbs of cities, the government has developed a large number of rural parks and wetland parks through land exchange. The number of open parks has grown from 181 in 2011 to 355 in 2021 (Hangzhou Bureau of Statistics, 2021).

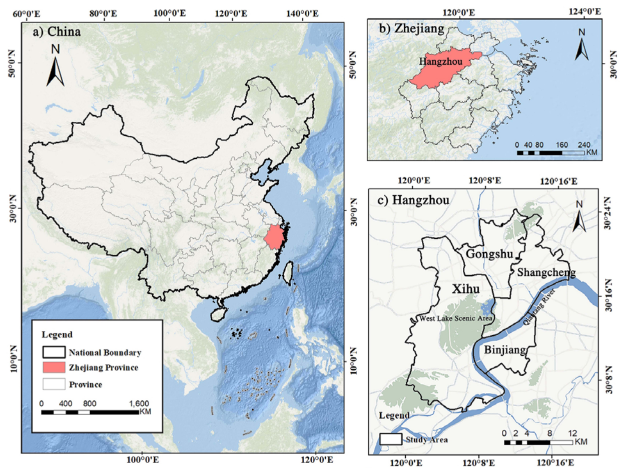

Figure 2. Location of study area

The study area consists of four districts: Shangcheng District, Xihu District, Gongshu District, and Binjiang District, including 47 subdistricts (Figure 2). This main urban area with an area of approximately 625.63 km^2 has experienced rapid expansion of population and built-up areas in the past 40 years, and is currently home to 4.245 million people (Hangzhou Municipal Government, 2024).

2.3. Methodology

2.3.1. Hedonic price model

The HPM measures the implicit price (i.e., the value of individual characteristics) of environmental goods or services that are not traded on the market through the observed prices of products traded on the market (Freeman III et al., 2014). HPM can be used to estimate the economic benefits or costs related to environmental quality and environmental convenience, thereby estimating people's willingness to pay for the environment (Alriksson & Öberg, 2008). HPM believes that housing are multi-attribute commodities, so their prices are determined by their characteristics, which can be divided into the following categories: structural characteristics, location characteristics, and neighborhood characteristics. HPM has been widely used in previous studies to measure the value of landscape elements related to housing prices, such as parks, forests, lakes, wetlands, etc. (Morancho, 2003; Reynaud & Lanzanova, 2017; Tapsuwan et al., 2009; Tyrväinen & Miettinen, 2000). After comparing various functional forms of HPM (log-log, lin-log, lin-lin, log-lin), and the log-lin functional forms was adopted. It can be described by:

$$\ln p = \beta_0 + \sum \beta_k S_k + \sum \beta_j L_j + u, \quad (1)$$

where: ln p is the natural log of the housing price of location; S_k is a matrix of structural characteristics and neighborhood characteristics; L_j is a matrix of landscape characteristics (urban blue space and green space); β_0 is the intercept coefficient, β_k, β_j, are the corresponding parameters and u is the random disturbance term.

2.3.2. Multiscale geographically weighted regression model

Previous studies often use the OLS method to construct HPM, which is a global regression model that assumes that all housing characteristics are homogeneous and independent of each other. However, these assumptions ignore the spatial heterogeneity and spatial autocorrelation of housing prices. Global regression models can only reflect global trends and may ignore some important spatial non-stationarity. Spatial non-stationarity means that the relationship between variables is not constant throughout the study area. The GWR model is a local linear regression model based on spatial variation relationship model. By introducing a spatial weight matrix, it can generate a regression model describing local relationships in each part of the study area to capture regional fixed effects. This allows it to effectively explain the local spatial relationships and spatial heterogeneity of variables, thus reducing the endogeneity issues that are inevitably caused by omitted variables in traditional HPM (Anselin, 1990; McMillen, 2004). Empirical research shows that GWR is more suitable to explain the effect of various variables on housing prices and its spatial heterogeneity (Anselin, 1990; Bitter et al., 2007; C. Wu et al., 2016).

However, the disadvantage of the classical GWR model is that it uses a fixed bandwidth to determine the boundaries of local regression (Fotheringham et al., 2022), that is, it assumes that all influencing factors have the same spatial scale. However, the spatial scales of different influencing factors are often not uniform. MGWR model is a further improvement of GWR model (Fotheringham et al., 2017). MGWR model allows different bandwidths for each independent variable. The multi-bandwidth method can analyse the influence scale of different factors and draw more accurate conclusions (Wolf et al., 2018; Yu et al., 2020). The equation is as follows:

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i,\ i = 1, 2, \ldots, n, \quad (2)$$

where: x_{ij} is the observation of the j independent variable at location i; β_{bwj} is the jth coefficient; bwj in β_{bwj} indicates the bandwidth used for calibration of the jth conditional relationship; (u_i, v_i) is the spatial coordinate of the i sample point; ε_i is the error term, and y_i is the housing price of location i.

In the calculation of MGWR, the spatial weight function needs to be introduced. The spatial weight function can be determined in several ways, such as through the threshold distance, inverse distance, bi-square function and Gaussian function. We chose Gaussian function as the adaptive bis-quared spatial kernel and use the golden section method and AICc information criterion to determine the optimal bandwidth (Fotheringham et al., 2017).

2.4. Data collection

2.4.1. Housing level data

In this stage, housing units were selected as the research unit, and the logarithmic form (LnP) of the unit price of each housing transaction data was used as the dependent variable to construct HPM. In terms of the selection of independent variables, HPM categorizes residential characteristics into three types: structural characteristics, neighborhood characteristics, and location characteristics. Previous studies generally employed the distance to the central business district (CBD) as a locational characteristic variable to reflect the accessibility of housing to city centers. However, Hangzhou has a unique "city-lake integrated" urban spatial structure, wherein the city center is situated proximate to large UBGS. To avoid severe collinearity issues, the location characteristics were incorporated into the blue and green space characteristics. Consequently, the final selection of independent variables was drawn from structural characteristics and neighborhood characteristics, and blue spaces characteristics and green spaces characteristics. Regarding structural characteristics, following previous research on Hangzhou's housing market (Wen et al., 2017; Wen & Jia, 2004), the variables most relevant to housing prices such as floor area, decoration level, lift and orientation were selected. Neighborhood characteristics indicate the convenience of public services or community facilities, encompassing amenities surrounding the residential area. Drawing upon previous research, the number of bus stops and subway stations were selected to reflect the transportation convenience. Furthermore, the number of educational facilities, hospitals, and supermarkets were chosen to reflect the living service level (Wen et al., 2015, 2017). Following the correlation test and stepwise regression analysis, the number of bus stops, educational facilities and hospitals were eliminated. Drawing on previous studies, this study explored the effect of blue and green space on housing prices in terms of accessibility, features and quality.

