**ARTICLE**

# Impact of different ecological landscapes on housing prices—empirical evidence from wuhan through the hedonic pricing model appraisal

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## Abstract

A close relationship exists between ecological landscape and housing prices. Taking Wuhan as the research object, this paper establishes a series of spatial generalized additive models based on the hedonic method to explore the effects of different ecological landscapes such as lakes, rivers, mountains, and parks on house prices. Results are as follows: (1) Overall, lakes, parks, and mountains have price elasticity values of approximately 0.62%, 1.30%, and 0.81%, respectively. However, the price elasticity values of 2-km inner and outer lakes are 0.18% and 3.39% respectively, with similar results in other landscapes. The existence of lakes, parks, and mountains can trigger the increase in housing price percentages by 34.61%, 43.12%, and decrease by 25.09%, respectively. (2) The nonparametric form shows that the influence of lakes and parks on housing prices within 2 km constantly changes around zero. The influence of rivers is always positive, whereas the influence of mountains is always negative. (3) Interaction occurs between landscapes. In the situation of interaction with lakes, the elasticity values of the distance among rivers, mountains, and parks become 0.50%, − 0.32% and 0.90%, respectively. Future research should focus on the nonlinear characteristics and interactive effects of landscape premium.

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# 1 Introduction

Expectations of residents for living conditions have increased together with the advancement of civilization and the increase in living standards. Forests, lakes, rivers, and parks are examples of urban ecological landscapes that not only improve the urban environment and safeguard the environment but also provide residents natural landscapes and recreational opportunities (Chen et al., 2015). Exploring eco-environmental value can also aid in the development of sustainable cities, allowing for the simultaneous realization of environmental quality, social fairness, and economic progress (Chiesura, 2004). Scholars have made attempts to quantify the worth of ecological landscape (Liu & Chen, 2020).

In the past, the willingness to pay approach was previously employed for evaluation, but due to its high subjectivity, producing consistent results was difficult (Mao et al., 2018). Hedonic price models are now commonly used to show how ecological landscapes affect property values. Ridker (1976), for example, established a hedonic model to confirm a significant negative link between air pollution and house prices. According to the hedonic method, any heterogeneous commodity in the market is a feature bundle composed of various feature attributes, and the price of heterogeneous goods is determined by various implicit hedonics (Clapp & Salavei, 2010). Consequently, the hedonic model is used in the research on the impact of influential factors on housing prices.

Zygmunt and Gluszak (2015) discovered that the presence of forests had a beneficial impact on the transaction price of surrounding real estate in their forest investigation. The impact of parks on real estate values has been a concern for a long time. Lutzenhiser and Netusil (2001) used an interactive term between open space type and area to accurately examine the marginal value of each open space type. According to Cen and Zhang (2018), a significant non-linear relationship exists between housing prices and distance to the ecological park; by calculating the extreme points, they determined that Foshan Park has an effective influence radius of 1,812 m on the surrounding houses. Moore et al. (2020) confirmed that lake clarity is one of the qualities that community members value in the surrounding environment using water quality data from 115 lakes across the United States. Although the existence of rivers is commonly thought to be an efficient way to widen the horizons of surrounding houses and raise housing prices, scholars have discovered that rivers, owing to pollution, floods, and other reasons, have a detrimental impact on neighboring houses (Chen, 2017; Kousky & Walls, 2014). The majority of the research examined the impact of ecological landscape on housing prices by measuring a single landscape feature from a single variable. However, as enlightened by Lutzenhiser and Netusil (2001), interactions occur between ecological landscape types and some of their own characteristics; thus, whether interactions happen among different landscape features or even whether different types of ecological landscape elements have the same complex interactions, which of them will affect housing prices through the people's perception? This particular landscape interaction deserves investigation as well, but few scholars have focused their efforts on it.

Thus, how do environmental landscapes influence housing prices? With the use of parameter setting, most scholars assumed that ecological landscape had a linear influence on housing prices, that is, housing prices rise or fall linearly with increasing distance from ecological landscape, and the specific value number of this effect was generally computed (Jiao et al., 2017; Jim & Chen, 2009). However, an increasing number of studies have built hedonic models using quadratic terms, logarithmic terms, and virtual variables based on distance interval within OLS method, and found that ecological landscape affects housing prices differently in different distance ranges. It implies that this impact does not always

remain the same with increasing distance from the landscape, and the impacts from different distance ranges on housing prices vary. For example, Anderson and West (2006) found that the value of the proximity of open space varies with the population density, income and other factors that affect the demand of open space, and they also found that the average effects may misrepresent substantially the effect of open space on home values in particular neighborhoods. Kovacs (2012) utilized a nonlinear variable to characterize the proportion of the park around the house and then regressed the distances approximately half a mile and five to ten miles to see how the park affected property value at different distances. According to Tapsuwan et al. (2015), properties within 10 km of the forest can rise in value by approximately 2,000 Australian dollars, while regular dwellings within 75 km can increase in value by approximately 290 Australian dollars. Similarly, the influence on the value of buildings within and outside a 50-km radius of a river flood zone differs significantly. Liu et al., () looked at the differences in housing prices between urban forest, cultivated land, wetland, and grassland, and discovered a significant inverted U-shaped spatial spillover effect between the grassland area and housing price as well as different spillover effects of cultivated land at different distances. This discovery is extremely beneficial to city planners and may provide theoretical support for them to make other scientific and sensible judgments in terms of urban planning, transformation, and rejuvenation. Ecological resource planners can use this knowledge to maximize the aesthetic, social, and ecological benefits of urban land when deciding on the optimal environmental arrangement for people. The nonlinear properties of the landscape value-added impact have mostly been acknowledged up to this point. However, in the research described above, the research distance is decided subjectively on the basis of previous research experience. Scholars limit the scope of their research to a specific time period and perform it by location or distance. Obviously, when the distance is too large, the value-added coefficient diminishes and vice versa. The relationship between ecological landscape and housing price is implicitly assumed by stating the implicit nonlinear relationship with quadratic and cubic factors with OLS method. In summary, several drawbacks exist when using a parametric model in a nonlinear field. In theory, this strategy may lead to inaccurate estimates of ecological landscape value, and applying it fairly in practice is difficult. Illustrating the value-added effect of ecological landscape in every position might be more realistic.

