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Value-added Benefits of Green Space: A Systematic Analysis of the Relationship between Urban Green Space and Commercial House Prices in Beijing Based on Remote Sensing Technology

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Urban green space is an important consideration when people purchase housing, and remote sensing technology makes it possible to acquire and analyze urban data on a large scale. The purpose of this article is, using remote sensing data on the Web, to quantify the relationship between urban green space and urban commercial house prices to reflect the increased importance that contemporary urban residents attach to urban green space and the potential economic benefits to real estate that green space enhancement may bring. We establish a model of the impact of urban green space on house prices for three districts in Beijing within the Fifth Ring Road using the hedonic price method, GIS spatial operation, and regression analysis. Then through questionnaire clustering, we summarize the preferences of people of different regions and social attributes in terms of green space accessibility, visibility, and availability indicators. We find that, holding other variables constant, the price of each residence decreases by 0.403 million yuan/m² for each 1 km increase in the distance from the house to the nearest park. Holding other variables constant, each unit increase in the rating of the nearest park increases the price of each residence by 0.144 million yuan/m². Respondents attach more importance to urban green space accessibility than to visibility and availability. Combining these two findings, we propose that the design of green space should take accessibility as the main consideration, that the construction of green space should enhance the coordination between green space and residences, and that the layout of green space should also be differentiated to improve the science of green space system planning. Through this study, we can explore ways to improve the social benefits of public space such as urban green space and help carry out more scientific and reasonable planning of urban green space, so as to promote the sustainable development of environmental and ecological spaces for human settlement.

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1. Introduction

Beijing's urban development is the epitome of China's rapid urbanization development. In the 1980s, comprehensive development and unified construction solved the housing shortage problem. At the end of the 1990s, the Party Central Committee and the State Council proposed and implemented far-reaching housing reform and quickly entered the commercial housing market. In the 21st century, the housing market has continued to develop rapidly, and residential areas have become refined and commercialized. People's requirements for the living environment are gradually increasing, and whether the green space around the housing is of sufficient quantity and high quality has become one of the most important considerations of homebuyers. After 2008, residential construction within the Fifth Ring Road gradually became saturated,[1,2] and in recent years, a relatively stable second-hand housing market has been formed. At the same time, people's living needs are gradually changing from "living" to "livable". Therefore, it is necessary to establish a relationship between the house price in the built-up area of the city and the quality and quantity of greenery in the local area.

On the other hand, the development of remote sensing technology makes it possible for us to acquire and analyze urban data on a larger scale, so that we can use sensing data to study the interrelationship between urban green space and the urban real estate economy on a larger spatial scale and summarize the laws of urban operation.

Research on the factors affecting house prices has mainly been carried out from five perspectives: supply and demand, individual consumer factors, housing characteristics, government policies, and spillover effects. Increasing attention is also being paid to the impact of individual consumer factors on house prices.[3] Kim *et al.* studied the impact of urban green spaces on single-family house prices through a hedonic pricing method (HPM). Larger regional parks around houses contribute more to house prices than fragmented, isolated, and irregular green spaces.[4] Black and Richards studied the increase in the prices of surrounding housing caused by the construction of the High Line in New York, and they considered that the impact of such supplementary construction is limited.[5] Sabyrbekov *et al.* studied the relationship between green space affinity and willingness to pay in Bishkek by means of a questionnaire.[6] Jensen *et al.* studied different people's preferences for large green spaces through a hedonic model.[7]

Veronika Liebelt's study used a scale-sensitive hedonic pricing analysis to find revealing preferences for Urban Green Spaces (UGS)[8] and demonstrate that the size of UGS affects price–distance slopes around them.[9] Ana Terra Amorim Maia measured the process of green gentrification using Cultural Ecosystem Services (CES).[10] Zhang Biao surveyed the relationship between the average house prices and parks in Beijing and calculated the total effect of real estate appreciation in urban public green space.[11] Xu Han used the buffer zone method and the network analysis method to study the accessibility of park green space.[12]

At this stage, the quantitative indicators of research on green space are mostly based on factors such as accessibility and straight-line distance in order to carry out research on the correlation between park green space and real estate prices. However, the specific attributes of the green space system (such as the number and quality of green spaces) have not been comprehensively analyzed and demonstrated, and there is a lack of a comprehensive discussion on the accessibility, visibility, and availability of green spaces.

In this study, we analyze the consumption willingness (the price consumers are willing to pay for surrounding green space) of different regions and consumer groups with different attributes for various characteristics of green space through two methods: a digital model and a questionnaire survey. On the basis of both objective data analysis and subjective respondent willingness analysis, we provide opinions regarding urban green space planning and configuration.

The scope of our research is three districts in Beijing within the Fifth Ring Road (Fig. 1): Haidian District, Chaoyang District, and Dongxicheng District (since Dongcheng District and Xicheng District are relatively similar in terms of urban spatial characteristics, we have merged them to form the third district). These districts are a relatively mature area of urban development and construction in Beijing. On the one hand, a mature and stable second-hand housing market has formed in the area within Fifth Ring Road.(13) On the other hand, the large-scale construction of green parks within Beijing's Fifth Ring Road is almost complete and the spatial structure is relatively mature. Therefore, we take this area as the research object to explore the price premium of urban green space and the reasonable allocation of residential and green space elements.