The 1,461 second-hand housing transaction data was collected in the study area from 2019 to 2022 through

Python 3.11. The data was obtained from Lianjia.com (Lianjia, n.d.), the largest real estate agency website in China. The housing transaction data included detailed structural characteristics and geographic location of houses. The second-hand housing with 70-year property rights was selected, and multi-storey villas and apartments were excluded. After removing the outliers and duplicate data with geographic information, the coordinate projection was converted to the WGS84 projection coordinate system. The spatial distribution of these data is presented in Figure 3. Given the long-term eastward urban expansion of Hangzhou, there are comparatively fewer residential points in the mountainous areas of the southwest. The point-of-interest (POI) data for subways and supermarkets were collected via Gaode Map, and the straight-line distance from each housing unit to its nearest POI, as well as the number of POIs within a specific distance, were calculated. Considering the 15-minute community living circle proposed by the Chinese government, which aims to provide basic service functions and public activity spaces for daily necessities within a 15-minute walking distance (approximately 1000 m) (Ministry of Natural Resources of the People's Republic of China, 2021), 1000 m was selected as the distance threshold for the calculations.

Green space data and water bodies data came from Baidu Maps. After remote sensing image interpretation and manual verification, 167 green space data and 110 water bodies data in the study area in 2022 were obtained. The blue spaces were divided into rivers and lakes according to different types (Table 1). The green spaces refer to open parks and scenic areas. Toll parks (golf courses, zoos) and inaccessible parks (nameless green spaces with isolation and protection, gated community green spaces) were not included in this study. According to the classification

Table 1. Descriptions of the variables

Characteristic types	Variables	Definition	Mean	SD	Expected sign
		Dependent variable			
	Lnprice	The natural logarithm of the house price	10.721	0.328	
		Independent variable			
Structure characteristic	Area	Total area of a house (m^2)	91.288	41.744	+
	Orientation	Dummy variable: 1 = south, southeast, and southwest, 0 = otherwise	0.970	0.180	+
	Decoration degree	Luxury decorations (2), common decorations (1), and no decoration (0)	1.420	0.554	+
	Lift	Dummy variable: 1 = with lift, 0 = otherwise	0.520	0.500	+
Neighborhood characteristic	Subway	Number of subway within 1 km around the community	7.990	7.186	+
	Supermarket	Number of supermarket within 1 km around the community	20.495	10.738	+
Blue space characteristic	DIS-West Lake	Distance to the West Lake (km)	5.247	3.254	–
	DIS-Lake	Distance to urban lake (km)	2.328	1.429	–
	DIS-Qiantang River	Distance to Qiantang River (km)	6.407	4.040	–
	DIS-Grand Canal	Distance to Grand Canal (km)	3.711	3.322	–
	DIS-urban river	Distance to urban river (km)	0.318	0.283	–
	RiverWidth	The width of the nearest river (m)	52.894	152.406	+
	LakeArea	The area of the nearest lake (ha)	123.954	249.465	+
	Water quality	The water quality of the nearest water: Grade V(1), Grade IV(2), Grade III(3), Grade II(4), Grade I(5)	2.860	0.899	+
Green space characteristic	DIS-small urban park	Distance to the nearest small urban park (km)	0.820	0.788	–
	DIS-medium urban park	Distance to the nearest medium urban park (km)	1.047	0.718	–
	DIS-large urban park	Distance to the nearest large urban park (km)	2.708	1.575	–
	DIS-Mega urban park	Distance to the nearest mega urban park (km)	3.035	1.880	–
	Park NDVI	Normalized Difference Vegetation Index of the nearest park	0.233	0.072	+
	Park area	The area of the nearest park (ha)	91.896	379.149	+

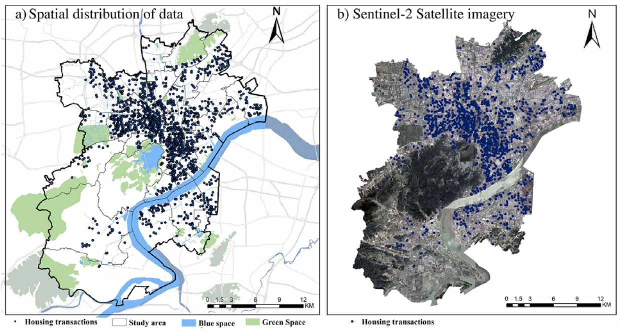

Figure 3. Distribution of UBGS and the housing transaction data used in the analysis area

standard of urban green space, this study categorized green spaces into four categories based on scale and service level: small parks (less than 2 ha, pocket parks), medium parks (2–10 ha, community parks), large parks (10–50 ha, comprehensive parks), and mega parks (more than 50 ha, country parks and scenic areas). Accessibility was measured by the straight-line distance from the housing units to the parks and water bodies. River width and park area were used to measure the features of blue and green spaces, both calculated in Arcgis10.8.

Then, the normalized difference vegetation index (NDVI) of the study area was calculated using ENVI 5.3. The remote sensing images used to calculate NDVI come from Sentinel-2 satellite images (spatial resolution 10 m) in the Geospatial Data Cloud (http://www.gscloud.cn/) in March 2023. NDVI represents the vegetation coverage in the parks, and a high NDVI value indicates a high density of green vegetation, which was used to measure the green spaces quality. Water quality data came from the Hangzhou Hydrology Bureau and was used to measure the blue space quality. According to China's surface water quality standards, it was divided into five grades (Grade I to Grade V). Grade I to III water is of good quality and can be used for drinking purposes. Grade IV water is slightly polluted and suitable for industrial use and non-contact recreational activities. Grade V water is moderately to heavily polluted, suitable for agricultural and landscape uses.

Before conducting the calculations, Moran's *I* for the dependent variable and variance inflation factors (VIF) for the independent variables were computed to verify the existence of spatial autocorrelation and multicollinearity. The results showed that the collinearity of the independent variables was not obvious (VIF $\leqslant$ 2.5). With a Moran's *I* of 0.291 and a *z*-score of 57.65, which is greater than 2.58, the existence of spatial autocorrelation was confirmed, justifying the application of GWR and MGWR models.

In this part, four MGWR-based hedonic price models were established to answer the first research question. Model 1 and Model 3 were both from the perspective of accessibility. Model 1 was used to reveal the effect of distance from different types of rivers and lakes on housing prices. Model 3 was used to explored the effect of distance from different types of parks on housing prices. Model 2 and Model 4 respectively examined the effect of the features and quality of blue and green spaces on housing prices.

2.4.2. District level data

On the basis of the housing level research, in this part, the study area was divided into 676 1 km*1 km grids as research units, trying to answer the second and third research questions from the district scale. Using inverse distance weighted (IDW) interpolation, the average housing price of each grid was obtained as the dependent variable. The blue spaces area ratio (*Blue_ratio*), green spaces area ratio (*Green_ratio*) and green-blue spaces area ratio (*GB_ratio*) of each grid were calculated and used as independent variables. Then, four MGWR models were established to explore the effects of blue-green spatial pattern on the spatial heterogeneity of housing prices (Table 2), and the calculation equation is shown as Equation (2).

