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CAPITALIZATION EFFECTS OF RIVERS IN URBAN HOUSING SUBMARKETS – A CASE STUDY OF THE YANGTZE RIVER

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Abstract. The study aims to investigate the heterogeneity of the Yangtze River's impact on housing prices, using the data of 12,325 residential transactions within 8 kilometers of the Yangtze River in Wuhan, based on submarkets divided according to geographical location and buyer groups. The kernel density plots reveal that properties near the Yangtze River have the highest price and the lowest density, while properties further away from the river exhibit the opposite trend. Then the Spatial Generalized Additive Model and the Spatial Quantile Generalized Additive Model show the following results, respectively: (1) The Yangtze River has an influence range of roughly 5 kilometers on adjacent dwellings, with an average impact of 0.035%. However, within the chosen geographical interval, the impact rises from 1.582% to 2.072%. (2) The Yangtze River has the greatest impact on middle-priced houses, followed by high-priced houses, and the least impact on low-priced houses. (3) The Spatial Generalized Additive Model and the Spatial Quantile Generalized Additive Model have been proven to be effective at capturing spatial and temporal impacts on data. In conclusion, this article advises that the government should pay more attention to non-central locations with limited natural resources.

Keywords: ecological landscape, hedonic price method, housing submarket, the spatial generalized additive model, the spatial quantile generalized additive model.

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1. Introduction

The rapid urbanization process has led to the deterioration of the ecological environment and has brought great pressure and risks to the health and life of urban residents. To cope with these urban environmental problems, urban ecological landscape is increasingly favored by people (Huang et al., 2021). Generally speaking, urban ecological landscape can be divided into two categories (Nutsford et al., 2016): green space (such as green space, parks and forests) and blue space (such as lakes, wetlands and streams). For individual residents, the ecological landscape includes aesthetic, entertainment, social, and cultural benefits, alongside unique advantages for human physiology, mental health, and interpersonal communication (Tawfeeq Najah et al., 2023). Within the urban environment, ecological landscape can efficiently combat the urban heat island effect, minimize air pollution, and ensure the city's long-term development (Geng et al., 2022). For urban and rural planning and economic growth, environmental friendliness can be ensured for urban economy and development through the logical distribution of ecological landscape in cities (Jia & Zhang, 2021).

Many researchers attempt to quantify the value of urban green space and blue space in light of the benefits of ecological landscape. Because directly evaluating the non-market worth of this landscape is challenging, scholars have utilized the Hedonic Pricing Method to find evidence indicating that homeowners pay for the surrounding ecological landscapes through the real estate market (Potrawa & Tetereva, 2022). While open public green spaces like forests and parks and natural urban water bodies such as lakes and wetlands are believed to increase the price of surrounding properties due to visibility and accessibility (Mittal & Byahut, 2019), other landscape features such as size, quality, and diversity may also influence the capitalization value of the landscape in housing prices (Bonetti et al., 2016). Conversely, the presence of unpleasant landscapes or amenities, such as waste disposal facilities (Rivas Casado et al., 2017), prisons (Shehata et al., 2021), and polluted rivers (Cho et al., 2011) may have a detrimental impact on housing prices. In addition, air quality is an intangible public environmental resource and an important indicator to measure the urban ecological environment. Under the influence of environmental laws and pollution facilities, the improvement of quality or air pollution will also have a certain impact on housing prices (Grainger, 2012). Wang and Lee (2022)'s research shows that housing prices in large and medium-sized cities are more sensitive to air quality. To sum up, although the research trend of urban ecological landscape benefits is increasing, these studies mainly focus on specific landscapes such as parks and lakes, and the research on the capitalization of residential market by rivers with scarce ecological landscape in compact cities is still limited.

Currently, studies examining landscape value are beginning to analyze the subdivision of the housing market in order to deeply study the variability of capitalization of landscapes in submarkets and the driving forces behind it, given that the housing market inside the city is differentiated and heterogeneous (Bohman, 2021; Bangura & Lee, 2023). Firstly, the influence of landscapes on housing prices varies across time and geography (Lamond et al., 2010). Scholars generally believe that dividing submarkets based on geographical or administrative boundaries is appropriate, as the housing market in a specific geographical area tends to be homogeneous. Thus, some studies have investigated the heterogeneity of the impact of ecological landscapes on housing prices in different submarkets within the same geographical scope. The method involves dividing the study area into multiple submarkets using various methods such as geographical intervals, administrative regions and others, and then incorporating dummy variables representing these submarkets in the model. For example, Chen et al. (2015) and Wen et al. (2014) divided residential areas around ecological landscapes such as parks and lakes based on different distances and directions. They investigated the impact of landscape on the value of homes within different geographic areas and confirmed the heterogeneity of the landscape capitalization effect in residential submarkets. Secondly, different types of property buyers are heterogeneous, and their sensitivity to ecological landscapes is heterogeneous (Rajapaksa et al., 2017). In the context of consumer demand dominating the Chinese housing market, do all customers regard ecological landscapes in the same way? The answer is most likely no. People will live in communities that fit their own preferences due to varied income levels and social standing, as Tiebout's public goods supply model indicates that there is a sorting effect in residents' consumption characteristics of public goods (Tiebout, 1956). Residents have various expectations for consumer goods, like housing, due to distinct features such as their own preferences and needs, which contributes to the segmentation of the housing market at different price ranges. Therefore, considering that buyers in different income groups have different willingness to pay for ecological landscapes, the impact of ecological landscape on high, medium and low-value properties may also be heterogeneous. Wen et al. (2021) explored the internal relationship between landscape preferences and home values of different types of homebuyers based on Hedonic Pricing Method and Quantile Regression Model. The study showed that buyers who buy high-priced houses are more willing to pay for attractive landscapes than those who buy low-priced houses.

Generally speaking, compared with evaluating the average capitalization effect of ecological landscapes from the perspective of the whole market, the heterogeneity of capitalization effect of ecological landscape in different residential submarkets can be analyzed by subdividing the residential market considering geographical areas and residents' needs, which makes the research results more in line with the actual situation. However, the existing literature rarely discusses the heterogeneity of the response of different residential submarkets to river landscapes. So it is necessary to further analyze the capitalization effect of river landscapes.

Furthermore, in the study of Hedonic Pricing Method, scholars generally take into account the spatial correlation and heterogeneity of observation samples in order to improve model accuracy (Shi et al., 2022). In recent years, spatial matrices have frequently been incorporated into models to create Spatial Error Models, Spatial Lag Models, and others to control spatial effects.

Compared to the traditional Hedonic Pricing Method, this model not only displays the variability of the coefficient of influence of ecological landscapes on housing prices in different spatial scopes, but also significantly enhances the model's performance. However, capturing spatial impacts in the model requires a more flexible strategy that adheres to the actual spatial properties. The estimation of spatial effects in the aforementioned applications is mostly dependent on the spatial weight matrix. But spatial trends and forms in data are hidden and unknown, embedding the spatial weight matrix in the model directly may result in incorrect coefficient estimation (Elhorst, 2014). In contrast to the parametric spatial matrix approach, the use of nonparametric and semiparametric methods is based on the real model structure. The control of spatial effects in the nonparametric model is based on a multidimensional smoothing function, in which the model is driven by data, allowing the true geographical link to be exposed (Zemo et al., 2019). However, nonparametric and semiparametric approaches continue to receive minimal attention in the existing literature. Only a few scholars have done exploratory research on urban green space, biogas plants and railway transportation facilities by using a semiparametric model, the Generalized Additive Model (GAM) (Le Boennec et al., 2022; Panduro & Veie, 2013; Zemo et al., 2019). It can be seen that this method still has great exploration space in the study of the influence of urban ecological landscape such as rivers on residential value.

Based on this, this paper uses the Yangtze River, the largest river in China, as the research object, and based on the basic framework of the Hedonic Pricing Method, constructs a Spatial Generalized Additive Model (SGAM) and a Spatial Quantile Generalized Additive Model (SQGAM) to investigate the heterogeneity of capitalization effect of river landscapes in different submarkets between 2016 and 2021. The purpose of this paper is to provide answers to the following questions: First, from the accessibility point of view, does the Yangtze River have any value-added effect on the nearby houses? Second, is the value-added effect of the Yangtze River on house prices in different areas heterogeneous? Finally, in the housing submarkets divided by purchasing groups, will the capitalization effect of the Yangtze River have the same heterogeneity due to the different housing price distribution? The research findings can serve to clarify urban inhabitants' housing preferences, assist the government in developing urban planning and real estate-related policies, as well as help buyers in making judgments. Compared with existing research, this research has two unique characteristics. Firstly, the research object focuses on urban river landscapes and subdivides the residential market from two aspects: geographical area and buyers, in order to comprehensively explore the spatial heterogeneity of the influence of river landscapes on the residential submarkets and the heterogeneity of buyers' preferences for river landscapes, and this study is one of the first studies to analyze the heterogeneity of river landscape impact from the perspective of multi-dimensional residential submarkets. Secondly, the research method uses a semiparametric method to capture spatial effects, realizes the optimization of the traditional Hedonic Pricing Method, and makes the quantitative results of landscape capitalization effects more stable by introducing SGAM and SQGAM, which is also an innovative research to analyze the influence of ecological landscape capitalization effect by using SQGAM.

2. Theoretical framework and hypothesis development

The introduction has emphasized the importance of analyzing the capitalization effect of river landscape from the housing submarkets. Therefore, in order to investigate the heterogeneity of the influence of river landscape on housing prices in residential submarkets based on geographical location and purchasing groups, this section will continue to build a theoretical framework to support this micro-analysis and put forward corresponding hypotheses.

H1. In the housing submarkets divided by geographical location, the value-added effect of the Yangtze River on house prices in different areas is heterogeneous.