Controlling the spatial correlation of a price model is another issue that is frequently explored. Scholars utilized to integrate spatial matrices into hedonic pricing models to build spatial econometric models (Fernandez et al., 2018; Li & Saphores, 2012) due to the general clear geographical correlation of housing prices (Helbich et al., 2012). In recent years, scientists have begun to use nonparametric structures in hedonic models to overcome the problem (Jose-Maria et al., 2017). Spatial generalized additive models (SGAM) with nonparametric structures, for example, can flexibly fit geographic data and control unknown spatial forms (Marcelo & Sebastian, 2018), outperforming spatial models fitted in parametric forms, such as spatial lag models based on spatial weight matrices (Rebhi & Malouche, 2017). In addition, SGAMs can directly investigate the nonlinear aspects of landscape impact on housing prices utilizing nonparametric terms, avoiding the above-mentioned subjective study distance demarcation (Yamagata et al., 2016). Although the spatial generalized additive model has been used in ecology and other domains, it is less well-known in real estate and hedonic pricing functions. Thus, using a spatial generalized additive model in this sector deserves further investigation given the efficiency with which spatial effects can be controlled and the capacity to study nonlinear characteristics.

Overall, academics have conducted useful research on the hedonic price model in ecological landscapes, but a considerable potential for improvement remains. First, landscape

interaction, whether between factors or types of landscape, is rarely considered by scholars. Second, prior research has focused on the variability of the impact of landscape on housing prices at different distances, but the parametric method may cause difficulty in adequately detecting this nonlinear effect. Finally, recent popular nonparametric and semiparametric models can better manage the spatial effect than a combination of parametric model and spatial matrix. In addition, they can handle the nonlinear problem of landscape value-added effect. For the reasons stated above, this paper uses Wuhan, China as an example, building hedonic models based on dwelling, neighborhood, location, and landscape variables; selecting 9,518 valid sample data from 1,209 residential districts in Wuhan; and studying the nonlinear effects of various ecological landscapes such as lakes, rivers, mountains, and parks on housing prices. With the help of SGAM, this paper will reveal the interaction between different landscape types and their impact on housing prices. Unlike prior study, which concentrated on a single ecological landscape type, this paper examined the nonlinear properties of multiple ecological landscape premiums and demonstrated the interacting impacts of different ecological landscapes.

## 2 Study area and data collection

### 2.1 Study area

The premise of the application of the characteristic model is that the market will reach the equilibrium state of supply and demand when in complete competition. However, adjusting the supply and demand state takes time for the market. Therefore, the ideal equilibrium state of the market cannot be achieved completely (Myrick Freeman et al. 2014).This paper takes Wuhan as the case study, as it is a super-large city in central China, and the housing market in Wuhan is in a balanced state of supply and demand, which meets the assumptions of the Hedonic pricing model. According to the data of Wuhan Land Market website (http://www.whtdsc.com/), in 2019, the approved listed area of commercial housing in Wuhan was 21.347 million km$^2$, the sales area was 18.85 million km$^2$, and the ratio of sales to supply reached 0.9, achieving a balance between supply and demand.

Wuhan has a distinctive and diverse ecological landscape of rivers, lakes, parks, and mountains. The Yangtze River and its major tributary, the Han River, converge in the city, establishing a pattern of three districts divided by rivers. Consequently, based on the relevant data of Wuhan from 2017 to 2019, this study examines the capitalization effect of various ecological landscapes such as rivers, lakes, parks, and mountains on residential property prices as well as the premium effect and geographical characteristics of various urban ecological landscapes.

### 2.2 Housing data sources

This research takes the second-hand housing of ordinary residential buildings in Wuhan as the research object, and the relevant residential data samples cover 11 administrative districts in Wuhan, including Hongshan District, Jiang 'an District, Wuchang District, and Hanyang District, among others, with a total of 9,518 pieces of residential transaction data in 1,209 communities. The transaction time is from January 2017 to December 2019. As shown in Fig. 1, the housing price distribution in the main urban area of Wuhan presents the characteristics of multi-core spatial distribution, which is closely related to
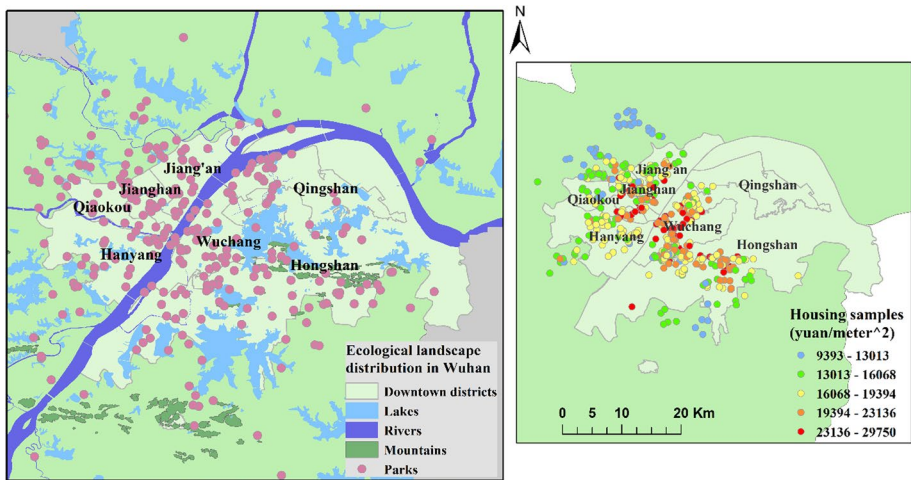
**Fig. 1** Distribution of ecological landscape and residential samples

the landscape separation of rivers dividing towns and the multi-center cluster urban spatial structure. To ensure the comparability of data, this study only selects the second-hand housing data of multi-story and high-rise ordinary houses to eliminate the influence of high-priced houses such as villas.