Next, the interaction effect of blue and green space on housing prices was also explored, by adding an interaction term (Green*Blue) in the regression model. The MGWR model can generate a local regression model for each grid in the study area. The significance and sign direction of the interaction terms in the local regression model for each grid were observed. In the event that the direction of the interaction term aligns with the green space variable, it implies that blue spaces enhance the effect of green spaces. Conversely, if the direction of the interaction term is opposite to that of the green space variable, it indicates that blue spaces mitigate the effect of green space. All MGWR models were performed using the Python code shared by (Oshan et al., 2019).

Table 2. Descriptions of the variables

Variables class	Variables	Equation	Definition
		Dependent variable	
Housing price	Price		Average housing price of each grid
		Independent variable	
Blue space	Blue_ratio	A_{blue}/A_{grid}	The proportion of blue spaces area of each grid
Green space	Green_ratio	A_{green}/A_{grid}	The proportion of green spaces area of each grid
Blue-green relation	GB_ratio	A_{green}/A_{blue}	Ratio of green spaces area to blue spaces area of each grid
	Green*Blue	Green_ratio*Blue_ratio	Interaction terms of blue and green spaces

3. Results and discussion

3.1. The heterogeneous effects of blue and green space on housing prices

The results of Models 1–4 show the heterogeneous effect of various attributes of UBGS on housing prices from the housing level. Adjusted R^2 shows that the selected independent variables can explain 68.6% to 71.5% of housing prices. The MGWR results were compared with the OLS model. The AICc and RSS of the MGWR model are significantly lower than those of OLS model (Table A1). The Moran's *I* statistics of all MGWR model residuals are not significant ($p > 0.05$), which indicates that after considering spatial heterogeneity and spatial dependence, the models do not have significant spatial effects. All structure and neighborhood characteristics variables are significant and showed results consistent with the research hypotheses. To support the research's focus and streamline the results, we specifically focus on the significant variables ($p < 0.05$) related to blue space and green space characteristics, and visualizes them for clarity.

3.1.1. Accessibility, types and features of blue spaces

The results of Model 1 are shown in Table 3 and Figure 4. *DIS-Qiantang River*, *DIS-Grand Canal*, *DIS-Urban River*, *DIS-West Lake* are all significant at the 5% level. Only the *DIS-Lake* is not significant. It should be pointed out that considering the special economic and cultural value of the West Lake as a World Heritage site and a city center, this study divided the West Lake from other lakes. The Lake variable refer to landscape lakes and natural lakes in parks except the West Lake. This result shows that the effect of the West Lake on housing prices is much greater than that of other lake.

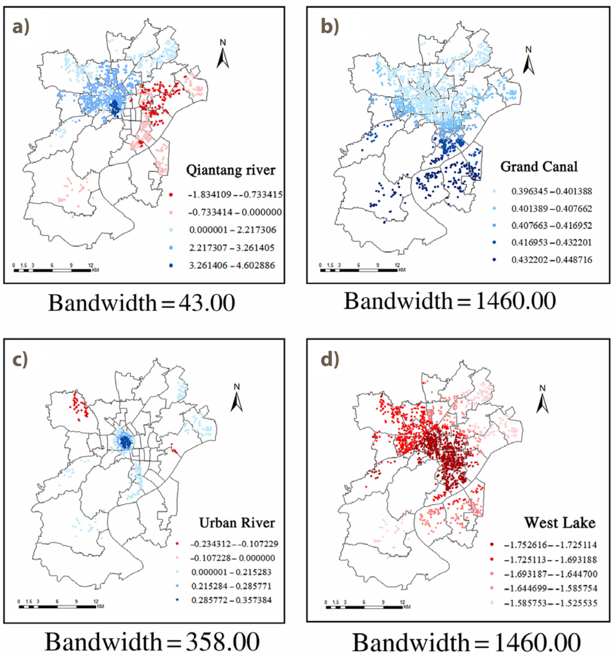

Figure 4. Spatial distribution of regression coefficients for Model 1 ($p < 0.05$)

In the visualization results of the MGWR model, red dots represent negative regression coefficients, while blue dots represent positive coefficients. Sorted by the absolute value of the negative regression coefficient, the effect of different blue spaces on housing prices in descending order is the West Lake, the Qiantang River, the Grand Canal, urban rivers. Bandwidth indicates the scale of the influencing factors. When the bandwidth is closer to the total number of samples, it suggests that the spatial influence range of the variable is closer to the global scale. According to the variable bandwidth identified by the MGWR model, it can be observed that the spatial scales of the effect of various blue space on housing prices are in descending order: the West Lake/the Grand Canal, urban rivers, the Qiantang River.

The West Lake and the Grand Canal are the two oldest and longest artificially managed blue spaces, which have shaped the urban layout of Hangzhou. Therefore, they have the largest bandwidth (bandwidth = 1460) and exert a relatively stable influence on housing prices throughout the entire study area. Figure 4d illustrates the overall promotive effect of the West Lake on housing prices, with almost all observation points achieving a significance level of 1% by p value. When the distance to the West Lake decreases by 1 kilometer, the housing unit price increases by 1.526–1.753%. The highest regression coefficients are in the northern and eastern areas of the West Lake, which are the traditional central urban areas of Hangzhou with convenient public facilities. As the largest blue open space in the center of Hangzhou, the West Lake holds significant landscape and cultural value. Over a long period, the West Lake has played a leading role in shaping the spatial structure of housing prices in Hangzhou (Wen et al., 2014). Consumers are willing to pay higher prices to reside close to the West Lake, aligning with the previous research (Wen et al., 2015, 2017). The regression coefficient of the Grand Canal is globally positive (Figure 4b), showing that when the distance to the Grand Canal decreases by 1 kilometer, the housing unit price decreases 0.396–0.449%. According to Wen et al. (Wen et al., 2015), a possible explanation is that the Grand Canal is a shipping river, and the exhaust gas and noise generated by the large volume of ships may have adversely impacted the quality of life for residents living in close proximity.

The Qiantang River is the most heterogeneous local variable with the smallest bandwidth (bandwidth = 43). Although the Qiantang River is also an important river in Hangzhou, it was only after the city proposed the "River-supporting Development" strategy in 2000 that extensive landscape and residential development emerged along its banks. Therefore, the scale of its effect on housing prices is not as significant as that of the West Lake and the Grand Canal. Nevertheless, the superior riverside scenery and the location of the new city center still exert a considerable positive influence on housing prices. In the red area in Figure 4a, housing prices exhibit a decreasing trend as the

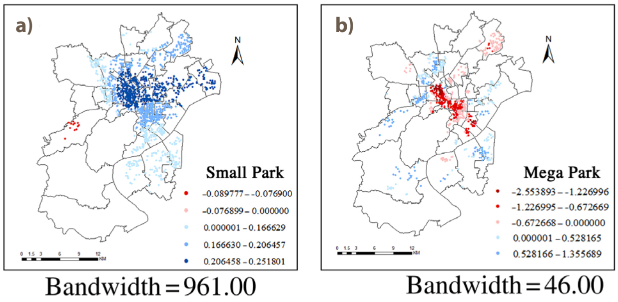

Figure 5. Spatial distribution of regression coefficients for Model 3 ($p < 0.05$)

distance from the Qiantang River increases, aligning with previous findings (Wen et al., 2015). When the distance to the Qiantang River decreases by 1 kilometer, the housing unit price increases by up to 1.834%.