In the previous studies on the capitalization effect of ecological landscape, the ordinary least squares regression method is often used to estimate the Hedonic Pricing Model, so as to measure the average value-added effect of ecological landscape on surrounding houses (Alas, 2020). However, further research by scholars found that the environmental comfort of the same ecological landscape may have spatial heterogeneity, which is manifested in the nonlinear relationship between house prices and landscape accessibility. For example, Łaszkiewicz et al. (2022) proved that the accessibility of urban green space, measured by walking distance, has a highly nonlinear influence on real estate prices. The existence of this nonlinear relationship can be explained by landscape features such as size and type (Liebelt et al., 2019) or negative externalities of landscape such as noise (Piaggio, 2021), and the river landscape also has such characteristics. On the one hand, houses close to rivers often have the characteristics of beautiful environment, broadened horizons, comfort and quietness, from which people can obtain ecological benefits, a livable environment and a certain sense of happiness, thus promoting the rise of house prices. On the other hand, when faced with potential unfavorable factors such as water pollution, ship noise and flood risk, the house prices of the neighboring rivers will also be negatively affected. However, compared with the positive benefits brought by accessibility, the negative impact of river landscape on neighboring houses seems relatively small (Wen et al., 2017). Generally speaking, under the dual effect of river landscape on neighboring houses, the relationship between housing price and river landscape accessibility may also be nonlinear. In other words, the value-added effect of the Yangtze River on housing prices in different regions is heterogeneous in the housing submarkets divided by geographical location.

H2. In the housing submarkets divided by purchasing groups, the capitalization effect of the Yangtze River is heterogeneous due to the different housing price distribution.

In fact, according to the consumer theory, due to the differences in demand preference and income level, buyers' willingness and ability to pay a premium for the attached landscape of a specific house are different. Generally speaking, low-income people are often unable to pay a premium for the ecological landscape attached to the house, because they have to give up on account of other rigid needs at present, they can only choose low-priced houses without attached ecological landscape. High-income people are economically affluent, and their ability to independent choice and investment is greater. However, considering that the adjacent open ecological landscape has a certain negative impact, and high-income people often cause unfair phenomena in other hedonic attributes that are scarce and can show their status, such as hospital accessibility (Gu et al., 2023), they are not necessarily willing to spend a lot of money to buy high-priced houses with high ecological landscape value. Middle-income people are the most willing to pay extra for the ecological landscape around their houses. Compared with the rich, they have sufficient economic ability and pay more attention to the comfort and satisfaction brought by open ecological landscapes such as parks and green spaces (Chen et al., 2022), and they are more inclined to choose middle-priced houses that can enjoy the ecological landscape and are relatively cheap. Therefore, influenced by the demand difference and income difference among different buyers, the capitalization effect of the Yangtze River may be heterogeneous in the housing submarkets divided by purchasing groups.

3. Research area and methods

3.1. Study area

As an international comprehensive transportation hub city with a national key layout, Wuhan has a resident population of 13.65 million in 2022, with a GDP of 1,886.64 billion yuan. Wuhan has an abundance of water, the most visible of which is the Yangtze River, which runs through the city. The Yangtze River serves an incredibly essential shipping function as part of the Yangtze River Economic Belt's comprehensive transportation system, but this also causes significant damage to the Yangtze River's ecological environment. In recent years, the government has consistently contributed to the Yangtze River's conservation, banned illegal docks and sand dumps along it, and implemented pollution prevention and control of ships and ports, all with the goal of safeguarding and repairing the Yangtze River's ecological environment. As a result, its large water surface, wide vision, and diverse ecological functions have begun to provide residents with a pleasant viewing experience. The Yangtze River section flowing through Wuhan is the study area, and the houses within 8 km of it are chosen as the research objects. Figure 1 depicts the distribution of the study area.

3.2. Study methods

This study is based on the theory of the Hedonic Pricing Method, and SGAM and SQGAM are built using semiparametric methods to investigate the impact of the Yangtze River on housing in multiple submarkets. Figure 2 depicts the research concept.

The Hedonic Pricing Method is based on Lancaster's consumer theory. According to this methodology, the benefit offered by a commodity having several qualities comes from each attribute rather than the commodity itself. Hence, consumers make purchasing decisions based on the number and the unit cost of each feature (Lancaster, 1966). Ridker and Henning (1967) then applied this theory to housing prices, resulting in the Hedonic theory of housing. In the same way, the basis of this theory is that the demand of buyers to buy a house comes from numerous characteristics of the house. Therefore the total price of the house that people trade in the market is the sum of the values of various characteristics. The following is the Hedonic Pricing Method:

$$p = \beta X + \varepsilon, \quad (1)$$

where: p represents the housing price; β is a variable coefficient matrix; X is the independent variable matrix, including the dwelling, neighborhood, and location variables of the house; ε represents error.

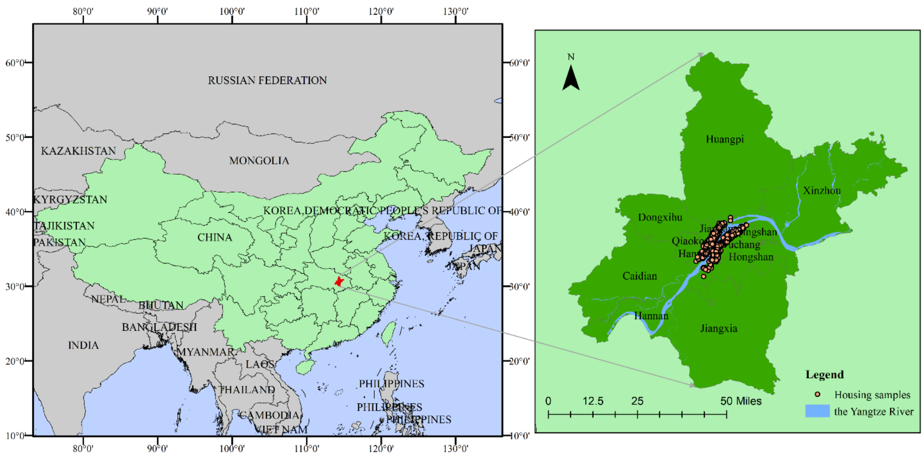


Figure 1. Research area

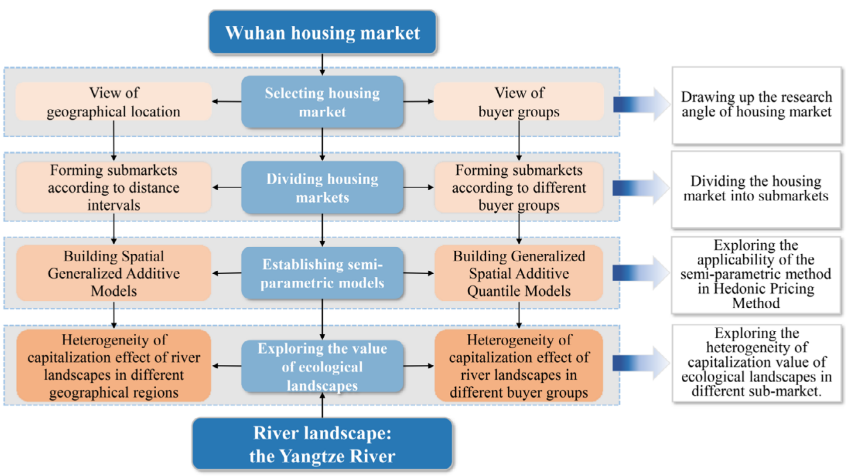


Figure 2. Research flowchart

The nonparametric Generalized Additive Model is created by inserting the nonparametric structure into the Generalized Linear Model, and the semiparametric Generalized Additive Model is created by retaining the parameter items in the nonparametric Generalized Additive Model. Nonparametric and semiparametric regression models do not rely on the assignment of spatial weights but instead use a smoothing function to capture spatial effects, which is a more flexible technique to capture spatial effects. To reduce error variance, they allow covariates to take the shape of nonlinear functions. The model's semiparametric version is as follows:

$$g\left(E\left(Y\right)\right)=\sum_j \beta_{ij}x_{ij}+\sum_k f_k\left(x_{ik}\right)+\varepsilon_i\beta_{ij}, \tag{2}$$

where: $g()$ is a connection function, which can be a unit function, logarithmic connection, etc.; E stands for expectation; y is dependent variable; x is independent variable; $\sum_k f_k(x_{ik})$ is a nonparametric item of the model; $\sum_j \beta_{ij}x_{ij}$ is the parameter part of the model.

The influence of independent variables on multiple quantiles of dependent variables can be reflected via quantile regression. The quantile model in its most general version is $\mu_\tau(x)=\beta_\tau X=\beta_1x_1+\ldots+\beta_\rho x_\rho$. τ represents quantiles. By embedding a nonparametric structure into a quantile model, an additive quantile model can be reached, in which the quantile model can be fitted using a fixed or smooth effect. The SQGAM suggested by Fasiolo et al. (2021) is used in this study. His modified additive quantile regression method can be utilized for conditional quantile calibration and automatic estimation of smoothing parameters while maintaining the same numerical estimation efficiency and stability as existing quantile models. The general semiparametric SQGAM, constructed by this method, is as follows:

$$Q\left(E\left(Y\right)\right)=\sum \beta_\tau X+\sum_k f_k\left(x_{ik}\right)+\varepsilon_i\beta_{ik}, \tag{3}$$

τ stands for the quantile. Based on the quantile theory, the housing samples in this paper can be divided into different price ranges, such as high-, middle-, and low-priced housing. The Hedonic Pricing Method with quantiles can address the shortcoming that it only estimates the influence of factors on the average housing price in early studies.

4. Variable selection and model building

4.1. Variable selection

This study constructs a variable system using the framework of the Hedonic Pricing Method. Environmental variables are formulated, wherein the linear distance between the housings and the Yangtze River is used to assess the difficulty of the residents to reach the Yangtze River. To divide the submarkets, this paper divides the dwellings around the Yangtze River into six intervals based on their distance from the Yangtze River, as indicated in the table below. Furthermore, housing prices are measured as a unit price to eliminate the influence of housing area and 25 variables are determined. The dependent variable is housing prices, the independent variable is the distance to the Yangtze River, and the other factors are the control variables. Table 1 shows the variables identified in this study, as well as their definitions and values.