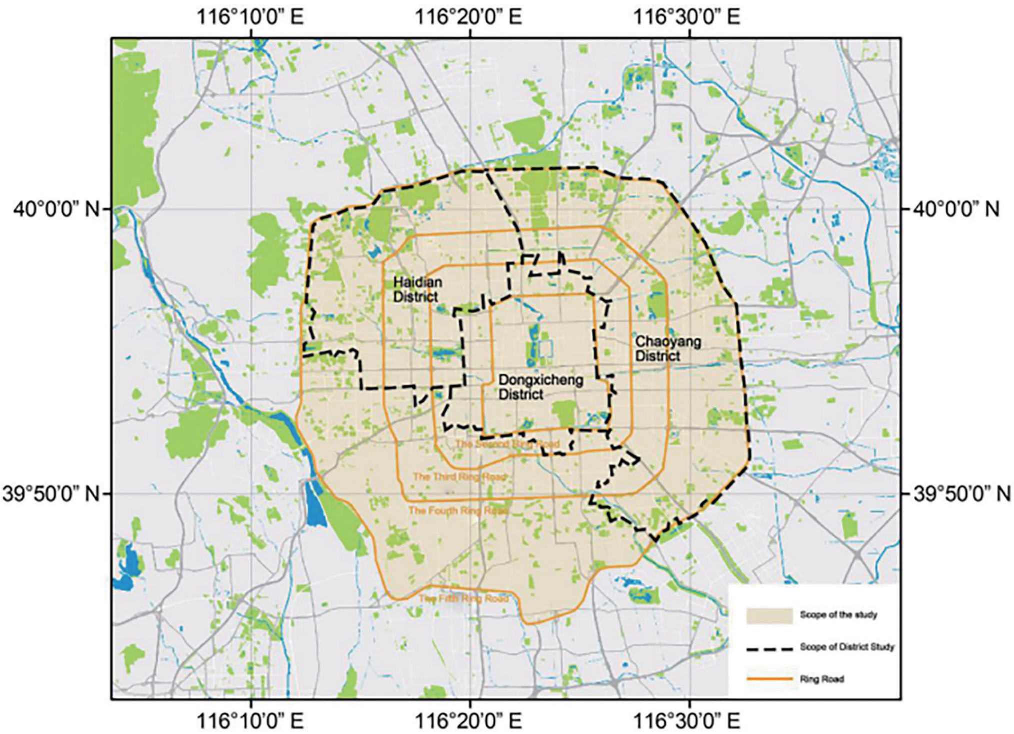

Fig. 1. (Color online) Research area.

2. Materials and Methods

2.1 Digital model analysis

2.1.1 Selection of variables

We explore the relationship between house prices and green space by using the HPM, which assumes that for products with multiple attributes, the maximum price a consumer is willing to pay for one additional unit of a particular commodity attribute is the hedonic price of that attribute's characteristics. Therefore, the house price can be thought of as the sum of the prices of various attributes. In this paper, it is the sum of the locational (L), internal (I), and neighborhood (N) characteristics of a dwelling.

We summarize the relevant literature that examines the relationship between green space distribution and urban house prices.[14,15] Among the many summarized indicators, we select 13 characteristic variables with relatively complete and easily available data for our study. These 13 characteristic variables are set in the above three characteristics: there is one internal characteristic variable (neighborhood rating), five neighborhood characteristic variables (primary school education facility rating, secondary school education facility rating,[16] medical facility rating, green space rating, amenities), and seven location characteristic variables (distance to nearest park, density of education facilities, density of medical facilities, density of bus stops, density of metro stops, road accessibility, public transport accessibility).[17] The distance to the nearest park (X1) and the rating of nearby green spaces (X12) are related to green spaces. The way in which the variables are quantified and their expected impact on residential prices are shown in Table 1.

2.1.2 Data collection

We collected data related to commercial houses, roads, and various facilities within the Fifth Ring Road by fetching data from the OpenStreetMap platform, Baidu Map API, Anjuke, Popular Reviews, etc. The specific data types are shown in Table 2.

Point data of commercial houses on sale (1844 items) are first collated, from which villas and affordable houses are excluded, and the ratings data fetched from a popular review website are associated by district name. Points of interest (POI) data of primary schools, secondary schools, medical facilities, metro stations, bus stops, and amenities in the study area are collected on Baidu Maps using OSpider software, and primary school ratings, secondary school ratings, and medical facility ratings are manually entered for the POI data. We download roads (line data, retaining several grades of main, primary, secondary, and tertiary roads) and green space data (surface data) within the Fifth Ring Road via the OpenStreetMap platform and manually enter green space ratings (popular review rating 0–5). The spatial relationship of housing points, green spaces, roads, and other data presented in GIS is shown in Fig. 2.

Table 1
Quantification method and expected impact of characteristic variables.