The data of this paper include those on housing price and housing characteristics, among which the housing price data are obtained from the Lianjia website, and some missing data are crawled from the Anjuke website. The number of second-hand houses listed and sold on Lianjia website accounted for about 80% and 30% respectively of all the listed second-hand houses in Wuhan. Data on residential characteristics are obtained from Lianjia website and Anjuke website, such as greening rate, property fee, plot ratio, total number of households, and average parking space of each household. The variable data in the location features come from the Point of Interest (POI) data of Baidu map, such as the distance to the third ring, education, and transportation facilities. The landscape data come from the 10-m global land cover map of Tsinghua University.

# 3 Variable selection and model building

## 3.1 Variable selection

The dependent variable was chosen as the unit price of a residential transaction. Environmental landscape, dwelling characteristics, neighborhood characteristics, and locational features were classified into four categories of characteristic variables that determine real estate values in this study. The ecological landscape variable was the explanatory variable, and the other variables were the control variables. The ecological landscape addressed in this research comprises lakes, rivers, mountains, and parks, and it refers to the ecology and natural landscape around residential quarters. Distance is a typical metric for measuring various types of ecological land, and this study also considers ecological landscape area features. Consequently, the association between four types of ecological landscapes

and housing prices was investigated in this study utilizing distance and area factors. The park only has the distance variable due to a data collecting difficulty.

Dwelling attributes were one of the control variables, and they referred to the actual structural aspects of homes, such as the number of rooms, levels, building area, construction duration, as well as other factors. Neighborhood characteristics showed the convenience of public services or community amenities, including supporting facilities such as hospitals and living surrounding the dwelling. To consider the quality of educational facilities in the neighborhood, two education-related variables were added to the neighborhood characteristic variables in this study: the number of colleges and universities within 500 m of the residential compound and the distance to the nearest key primary and secondary schools in the same district. In Wuhan, numerous expressways connect the city as a whole and play an essential role in the internal transportation system. Consequently, the loop line was chosen to characterize the location characteristics in this study. Table 1 shows the variable definition.

## 3.2 Data processing

After obtaining the original data of various variables, the next step is to preprocess the data. First, the original data of various variables are merged, and the housing transaction records containing missing values are deleted. Second, the data formats are sorted out, and units of each variable data are unified. Finally, the data that can be used for operation are finally obtained by extracting the text, taking the value of the data by certain logic, and obtaining the distance data with ArcGIS.

The data processing related to the explanatory variable—ecological landscape in this paper—is divided into the following steps. First, the raster images of lakes, rivers, and mountains in Wuhan are extracted from the map by ArcGIS. Then, the raster image is converted into a vector image. Finally, the area data of various landscapes are extracted from vector images, and the distance between residential samples and the nearest ecological landscape is calculated by using NEAR function. Data of parks are obtained as POI data, and the distance from the nearest park POI to the housing is calculated by the NEAR function. Figure 2 shows the process of data acquisition and processing.

## 3.3 Model specification

This research explores the influence of four natural landscapes: lakes, rivers, mountains, and parks on the housing prices using semi-parametric SGAMs. sales price.

Model 1 is used to investigate the value-added effect of the natural landscape on sales price. For distance-based variables, previous feature studies supported the use of log–log functional forms (Pandit et al., 2013). Consequently, log–log specifications were employed to fit distance variables and residential transaction prices in this study, resulting in a model with additional explanatory power. The regression coefficient of the model is regarded as elasticities in the double logarithmic model, and it is constant within the numerical range of explanatory variables. Hence, all ecological landscape distances and area variables are fitted in logarithmic form in Model 1, and other control variables are incorporated into the model in linear or logarithmic form depending on actual operating conditions.

To explore the scope of influence, considering the uneven distribution of mountains and rivers in Wuhan, interaction terms were added to Model 1 to control the distance of ecological landscape to form Model 2. Model 2 can tell if different natural landscapes

**Table 1** Definitions of variables

| Categories | Variables | Descriptions | Mean | Min | Max | Standard deviation | Expected sign |
|---|---|---|---|---|---|---|---|
| Housing price | Price | Transaction unit price of housing (Yuan /m$^2$) | 18,762.46 | 6902.00 | 40,927.00 | 4762.71 | |
| Ecological landscape variables | Lake.dis | Distance from the community to the nearest lake (m) | 1190.50 | 15.64 | 5047.46 | 836.00 | − |
| | Lake.area | Area of nearest lake (km$^2$) | 6.58 | 0.01 | 47.14 | 12.56 | + |
| | River.dis | Distance from the community to the nearest river (m) | 3809.82 | 21.06 | 13,018.40 | 3308.93 | − |
| | River.area | Area of nearest river (km$^2$) | 5103.06 | 17.44 | 19,086.26 | 8074.41 | + |
| | Mountain.dis | Distance from the community to the nearest mountain (m) | 4786.60 | 50.55 | 21,040.07 | 3866.09 | + |
| | Mountain.area | Area of nearest mountains (km$^2$) | 0.54 | 0.07 | 4.43 | 0.44 | − |
| | Park.dis | Distance from the community to the nearest park (m) | 1181.58 | 45.09 | 4971.11 | 763.69 | − |
| Dwelling variables | Area | Gross floor area of a dwelling (m$^2$) | 91.23 | 12.25 | 316.13 | 31.93 | + |
| | Orientation | Orientation of a dwelling (south or not) | | | | | |
| | Decoration | Decoration of a dwelling (luxury, fine, simple, rough) | | | | | |
| | Building | Structure of the building (multi-story: 4–6 stories; medium–high: 7–11 stories; high: 12–30 stories; super high: above 30 stories) | | | | | |
| | Rooms | Number of rooms | 6.21 | 1.00 | 14.00 | 1.53 | + |
| | Time.sold | Time of sale | | | | | |
| | Time.built | Time of building | | | | | |
| Neighborhood variables | Green | Greening rate of the community | 0.35 | 0.08 | 0.68 | 0.06 | + |
| | Property | Property fee of the community (Yuan /m$^2$/ month) | 1.57 | 0.10 | 8.00 | 0.73 | + |
| | Plotratio | Plot ratio of the plot | 2.70 | 0.34 | 9.95 | 1.11 | − |
| | Households | Total number of households in the community | 1925.88 | 28.00 | 8817.00 | 1398.25 | + |
| | Parkings | Average number of parking spots per household in the community | 0.45 | 0.01 | 3.73 | 0.40 | + |
| | Uni.500 | Number of colleges and universities within 500 m of the community | 0.26 | 0.00 | 5.00 | 0.65 | + |