The bandwidth of urban river is 358, indicating that the effect on housing prices exhibits spatial heterogeneity. Different from previous studies (Wen et al., 2015), this study found that the distance to urban rivers has both positive and negative effects on housing prices (Figure 4c). Urban rivers have a restraining effect on housing prices in most areas, and only a promoting effect in the northwestern suburbs (0.107–0.234%). As confirmed by Peng et al. (2023), small rivers in cities do not have a significant positive impact on housing prices as main rivers. This may be attributed to the considerable variations in the attributes of urban rivers in Hangzhou, where some are equipped with excellent riverside greening, while others suffer from severe pollution.

The results of the effect of distance to various types of parks on housing prices are shown in Model 3. The results show that only *DIS-small urban park* and *DIS-mega urban park* are significant ($p < 0.05$) (Figure 5). The regression coefficients of mega parks exhibit spatial heterogeneity (bandwidth = 46), indicate a relatively limited scale of influence. The area with negative effect concentrated around the West Lake Scenic Area in the city center and the Banshan Forest Park in the northeast of the city. As one of Hangzhou's renowned World Heritage Sites, the West Lake Scenic Area is a large-scale landscape scenic area located in the urban core. This vast UBGS comprises mountains, lakes, and exquisite parks, boasting well-designed landscapes and excellent maintenance. The Banshan National Forest Park is a forest park located in a large mountain area with large areas of natural forest and high levels of air quality. The results support evidence from previous observations that proximity to mountains and forests has a positive effect on housing prices (G. Liu et al., 2019; T. Liu et al., 2020). In contrast, small parks serve as global variable (bandwidth = 961), exhibiting a relatively stable but subtle positive effect in entire study area of Hangzhou. Only some residential areas close to the mountains and farmland are negative. The possible explanation might be that in recent years, Hangzhou has added numerous fragmented small parks within the main urban area, leading to a decrease in their appeal to buyers due to their high accessibility. But in the western suburbs, surrounded by enclosed university green spaces and mountains, residents are primarily exposed to a simplified type of green space (i.e., natural forests with steep slopes and dense vegetation), so scarce small parks that provide recreational activities may be preferred by residents. This result confirms previous findings that small and scattered parks provide residents with more equal access to green spaces resources. When the surrounding green spaces resources are adequate, the housing prices will not be greatly increased (J. R. Wolch et al., 2014). However, as rare large-scale green infrastructure in the city, mega parks are often strategically integrated into urban development plans and are more likely to promote the rise of housing prices, which are prevalent in numerous major cities (Immergluck, 2009; Lim et al., 2013; Tajima, 2003).

3.1.2. Types and features of blue and green spaces

Models 2 and 4 reveal the effect of the feature and quality of UBGS on housing prices. For the blue spaces, the variable *River width*, *Lake area*, and *water quality* are all significant at the 5% level. These three variables are all local variables and reflect spatial heterogeneity. This result diverges from the findings of Peng et al.'s cross-city-scale study, which concluded that lake area does not significantly influence housing prices (Peng et al., 2023). Our single-city study found that lake area has different effects on housing prices in different parts of the city. In the core built-up areas of Hangzhou, larger lake areas and narrower river widths lead to an increase in housing prices, whereas the opposite phenomenon is observed in the outer suburbs (Figure 6a and 6b). A plausible

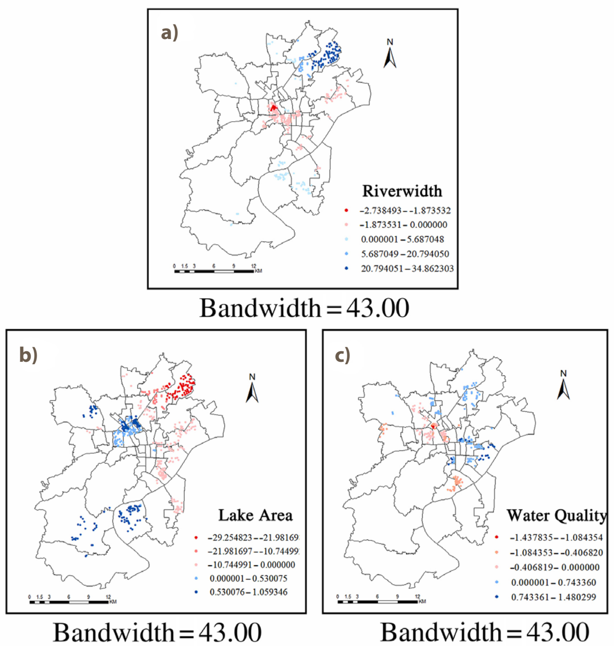

Figure 6. Spatial distribution of regression coefficients for Model 2 ($p < 0.05$)

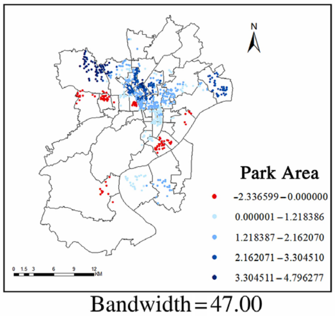

Figure 7. Spatial distribution of regression coefficients for Model 4 (p < 0.05)

explanation is that in high-density urban cores, larger water bodies offer enhanced ecosystem services, particularly in mitigating the urban heat island effect (Hou & Estoque, 2020). However, wider rivers may contribute to increased noise and transportation costs. In the suburbs with incomplete urban infrastructure, abundant urban rivers emerge as the most significant blue space resources, thus making residents more sensitive to the feature of urban rivers.

The *water quality* variables show spatial variation and are positive in most regions (Figure 6c). The positive coefficient is primarily concentrated in the historical old urban area of Hangzhou (also known as the former imperial city). Several north-south rivers with expansive widths here have assumed important functions since ancient times, such as drinking, transportation, landscape. Clear water has a significant positive impact on house prices (Moore et al., 2020). Walsh et al. also reported similar findings, stating that the effect of water quality on housing prices depends on the location of the residence and the size of the water body, with larger water bodies demonstrating a stronger capability to elevate housing prices compared to smaller water bodies (Walsh et al., 2011).