Control level	Indicator layer	Variable code	Quantification of indicator	Expected impact
Location characteristics (L)	Distance to nearest park	X1	Distance (m) to nearest urban park in study area (excluding parks within settlements etc.)	−
	Primary school density	X2	Reclassified into seven categories by POI kernel density map of primary schools within study area	+
	Secondary school density	X3	Reclassified into seven categories by POI kernel density map of secondary schools within study area	+
	Density of medical facilities	X4	Reclassified into seven categories by POI kernel density map of healthcare facilities within study area	+
	Bus stop density	X5	Reclassified into seven categories by POI kernel density map of bus stops within study area	+
	Density of metro stations	X6	Reclassified into seven categories by POI kernel density map of metro stations within study area	+
	Road accessibility	X7	Reclassified into seven categories by urban road density map within study area	+
Internal characteristics (I)	Housing estate rating	X8	On a scale of 0–5, obtained via popular review site	+
Neighborhood environment (N)	Primary education facilities rating	X9	Four grades: First Class I-4, First Class II-3, Second Class I-2, Second Class II-1	+
	Secondary education facilities rating	X10	Three grades: city priority-5, district priority-3, general-1	+
	Medical facilities rating	X11	Nine grades: Grade 1C-1, Grade 1B-2, Grade 1A-3, Grade 2C-4, Grade 2B-5, Grade 2A-6, Grade 3C-7, Grade 3B-8, Grade 3A-9	+
	Green rating	X12	On a scale of 0–5, obtained via Baidu Maps	+
	Amenities	X13	Reclassified into seven categories by POI kernel density map of amenities within study area	+

Table 2
Data sources and data types.

Data source	Data type	Associated indicators
Lianjia	Subdivision names, house prices, coordinate data, Excel spreadsheet	X8
Baidu Map API	POI data, shapefile file	X2, X3, X4, X5, X6, X13
Popular Reviews	Green, housing estate rating, Excel spreadsheet	X8, X12
Sina.com, Zhihu, etc.	Primary, secondary, hospital rating data, Excel spreadsheet	X9, X10, X11
OpenStreetMap	Roads (lines), green (surfaces), shapefile files	X7, X1

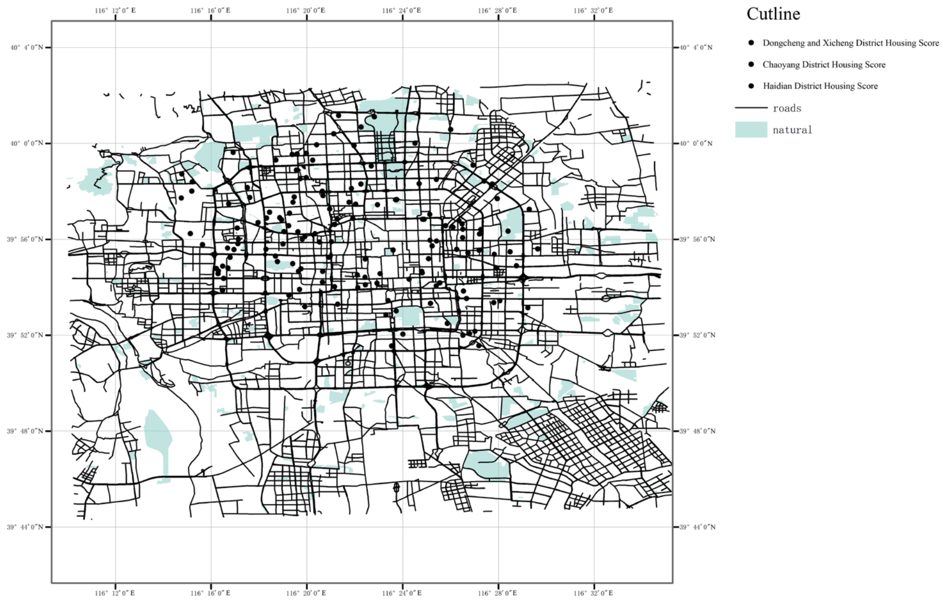

Fig. 2 (Color online) Distribution of study parks and sample properties.

2.1.3 Data processing

2.1.3.1 Incremental spatial autocorrelation analysis

To perform density calculations of point data such as schools, central business districts, hospitals, and green spaces in the GIS platform, incremental spatial autocorrelation tools are required to calculate the search radius for inverse distance analysis and kernel density analysis. Incremental spatial autocorrelation means measuring the spatial autocorrelation of a series of distances and selectively creating a line graph of these distances and their corresponding Z-scores. Z-scores reflect the degree of spatial clustering, with statistically significant peaks indicating the distances that promote the most significant clustering of spatial processes; typically, an increase in distance (and Z-score) indicates enhanced clustering. As an example, in Fig. 3, the first peak of the Z-score is at a distance of 70 m, indicating that 70 m is a suitable radius for inverse distance and kernel density analysis.