Table 1. Definition of variables

Variable categories	Variable names	Variable definitions and values	Expected sign
Housing prices	*PRICE*	Transaction Unit price of housing (Yuan/m^2)	
Environmental variables	*DIS-YANGTZE*	Distance from the community to Yangtze River (m)	–
	DISTANCE	Interval of distance to the Yangtze River: D1: 0–1 km; D2: 1–1.5 km; D3: 1.5–2 km; D4: 2–3 km; D5: 3–5 km; D6: 5–8 km	unknow
Dwelling variables	*AREA*	Gross floor area of a dwelling (m^2)	+
	ORIENTATION	Orientation of a dwelling (South: 10; Not: 0)	+
	DECORATION	Decoration of a dwelling (Luxury: 40; Fine: 30; Simple: 20; Rough: 10)	+
	BUILDING	Structure of the building (Multi-storey: 10; Medium-high: 20; High: 30; Super high: 40)	+
	ROOM	Number of rooms	+
	SOLD	Time of sale	unknow
	BUILT	Time of construction	unknow
Neighborhood variables	*GREEN*	Greening rate of the residential quarter	+
	PROPERTY	Property fee of the residential quarter (Yuan/m^2/month)	+
	PLOTRATIO	Plot ratio of the residential quarter	-
	HOUSEHOLD	Total number of households in the residential quarter	+
	PARKING	Average parking spots per household in the residential quarter	+
	UNIVERSITY	Number of colleges and universities within 500 m	+
	DIS-KG	Distance to the nearest kindergarten (m)	–

End of Table 1

Variable categories	Variable names	Variable definitions and values	Expected sign
	DIS-EDUCATION	Distance to the nearest key primary and secondary schools (m)	–
	DIS-PARK	Distance to the nearest park (m)	–
	LIFE	Number of supermarkets, banks, food markets, hospitals and post offices within 1000 m	+
	NIMBY	Number of burial places within 500 m	–
Location variables	*LONGITUDE*	Location longitude of the residential quarter	unknow
	LATTITUDE	Location latitude of the residential quarters	unknow
	LOOPLINE	Location in the city (Inner ring: 40; Second ring: 30; Third ring: 20; Fourth and fifth ring: 10)	+
	DIS-SUB	Distance to the nearest subway station (m)	–

In addition, in order to avoid the multicollinearity among the chosen independent variable and control variables, this paper uses variance inflation factor (*VIF*) and Pearson correlation coefficient to test, and the results are shown in Table A1. Notably, due to a high correlation coefficient of 0.85 between the variables *AREA* and *ROOM*, the variable *ROOM* was subsequently excluded. Following the removal of the highly correlated variable, the absolute values of the Pearson correlation coefficients among the independent variable and the control variables were within the range of 0 to 0.62, and the variance inflation factors were between 1 and 3, which indicates that the problem of multicollinearity among the variables has been solved, and it does not affect the subsequent empirical analysis (Chwiałkowski & Zydroń, 2022; Olszewski et al., 2017).

4.2. Data sources and processing

The research object in this study is residential houses in residential compounds in Wuhan, and the samples are of 12,325 housing transactions within 8 kilometers of the Yangtze River in Wuhan, from 2016 to 2021. This data set is divided into housing price data and housing attribute data (dwelling, neighborhood, location and environmental variables). Housing prices are primarily gathered from the Lianjia website (https://wh.lianjia.com/). Dwelling and neighborhood variable data is gathered from both the Lianjia website and the Anjuke website (https://wuhan.anjuke.com/). Location variable data is derived from Baidu Map (https://map.baidu.com/) POI (Point of Interest) data. Data related to the Yangtze River comes from Tsinghua University's 10 m resolution global land cover map (https://data-starcloud.pcl.ac.cn/resource/1).

The original data for various variables needs to be preprocessed before being used. To begin with, the original data is calculated using certain logic to produce the final data. For example, the transaction year is used to minus the construction year to get the housing age, valuing rules are established to get values of scoring variables like *ORIENTATION* and *DECORATION*. Obtaining values of distance variables such as *DIS-EDUCATION*, *DIS-PARK* and *DIS-YANGTZE* with the Near function in ArcGIS and getting values of quantitative variables with the Spatial Join function. Second, unifying the data format and unit of each variable. Last, the original data is merged into complete housing transaction records, and any records with missing value and outliers are discarded. Figure 3 depicts a process summary of data acquisition and processing.

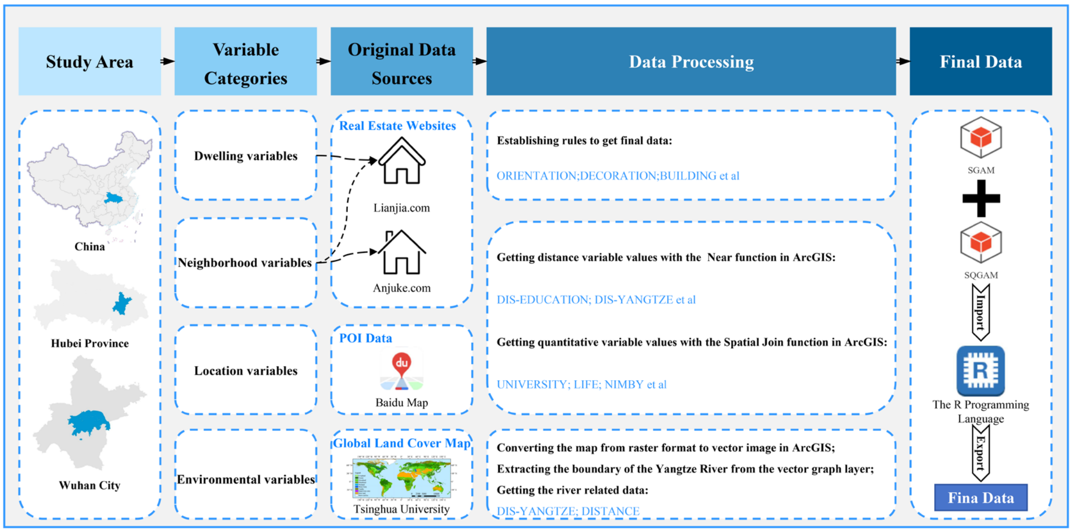


Figure 3. Data processing flowchart

4.3. Model specification

This paper discusses the capitalization effect of river landscapes in the urban housing market. Firstly, a SGAM is established to investigate the capitalization effect of the Yangtze River in different distance areas around houses. Among them, distance variables (*DIS-YANGTZE*) and its interaction term with regional dummy variables (*DISTANCE*) are used in the model representing the Yangtze River, respectively, forming Model 1.1 and Model 1.2.

$$\ln(P) = \alpha + \sum f(X) + f_1(x_j, y_j; S_j) + f_2(B_j, D_j; S_2) + YANGTZE + \mu_j. \quad (4)$$

Second, a SQGAM is developed to account for the Yangtze River's influence on the surrounding homeowners with varying purchasing power in different dwellings. The distance variable and a dummy variable are combined to create an interaction term in Model 2.1. Significance at different quantiles of the regression coefficient is able to demonstrate the feature's heterogeneous influence on housing prices.

$$\ln(P_\tau) = \alpha + \sum f(X) + f_1(x_{j\tau}, y_{j\tau}; S_j) + f_2(B_{j\tau}, D_{j\tau}; S_2) + YANGTZE + \mu_{j\tau}, \quad (5)$$

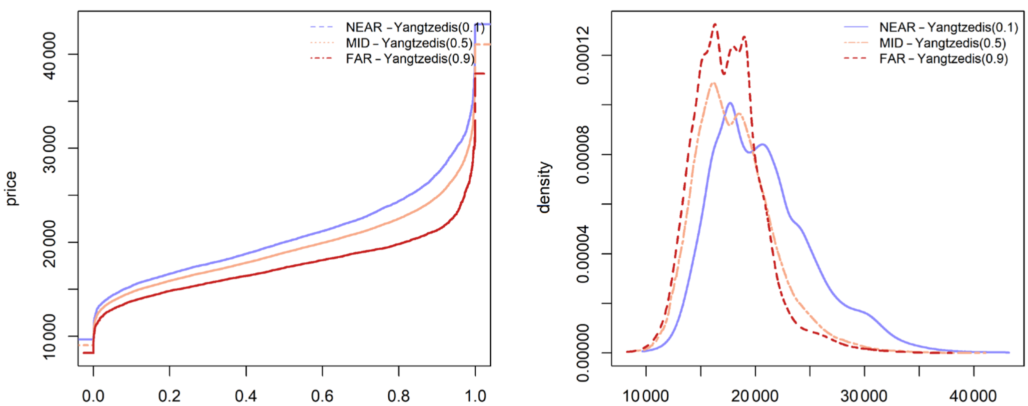
where: P is housing prices; τ is the quantiles of housing prices and 9 quantiles ranging from 0.1 to 0.9 are selected; J is the J_{th} transaction house; α is the coefficient to be estimated; f is the function in parameter form; X is the residential dwelling, neighborhood and location variables; f_k is the nonparametric smoothing function, k = 1, 2, m; (B, D) is the interactive term of construction and transaction time; S_k is the parameter of a nonparametric smoothing function, k = 1, 2, m; (x, y) is the longitude and latitude of the houses; *YANGTZE* is the independent variable, taking *DIS-YANGTZE* and its interaction with *DISTANCE* (the dummy variable) respectively; μ is error term.

The models presented above are built on the variable framework of the Hedonic Pricing Method, linked by a normal distribution and a unit function, and fitted with a spline function. The transaction and sale time of the house are fitted in form of an interaction term. The dependent variable is the unit price of housing in logarithmic form.

5. Results and discussion

5.1. Kernel density estimate of the relationship between Yangtze River accessibility and housing prices

The heterogeneity of dependent variables can be demonstrated by the varied distribution of house prices at multiple quantiles (Coulson & McMillen, 2007). Consequently, this paper initially draws kernel density curves and examines the price distribution of residences with varied Yangtze River accessibility, with the results displayed in Figure 4. The figure on the left depicts the residential pricing distribution corresponding to the Yangtze River residential samples at three quantiles (10%, 50%, and 90%). The figure on the right depicts the density of residential samples at various quantiles of distance from the Yangtze River. The three lines indicate residential samples with 10%, 50%, and 90% quantiles from the Yangtze River's edge, respectively. The graphic illustrates that the houses closest to the Yangtze River (0.1) have the highest price and the lowest density, whereas the houses farthest away from the Yangtze River (0.9) have the lowest price and the highest density, and the price distribution and density of houses in the middle (0.5) are closer to those along the Yangtze River (0.1). The left and right figures confirm that the distance variable has heteroscedasticity, implying that the relationship between the distance from the house to the Yangtze River and the housing price deserves an in-depth discussion.



a) tau (price) b) price

Note: Figure 4a: the horizontal axis: the quantile of residential prices; the vertical axis: the housing prices; Figure 4b: the horizontal axis: the housing prices; the vertical axis: distribution density of houses; Three lines: the residential samples in the short distance (0.1 quantiles of the distance to the Yangtze River), the middle distance (0.5 quantiles) and the long distance (0.9 quantiles).