**Table 1** (continued)

| Categories | Variables | Descriptions | Mean | Min | Max | Standard deviation | Expected sign |
|---|---|---|---|---|---|---|---|
| | Hqedu.dis | Distance to the nearest key primary and secondary schools in the same district (m) | 2300.58 | 61.56 | 16,922.43 | 1806.95 | – |
| | Life.1000 | Number of supermarkets, banks, food markets, hospitals, and post offices within 1000 m of the community | 44.20 | 0.00 | 135.00 | 23.87 | + |
| | Nimby.500 | Number of burial places within 500 m of the community | 0.34 | 0.00 | 10.00 | 0.70 | – |
| Locational variables | Loopline | Location in the city (inner ring, second ring, third ring, fourth ring, and fifth ring) | | | | | |
| | Dis.bus | Distance to the nearest bus stop (m) | 221.15 | 20.06 | 856.29 | 115.35 | – |
| | Dis.sub | Distance to the nearest subway station (m) | 1076.20 | 11.80 | 7863.91 | 906.75 | – |
| | Asce.500 | Number of A-level scenic spots within 500 m of the community | 0.01 | 0.00 | 1.00 | 0.09 | + |
| | Pedensity | Average population density (person/km$^2$) of the District in 2016–2017 (person/ km$^2$) | 8745.32 | 433.00 | 25,788.00 | 8254.22 | + |
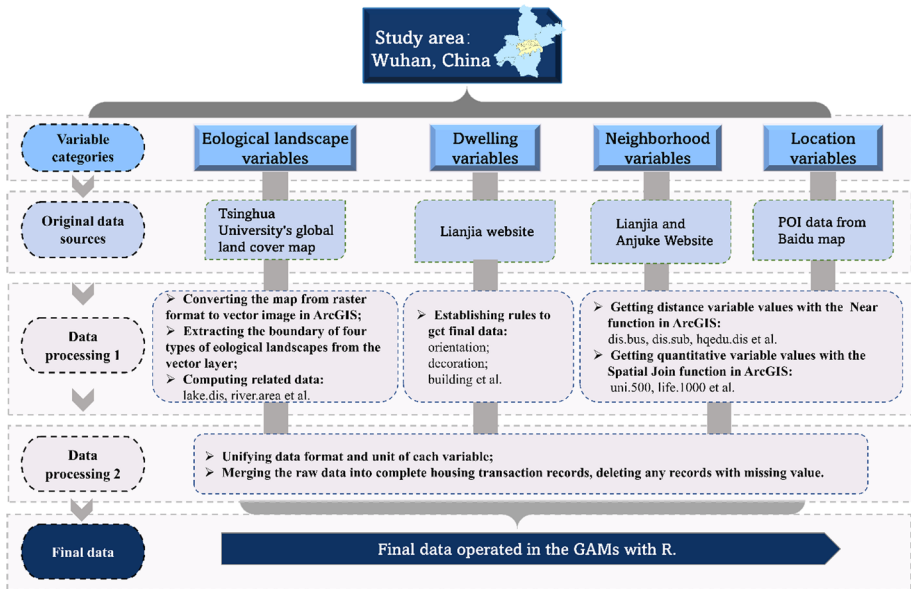
**Fig. 2** Data acquiring and processing

exist in a given range near residential buildings, avoiding averaging the value-added effect throughout the entire city and resulting in additional accurate results. In the formula (2), $\ln(E_m^d) \cdot F_m$ is the interaction term, indicating that distance studied of ecological landscape is controlled. $F_m$ is a dummy variable and represents the research distance. Models 1 and 2 are depicted below.

$$\text{Model 1}: \quad \ln(P_j) = \alpha + \sum f(X) + f_1(B_j, D_j; S_1) + f_2(x_j, y_j; S_2) + \beta_1 \cdot \ln(E_m^d) + \beta_2 \cdot \ln(E_m^a) + u_j \tag{1}$$

$$\text{Model 2}: \quad \ln(P_j) = \alpha + \sum f(X) + f_1(B_j, D_j; S_1) + f_2(x_j, y_j; S_2) + \beta_1 \cdot \{F_m \cdot \ln(E_m^d)\} + \beta_2 \cdot \ln(E_m^a) + u_j \tag{2}$$

$p$: Sale price of the dwelling; $j$: the $j$th transaction dwelling; $\alpha$: coefficient to be estimated; $f$: functions in the form of parameters; $X$: the dwelling, neighborhood and location variables of the dwelling; $f_k$: nonparametric smoothing function, k = 1, 2, m; $(B, D)$: interactive items of construction time and sale time; $S_k$: parameter of nonparametric smoothing function, k = 1, 2, m; $(x, y)$: longitude and latitude of the trading house; $\beta$: *Coefficientofparametricvariable*. $E^d$: the distance variable of ecological landscape; $E^a$: the area variable of ecological landscape; $m$: the $m$th ecological landscape, m = 1, 2, 3, 4, which represent lakes, rivers, mountains, and parks; and $\mu$: error term.