2.1.3.2 GIS data processing

The distance of each house point location from the nearest green space was calculated by ArcGIS. We calculate the kernel density with search radius Z_X for elementary school, middle school, and bus stop point data. We calculate the line density for road route files. We analyze inverse distance weights with search radius Z_Y for the rating fields of elementary schools, middle schools, medical facilities, and other point data. We reclassify the computed rasters so that they are all classed as level 7 and can be compared with each other and to perform

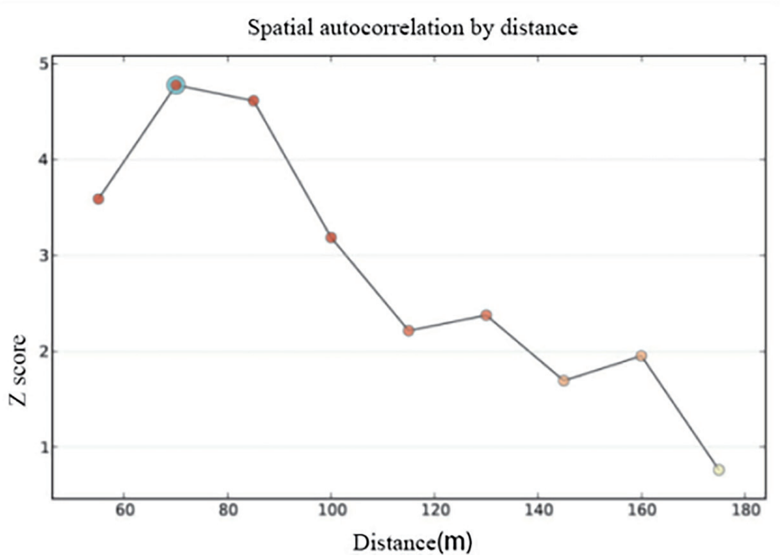

Fig. 3 (Color online) Example of incremental space autocorrelation analysis.

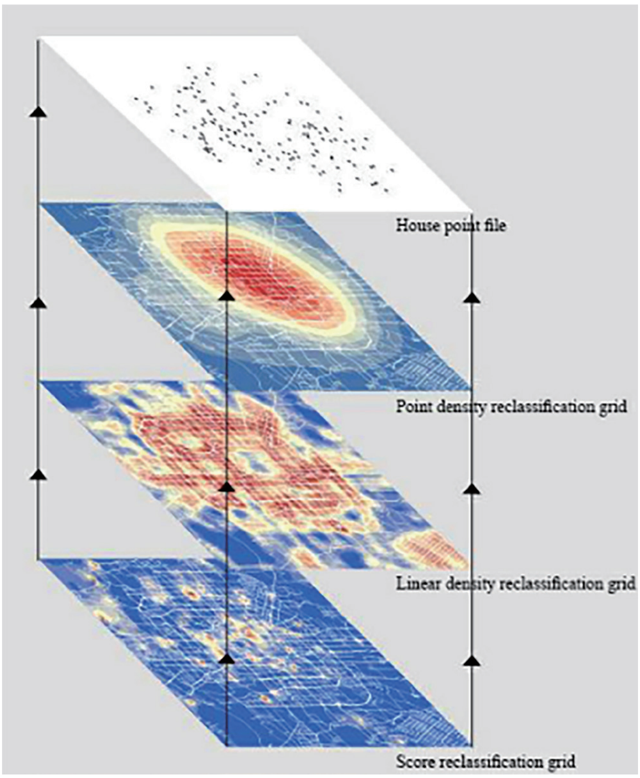

Fig. 4 (Color online) Data extraction mode.

operations. Then we extract the raster data of each independent variable into the attribute table of the point data of the house, the principle of which is shown in Fig. 4. The attribute table is exported to form the base database.[18]

2.1.3.3 Regression analysis

We perform stepwise regression using the SPSS platform to control the use probability of the F value. If the significance level of the F value of the variable is less than 0.10, then the variable is included in the model, and if the significance level is greater than 0.15, then the variable is removed from the model. In this way, the characteristic price model is constructed and analyzed. After the overall analysis, the data are extracted by urban areas, and we perform stepwise regressions for Chaoyang and Haidian Districts within the Fifth Ring Road and Dongxicheng District to find possible differences in influencing factors between districts.

2.2 Questionnaire analysis

2.2.1 Questionnaire design

The questionnaire consists of two parts. The first part includes questions about respondents' profiles (age, education, suburb of residence, and income), providing the underlying data for subsequent respondent group classifications. The second part deals with structuring issues concerning homebuyers' willingness to pay a premium for various qualities of green space, including the three dimensions of accessibility, usability, and visibility.(19) Among them, accessibility includes the convenience of access, distance, and convenience of entrance and exit; usability includes environmental sanitation, public security management, scale, and infrastructure configuration; visibility includes green viewing rate, site design sense, and water landscape.

2.2.2 Data collection

The data for respondent preference analysis is provided by online and offline questionnaires distributed by the authors. The sample size for each respondent group is at least 40 but not more than 70. Respondent groups are divided into Haidian District, Chaoyang District, and Dongxicheng District respondent groups according to their regions.

A total of 177 questionnaires are collected, and 19 questionnaires and one invalid questionnaire from other areas are screened out to obtain a total of 157 samples: 41 from Chaoyang District, 62 from Haidian District, and 54 from Dongxicheng District.