Figure 4. Kernel density plot of the housing prices and the Yangtze River accessibility

5.2. Heterogeneity of the Yangtze River affecting housing prices among geographical regions

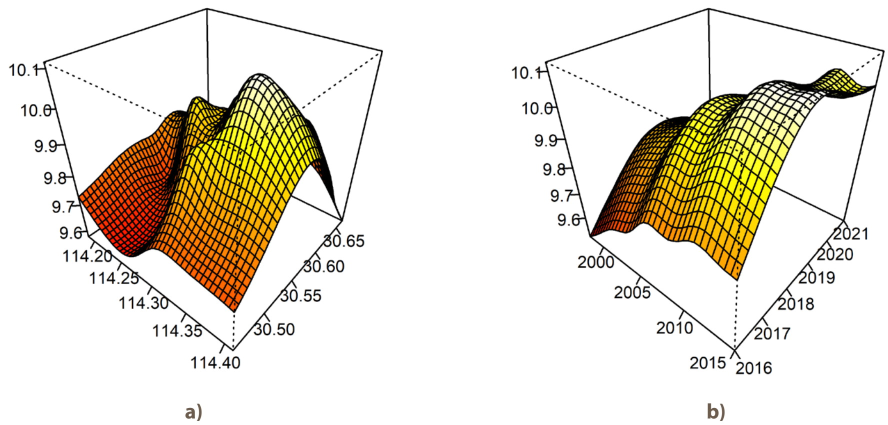
With the help of the MGCV package in R, the SGAM is constructed and calculated, and the maximum likelihood method is used to estimate the model. According to the AIC value, explanatory deviation of the model and significance of each explanatory variable, the optimal model is determined.

By fitting the geographical coordinates of dwellings with a spline smoothing function, SGAM controls the spatial trend in the data. Figure 5 depicts a smooth image that regulates spatial impacts in data with three geographically distinct peaks in Wuhan's housing prices, which corresponds to reality. The Yangtze River and the Han River flow through Wuhan, transforming it into a multi-center city with centers in Wuchang, Hankou, and Hanyang. The image on the right depicts the interactive influence of the residential sample's sale and transaction time on the housing prices. Within the same construction year, the sale price climbed in a wave-like fashion from 2015 to 2021, with a high increase from 2015 to 2018. Among them, the longer the houses have been built, the lower the transaction price was. The cycle of the Wuhan housing market always follows China's macroeconomic policies. Due to China's policy of restraining purchases and loans from 2012 to 2015, China's real estate industry has maintained a steady and modest growth pattern. Since 2015, the Central Bank of China has consistently reduced interest rates and the statutory deposit reserve ratio, as well as implemented policies such as lowering taxes and fees and lowering the down payment ratio for second suites. Housing prices in Wuhan skyrocketed almost immediately.

Models 1.1 and 1.2 use *DIS-YANGTZE* and *DIS-YANGTZE*DISTANCE* as explanatory variables to investigate the value-added effect of the Yangtze River on housing prices at various distances around the Yangtze River. Table 2 displays the results. The adjusted-R^2 is 0.694 and 0.699, indicating that they can explain almost 70% of the variance in house prices. Model 1.2 has a better fit than Model 1.1. It is clear that the dummy variable (*DISTANCE*) improves the model's interpretation degree to some extent. As studied by Shao et al. (2023), compared with houses without any ecological landscapes at all, the existence of a certain number of ecological landscapes around them will greatly increase the price of houses.

In terms of dwelling characteristics, factors like floor area (*AREA*), house orientation (*ORIENTATION*), decoration (*DECORATION*), and building floor height (*BUILDING*) exhibit the anticipated positive influence on housing prices. Among them, the floor area of a home is the most important dwelling characteristic that affects the price of a home, which is consistent with the findings of Wu et al. (2015). From the perspective of the building itself, a larger floor area means a richer spatial layout and better functional zoning inside the residence, which can satisfy homebuyers' higher pursuit of the quality of life. In addition, the orientation of the house and the height of the building floor directly affects the ventilation and lighting effect of the house, and the decoration situation relates to the user's sense of living experience, which all directly affect the price of housing.

In terms of neighborhood characteristics, all types of neighborhood amenities, except for the variable *PROPERTY*, have a significant impact on home prices. Among them, the internal conditions of the neighborhood, such as the green area ratio (*GREEN*), plot ratio (*PLOTRATIO*), and the total number of households (*HOUSEHOLD*), have the most significant impact on housing prices. This is because the higher the green space rate, the more conducive it is to the health of residents and it also helps to improve the grade of the community. Conversely, if the plot ratio is too high, the residents' outdoor activity space is limited and it also increases noise and traffic congestion in the district. This directly affects the residents' living experience and quality of life. The increase in the number of households means that there is higher demand for public space and the community's utilization of various types of public facilities will also increase. The utilization rate of various public facilities



Note: a) is an image of fitting the geographical coordinates of a house with a smoothing function. The right and left axes respectively represent the latitude and longitude of the house. b) is an image of fitting the construction and transaction time of the house with a smooth function. Right and left axes represent the construction and transaction time.

Figure 5. Smooth images of spatial and temporal effects

Table 2. Parameter estimate results of SGAMs

	Model 1.1	Model 1.2
CONSTANT	9.8144***(0.1003)	10.2386***(0.174)
log(DIS-YANGTZE)	–0.0346***(0.0113)	–0.1083***(0.0234)
log(DIS-YANGTZE) DISTANCE-D2*		–1.5819***(0.0412)
log(DIS-YANGTZE) DISTANCE-D3*		–2.0715***(0.0498)
log(DIS-YANGTZE) DISTANCE-D4*		–1.6581***(0.0445)
log(DIS-YANGTZE) DISTANCE-D5*		–1.8402***(0.0602)
log(DIS-YANGTZE) DISTANCE-D6*		2.1973***(0.0986)
log(AREA)	0.0283***(0.0036)	0.0279***(0.0036)
ORIENTATION	0.0032***(0.0006)	0.0033***(0.0006)
BUILDING	0.0016***(0.0002)	0.0016***(0.0002)
DECORATION	0.0015***(0.0002)	0.0015***(0.0002)
GREEN	0.3611***(0.02)	0.3497***(0.0201)
PROPERTY	0.0008(0.0012)	0.0005(0.0012)
PLOTRATIO	–0.0087***(0.0013)	–0.0093***(0.0013)
log(HOUSEHOLD)	0.0398***(0.0017)	0.0416***(0.0017)
PARKING	0.0198***(0.0027)	0.0202***(0.0027)
UNIVERSITY	0.0109***(0.0021)	0.0114***(0.0021)
log(DIS-EDUCATION)	–0.0093***(0.0017)	–0.0123***(0.0017)
log(DIS-PARK)	–0.0279***(0.0024)	–0.0253***(0.0025)
log(DIS-KG)	0.0132***(0.0016)	0.0122***(0.0016)
LIFE	0.0003***(0.0001)	0.0005***(0.0001)
NIMBY	–0.0054***(0.0015)	–0.005***(0.0015)
LOOPLINE	0.0065***(0.0004)	0.0066***(0.0004)
log(DIS-SUB)	–0.0492***(0.0023)	–0.051***(0.0023)
R^2	0.694	0.699

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; standard errors in parentheses.

in the community will also increase accordingly, while the construction cost and operation and maintenance cost of these facilities will be shared with each resident through the price of the house. In addition, educational facilities such as key schools and universities, and living facilities such as parks, supermarkets and banks have a significant value-added effect on housing prices. Within the competitive educational landscape in China, the housing in school district adjacent to key schools has gradually become a sought-after resource in the city, which in turn has led to a rise of housing prices in school district (Wen et al., 2019). However, kindergartens have a negative impact on the prices of neighboring houses, which may be because the distance between the sample houses and the nearest kindergarten is mostly within 800 meters. Too close a distance may cause neighboring residents to face a series of problems brought by the kindergarten parents to pick up and drop off their children, such as traffic congestion and noise pollution. The level of amenities is also critical to the living experience of the residents. Complete living facilities like supermarkets and parks contribute to enhanced convenience and comfort, thereby augmenting overall life satisfaction. This kind of good living experience will often attract more residents to buy or lease real estate, which will push up the house prices. On the contrary, "Not In My Backyard" facilities that evoke psychological discomfort, such as cemeteries, can lead to a depreciation of the surrounding real estate.

In terms of location characteristics, the subway station (*DIS-SUB*) has a significant positive impact on residential prices. This is because with the advancement of Wuhan's rail transit construction and the increase of planned lines, the subway has gradually become the main means of public transportation for residents to travel, and the subway greatly alleviates the problem of "traffic congestion" on the ground level of the city, so the price of residences near the subway is significantly higher due to the convenience of travel (Xu & Zhang, 2016). In addition, the quality of the environment provided by the inner circle of the city (*LOOPLINE*) and its unique geographic location also bring significant gains in the prices of neighboring residences.

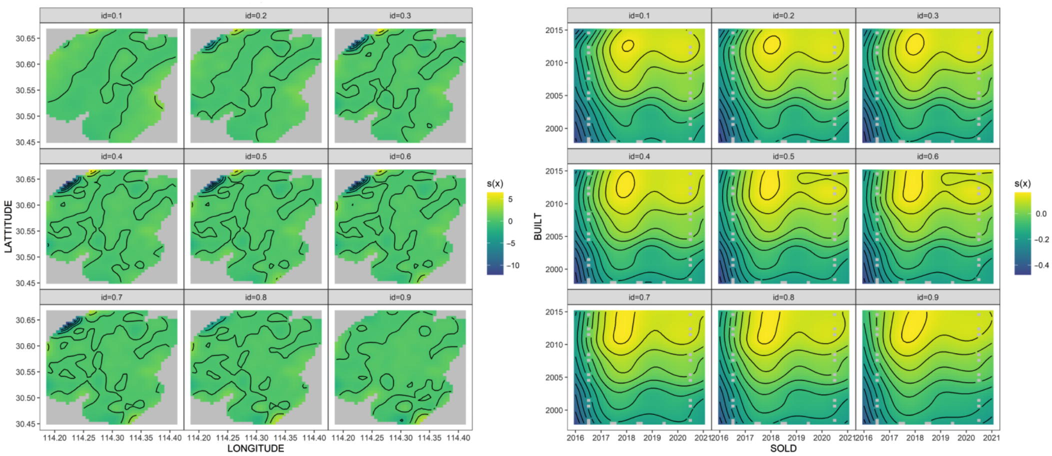
The variable of distance to the Yangtze River (*DIS-YANGTZE*) is significant at 1% in Model 1.1 with a number of –0.0346%, which means that every 1% increase in straight-line distance to the Yangtze River reduces the unit price of adjacent houses by 0.0346 percent on average, assuming all other conditions remain constant. This estimate, however, represents the typical impact of residential dwellings within 0.5–8 km or even further away from the Yangtze River. In fact, many studies have underlined the non-linear aspects of housing factors (Worku, 2017; Xiao et al., 2019). The results of Model 1.2 support this non-linear speculation. The interaction between the variables *DISTANCE* and the *DIS-YANGTZE* is included in Model 1.2 to assess the value-added effect of dwellings at various distances along the Yangtze River. The price elasticity of the Yangtze River in the corresponding interval is represented by the coefficient D2-D6. The findings reveal that the value-added impacts of houses at various distance intervals around the Yangtze River vary. The housing price has the highest price elasticity in the D3 range, followed by the D5 range, the D4 range, and finally the D2 range. This suggests that the premium on the Yangtze River can reach 2.0715% in the 1.5–2 km range, 1.6581% in the 2–3 km range, and 1.8402% in the 1–1.5 km range. This means that as the distance to the Yangtze River has increased, the premium of the Yangtze River has developed a wavy curve development tendency. It proves that in the housing submarkets divided by geographical location, the value-added effect of the Yangtze River on housing prices in different regions is heterogeneous, that is, hypothesis 1 holds. This premium impact has vanished in the D6 interval (5–8 km), showing that the Yangtze River's favorable influence range is restricted to around 5 km.