For green spaces, the variable *Park NDVI* is not significant, while *Park area* passes the 5% significance test and shows spatial heterogeneity (bandwidth = 47). This suggests that residents in different regions have considerably varying preferences for park area. The *park area* has a positive effect on the housing price in most areas. Specifically, the positive coefficient reaches the highest value in the area along the Grand Canal, indicating that along the Grand Canal, an increase in park area by 1 ha can lead to a maximum increase in housing unit prices of 4.796% (Figure 7). The results also confirm previous studies that have suggested that waterfronts greening can enhance housing values (Bin et al., 2009). As the oldest and widest rivers in Hangzhou, the government had built a large number of linear waterfront parks along the Grand Canal during the river reconstruction project. These parks, together with the water bodies, form ventilation corridors and biological habitats, exerting ecological and cooling effects. Although from the perspective of types and features of blue spaces, the Grand Canal, urban river and river width do not promote the rise of housing prices in the urban core area. However, when considering green space, the study indicates that the area with the most obvious effect of park area on housing prices is located near the rivers. It indicates that the effect of blue spaces on housing prices in real urban environment is intricate and spatially varied, and may be positively or negatively affected by green spaces, contradicting the findings of previous studies. Solely assessing the effect of blue or green spaces on housing prices from a single perspective, while overlooking the interactive effects of the actual UBGS layout and planning policies, may lead to inaccurate estimations. In addition, the outer suburbs of the city (east and northwest of the study area) also show a promotion effect of park area on housing prices (2.162–4.796%), and the scarcity of green space in these areas may have contributed to this result. Interestingly, in some areas, a negative correlation is

Table 3. MGWR regression results for Models 1–4

Model 1				Model 2				Model 3				Model 4			
	p ≤ 0.05 (%)	Max	Min		p ≤ 0.05 (%)	Max	Min		p ≤ 0.05 (%)	Max	Min		p ≤ 0.05 (%)	Max	Min
Intercept	84.13	1.186	–2.817	Intercept	52.16	0.909	–8.779	Intercept	57.70	1.383	–1.898	Intercept	56.60	1.533	–1.490
Area	46.93	0.610	–0.466	Area	100	0.220	0.203	Area	100	0.229	0.207	Area	100	0.229	0.210
Orientation	100.00	0.068	0.051	Orientation	100	0.052	0.035	Orientation	100	0.058	0.042	Orientation	100	0.055	0.042
Decoration	83.17	0.282	0.021	Decoration	100	0.177	0.107	Decoration	100	0.221	0.092	Decoration	80.01	0.318	0.000
Lift	56.20	0.336	–0.020	Lift	29.02	0.618	–0.499	Lift	40.94	0.310	–0.132	Lift	38.06	0.542	–0.332
Subway	4.16	0.062	0.053	Subway	31.01	1.500	–0.941	Subway	100	0.112	0.097	Subway	100	0.118	0.104
Supermarket	100.00	–0.101	–0.110	Supermarket	20.33	0.746	–1.444	Supermarket	100	–0.105	–0.118	Supermarket	22.72	0.502	–1.387
DIS-Grand Canal	100.00	0.449	0.396	Riverwidth	17.52	34.862	–2.738	DIS-Small park	90.12	0.252	–0.098	Park NDVI	0	–0.008	–0.026
DIS-QT River	74.18	4.603	–1.834	Lakearea	26.76	1.059	–29.255	DIS-medium park	0	0.025	–0.030	Park area	48.39	4.796	–2.337
DIS-urban river	30.25	0.357	–0.234	Waterquality	17.52	1.438	–1.480	DIS-large park	0	–0.035	–0.051				
DIS-lake	0	0.037	0.001					DIS-mega park	51.36	1.356	–2.554				
DIS-West Lake	100.00	–1.526	–1.753												
AICc		2595.850				2780.451				2651.581				2658.434	
Adj. R^2		0.715				0.719				0.686				0.701	

observed between park area and housing price, indicating that the relationship between park area and housing premium is not merely a uniform positive linear trend; rather, it exhibits diverse positive or negative effects across spatial locations. Our subsequent analysis will further elucidate this phenomenon.

3.2. nteraction effects and spatial patterns of blue and green spaces

The regression results of Models 5–8 show the effect of the distribution of blue and green spaces at the district level on housing prices. The adjusted R^2 reaches 0.701–0.831. The interaction term in Model 8 is significant at the 5% level. And after adding the interaction term, the adjusted R^2 of Model 8 increased to 0.855, which confirmed the previous hypothesis of the study that there is an interaction effect between blue spaces and green spaces on housing prices. The regression coefficients of all variables exhibit spatial heterogeneity.

Figure 8a and 8b present the regression coefficients of blue spaces and green spaces area in each grid on housing prices, respectively. Figure 8c shows the regression coefficients of the ratio of green spaces to blue spaces in the grid. The blue spaces area exerts a positive impact on all observation points (Figure 5b), indicating that as the blue space area increases, the housing prices also rise. This positive effect reaches its highest point in area along the Qiantang River.

However, there is a positive and negative differentiation in the impact of green space area on housing prices. Consistent with the findings in Section 3.1.2, the area of the West Lake Scenic Area in the urban core and the Banshan National Forest Park in the north of the city have positive effect on the housing prices. However, the area of natural reserves such as wetlands and forest parks in the western and southern regions of the city exhibit a negative influence. There are several possible explanations for this result. While some studies have argued that proximity to national parks and nature reserves raises property prices (Cheung & Fernandez, 2021; Dell'Anna et al., 2022), other studies have reported the opposite (Neumann et al., 2009). If the public only has limited access to protected areas, they may not be as concerned about their existence. At the same time, these nature reserves are far from the urban core, and their large scale also means inconvenient transportation. In contrast, large UBGS like the West Lake Scenic Area and Banshan National Forest Park are proximal to the city center, offering vast surrounding land suitable for real estate development. The diverse functionality, abundant recreational facilities, and diligent excellent maintenance within the parks contribute to a premium on housing. Notably, in the suburban areas (depicted as dark blue in Figure 8b), the public exhibits the highest sensitivity to green space area. Residents in the suburbs, potentially due to their distance from large UBGS in the city center, are more concerned about UBGS surrounding their residences.