2.2.3 Questionnaire data processing

In the respondent preference part, we create a demographic database through data collection and analyze the relationship between multiple variables using SPSS. We use cluster analysis to divide the respondents into nine subgroups of landscape respondents (Table 3).

Qualitative data in the questionnaires were quantified by a hierarchical assignment method to create a contingency table of respondent subgroups and green space attributes. Correspondence analysis (CA) is then performed to extract dimensions and relationships between variables of

Table 3
Table of respondent subgroup characteristics in the three regions.

Subgroup district	Subgroup number	Sample size	Average age	Average education	Average annual income
Haidian District	H1	11	3	3	3
	H2	10	3	2	2
	H3	41	2	2	2
Chaoyang District	C1	16	2	2	2
	C2	13	3	1	2
	C3	12	3	2	3
Dongxicheng District	DX1	20	2	2	2
	DX2	10	3	3	3
	DX3	24	3	1	2

Note: For average age, 2 represents 18–30 years old and 3 represents 30–65 years old. For average education, 1 represents below undergraduate, 2 represents undergraduate, and 3 represents master's and above. For average annual income, 2 represents an annual income of 100000–300000 yuan, 3 represents an annual income of 300000–1000000 yuan, and 4 represents an annual income of 1000000 yuan or more. In the interview, because people under 18 years old or with annual income less than 100000 yuan had insufficient income to buy a house and the number of people over 65 years old was small, they were not included in the research scope.

categorical data in the dimension graph. The abstract cross-tab information is visualized using a graphical (2D map) approach.

3. Results

3.1 Spatial data operation results

Using the SPSS software platform, the sample data are substituted into the locational (L), internal (I), and neighborhood (N) models commonly used for characteristic price models for stepwise regression. From the fitting effect of the models (Table 4), we find that the R^2 and adjusted R^2 values of the linear function model are greater than those of the other two models, and the model can explain about 49.4% of the variance of the dependent variable, which is the best fitting effect.

3.1.1 Overall regression results

Ten characteristic variables were entered into the regression model (Table 4): distance to nearest park, primary school density, secondary school density, density of medical facilities, density of subway stations, housing estate rating, rating of elementary school education facilities, rating of medical facilities, nearby green space ratings, and amenities.

The coefficient signs of the significant variables are consistent with expectations, except for the density of medical facilities and primary school density. The variables with positive effects on residential price are secondary school density, density of medical facilities, subway station density, housing estate rating, elementary school education facility rating, medical facility rating, nearby green space ratings, and amenities; the negative effect on residential price is distance to nearest park.

Table 4
Overall regression results of the characteristic price model.

Models		Unstandardized coefficient *B*	Significance	Covariance statistics tolerances	VIF
(Constant)		4.44	0.005		
Distance to nearest park	X1	−0.403	0.114	0.89	1.123
Primary school density	X2	−0.777	0.002	0.048	20.952
Secondary school density	X3	0.576	0.005	0.061	16.391
Density of medical facilities	X4	−0.571	0.007	0.332	3.015
Subway station density	X6	0.487	0.003	0.122	8.198
Housing estate rating	X8	0.968	0.000	0.863	1.159
Rating of elementary school education facilities	X9	0.277	0.002	0.801	1.248
Medical facility ratings	X11	0.342	0.000	0.767	1.304
Nearby green space rating	X12	0.144	0.125	0.712	1.405
Amenities	X13	0.508	0.000	0.657	1.523

From the regression results, the characteristic price equation for residential housing can be derived as

$$Y = -0.403X_1 - 0.777X_2 + 0.576X_3 - 0.571X_4 + 0.487X_6 \\ + 0.968X_8 + 0.277X_9 + 0.342X_{11} + 0.144X_{12} + 0.142X_{13}. \tag{1}$$

It is concluded that for every 1 km increase in the distance from the residence to the nearest park, the price per residence decreases by 0.403 million yuan/m^2, with all other variables held constant. For each unit increase in the rating of the nearest park of a residence, the price per residence increases by 0.144 million yuan/m^2, with all other variables held constant.

3.1.2 Regression results for partitioning

On the basis of the overall regression results, the regression analysis of the overall data classified by geographic location is conducted for Chaoyang and Haidian Districts (within the Fifth Ring Road) and Dongxicheng District to compare the differences in the quantity and quality of green space on house prices that may be caused by the differences in their regional functions in the three types of urban areas. Chaoyang District represents the commercial center, Haidian District represents the scientific and educational urban area, and Dongxicheng District represents the old urban area. The regression results for the three districts are shown in Table 5. The regression results for Chaoyang District include the nearby green space rating (X12) and exclude the distance to the nearest park (X1). With other densities held constant, each unit increase in the nearby green space rating for residential areas in Chaoyang District is associated with a 0.392 million yuan/m^2 increase in house price.

The regression results for Haidian District include the distance to the nearest park (X1) and exclude the nearby green space rating (X12). For every 1 km increase in the distance to the nearest park, the house price decreases by 0.617 million RMB/m^2. The distance to the nearest

Table 5
Regression results of the characteristic price model for each district.