Many high-end real estate projects have been developed along the Yangtze River, attracting a large number of buyers, which is caused by the gradual change in people's purchase behaviors from rigid demand to improved demand. Inhabitants are prepared to pay for Yangtze River accessibility to improve their living environment. In the meantime, the Yangtze River serves as a primary commerce route, and passing ships generate noise, water pollution, and air pollution, which may lessen locals' preference for the Yangtze River. This demonstrates the duality of inhabitants' attitudes towards the Yangtze River, which leads to the nonlinear characteristics of the Yangtze River premium.

5.3. Heterogeneity of the Yangtze River affecting housing prices among buyer groups

The value of the river landscapes to different households is discussed in this section by the quantile regression model. The geographical location, as well as the sale and construction time, are formed as interaction terms, respectively, then nonparametrically fitted into the model using smoothing terms, and the image is shown in Figure 6. Figure 6a demonstrates that low-priced houses (0.1–0.3τ) are broadly and equally distributed in urban areas, while middle-priced houses (0.4–0.6τ) are dispersed, and high-priced houses (0.7–0.9τ) are the most scattered. Each subpicture in Figure 6b demonstrates that as the construction (2000–2015) and transaction (2016–2021) time pass, the coefficient of residential pricing tends to shift from negative to positive. This means that the prices of houses built and sold earlier are suppressed, whereas the houses in the years later tend to be worth much more as economic development changes. This effect is particularly visible in houses built between 2010 and 2015 and sold between 2018 and mid-2020, with the time span increasingly shrinking from the low-priced to the high-priced houses.

Table 3 demonstrates that the majority of control factors have a significant impact on houses that are valued differently. In particular, the impact of the quality of basic educational resources (*DIS-EDUCATION*) on the price of homes is significantly diverse across residential submarkets. The variable *DIS-EDUCATION* has a significant effect primarily on homes in the 0.1τ and 0.7τ and above, implying a higher level of willingness to pay for the quality of schools in the neighborhood for residents who buy high-end and low-end houses. This is because residents of high-end residences usually have higher economic strength and a good educational background. When purchasing properties, they pay more attention to the quality



a) b)

Note: Figure 6a is an image of fitting the geographical coordinates of a house at each quantile with a smoothing function. The X and Y axes are the longitude and attitude of the house. Figure 6b is an image of fitting the construction and transaction time of the house at each quantile with a smooth function. The X and Y axes are the transaction and construction time of the house.

Figure 6. Smooth images of spatial and temporal effects among housing price quantiles

of neighboring schools and are willing to pay higher prices for quality schools. Second, key primary and secondary schools in China have better educational resources and higher graduation rates in prestigious schools. In the context of Wuhan's enrollment policy of "zoning to the right school, near to the nearest school", low-income families purchasing low-priced housing are willing to pay a premium for an excellent school district in order to achieve their children's class transitions through education. To sum up, elements that have a significant impact on house prices in Model 1.1 show different changing trends in each price category now. Figure 7 depicts the situation more intuitively, confirming that different types of buyers have distinct preferences for housing attributes.

Table 3. Parameter estimate results of SQGAMs

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
CONSTANT	9.5635***	9.9003***	10.2436***	10.4853***	10.4347***	10.5563***	10.3726***	10.3652***	10.456***
	(0.6685)	(0.6822)	(0.6324)	(0.6228)	(0.5995)	(0.6342)	(0.6737)	(0.5877)	(0.5822)
log(*DIS-YANGTZE*)	–2.9705***	–3.3698***	–3.6727***	–3.9437***	–3.8884***	–4.0086***	–4.0068***	–3.7844***	–3.6511***
* *DISTANCE-D2*	(0.0813)	(0.0744)	(0.0692)	(0.0663)	(0.0622)	(0.0637)	(0.0674)	(0.0658)	(0.0724)
log(*DIS-YANGTZE*)	–3.3181***	–4.2351***	–4.7722***	–5.0236***	–4.4058***	–4.0316***	–3.4761***	–2.6068***	–2.9637***
* *DISTANCE-D3*	(0.1215)	(0.112)	(0.1071)	(0.1021)	(0.0954)	(0.0967)	(0.0995)	(0.0942)	(0.1008)
log(*DIS-YANGTZE*)	–0.17	–2.0584	–3.5672***	–4.3436***	–3.8125***	–3.6218***	–3.5266***	–3.0023***	–4.1567***
* *DISTANCE-D4*	(0.1821)	(0.1735)	(0.163)	(0.1553)	(0.146)	(0.1504)	(0.157)	(0.1536)	(0.1658)
log(*DIS-YANGTZE*)	7.1432***	5.3986***	4.1714**	3.1401*	2.7551*	2.5851	1.6576	0.6839	–1.8962
* *DISTANCE-D5*	(0.2934)	(0.2676)	(0.242)	(0.2239)	(0.2075)	(0.215)	(0.2301)	(0.2318)	(0.2519)
log(*DIS-YANGTZE*)	13.0347***	6.2172**	2.4041	0.505	1.1135	1.2492	1.6985	3.7176	1.0617
* *DISTANCE-D6*	(0.3994)	(0.3577)	(0.3259)	(0.305)	(0.2896)	(0.2975)	(0.3176)	(0.3258)	(0.3511)
log(*AREA*)	–0.0128**	–0.0115***	–0.0092**	–0.0051	–0.0004	0.0006	0.0016	0.0029	0.006
	(0.0051)	(0.0043)	(0.004)	(0.0038)	(0.0036)	(0.0037)	(0.0039)	(0.004)	(0.0043)
ORIENTATION	0.0037***	0.0033***	0.0034***	0.0036***	0.0038***	0.0039***	0.0037***	0.0031***	0.0022***
	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0007)
BUILDING	0.0017***	0.0015***	0.0014***	0.0014***	0.0015***	0.0014***	0.0013***	0.0012***	0.0008***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
DECORATION	0.002***	0.0019***	0.0018***	0.0017***	0.0018***	0.0017***	0.0016***	0.0015***	0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
GREEN	0.3162***	0.3205***	0.2916***	0.2661***	0.2637***	0.2496***	0.2542***	0.3002***	0.3156***
	(0.0297)	(0.0255)	(0.0237)	(0.0227)	(0.022)	(0.0231)	(0.0252)	(0.0265)	(0.031)
PROPERTY	0.0004	–0.0001	–0.0024*	–0.0032**	–0.0034***	–0.0031**	–0.0026*	–0.0018	–0.0002
	(0.0019)	(0.0016)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0015)	(0.0016)	(0.0016)
PLOTRATIO	0.0003	0.0007	0.0005	0.0006	0.0008	0.0016	0.0023	0.0018	0.0022
	(0.002)	(0.0017)	(0.0015)	(0.0015)	(0.0014)	(0.0015)	(0.0016)	(0.0017)	(0.0019)
log(*HOUSEHOLD*)	0.0618***	0.0586***	0.0559***	0.0533***	0.0516***	0.0494***	0.0469***	0.0449***	0.0418***
	(0.0027)	(0.0023)	(0.0021)	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.002)	(0.0023)
PARKING	0.0305***	0.0264***	0.0241***	0.0231***	0.0228***	0.022***	0.0225***	0.024***	0.0249***
	(0.0037)	(0.0033)	(0.0031)	(0.003)	(0.0029)	(0.0031)	(0.0034)	(0.0037)	(0.0044)
UNIVERSITY	–0.0174***	–0.0163***	–0.0162***	–0.0163***	–0.0171***	–0.0177***	–0.0168***	–0.0161***	–0.0087**
	(0.0037)	(0.0032)	(0.0028)	(0.0026)	(0.0025)	(0.0026)	(0.0029)	(0.003)	(0.0034)
log(*DIS-*	–0.0082***	–0.0019	–0.0009	–0.0011	–0.0027	–0.0032	–0.0052**	–0.0082***	–0.0114***
EDUCATION)	(0.003)	(0.0025)	(0.0023)	(0.0021)	(0.0019)	(0.002)	(0.0021)	(0.0022)	(0.0026)
log(*DIS-PARK*)	–0.0214***	–0.019***	–0.0148***	–0.0101**	–0.0061	–0.0023	0.0014	0.0022	0.0036
	(0.0058)	(0.0048)	(0.0043)	(0.0041)	(0.0039)	(0.0038)	(0.0037)	(0.0037)	(0.004)
log(*DIS-KG*)	0.0102***	0.0113***	0.0116***	0.0109***	0.01***	0.0086***	0.0088***	0.0103***	0.0129***
	(0.0025)	(0.0021)	(0.0019)	(0.0017)	(0.0017)	(0.0017)	(0.0019)	(0.002)	(0.0023)
LIFE	0.0015***	0.0017***	0.0018***	0.0018***	0.0017***	0.0017***	0.0015***	0.0013***	0.0011***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
NIMBY	–0.0072**	–0.0079***	–0.0061***	–0.0036*	–0.0025	–0.0008	0.0003	0.0017	0.0039
	(0.0029)	(0.0025)	(0.0023)	(0.0022)	(0.002)	(0.0021)	(0.0022)	(0.0024)	(0.0026)
LOOPLINE	0.0074***	0.0077***	0.008***	0.008***	0.0081***	0.0079***	0.0075***	0.0073***	0.0068***
	(0.001)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)
log(*DIS-SUB*)	–0.025***	–0.0191***	–0.0163***	–0.0153***	–0.0173***	–0.0178***	–0.0189***	–0.0307***	–0.0413***
	(0.004)	(0.0035)	(0.0033)	(0.0032)	(0.0031)	(0.0032)	(0.0036)	(0.004)	(0.0045)
Adjusted/Pseudo R^2	0.729	0.748	0.760	0.766	0.771	0.768	0.762	0.750	0.733

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; standard errors in parentheses.