In addition, the negative effect of *GB_ratio* was unexpected (Figure 8c). In the Qianjiang New City, the larger the green spaces beside the water bodies, the lower the housing prices. As a rare city park with an area exceeding 20ha in Hangzhou, large parks such as CBD Park and

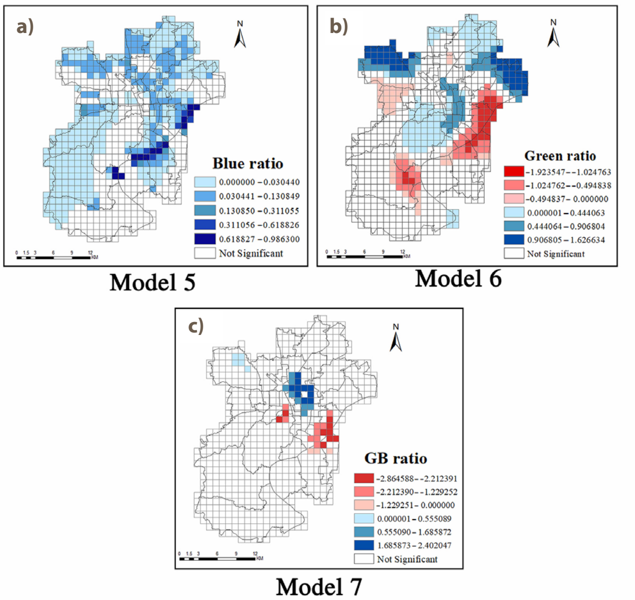

Figure 8. Spatial distribution of regression coefficients for Model 5–7 ($p < 0.05$)

Table 4. MGWR regression results for Models 5–8

	Variable	Max	Min	STD	$p \leq 0.05$(%)	AICc	Adj. R^2
Model 5	Blue_ratio	1.964	–0.665	0.518	52.96	799.209	0.831
	Intercept	1.755	–1.132	0.696	84.47		
Model 6	Green_ratio	1.627	–1.924	0.502	45.56	742.332	0.844
	Intercept	1.434	–1.586	0.721	91.42		
Model 7	GB_ratio	2.402	–2.865	1.058	20.85	369.038	0.701
	Intercept	1.120	–1.282	0.656	85.78		
Model 8	Blue_ratio	1.941	–0.577	0.498	48.82	742.134	0.855
	Green_ratio	0.748	–1.959	0.427	44.97		
	Green*Blue	2.297	–1.456	0.614	30.92		
	Intercept	1.401	–0.962	0.577	85.80		

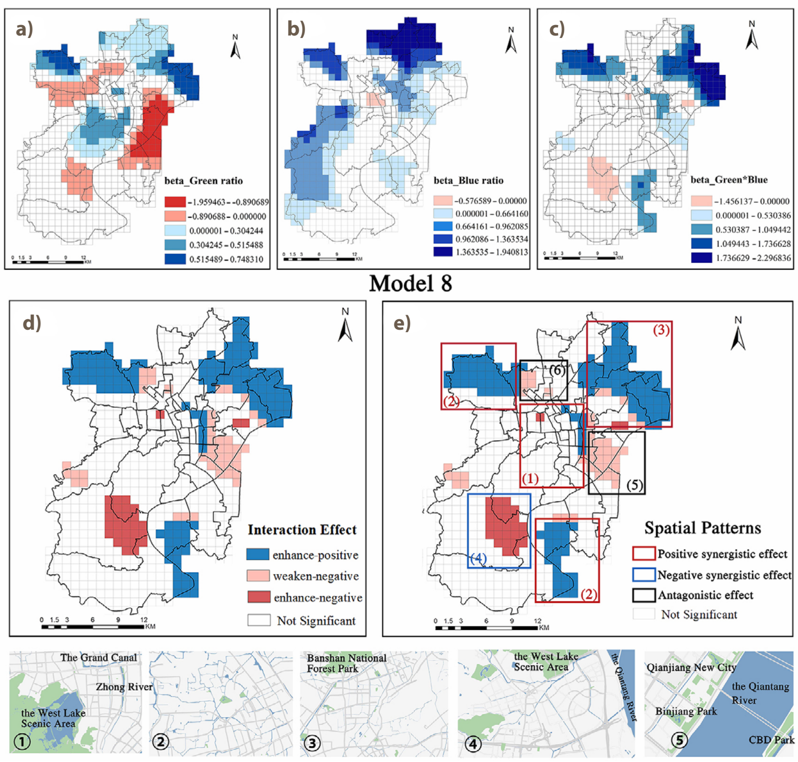

Figure 9. Regression coefficient distribution of Model 8 and spatial distribution of blue and green space interaction effects (p < 0.05)

Binjiang Park have failed to trigger a rise in housing prices in the surrounding areas. Several factors could explain this observation. As a prevalent strategy for urban expansion in China, the government has constructed numerous commercial office bulidings and high-tech centers in the Qianjiang New City. These commercial facilities have a stronger premium effect than parks (L. Wu & Rowe, 2022). The large parks within this area contribute to the overall urban appeal through commercial, urban display, and municipal activities. But the premium may be reflected in the rent of commercial spaces rather than in the surrounding residential properties. Although the park boasts exquisite greenery and high-quality maintenance, the increase in noise and traffic may have had a negative impact on the area (Anderson & West, 2006).

Finally, based on the significance and the sign of the interaction term from each local regression model in Model 8, the spatial distribution map of the blue-green space interaction effects was drawn (Figure 9). The spatial patterns of interaction effects can be categorized into three distinct types: the blue-green positive synergistic effect (enhance-positive), the blue-green negative synergistic effect (enhance-negative), and the blue-green antagonistic effect (weaken-positive, weaken-negative). On the one hand, blue-green synergistic effect refers to the phenomenon where blue and green spaces can work together to enhance the positive or negative effect on housing prices. The joint effect of these two spaces exceeds the sum of their individual benefits. On the other hand, the blue-green antagonistic effect refers to a situation where the blue and green spaces offset each other's positive or negative effects on housing prices, resulting in a weakening of their overall impact.

Almost 19.97% of the study areas exhibits a blue-green positive synergistic effect, indicating that blue spaces enhance the positive effect of green spaces on housing prices (enhance-positive). Area 1 corresponds to the West Lake (Figure 9e), which has long been the epicenter of Hangzhou's urban development. The West Lake is characterized by diverse blue space forms (bays, rivers, lakes) and rich green space types (waterfront parks, botanical gardens, forest parks, tea gardens), providing the public with a variety of leisure activity spaces and ornamental and educational values. The combination of carefully maintained green spaces, rivers and lakes for scenic purposes has triggered a significant increase in housing prices, ultimately once again motivating government investment in urban greening. Area 2 is the outer suburb with both urban development potential and large-scale green infrastructure. Real estate developers have constructed numerous luxury residential areas, leveraging the selling point of being "proximate to mountains and rivers". Area 3 is the undeveloped outer suburb characterized by a scarcity of UBGS. Residents' demand for UBGS leads to the fact that proximity to UBGS in the area will promote the rise of housing prices. As Liu et al. 's empirical study in Chongqing, China found, residents are willing to pay a premium for houses with "Shanshui" views (proximity to both mountains and rivers) (G. Liu et al., 2019). This study in Hangzhou also confirmed the existence of the blue-green positive synergy phenomenon. Whether in urban core areas or planned development area, the co-figuration of blue and green spaces will generate higher housing premiums.

Only 4.44% of the study areas shows a blue-green negative synergistic effect, where blue spaces promote the negative impact of green spaces on housing prices (enhance-negative). This effect was primarily concentrated in area 4, namely, the southwestern mountainous area of the West Lake. Due to the terrain barrier and the ecological protection requirements, there has been relatively little artificial development in this area, showing high vegetation coverage, forest parks with natural wild interest and large natural lakes. The primary purpose of these rivers is to irrigate farmland, rather than for landscaping. The effect of infrastructure construction on housing prices in this area is greater than that of UBGS. It can be observed that in ecological areas under strict government control, undeveloped, non-ornamental blue and green spaces may contribute to the decline of housing prices when combined collectively.