Models		Chaoyang District			Haidian District			Dongxicheng District		
		Unstandardized coefficient	*t*	Significance	Unstandardized coefficient	*t*	Significance	Unstandardized coefficient	*t*	Significance
Distance to nearest park	X1	—	—	—	−0.617	−2.374	0.019	—	—	—
Nearby green space ratings	X12	0.393	4.822	0	—	—	—	—	—	—

park (X1) and the nearby green space rating (X12) in Dongxicheng District did not pass the significance test.

3.2 Results of respondent preference analysis

The results of the questionnaire analysis (Fig. 5) show that the respondent groups placed higher importance on the accessibility of urban green spaces than on visibility and availability. In the accessibility dimension, the importance decreases in the order of distance, convenience of access, and convenience of entry, with the respondent group in Haidian District placing higher importance on accessibility than the other two districts. In the visibility dimension, the three groups of respondents generally place less importance on the design of the site, but there is a large difference between Dongxicheng District and the other two districts in terms of the importance of the water landscape. In terms of usability, the three groups of respondents place higher importance on the degree of infrastructure provision and security management. There is a greater need for large green spaces in Dongxicheng District than in the other two districts.

The 2D map in Fig. 6 explains 75.2% of the variance. Subgroups above the zero horizontal axis are concerned with the richness, diversity, and safety of the green space landscape, and these are mostly the highly educated, high-income, and elderly groups in Chaoyang and Dongxicheng District. Because of their high education level and age, they are more willing to pay for the comfort and aesthetics of green space in their neighborhood. Subgroups below the zero horizontal axis are more concerned with the accessibility and convenience of green space, and we name them "quantity demanders". They are mostly young people and the Haidian respondent group. On the right side of the zero vertical axis are mostly Chaoyang District respondents, who have a strong connection with the availability of green space. Subgroups on the left side of the zero vertical axis are named "landscape quality demanders". The strength of the association between the two groups and the availability of green space strongly depends on the importance that each district attaches to the construction of green open space in the city. Landscape quality demanders' preference for landscape quality is mainly due to the long history of the central urban area, which has well-established large urban green parks such as Beihai Park and Temple of Heaven Park. They have higher requirements for the richness of green landscape. However, owing to the scarcity of incremental construction space in the city center, large parks are common and the small green space in hutongs (narrow lanes) is limited, so these people's requirements have not yet been met.