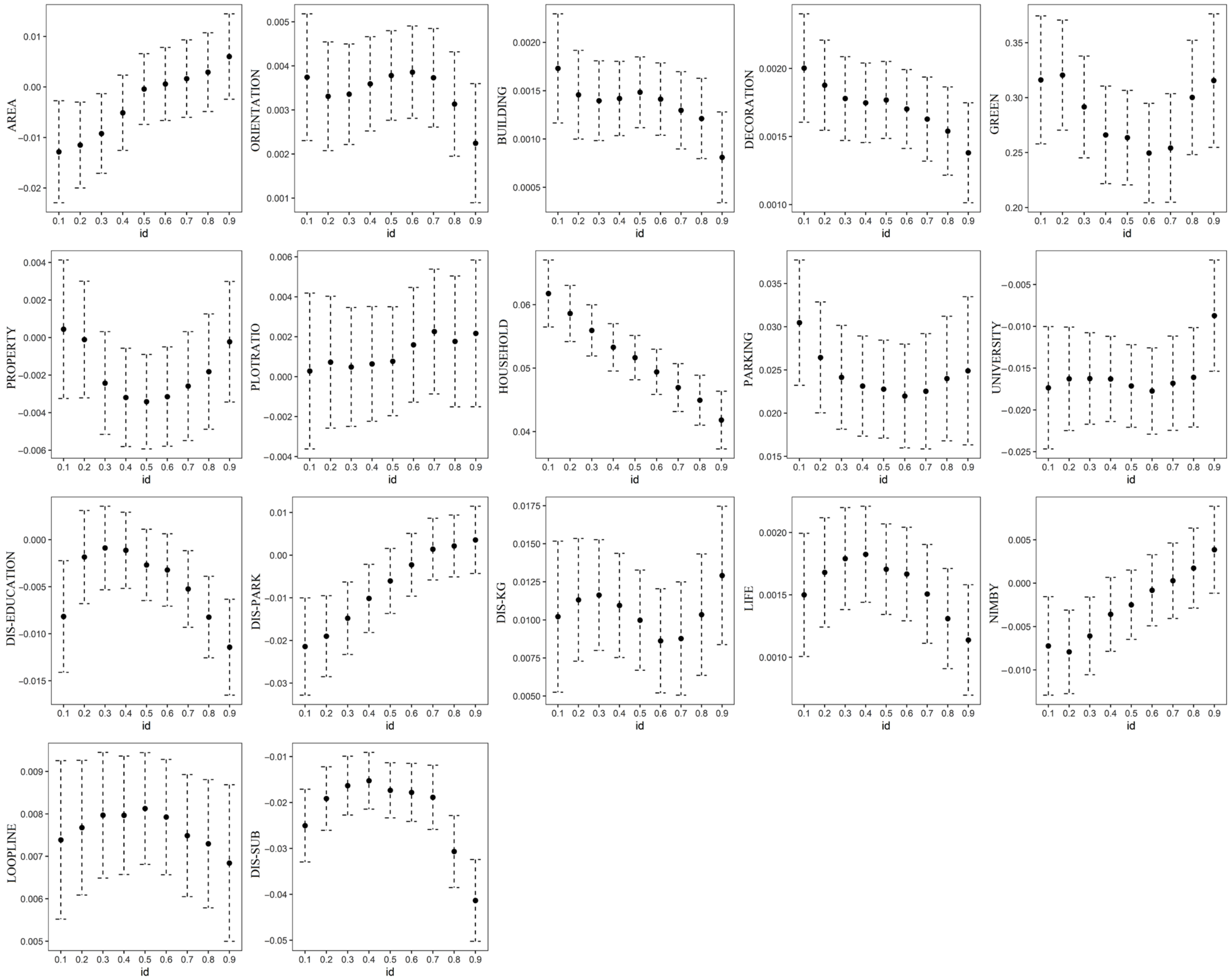
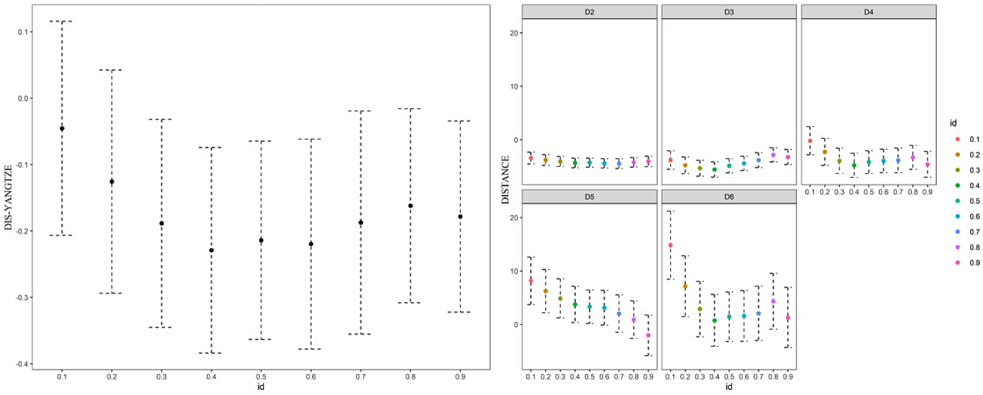


Figure 7. Visualization results of coefficients of SQGAM

The Yangtze River is included in the SQGAM with the interactive terms of *DIS-YANGTZE* and *DISTANCE*. Intervals D2, D3, and D4 passed the significance test at the 1% level. The coefficients of distinct quantiles within the same distance range differ. In conjunction with the consumer theory, residents who purchase low-end, middle-end, and high-end properties at varying costs have various perspectives on the Yangtze River. The coefficient indicates that the housing price will fall by 2.9705% to 4.0086% for every 1% increase in the distance to the Yangtze River in D2 (1–1.5 km), and by 2.6068% to 5.0236% in D3 (1.5–2 km), and by 3.0023% to 4.3436% in D4 (2–3 km). This demonstrates that D3 is the interval where the Yangtze River impacts the houses the most, which is the same as the results of Model 1.2. While in some quantiles in the D5 interval, increasing the distance to the Yangtze River will result in an increase of 2.7551% to 7.1432%, echoing the previous section's prediction that the Yangtze River's increment effect is wavy.

Figure 8 depicts the various reactions and shifting tendencies of houses that value the Yangtze River differently. Figure 8a depicts this impact first rising and then falling. That is, the Yangtze River has the greatest impact on middle-priced houses, followed by high-priced houses, and the least impact on low-priced houses. It provides empirical evidence for hypothesis 2. This shows that the Yangtze River is most appealing to inhabitants of medium-priced houses, followed by residents of high-priced houses, and least appealing to residents of low-priced houses. Figure 8b demonstrates that the further one gets away from the Yangtze River, the more distinct the perceptual divergence of different housing groups becomes.

The phenomenon depicted in Figure 8 can be described in view of the demands of the people. According to the basic assumptions of consumer theory, household income is an individual factor that influences residents' preferences for purchasing housing, and changes in income cause changes in the benefits that consumers seek when choosing residential goods. Thus, buyers of low-priced houses with substantial bank loans are more inclined to pay attention to what is just-needed while they underestimate the value-added services, such as the environment. They spend money on necessary housing elements (Rajapaksa et al., 2017). These people are not to buy



a) b)

Figure 8. Visualization results of coefficients of Yangtze River variables

the houses that needed to pay more for the environment and instead they will buy the houses without many ecological landscapes and with a lower price. As a result, they have to shift their needs to the nearby free ecological resources. They must walk to access different environmental resources nearby. The Yangtze River landscape, however, is difficult to achieve within a 15-minute walk because it is located in the center of the city. Buyers of high-priced houses prefer a better location and a more appealing setting, like living in a gated residential district with private gardens, having a wide range of ecological resource options, and may enjoy a better green environment and the benefits that come with it. Furthermore, these people are more likely to commute by automobile, so high-priced properties are more likely to be placed in areas with better medical, educational, and economical environments (Huang et al., 2021). In any event, wealthy residents are more capable of investing in their homes than other residents (Lee et al., 2020). Given that there are still some unfavorable aspects, such as noise and pollution near the Yangtze River, it may not necessarily be the first choice for wealthy individuals. According to Fernandez and Bucaram (2019), open areas such as these parks are more likely to cause noise and crowding for most dwellings (0.3 to 0.7τ). As a result, middle-priced houses have become the type with the strongest reaction to the Yangtze River environment, implying that middle-income people are the group with the highest reaction to the Yangtze River landscape. The coefficient result of the distance to the nearest park (*DIS-PARK*) provides some evidence for this phenomenon, as it is only significant at the 0.4 quantile and lower. This means that relatively impoverished residents pay extra attention to the surrounding parks. It can be shown that the right of obtaining ecological resources is unequal among Wuhan residents, and different levels of citizens have varied ways to obtain these resources.

6. Conclusions and recommendations

The existing literature focuses on the heterogeneity of the influence of different landscape categories on housing prices, but it rarely focuses on the heterogeneity that comes from purchasers' preferences, particularly in the study of river landscapes. To provide a thorough understanding of the heterogeneity of the impact of ecological landscapes on housing submarkets, this study uses the Yangtze River in Wuhan as an example, subdividing the housing market based on geographical location and buyer groups, and discusses the average effect and quantile effect of the Yangtze River on housing prices. This paper develops a SGAM and SQGAM, captures and visualizes the spatial correlation effect and the time interaction effect in residential samples using a nonparametric structure, and avoids the parametric assumption of an uncertain spatial and temporal structure. The following are the findings:

First, the Yangtze River has a 0.035% average influence on the surrounding houses within 8 km. However, within the chosen geographical interval, the impact rises from 1.582% to 2.072%, and the Yangtze River's influence range covers around 5 km. This proves that the heterogeneity of the Yangtze River affects housing prices across geographical regions and that this distance heterogeneity has a wavy tendency, supporting hypothesis 1.