About 6.51% of the study area shows the blue-green antagonistic effect, in which blue spaces inhibit the negative effect of green spaces on housing prices (weaken-negative). Area 5 is Qianjiang New City. Based on the above analysis, green spaces have a smaller impact on housing prices compared to blue spaces in this area. Area 6 is the gathering place of industrial renovation green spaces, which exerts a repressive effect on housing prices due to its unique land type and contaminated soil conditions. The results indicates that blue spaces can ameliorate the detrimental effects of industrial transformation green space on housing prices to a certain degree. Furthermore, no areas were identified in the study area where blue spaces inhibited the positive effect of green spaces on housing prices (weaken-positive). From a district level, blue spaces overall promote housing prices.

3.3. Implications for urban blue-green planning

Integrated development of UBGS is a crucial strategic measure for constructing sustainable and socially inclusive cities (Voskamp & Van de Ven, 2015; Lamond & Everett, 2019; Steingröver et al., 2010). Sustainable urban development necessitates a harmonious equilibrium between social imperatives, ecological constraints, and the quality of life (Baker, 2007). In China, the construction of numerous historical cities is intricately linked with the landscape environment. These cities are situated in proximity to mountains or rivers, and have relied on the creation of canals and ditches to irrigate farmland and drain water. Since ancient times, blue and green spaces have been recognized as interdependent elements in Chinese cities. However, in the development of China's high-density cities, green spaces and blue spaces belong to separate development and management modes, potentially leading to fragmentation and disconnect between these vital environmental components. Despite the strict top-down control over the planning quantity and scale of green spaces, the transformation and utilization of blue spaces is often not included in the consideration of urban ecosystem integration, and its economic value is often ignored. This study may serve as an impetus for local planners to adjust their single approach to green space planning, emphasizing joint consideration of blue space and green space. In particular, when planning the actual UBGS and formulating related land use policies, there is a need to create different combinations of UBGS with distinct characteristics in different urban environments, aligning UBGS optimization with residents' actual needs, in order to achieve a balanced development of economic and social benefits.

Drawing upon our research findings, we propose the following UBGS planning strategies for different geographical regions of Hangzhou (Figure 10).

Firstly, in order to maximize the economic benefits of local governments, planners need to enhance the accessibility of UBGS by incorporating river greenways and park greenways into road planning, as well as increasing the number of bus and subway stops in their vicinity. Secondly, to enhance the connectivity of UBGS, artificial lakes can be incorporated into the parks, or waterfront parks can be constructed along rivers. Thirdly, considering the positive effect of blue spaces on the overall housing prices, and the fact that the effect of urban rivers is greater than that of urban lakes, urban planners and managers need to give priority to the beautification and protection of urban rivers. Unlike green spaces, urban rivers are typically restored rather than created. In high-density urban environments, the width and area of rivers are often non-modifiable. However, the amenity of rivers can be enhanced through increased riparian greenery, providing appealing landscapes and recreational spaces for nearby residents. Fourth, the built-up areas of high-density cities are often constrained by land use, making it difficult to increase green space areas. This challenge can be addressed by converting brownfields and unutilized land into parks or by increasing vertical greening and pocket parks. Last, for certain green spaces that do not contribute to property values (such as municipal green spaces for sightseeing, industrial renovation green spaces, and closed green spaces affiliated with enterprises), it is possible to increase the housing prices by improving the surrounding blue spaces. This necessitates giving priority to improving water quality, expanding water bodies, and eliminating land pollution during the planning and implementation of UBGS.

Given the potential for maximizing economic benefits of UBGS planning to contribute to gentrification, thereby impeding equitable access to UBGS resources for marginalized groups (Gould & Lewis, 2016), we propose planning strategies from the perspective of promoting human well-being. The objective is to ensure equal accessibility to UBGS services for a broader range of residents.

Firstly, constrained by construction costs, planners often construct large parks in suburban areas utilizing existing mountains and forests resources. However, our finding

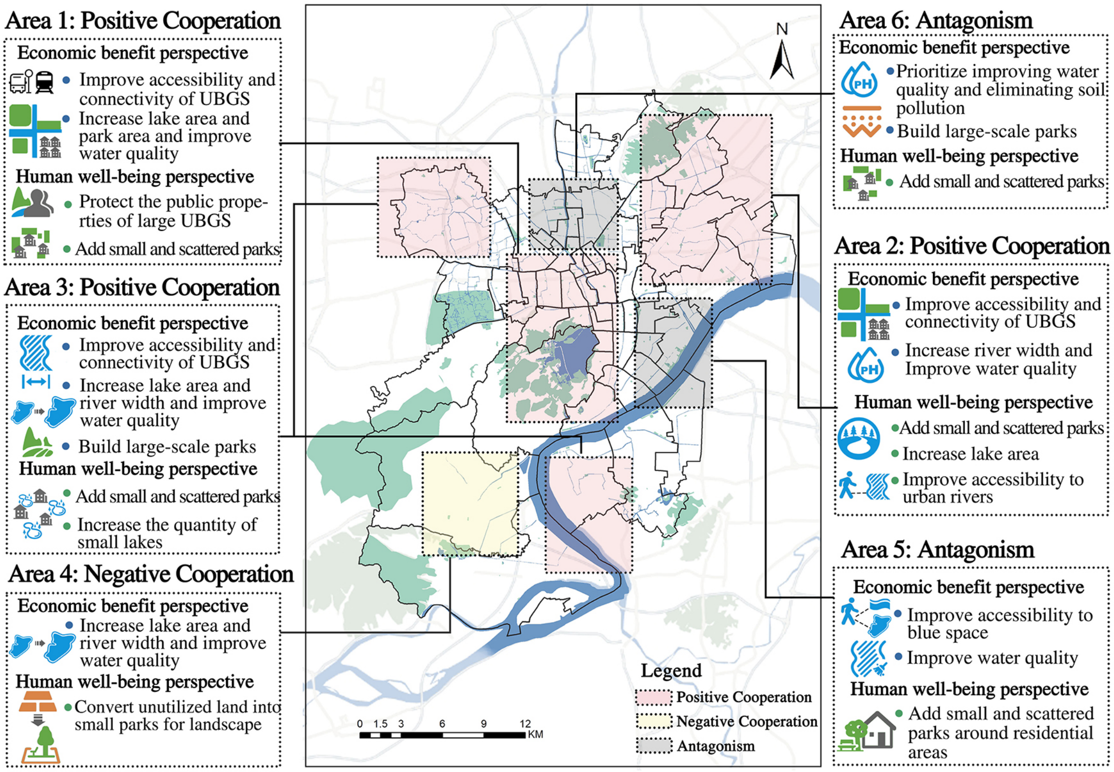

Figure 10. UBGS planning strategies for six regions in Hangzhou

shows that such large parks tend to cause a significant increase in housing prices within a certain surrounding area. Also, suburban residents are the most sensitive to park area. Therefore, we recommend implementing the "just green enough" strategy in the suburban, with building small and scattered parks (J. R. Wolch et al., 2014). This strategy provides residents with adequate and even green space services without causing a significant increase in housing prices. Secondly, the number of urban lakes should be appropriately increased, as they have minimal influence on housing prices while contributing to enhanced well-being by provisioning ecosystem services that ameliorate living conditions. More importantly, the public properties of the large UBGS resources need to be protected from private development and utilization by the wealthy class. In the development process of high-end residential areas, it is necessary to avoid encroachment on rivers and exclusive development methods such as sealing high-quality parks, thus ensuring equitable access to UBGS for a broader populace.