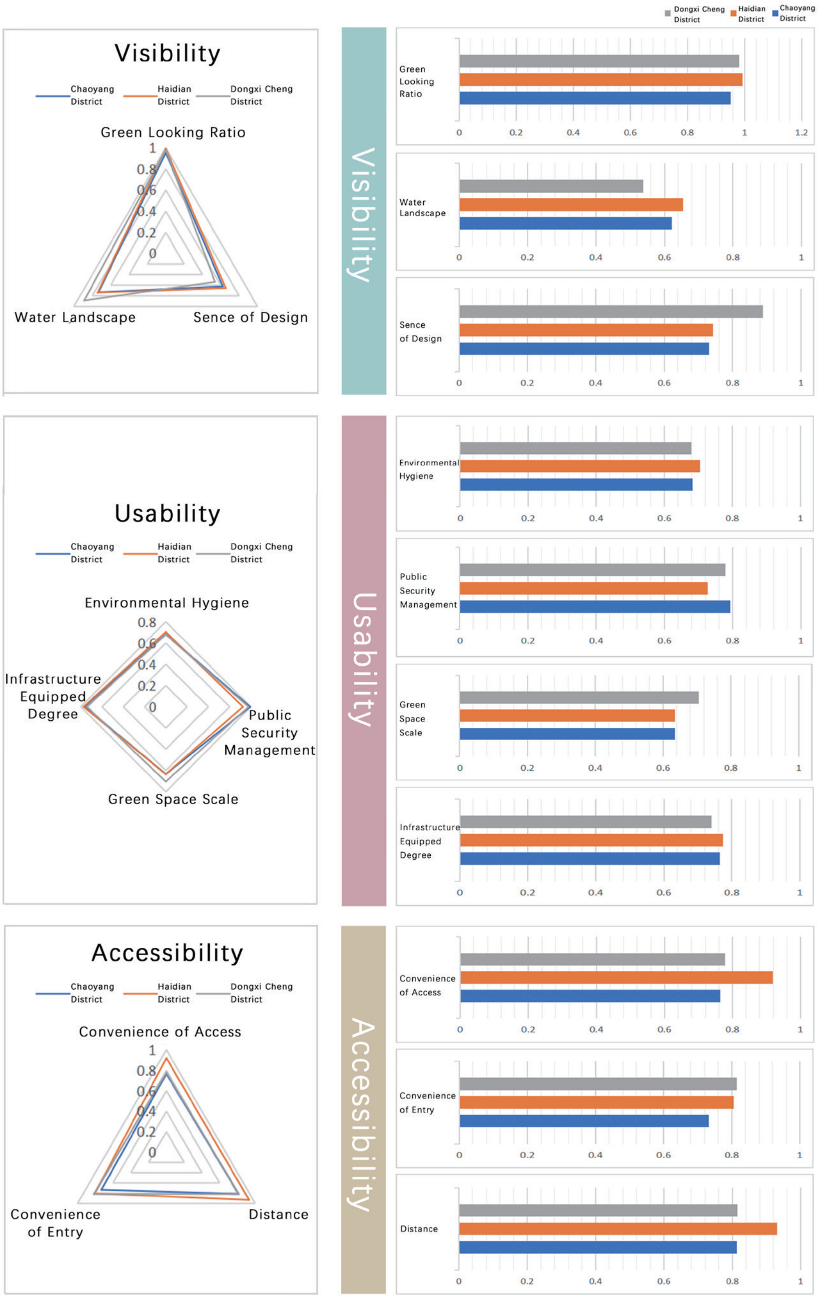

Fig. 5 (Color online) Questionnaire treatment of green space properties.

4. Discussion

4.1 Relationship between regression results of characteristic variables and expectations

The sign of the coefficient for medical facility density is different from the expected one, which may be due to the allocation pattern of medical facilities in Beijing and the perception of

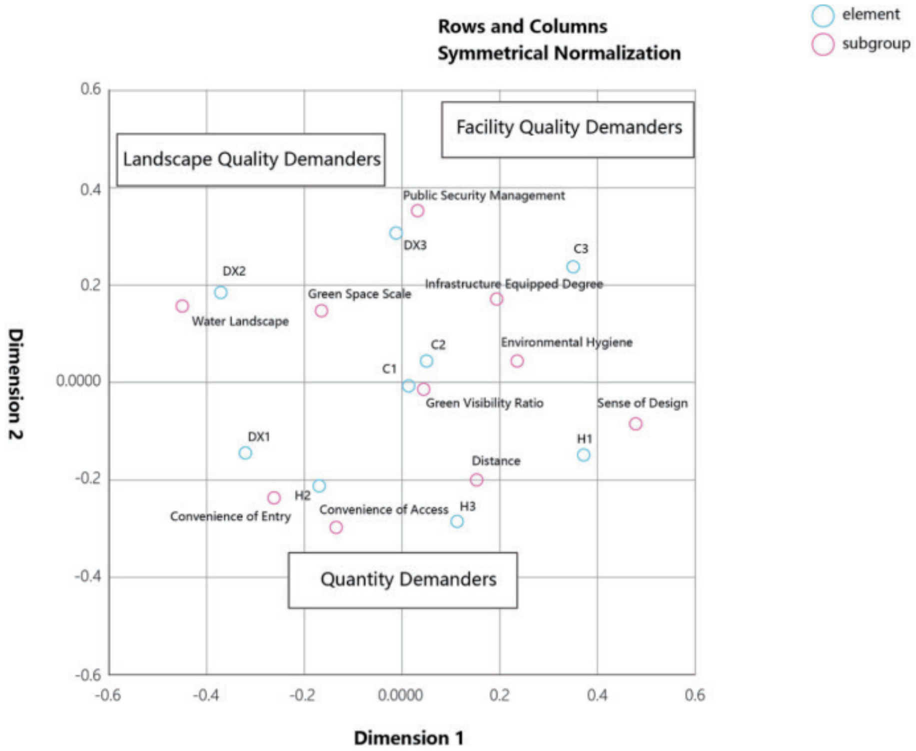

Fig. 6 (Color online) Chart showing results of subgroup user preference correspondence analysis.

medical facilities by residents. At present, there are few community-level medical resources in China's cities, the development of a hierarchical diagnosis and treatment system is slow, and the utilization rate of community hospitals and clinics is low, with people accustomed to going directly to large hospitals for medical treatment. Therefore, the configuration of community hospitals is generally not considered when purchasing a home, resulting in the density of medical institutions having a different impact on house prices from that expected.

Primary school density (X2) and secondary school density (X3) did not pass the collinearity test, probably because the centralized layout of primary and secondary schools and the increase in nine-year schools in recent years have led to similar spatial locations and the spatial convergence of elementary school density and secondary school density, resulting in greater collinearity for the extracted variables.

The variables that did not pass the significance test were bus stop density (X5), road accessibility (X7), and secondary education facility rating (X10), probably because places with a high bus stop density have a high population density and an underdeveloped infrastructure such as subways, resulting in the effect of X5 not being significant. Road accessibility is calculated using the line density of roads, but it seems to have little effect on the degree of accessibility. The insignificant effect of secondary school quality relies mainly on the fact that an increasing number of secondary schools have started to provide school accommodation in recent years, so the demand of residents for a secondary school in their district has decreased.

4.2 Analysis of regression results

In the overall calculation results, the distance to the nearest park (X1) was a significant factor, whereas the nearby green space rating (X12) had little effect on the house price. This may be because the high-quality green space within the Fifth Ring Road of Beijing is well distributed, with residents more concerned about whether the surrounding green space can meet their basic needs. The impact of the nearby green space rating (X12) on house prices is not obvious, probably because the rating data is not accurate enough; other indicators have a stronger impact on house prices.