Second, this article discovers that the influence of ecological landscape on real estate values is not fairly distributed among markets, which has been proved in other housing attributes, such as educational resources. The Yangtze River is most appealing to inhabitants of medium-priced houses, followed by residents of high-priced houses, and least appealing to residents of low-priced houses, confirming hypothesis 2. As urban ecological public goods, the findings of parks may supplement this discovery.

This paper indicates that, under this situation where the value of ecological service resources is monetized in the real estate market, low-income people will confront inequity when enjoying landscape resources. Low-income households can only afford the necessary residential elements while foregoing the environmental resources. High-income people can better satisfy their own self-pursuit of life quality and living conditions by obtaining river view rooms. This situation deserves the government's attention, especially when income inequality among people is gradually rising. To alleviate this problem, the Government can take the following measures to ensure equitable distribution of ecological resources, especially to provide more equal opportunities for low-income people to enjoy ecological resources:

To begin with, it is suggested that the government pay more attention to non-urban central areas and areas outside the third ring and focus on increasing the distribution of ecological resources such as parks and green spaces in these areas. The government should particularly provide more free ecological resources for low-income people in areas where landscape resources are generally scarce. This may include increasing the number of pocket parks and other small green spaces which can help improve the sense of housing well-being while attempting to control the cost of home ownership. Second, the service scope of key urban ecological landscapes should be expanded by improving the transportation network system. In urban transportation planning, government departments ought to prioritize the serviceable range encompassing the Yangtze River and other well-known urban ecological landscapes. They should reduce the commuting distance and time of urban residents by transforming some of the irrational road networks around the periphery. Additionally, they should increase the transportation routes from the outskirts of the city to the Yangtze River to enhance accessibility to river landscapes. This will enable more urban residents to equally benefit from the ecological advantages offered by the Yangtze River and other river landscapes.

This paper makes two theoretical contributions. Firstly, it sheds light on the pivotal relationship between residential prices and river landscapes, elucidating their importance for both residents and cities. Secondly, it realizes the extension of the application of the Hedonic Pricing Method while considering the spatial influence. This novel approach combines SGAM and SQGAM innovatively with the Hedonic Pricing Method to model the quantification of the capitalization effect of river landscapes in the housing market, captures the nonlinear and heterogeneous effects of some of the independent variables through interactions, and takes into account the geospatial correlation of house prices and their dynamics over time.

However, buyers have varying expectations for consumer items because of their different income levels and social positions, which arise from their personal qualities. As a result, it is possible that other qualities of purchasers, such as education level and occupation, may also influence their housing preferences. Further research needs to be done to determine these factors have an impact on property buyers. In addition, with the maturity of machine learning technology in dealing with spatial heterogeneity and nonlinearity, the effect of capturing spatial heterogeneity may be better than SGAM, so we may need to take this into account in the follow-up research, for example, combining machine learning with Hedonic Pricing Method to obtain more robust results.

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Availability of data and materials

All data and materials are given in the manuscript.

Consent to participate

All authors have given their consent to participate in submitting this manuscript to this journal.

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Disclosure statement

Ethics approval

We declare that all ethical guidelines for authors have been followed by all authors. Ethical approval is not required.

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The authors declare no competing interests.

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References

Alas, B. (2020). A multilevel analysis of housing submarkets defined by the municipal boundaries and by the street connections in the metropolitan area: Istanbul. *Journal of Housing and the Built Environment*, *35*(4), 1201–1217. https://doi.org/10.1007/s10901-020-09735-7

Bangura, M., & Lee, C. L. (2023). The determinants of homeownership affordability in Greater Sydney: Evidence from a submarket analysis. *Housing Studies*, *38*(2), 206–232. https://doi.org/10.1080/02673037.2021.1879995

Bohman, H. (2021). Same, same but different? Neighbourhood effects of accessibility on housing prices. *Transport Policy*, *107*, 52–60. https://doi.org/10.1016/j.tranpol.2021.04.016

Bonetti, F., Corsi, S., Orsi, L., & De Noni, I. (2016). Canals vs. streams: To what extent do water quality and proximity affect real estate values? A hedonic approach analysis. *Water*, *8*(12), Article 12. https://doi.org/10.3390/w8120577

Chen, G., Zhu, D., Su, Y., & Zhang, L. (2015). The effects of large-scale urban park green spaces on residential prices exemplified by Olympic Forest Park in Beijing. *Resources Science*, *37*(11), 2202–2210.

Chen, K. D., Lin, H. M., You, S. Y., & Han, Y. (2022). Review of the impact of urban parks and green spaces on residence prices in the environmental health context. *Frontiers in Public Health*, *10*, Article 993801. https://doi.org/10.3389/fpubh.2022.993801

Cho, S.-H., Roberts, R. K., & Kim, S. G. (2011). Negative externalities on property values resulting from water impairment: The case of the Pigeon River Watershed. *Ecological Economics*, *70*(12), 2390–2399. https://doi.org/10.1016/j.ecolecon.2011.07.021

Chwiałkowski, C., & Zydroń, A. (2022). The impact of urban public transport on residential transaction prices: A case study of Poznań, Poland. *ISPRS International Journal of Geo-Information*, *11*(2), Article 74. https://doi.org/10.3390/ijgi11020074

Coulson, N. E., & McMillen, D. P. (2007). The dynamics of intraurban quantile house price indexes. *Urban Studies*, *44*(8), 1517–1537. https://doi.org/10.1080/00420980701373446

Elhorst, J. P. (Ed.). (2014). Linear spatial dependence models for cross-section data. In *Spatial econometrics: From cross-sectional data to spatial panels* (pp. 5–36). Springer. https://doi.org/10.1007/978-3-642-40340-8_2

Fasiolo, M., Wood, S. N., Zaffran, M., Nedellec, R., & Goude, Y. (2021). Fast calibrated additive quantile regression. *Journal of the American Statistical Association*, *116*(535), 1402–1412. https://doi.org/10.1080/01621459.2020.1725521

Fernandez, M. A., & Bucaram, S. (2019). The changing face of environmental amenities: Heterogeneity across housing submarkets and time. *Land Use Policy*, *83*, 449–460. https://doi.org/10.1016/j.landusepol.2019.02.024

Geng, X., Yu, Z., Zhang, D., Li, C., Yuan, Y., & Wang, X. (2022). The influence of local background climate on the dominant factors and threshold-size of the cooling effect of urban parks. *Science of the Total Environment*, *823*, Article 153806. https://doi.org/10.1016/j.scitotenv.2022.153806

Grainger, C. A. (2012). The distributional effects of pollution regulations: Do renters fully pay for cleaner air? *Journal of Public Economics*, *96*(9), 840–852. https://doi.org/10.1016/j.jpubeco.2012.06.006

Gu, Z. N., Luo, X. L., Tang, M., & Liu, X. M. (2023). Does the edge effect impact the healthcare equity? An examination of the equity in hospitals accessibility in the edge city in multi-scale. *Journal of Transport Geography*, *106*, Article 103513. https://doi.org/10.1016/j.jtrangeo.2022.103513

Huang, T., He, Q., Yang, D., & Ouyang, X. (2021). Evaluating the impact of urban blue space accessibility on housing price: A spatial quantile regression approach applied in Changsha, China. *Frontiers in Environmental Science*, *9*, Article 696626. https://www.frontiersin.org/articles/10.3389/fenvs.2021.696626

Jia, J., & Zhang, X. (2021). A human-scale investigation into economic benefits of urban green and blue infrastructure based on big data and machine learning: A case study of Wuhan. *Journal of Cleaner Production*, *316*, Article 128321. https://doi.org/10.1016/j.jclepro.2021.128321

Lamond, J., Proverbs, D., & Hammond, F. (2010). The impact of flooding on the price of residential property: A transactional analysis of the UK market. *Housing Studies*, *25*(3), 335–356. https://doi.org/10.1080/02673031003711543

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*(2), 132–157. https://doi.org/10.1086/259131

Łaszkiewicz, E., Heyman, A., Chen, X., Cimburova, Z., Nowell, M., & Barton, D. (2022). Valuing access to urban greenspace using non-linear distance decay in hedonic property pricing. *Ecosystem Services*, *53*, Article 101394. https://doi.org/10.1016/j.ecoser.2021.101394

Le Boennec, R., Bulteau, J., & Feuillet, T. (2022). The role of commuter rail accessibility in the formation of residential land values: Exploring spatial heterogeneity in peri-urban and remote areas. *The Annals of Regional Science*, *69*(1), 163–186. https://doi.org/10.1007/s00168-022-01113-1

Lee, H., Lee, B., & Lee, S. (2020). The unequal impact of natural landscape views on housing prices: Applying visual perception model and quantile regression to apartments in Seoul. *Sustainability*, *12*(19), Article 8275. https://doi.org/10.3390/su12198275

Liebelt, V., Bartke, S., & Schwarz, N. (2019). Urban green spaces and housing prices: An alternative perspective. *Sustainability*, *11*(13), Article 3707. https://doi.org/10.3390/su11133707

Mittal, J., & Byahut, S. (2019). Scenic landscapes, visual accessibility and premium values in a single family housing market: A spatial hedonic approach. *Environment and Planning B: Urban Analytics and City Science*, *46*(1), 66–83. https://doi.org/10.1177/2399808317702147

Nutsford, D., Pearson, A. L., Kingham, S., & Reitsma, F. (2016). Residential exposure to visible blue space (but not green space) associated with lower psychological distress in a capital city. *Health* & *Place*, *39*, 70–78. https://doi.org/10.1016/j.healthplace.2016.03.002

Olszewski, K., Waszczuk, J., & Widłak, M. (2017). Spatial and hedonic analysis of house price dynamics in Warsaw, Poland. *Journal of Urban Planning and Development*, *143*(3), Article 04017009. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000394

Panduro, T. E., & Veie, K. L. (2013). Classification and valuation of urban green spaces–A hedonic house price valuation. *Landscape and Urban Planning*, *120*, 119–128. https://doi.org/10.1016/j.landurbplan.2013.08.009

Piaggio, M. (2021). The value of public urban green spaces: Measuring the effects of proximity to and size of urban green spaces on housing market values in San José, Costa Rica. *Land Use Policy*, *109*, Article 105656. https://doi.org/10.1016/j.landusepol.2021.105656