Model 3 is used to explore the nonlinear effect of ecological landscape on housing price. Different from the Models 1 and 2, Model 3 uses the nonparametric smoothing function $f_m$ to fit the distance and area variables of all ecological landscapes, $S_d$ and $S_a$ respectively, which are the nonparametric smoothing parameters of distance and area variables. Model 3 is as follows:

$$\text{Model 3}: \quad \ln(P_j) = \alpha + \sum f(X_n) + f_1(B_j, D_j; S_1) + f_2(x_j, y_j; S_2) + \sum f_m(E_m^d; S_d) + \sum f_m(E_m^a; S_a) + u_j \tag{3}$$

Models 4 and 5 are used to observe how different landscape characteristics interact with different landscape types. Model 4 is formed by removing the nonparametric landscape variables in Model 3 and adding the interaction item of distance and area of ecological landscape, $F_m \bullet \ln(E_{m1}^a)$. Model 5 is formed by adding the interaction item $F_m \bullet \ln(E_{m1}^d)$ of different types of ecological landscape. Models 4 and 5 have the following formulas.

$$\text{Model 4}: \quad \ln(P_j) = \alpha + \sum f(X_n) + f_1(B_j, D_j; S_1) + f_2(x_j, y_j; S_2) + \beta_1 \cdot \left\{ F_m \cdot \ln(E_{m1}^a) \right\} + u_j \tag{4}$$

$$\text{Model 5}: \quad \ln(P_j) = \alpha + \sum f(X_n) + f_1(B_j, D_j; S_1) + f_2(x_j, y_j; S_2) + \beta_1 \cdot \left\{ F_m \cdot \ln(E_{m1}^d) \right\} + u_j \tag{5}$$

All of the SGAMs listed above are built on the hedonic framework, with normal distribution and unit function links and spline function fitting.

# 4 Results and discussions

The GAMs are built and calculated using the R package mgcv, and the maximum likelihood approach is utilized to estimate the models in selecting reliable smooth parameter values. The control variables are fitted in linear and logarithmic forms, and the model performance is assessed using AIC, the interpretable deviation, and the importance of each explanatory variable to select the best form of the variables. $R^2$ of all models exceeds 80%, indicating that the explanatory power of the models is good. Owing to the limited space of the paper, some results of the model are shown in the attached materials.

## 4.1 Marginal implicit prices of ecological landscape

SGAM has good fitting ability to temporal and spatial trends. All models use spline smoothing function to control the spatial and temporal trends in the data, and the nonparametric fitting effect has passed the 5% level significance test.

We now discuss how the construction time and the sale time interact to determine the housing price. The selling price gradually climbed continuously with the growing years of residential building from 1998 to 2015, when the transaction time was regulated. The selling price of residential structures displayed a wave-like increasing tendency from 2015 to 2018 and then gradually decreased and tended to remain constant in the following years under the condition of a fixed construction year. The graphic on the right depicts the house price dispersion in Wuhan. The picture depicts three peaks in the price of housing in Wuhan, which corresponds to reality. According to Liu et al., (2020a, 2020b), Wuhan is a typical polycentric metropolis; its central city is divided into three towns by the Yangtze River and the Han River: Wuchang, Hankou, and Hanyang. With the distribution of property prices, this image demonstrates a multi-center feature of Wuhan. Figure 3 shows the time effect and space effect of housing prices in Wuhan.

We fit the distance and area variables in the logarithmic form to explore the effect of ecological landscape on housing prices. Model 1 is used to measure the overall impact of ecological landscape on house prices, and Model 2 focuses on the price elasticity of ecological landscape in a certain distance interval. The calculation results show that most
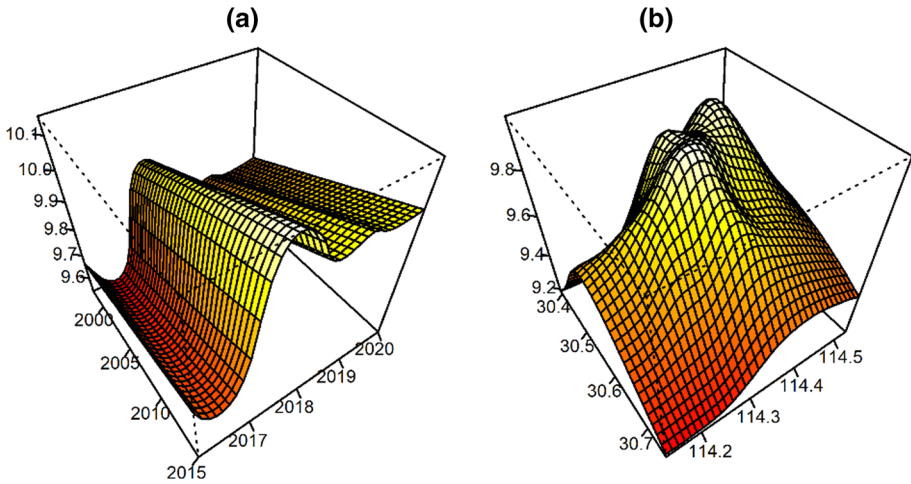
**Fig. 3** Smooth images of temporal and spatial effects. **a** X and Y axes represent the sale and construction times. **b** X and Y axes represent the latitude and longitude

variables of Models 1 and 2 are significant, and the symbols of the variables are consistent with the expectations.