4. Conclusions

This study used an innovative spatial statistical method to comprehensively evaluate the effect of UBGS on housing prices in Hangzhou housing market. Based on 1,461 second-hand housing transaction data in Hangzhou, this study extended the traditional HPM model by using MGWR model, and comprehensively considered the spatial heterogeneity and interaction effect of UBGS on housing prices. The study utilized two scales for analysis: the housing level to obtain more specific and detailed results, and the regional level to consider the spatial pattern of UBGS as a whole. Furthermore, this study extends the current single-scale independent discussion on the impact of blue or green spaces on housing prices, and offered novel insights and revelations.

(1) The types and accessibility of blue spaces, the width, area and quality of water bodies all have significant heterogeneous effects on housing prices. The influence of various blue spaces on housing price in descending order is the West Lake, the Qiantang River, the Grand Canal, urban rivers. The spatial scales of the influence of various blue space on housing prices are in descending order: the West Lake/the Grand Canal, urban rivers, the Qiantang River. Specifically, the West Lake and the Grand Canal are global variables, with their effect on housing prices exhibiting relatively spatial stability. In the whole main urban area, when the distance to the West Lake decreases by 1 kilometer, the housing unit price increases by 1.526–1.753%. When the distance to the Grand Canal decreases by 1 kilometer, the housing unit price decreases 0.396–0.449%. The positive effect of the Qiantang River and urban rivers on housing prices is limited, with the proximity to Qianjiang River and urban rivers respectively increasing the housing unit price by up to 1.834% and 0.234%. Urban lakes (except West Lake) have no significant effect on housing prices.

(2) The NDVI of the park does not significantly affect housing prices, whereas the accessibility and area of the park does. Two mega parks (the West Lake Scenic Area

and the Banshan National Forest Park) exhibit a significant positive effect on housing prices (up to 2.554% and 1.227%, respectively), while smaller parks do not. The area with the largest positive impact of park area on housing prices is located near the Grand canals. For every 1 ha increase in the area of the park near the Grand canals, the housing unit price can increase by up to 4.796%.

(3) In 30.92% of the main urban area of Hangzhou, the effect of blue and green spaces on housing prices exhibits interactive effects. And the spatial patterns are divided into blue-green positive synergistic, antagonistic and negative synergistic regions. The specific UBGS planning recommendations for each spatial patterns are provided.

(4) In urban core areas and planned development zones, the co-figuration of blue and green spaces will generate higher housing premiums. However, near ecological conservation areas, they jointly suppress housing premiums. The water bodies can promote the positive effect of green spaces on housing prices or alleviate the negative effect, except for unexploitable areas under ecological protection. Green spaces have positive and negative effects on housing prices, while blue spaces only have positive effects at the district level. The economic value of blue spaces does not vary as much as green spaces due to land use and ecological control, but is more influenced by its internal features and specific types. The results indicate that planners must consider the integration of blue space into green space planning, rather than a single focus on blue or green space planning. The research has knowledge transfer potential and applicability, which can be extended to other cities.

There are still some limitations in this study. Firstly, MGWR model requires a large amount of computation and is limited by the amount of data in the same geographic coordinate. Therefore, we only sampled one housing unit in the same geographic location for regression, and did not include the influence of storey height. But storey height has been proved to be an important influencing factor (Xiao et al., 2019). Secondly, constrained by the availability of data, variables such as the age of the house and the green rate of the residential area were omitted from our analysis. Incorporating these covariates in future studies is expected to enhance the model's fitting accuracy. Thirdly, this study employed cross-sectional data, but the premium of landscapes may fluctuate over time. Future research should consider employing longitudinal panel data based on time series in order to capture the influence of transaction time differences among residential properties. Fourthly, given that this study was conducted at an urban scale with significant number of parks and water bodies, we have adopted straight-line distance to represent accessibility. Although this method has the advantage of simplicity in calculations, it may lead to certain errors in studies with complex topographical conditions (Lu et al., 2014). Future research should utilize more precise walking distance data to represent the accessibility of blue spaces. Furthermore, we did not account for landscape visibility, despite its proven ability to increase housing prices in some studies (Dai et al., 2023). In future research, incorporating 3D models of the urban environment could facilitate discussions on visibility (Gu et al., 2021). Last, the data used in this study is second-hand housing transaction data, which may lead to neglect of renters and low-income groups. Nonetheless, the unequal distribution of UBGS resulting from residential segregation is a crucial topic that cannot be ignored (Xiao et al., 2017). This suggests future research directions that aim to investigate effective strategies for providing equal and equitable access to UBGS, with the ultimate goal of improving social well-being and promoting the creation of equitable and sustainable cities.

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Author contributions

Conceptualization, H. C., L. H. and B. C.; methodology, H. C., L. H. and B. C.; software, H. C. and Z. L.; validation, H. C.; formal analysis, H. C. and Z. L.; investigation, H. C. and Z. L.; resources, L. H.; data curation, H. C.; writing–original draft preparation, H. C.; writing–review and editing, H. C., L. H. and Z. L.; visualization, H. C.; supervision, L. H. and Z. L.; project administration, H. C., L. H. and Z. L.; funding acquisition, L. H. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The authors declare no conflict of interest.

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Appendix

Table A1. Comparison between MGWR, GWR, and OLS model

		AICc	R^2	Adj. R^2	RSS
Model 1	OLS	3536.622	0.360	0.355	939.211
	GWR	2903.728	0.661	0.622	494.954
	MGWR	2595.850	0.760	0.716	358.441
Model 2	OLS	3837.610	0.203	0.198	1165.047
	GWR	3084.334	0.601	0.563	582.718
	MGWR	2780.451	0.783	0.719	317.060
Model 3	OLS	3837.538	0.214	0.208	1154.487
	GWR	2833.166	0.729	0.675	398.556
	MGWR	2651.581	0.719	0.686	412.720
Model 4	OLS	3850.395	0.194	0.190	1176.922
	GWR	3137.348	0.581	0.544	611.647
	MGWR	2658.434	0.746	0.701	371.567