Potrawa, T., & Tetereva, A. (2022). How much is the view from the window worth? Machine learning-driven hedonic pricing model of the real estate market. *Journal of Business Research*, *144*, 50–65. https://doi.org/10.1016/j.jbusres.2022.01.027

Rajapaksa, D., Wilson, C., Hoang, V.-N., Lee, B., & Managi, S. (2017). Who responds more to environmental amenities and dis-amenities? *Land Use Policy*, *62*, 151–158. https://doi.org/10.1016/j.landusepol.2016.12.029

Ridker, R. G., & Henning, J. A. (1967). The determinants of residential property values with special reference to air pollution. *The Review of Economics and Statistics*, *49*(2), 246–257. https://doi.org/10.2307/1928231

Rivas Casado, M., Serafini, J., Glen, J., & Angus, A. (2017). Monetising the impacts of waste incinerators sited on brownfield land using the hedonic pricing method. *Waste Management*, *61*, 608–616. https://doi.org/10.1016/j.wasman.2016.10.036

Shao, J., Zhou, Y., Luo, H., Wang, J., & Zhang, Q. (2023). Comparative analysis of visual amenity services valuation: A nationwide assessment through propensity scoring matching and hedonic regression. *Journal of Environmental Management*, *325*, Article 116564. https://doi.org/10.1016/j.jenvman.2022.116564

Shehata, W., Abu Arqoub, M., Langston, C., Elkheshien, R., & Sarvimaki, M. (2021). From hard bed to luxury home: Impacts of reusing HM Prison Pentridge on property values. *Journal of Housing and the Built Environment*, *36*(2), 627–643. https://doi.org/10.1007/s10901-020-09766-0

Shi, L., Chen, B., Chen, X., & Chen, Z. (2022). Assessing the impact of wildfires on property values in wildland-urban intermix and interface in Colorado: A hedonic approach. *Journal of Environmental Management*, *319*, Article 115672. https://doi.org/10.1016/j.jenvman.2022.115672

Tawfeeq Najah, F., Fakhri Khalaf Abdullah, S., & Ameen Abdulkareem, T. (2023). Urban land use changes: Effect of green urban spaces transformation on urban heat islands in Baghdad. *Alexandria Engineering Journal*, *66*, 555–571. https://doi.org/10.1016/j.aej.2022.11.005

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy*, *64*(5), 416–424. https://doi.org/10.1086/257839

Wang, J., & Lee, C. L. (2022). The value of air quality in housing markets: A comparative study of housing sale and rental markets in China. *Energy Policy*, *160*, Article 112601. https://doi.org/10.1016/j.enpol.2021.112601

Wen, H. Z., Xiao, Y., & Zhang, L. (2017). Spatial effect of river landscape on housing price: An empirical study on the Grand Canal in Hangzhou, China. *Habitat International*, *63*, 34–44. https://doi.org/10.1016/j.habitatint.2017.03.007

Wen, H., Bu, X., & Qin, Z. (2014). Spatial effect of lake landscape on housing price: A case study of the West Lake in Hangzhou, China. *Habitat International*, *44*, 31–40. https://doi.org/10.1016/j.habitatint.2014.05.001

Wen, H., Li, S., Hui, E. C. M., Jia, S., & Cui, W. (2021). Purchase motivation, landscape preference, and housing prices: Quantile hedonic analysis in Guangzhou, China. *Journal of Urban Planning and Development*, *147*(3), Article 04021033. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000734

Wen, H., Xiao, Y., & Hui, E. C. M. (2019). Quantile effect of educational facilities on housing price: Do homebuyers of higher-priced housing pay more for educational resources? *Cities*, *90*, 100–112. https://doi.org/10.1016/j.cities.2019.01.019

Worku, G. B. (2017). House price drivers in Dubai: Nonlinearity and heterogeneity. *International Journal of Housing Markets and Analysis*, *10*(3), 384–409. https://doi.org/10.1108/IJHMA-06-2016-0048

Wu, J., Wang, M., Li, W., Peng, J., & Huang, L. (2015). Impact of urban green space on residential housing prices: Case study in Shenzhen. *Journal of Urban Planning and Development*, *141*(4), Article 05014023. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000241

Xiao, Y., Hui, E. C. M., & Wen, H. (2019). Effects of floor level and landscape proximity on housing price: A hedonic analysis in Hangzhou, China. *Habitat International*, *87*, 11–26. https://doi.org/10.1016/j.habitatint.2019.03.008

Xu, T., & Zhang, M. (2016). Influences of regional development conditions on the railway transit access premium: Evidence from Wuhan City. *Urban Problems*, *9*, 48–57.

Zemo, K. H., Panduro, T. E., & Termansen, M. (2019). Impact of biogas plants on rural residential property values and implications for local acceptance. *Energy Policy*, *129*, 1121–1131. https://doi.org/10.1016/j.enpol.2019.03.008

Appendix

Table A1. Variable correlation analysis

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	VIF
1: *DIS-YANGTZE*	1.00	***	***	–	***	***	***	***	***	***	***	***	–	***	–	***	***	***	***	***	***	***	***	1.58(1.58)
2: *AREA*	0.10	1.00	***	***	***	***	***	***	***	***	***	***	***	–	***	–	–	***	***	**	*	–	***	4.67(1.25)
3: *ORIENTATION*	0.08	0.28	1.00	***	***	***	***	***	***	***	***	***	–	**	***	–	***	***	***	**	*	***	**	1.22(1.19)
4: *DECORATION*	–0.01	–0.13	–0.19	1.00	***	***	***	***	***	***	***	***	***	***	–	***	***	***	***	***	***	***	***	1.56(1.53)
5: *BUILDING*	–0.06	–0.17	–0.10	0.15	1.00	***	***	***	***	***	***	***	***	***	***	–	***	–	***	***	***	***	***	2.18(2.18)
6: *ROOM*	0.11	0.85	0.28	0.05	–0.10	1.00	***	***	***	***	***	***	***	**	***	***	***	***	***	**	**	***	***	4.53(–)
7: *SOLD*	0.03	0.14	0.22	–0.54	–0.16	–0.07	1.00	***	***	***	***	***	***	***	***	***	***	***	***	***	***	*	***	2.1(1.98)
8: *BUILT*	0.03	–0.20	–0.05	0.21	0.61	–0.08	–0.24	1.00	***	***	***	***	***	***	***	***	***	***	***	–	***	***	***	2.25(2.25)
9: *GREEN*	0.08	0.22	0.05	0.07	0.04	0.21	–0.04	0.06	1.00	***	***	***	***	***	–	***	***	***	***	***	**	***	***	1.20(1.20)
10: *PROPERTY*	–0.09	–0.04	0.11	–0.34	0.27	–0.12	0.44	0.08	–0.17	1.00	***	***	***	–	***	***	***	***	***	***	***	***	***	1.80(1.79)
11: *PLOTRATIO*	–0.08	–0.23	–0.29	0.44	0.44	–0.10	–0.56	0.42	–0.10	–0.19	1.00	***	***	***	***	**	***	***	***	*	**	***	***	2.25(2.25)
12: *HOUSEHOLD*	–0.03	–0.15	–0.06	0.23	0.22	–0.04	–0.26	0.34	0.14	–0.16	0.22	1.00	***	***	***	***	***	***	***	***	–	***	***	1.48(1.48)
13: *PARKING*	–0.01	0.06	0.01	0.03	0.18	0.06	–0.07	0.23	0.03	0.07	0.15	–0.13	1.00	*	***	***	***	***	***	***	*	***	**	1.20(1.20)
14: *UNIVERSITY*	0.07	0.00	–0.02	–0.03	–0.03	–0.02	0.03	–0.05	–0.04	0.01	–0.03	–0.09	–0.02	1.00	***	–	**	***	***	***	***	***	***	1.16(1.16)
15: *DIS-KG*	0.01	0.03	0.03	–0.01	0.10	0.05	–0.05	0.09	–0.01	0.07	0.08	–0.12	0.09	0.03	1.00	–	***	***	***	***	***	***	***	1.10(1.10)
16: *DIS-EDUCATION*	0.05	0.00	0.01	0.06	0.00	0.04	–0.05	0.11	0.05	–0.12	–0.02	0.08	0.10	–0.01	–0.01	1.00	***	***	***	***	***	***	***	1.11(1.11)
17: *DIS-PARK*	0.10	0.00	0.06	0.06	–0.08	0.07	–0.06	0.18	0.15	–0.24	–0.08	0.20	0.06	–0.02	–0.06	0.05	1.00	***	***	***	***	***	***	1.47(1.47)
18: *LIFE*	–0.30	–0.09	–0.12	–0.04	0.01	–0.13	0.05	–0.22	–0.22	0.22	0.11	–0.19	–0.07	0.05	–0.06	–0.17	–0.33	1.00	***	***	***	***	***	1.67(1.67)
19: *NIMBY*	–0.19	–0.07	–0.03	–0.05	–0.12	–0.10	0.07	–0.16	–0.10	0.07	–0.04	–0.12	–0.09	–0.11	–0.04	–0.06	–0.11	0.33	1.00	***	***	***	***	1.21(1.21)
20: *LONGITUDE*	–0.29	0.02	–0.02	0.05	0.02	0.02	–0.06	–0.01	0.11	–0.10	–0.02	0.04	0.08	0.18	0.03	0.04	0.17	–0.06	–0.14	1.00	***	***	***	1.45(1.45)
21: *LATTITUDE*	–0.08	0.02	0.02	–0.05	–0.08	–0.02	0.08	–0.10	0.02	0.03	–0.02	0.01	0.02	–0.25	–0.18	–0.17	0.14	0.07	0.09	–0.17	1.00	–	***	1.40(1.40)
22: *LOOPLINE*	–0.48	–0.01	–0.12	–0.04	0.15	–0.08	–0.02	–0.15	–0.08	0.19	0.12	–0.26	0.10	–0.06	0.07	–0.16	–0.37	0.39	0.14	0.16	0.00	1.00	***	2.12(2.11)
23: *DIS-SUB*	0.16	–0.04	0.02	0.04	0.03	0.03	–0.03	0.16	0.08	–0.10	–0.04	0.05	0.02	0.15	0.10	0.10	0.12	–0.36	–0.21	0.26	–0.38	–0.33	1.00	1.61(1.61)

Note: The Pearson correlation coefficients between the variables in the lower left corner, and the corresponding significance levels in the upper right corner; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; the *VIF* values of the independent and control variables, after removing the variable *ROOM*, are enclosed in parentheses.