All kinds of ecological landscapes have a significant impact on housing prices, except the distance to the nearest river (river.dis). Among them, lakes and parks have a positive impact on the surrounding residential housing prices, with price elasticity of approximately 0.62% and 1.30%. Mountains have a certain negative impact on the price of houses, with a price elasticity of −0.81%. These results are basically similar to previous studies (Schläpfer et al., 2015). The insignificant influence of rivers is related to the scarcity of river distribution. Hundreds of lakes are widely distributed in Wuhan. However, only the Yangtze River is the main river, which explains why most houses are located far away from the river. The calculation results of Model 1 are shown in Table 2.

We now turn to the price elasticity of ecological landscape in a certain distance interval. Following the study of Xiao et al. (2019) on the nonlinear impact of landscape proximity on housing prices, this paper chooses 2 km as the research distance to describe the demarcation line of the nearest distance to the surrounding landscape of houses. Using Model 2, we calculate three kinds of price elasticity: landscape distance elasticity within the specific distance (EID), landscape distance elasticity outside the specific distance (EOD), and elasticity of landscape presence(EOP).

The residential premium caused by landscape is nonlinear, and the price elasticity of landscape varies in different distance ranges. Take lakes as an example. With the increase of the distance to the lake, the housing price will gradually increase and reach the peak at a distance of approximately 2 km. When the distance between a house and the nearest lake is less than 2 km, its price elasticity EID is -0.18%, which means every 1% reduction in the distance between the houses and the lakes will increase the value of the houses by 0.0018%. When the distance between a house and the nearest lake is more than 2 km, its price elasticity EOD is 3.39%, which means every 1% increase in the distance between the house to the lake, the house price will increase to 0.0339%. The price elasticity of lake existence variables (EOP) is 34.61%, which shows that the existence of a lake landscape within 2 km around the house may lead to a premium of 30% or more. This finding is the

**Table 2** Price elasticity of ecological landscapes in Model 1 and Model 2

| Variables | Model 1 | | Model 2 | | | |
|---|---|---|---|---|---|---|
| | Coefficient | Elasticity at the mean of the variable | Coefficient | Landscape distance elasticity within the specific distance (EID) | Landscape distance elasticity outside the specific distance (EOD) | Elasticity of landscape presence (EOP) |
| Constant | 9.9522*** | | 9.5171*** | | | |
| log(lake.area) | 0.0033*** | 0.33% | 0.0030*** | 0.30% | | |
| log(river.area) | − 0.0026*** | − 0.26% | − 0.0022** | − 0.22% | | |
| log(mountain.area) | − 0.0095*** | − 0.95% | − 0.0107*** | − 1.07% | | |
| log(lake.dis) | − 0.0062*** | − 0.62% | 0.0339 | − 0.18% | | |
| log(river.dis) | − 0.0022 | NA | − 0.0092* | − 0.58% | | |
| log(moutain.dis) | 0.0081*** | 0.81% | − 0.0099** | 2.90% | | |
| log(park.dis) | − 0.013*** | − 1.30% | 0.0288 | − 2.11% | | |
| lake.2000 | | | 0.2972* | | | 34.61% |
| river.2000 | | | − 0.0380 | | | − 3.73% |
| moun.2000 | | | − 0.2888*** | | | − 25.09% |
| park.2000 | | | 0.3585* | | | 43.12% |
| log(lake.dis):lake.2000 | | | − 0.0357** | | 3.39% | |
| log(river.dis):river.2000 | | | 0.0035 | | − 0.92% | |
| log(mountain.dis):moun.2000 | | | 0.0388*** | | − 0.99% | |
| log(park.dis):park.2000 | | | − 0.0499** | | 2.88% | |
| N | 10,739 | | 10,739 | | | |
| R²(adj) | 0.833 | | 0.835 | | | |

***, **, and * represent significance levels of 1%, 5%, and 10%. Dependent variable: ln(price)

same as the research conclusion of Day et al. (2007): compared with houses without environmental facilities at all, the existence of surrounding environmental facilities can largely increase the price of houses.

## 4.2 Non-parametric results of ecological landscape variables

Most studies fit landscape variables in linear, logarithmic, or quadratic form, although it makes early assumptions about the impact characteristics. To address the difficulty described above, this paper uses the nonparametric smoothing function to fit the distance and area variables of all ecological landscapes. Our study shows: A non-linear relationship exists between the ecological distance variable and the housing price, whereas the area variable has a linear relationship with the housing price. As can be seen from Table 3, among the distance variables, edf values of lakes, parks, mountains, and rivers are all far greater than 1, indicating that the influence of the distance of ecological landscape on housing prices is nonlinear. However, the edf values of area variables are all close to 1, indicating that the influence of area variables on housing prices is close to linear.

We now discuss the nonlinear relationship between the distance variable of ecological landscape and the housing price. Surprisingly, the influence of lakes and parks on housing prices fluctuates around zero value all the time, showing the characteristics of wave nonlinear change. Figure 4 shows the characteristics of the influence of distance variables on housing prices. When the distance from the lake to the house is less than 500 m, the impact of the lake on the house price is negative. In the case of the rainfall is heavy, problems may arise, such as humidity and mosquitoes near the lake, and a risk of flooding, which will have a negative impact on the housing prices near the lake. Liu et al., (2020a, 2020b) discovered that when the distance between the residence and the marsh is less than 176 m, the house price is lower. Previous research has identified the positive effects of lakes within a specific distance (Isely et al., 2018) and has seldom discovered the negative effects. This finding is due to the fact that most previous research used parameter form, which means that the data can only reveal the averaged favorable external influences and that revealing the concealed negative effects is difficult.