The regression results for the Chaoyang District subdivision include the rating of nearby green spaces (X12) and do not include the distance to the nearest park (X1). The reason is that Chaoyang District has a large number of high-quality large parks and green spaces. Chaoyang District citizens with a high standard of living value the quality of green spaces and can ignore the distance to the nearest park to a certain extent. The distance to the nearest park can significantly affect house prices. In Dongxicheng District, neither the distance to the nearest park (X1) nor the rating of nearby green space (X12) passed the significance test. This may be because of the large number of high-quality large green spaces within Dongxicheng District that can accommodate a wide range of needs, correspondingly mitigating the need for homes to be close to parks. Thus, the ratings of the parks and the distance to the nearest park do not have a significant effect on house prices.

4.3 Significance of study on correlation between urban green space and commercial house prices

In recent years, the quality of urban construction has been improving, and urban green space, as an important public service facility, has become an important factor influencing the public's choice of home purchase. We use the HPM to explore the overall influence of green space on house prices. On the basis of the overall regression results, we conduct regression analyses for Chaoyang and Haidian Districts (within the Fifth Ring Road) and Dongxicheng District to compare the differences in green space and other influencing factors among homebuyers in the three types of urban areas. Using macro data, we take the consumption intention of various types of attribute consumer groups in the three types of urban areas regarding green space features as an innovative point for analyzing respondent preferences, which is meaningful for future urban green space planning and real estate development.

By comparing this study with overseas studies on the impact of green space on house prices, we conclude that the study has the following implications for the planning and design of future urban green space and its index evaluation (visibility, utility, and accessibility) in China.

First, previous domestic and overseas studies have mainly used the HPM to determine the relationship between house prices and green space characteristic factors but have lacked a more in-depth exploration of the influence of individual factors of different consumer attributes on house prices. In this study, on the basis of the regression model, a questionnaire survey was used to conduct CA on nine types of landscape respondents grouped together, which strengthens the analysis of respondent group preferences regarding different properties of green space.

Second, the urbanization process is different in China and overseas, and existing studies carried out overseas are not applicable to China's urban development period. For example, in the United States, the overall average urbanization rate is as high as 83%, with the urbanization rate of some metropolitan areas already close to 100%. In contrast, China, which is in a period of rapid urbanization, had an urbanization rate of about 64% in 2021. The difference in urbanization determines the timing of real estate development and greenfield planning, making it meaningful to choose built-up areas of domestic cities for study in China.

Thirdly, the consumption patterns in China and overseas are different. In developed cities such as Tokyo and New York, for example, house prices are regulated through real estate taxes, housing management fees that grow with the age of the housing, and depreciation fees for second-hand houses, making house prices relatively stable and difficult to purchase as investments, while the regulation of house prices in China is still being developed. Different consumer psychology and demand patterns in each country lead to different public demand patterns for public service facilities near housing and for green space functions. We have therefore analyzed the respondent group preferences of green space in a way suitable for Chinese conditions.

5. Conclusion

We have constructed a mathematical model by setting 13 characteristic variables to explore the relationship between green space and house price, and used questionnaires to analyze the consumption intention of different regions and different types of consumer groups for each characteristic of green space. We found that the higher the rating of nearby green space, the higher the house price, and that the house price is negatively correlated with the distance to the nearest green space. The spatial distribution of high and low house prices is different from that of green space. High house prices are associated with better green space resources, whereas low house prices have no correlation with green space distribution. Holding other variables constant, the price of a house decreases by 0.403 million yuan/m^2 for each 1 km increase in the distance from the house to the nearest park. Holding other variables constant, each unit increase in the rating of the nearest park increases the price of each unit by 0.144 yuan/m^2.

The different distributions of resources in different regions lead to different demand patterns. In Haidian District, where educational resources dominate, distance to the nearest park is an important factor in house prices. In Chaoyang District, where the standard of living is high and commercial business dominates, the nearby green space rating is an important factor in house prices, and in Dongxicheng District, which is the old town of Beijing, neither of these two indicators significantly affects house prices.

Respondent groups attach more importance to urban green space accessibility than to visibility and availability. In terms of green space attribute preference, we observed the order green visibility > accessibility = distance > infrastructure equipment = access convenience. As shown in a 2D map, "greenbelt landscape lovers" pay more attention to landscape diversity and richness, which can be divided into "facility quality type" and "landscape quality type". "Quantitative consumers" pay more attention to the accessibility and convenience of green space. Groups with high education and income and elderly people pay more attention to the diversity and richness of green spaces, young groups pay more attention to the quantity of green spaces, and some groups with a high quality of life pay more attention to the quality of facilities in green spaces. Personal economic circumstances and education level significantly affect people's demand for green space quality. With the development of society, the demand for a landscape rich in green spaces is also increasing gradually among young people. When planning a green space system, we should quantitatively analyze the green space service capacity of different regions and strengthen the consideration of the needs of different social groups in different regions. We should differentiate the layout of green space between the urban center and the suburbs to balance the supply and demand for green space.

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