The nonlinear relationship between the variables of mountain and river distances on the housing price is relatively stable. Specifically, the influence value of river is always positive, and the influence of mountains is always negative. The main river in Wuhan is the Yangtze River, the largest river in China. The unique geographical culture of the Yangtze River has a premium effect on the surrounding houses, and a large area of parks along the coast has been developed along the Yangtze River, and these

**Table 3** Results of ecological landscapes smoothing terms in Model 3

| Smooth terms | Edf | Smooth terms | Edf |
|---|---|---|---|
| s(lake.dis) | 5.774*** | s(lake.area) | 1.965*** |
| s(river.dis) | 6.615*** | s(river.area) | 1.000*** |
| s(mountain.dis) | 4.209*** | s(mountain.area) | 1.947*** |
| s(park.dis) | 7.913*** | | |
| $R^2$(adj) | 0.841 | | |
| N | 10,739 | | |

***, **, and * represent significance levels of 1%, 5%, and 10%. Dependent variable: ln(price)
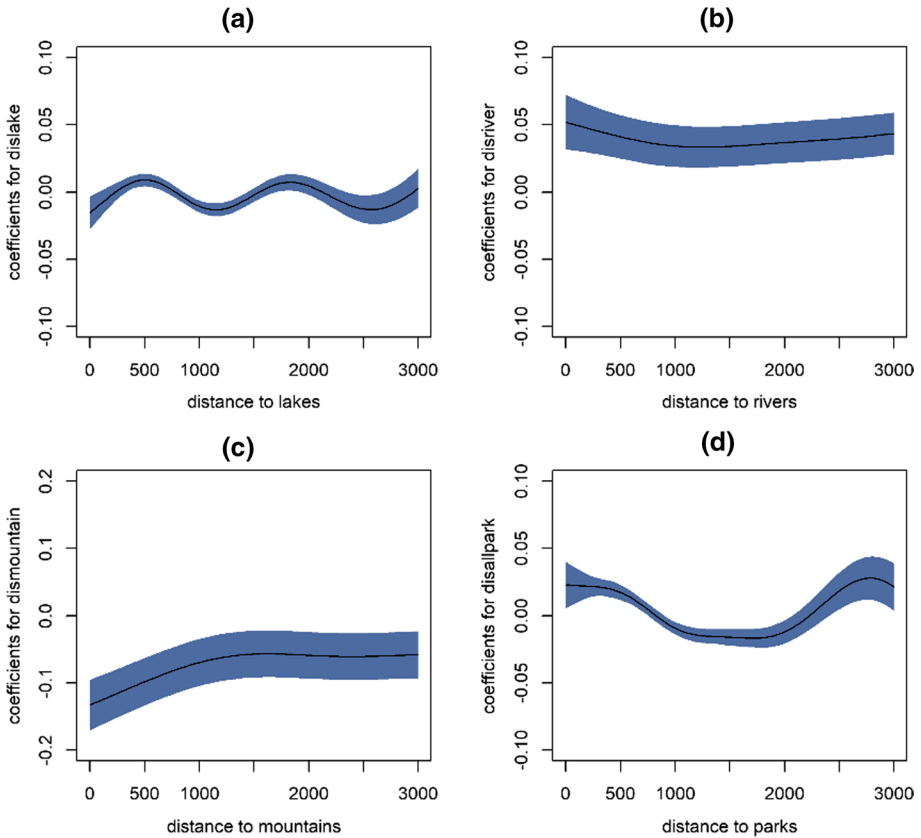
**Fig. 4** Smooth image of the effect of ecological landscape distance variables on housing prices

recreational facilities have further increased the prices of houses along the Yangtze River. The negative impact of the mountain on the surrounding houses comes from its potential safety risks. When the house is too close to the mountain, residents will face the risk of landslides and debris flows, while those who live near mountains covered in woods will have to be wary of forest fires (Kim et al., 2017; Mueller et al., 2018). With the increase in distance, the negative impact gradually decreases. As Jim and Chen (2010) studied, the price of an apartment will increase by about 1.2% when the distance between the apartment and the mountain increases by one meter.

To sum up, in comparison to the disadvantages of parametric regression models, such as being limited by data samples, the regression findings are insignificant over a certain distance, demonstrating the benefits of generalized additive models, particularly in data-driven models. SGAM can visually show the regression coefficients of independent variables in each observation and connect the regression coefficients with smooth curves to demonstrate the changing trend of the influence of independent variables on dependent variables.

### 4.3 Interaction of ecological landscape

By combining several types of landscapes, a new landscape with a higher premium degree may be created. Consequently, Models 4 and 5 are used to discuss the interaction of different landscape features and landscape kinds, and the research distance is set as 2 km. The complete estimation results of Models 4 and 5 may be found in Tables 5 to 6 in Supplementary Materials.

The interaction between the distance and the area of ecological landscapes also has an impact on housing prices. Taking lakes as an example, the price elasticity of lake area within 2 km of residential buildings is 0.17%. Meaning, the area of the lake within 2 km of the house increases by 1%, which will increase the value of the house by 0.0017%. The price elasticity of lakes 2 km away from residential buildings is 0.76%. It means that the lake area will increase by 1%, and the residential premium will be 0.0076%. This finding shows that the price change intensity caused by the increase in the lake area varies according to the distance between the lake and the house, and the premium of the lake area beyond 2 km is greater. See Table 4 for specific results. Table 4 presents the interactive ecological landscape results.

The combination of landscapes will "neutralize" the independent influence of landscapes on housing prices in this combination. As shown in Table 4, the directions of the interaction coefficients of rivers, mountains, and parks (with lakes) are all opposite to those of individual cases, and the absolute values of the distance coefficients of the three in the case of landscape interaction are smaller than those of the original distance coefficients. For example, the influence coefficient of a mountain on a house in a single case is 0.0432, which is weakened by the interaction coefficient [lake.2000: log(mountain.dis)] − 0.0464 to − 0.0032; The coefficient of − 0.0338 in the case of a park alone is neutralized to − 0.0009 by the coefficient of 0.0249 of the interactive term [lake.2000: log(park.dis)]. This interaction comes from the complementarity of housing attributes (Shr & Zipp, 2016). This complementarity enables the combined supply mode of environmental elements to influence the value of the environment, and the specific role depends on the complementary or alternative relationship between landscapes (Franco & Macdonald, 2018). Liu et al. (2019) provide an alternative explanation by demonstrating that the landscape interaction near the house reduces the absolute influence of rivers, mountains, and parks.

## 5 Conclusions and policy implications

In this paper, we establish a series of spatial generalized additive models based on the hedonic method to explore the effects of different ecological landscapes on house prices. We consider several types of ecological landscapes, including lakes, rivers, mountains, and parks. Importantly, we use the nonparametric smoothing function to fit the distance and area variables of all ecological landscapes, and discuss the nonlinear relationship between the distance variable of ecological landscape and housing price. Finally, we investigate the interaction of different landscape features and landscape kinds. Conclusions are as follows:

Firstly, all kinds of ecological landscapes have a significant impact on housing prices, except the distance to the nearest river (river.dis). Lakes and parks have a

**Table 4** Results of ecological landscapes interaction terms in Model 4 and Model 5

| Model 4 | | | | Model 5 | | |
|---|---|---|---|---|---|---|
| Variables | Coefficient | Area elasticity within the distance | Area elasticity out of the distance | Variables | Coefficient | Elasticity (of distance variable) in the interaction |
| Constant | 9.8711*** | | | Constant | – | |
| Log(lake.area) | 0.0076*** | 0.17% | 0.76% | lake.2000 | − 0.1517*** | 0.50% |
| Lake.2000 | 0.0169*** | | | log(river.dis) | − 0.0188*** | |
| Lake.2000: log(lake.area) | − 0.0059*** | | | lake.2000: log(river.dis) | 0.0238*** | |
| Log(river.area) | − 0.0029** | NA | NA | lake.2000 | 0.4177*** | − 0.32% |
| River.2000 | − 0.0008 | | | log(mountain.dis) | 0.0432*** | |
| River.2000: log(river.area) | 0.0002 | | | lake.2000: log(mountain.dis) | − 0.0464*** | |
| Log(mountain.area) | − 0.0064* | | 0.64% | lake.2000 | − 0.1448*** | − 0.90% |
| Mountain.2000 | − 0.0215*** | NA | | log(prak.dis) | − 0.0338*** | |
| Mountain.2000: log(mountain.area) | − 0.0061 | | | lake.2000: log(prak.dis) | 0.0249*** | |
| N | 10,739 | | | N | 10,739 | |
| $R^2$(adj) | 0.836 | | | | – | |

\***, \**, and \* represent significance levels of 1%, 5%, and 10%. Dependent variable: ln(price)

positive impact on the surrounding residential prices, with price elasticity of approximately 0.62% and 1.30%. Conversely, mountains have a negative impact on the residential prices, with price elasticity of 0.81%. The influence of rivers on housing prices in Wuhan is insignificant.

Secondly, the residential premium caused by landscape is nonlinear, and the price elasticity of landscape varies in different distance ranges. In addition, the value of landscape existence is much higher than the value brought by the distance variable. The existence of lakes, parks, and mountain landscapes within 2 km around the house may increase the house prices by 34.61%, 43.12%, and decrease the house price by 25.09%, respectively.

Thirdly, the relationship between the distance variable of ecological landscape and housing price is nonlinear. Among them, the impact of lakes and parks on housing prices within 2 km always fluctuates around zero value. The nonlinear influence of mountains and rivers on housing prices is relatively stable, the influence value of rivers is always positive, and the influence value of mountains is always negative.

Finally, the combination of landscapes will "neutralize" the independent influence of landscapes on housing prices in this combination. In the case of interaction with lakes, the elasticity values of the distance among rivers, mountains, and parks are 0.5%, −0.32% and −0.9%, respectively. Furthermore, the interaction between the distance and area of ecological landscapes also has an impact on housing prices, and the price elasticity values of the lake area within 2 km around the house are 0.17% and 0.76%, respectively.

This paper has several limitations. Firstly, it only explores the interaction between lakes and other landscape types. In the future, we would explore the value of various new ecological facilities combinations, such as mountains and parks, rivers and parks, etc., and explore the premium space they bring to surrounding houses. Secondly, the hedonic price model assumes equilibrium in the housing market, and also the existence of a competitive market. Therefore, the research conclusion of this paper is only applicable to cities where the housing real estate market is balanced, and those that have many different natural ecological landscapes. However, the research methods and the series of characteristic price models constructed in this paper are applicable to the research of other related topics. This paper confirms the applicability of SGAM in the characteristic price model, so this method can be used to improve the estimation of the characteristic price model and control the influence of the spatial correlation of the model in related research.

This paper contributes to the existing literature by exploring systematically how the effect of ecological landscape on housing prices varies spatially. Previous research has typically determined the average marginal price of the residential external environment, which may obscure the initial negative impact and nonlinear aspects of the environment. Unlike earlier studies that have focused on a single type of ecological landscape in the city, this paper not only investigates the external effects of many types of landscapes, but also demonstrates the nonlinear effects of ecological landscapes as well as the interactions between ecological landscapes. It also confirms the availability of SGAM in the hedonic pricing model.

Our results suggest that governmental management departments should give full consideration to the impact of ecological landscape on housing in urban planning. On the one hand, the government should implement a differentiated ecological land use policy as well as compensation mechanisms for different types of ecological landscape land to ensure the long-term supply of ecological landscape. On the other hand, the government should not only consider the heterogeneity of various landscapes but also pay attention to the complementarity and substitutability of landscapes. Optimizing the ecological landscape construction scheme to gain market advantage will be a new consumption growth point.

**Data availability** Anonymized housing prices data with quantitative values of some of the explanatory variables used during the study are available from the corresponding author upon reasonable request.

## Declarations

**Competing interests** The authors have no competing interests to declare that are relevant to the content of this article.

**Research involving Human Participants and/or Animal** The research object of this paper does not involve human beings or animals.

**Informed consent** The research object of this paper does not involve human beings and there is not informed consent.

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