

ICEST 2021**II International Conference on Economic and Social Trends for Sustainability of Modern Society****MEASURING THE VALUE OF URBAN GREEN SPACE USING
HEDONIC PRICING METHOD**

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Abstract

Environmental problems are becoming the focus of the world and China. As an important environmental resource, urban green space ecology plays an important role in solving urban environmental problems and urban sustainable development. This paper mainly studies the value evaluation of urban green space resources. To a large extent, the solution of this problem depends on the economic evaluation method of public goods, which will provide better sustainable urban development management suggestions for the government and policy makers. In this paper, the characteristic pricing method is used to price urban green space. The innovation of this study is to add the spatial matrix into the hedonic price method to build a spatial hedonic price model, and to study the role of spatial correlation between different cities in the evaluation of urban green space. This paper selects forest cities in China as samples to demonstrate the ecological value of urban green space and the ecological interaction of green space between different cities, that is, green space resources have spill over effect between cities. This will help improve the environmental efficiency of these solutions, thereby improving the environmental quality of Chinese cities. Based on the analysis of the evaluation results of urban green space economy, the externality of forest city is found out, and some suggestions are put forward for the formulation of sustainable development policies in urbanization areas.

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1. Introduction

China's economy has grown rapidly in the past 10 years. The rapid economic growth is bound to have a certain negative impact on the natural ecological environment, and the environmental and ecological problems are becoming increasingly prominent. With the proposal of the concept of sustainable development, environmental issues are more and more concerned while paying attention to economic growth. The rapid development of urbanization makes the sustainable development of cities more important. The sustainable development of the city is inseparable from the solution of urban ecological environment problems. Urban green space resource is an important part of urban ecological environment. Paying attention to the development and growth of urban green space is the key to the sustainable development of the city (Lazareva et al., 2016; Lazareva & Karaycheva, 2018).

In addition to the forest, grassland, wetland and other natural ecosystems in the city, there are artificial parks, gardens and other urban ecosystems, which can be classified as urban green space (Wolch et al., 2014). The urban system is composed of many subsystems, such as infrastructure system, rail transit system, human system and so on. These subsystems will have an impact on the urban ecological environment. Among the many subsystems, the urban green space subsystem has a more significant impact on the urban ecological environment system. The impact of urban green space subsystem on urban ecosystem is mainly reflected in three aspects: 1. Urban green vegetation can play a cooling role, and then reduce the urban heat island effect; 2. Urban green plants absorb carbon dioxide and release oxygen through photosynthesis and respiration, which can purify the air to a certain extent; 3. Urban green plants can also increase humidity and regulate urban climate (Sun et al., 2017). In addition to the above ecological effects, urban green space can also enrich the leisure and recreational activities of urban citizens (Heikinheimo et al., 2020), even the health of the citizens (Kondo et al., 2018). From the above studies, we can see that urban green space resources can influence the ecological environment of cities, and they also have positive externalities on the economic and social development of cities (Aram et al., 2019). Therefore, the estimation of urban green space can help us better understand the value of urban green space, and firstly, it can further improve the efficiency of using and developing urban green space. Urban green space and sustainable urban development are also closely related, and urban green space development can be compatible with urban economic and social development (Du & Zhang, 2020). By estimating the value of green spaces, policy makers can better formulate policies related to urban environment and sustainable urban development.

The Hedonic Pricing Method (HPM) is a more commonly used method for valuing natural resources as a non-market commodity. By using this method, researchers assess the invisible price of non-market goods through observable market transactions, more commonly known as the housing market. In our study, we valued urban green space by observing prices in the housing market. In previous studies, economists have used hedonic pricing models to evaluate environmental attributes, such as air quality (Mei et al., 2020) and water quality (Artell, 2014).

The more commonly used method for studies on HPM is ordinary least squares (OLS) regression. This is because OLS makes the model simple and easy to interpret. However, one of the drawbacks of OLS is that it does not allow for better testing of spatial correlation. Another problem of OLS is that it does not respond well to spatial heterogeneity. To avoid these problems and to increase the validation of HPM spatial

correlation, our study introduces the spatial weight matrix into the HPM method to achieve the test for spatial correlation and to better avoid spatial heterogeneity.

The purpose of this study is to explore the spatial relationship between urban green space values and property prices in forest cities. Our study on non-market valuation has three innovative points. First, from the methodological point of view, previous HPM studies have more often used OLS estimation methods, and our study adds a spatial weight matrix based on previous studies, combining HPM and spatial weight matrix. A city's green space resources will not only bring positive environmental, economic and social externalities to the city, but also the environmental effects of a city's green space resources will easily affect its neighboring cities, so we added a spatial weight matrix to the HPM method to better consider the spatial correlation when studying the value of urban green space. Second, in terms of data sample selection, we chose to use forest cities as our sample space in order to better study urban green space values. We selected 62 Chinese forest cities as our sample. And we created a panel dataset instead of the widely used cross-sectional dataset. The third point is reflected in the spatial weight matrix, where we used two spatial contiguity weights in our study. These two spatial weight metrics are based on different polygon continuities. One spatial weight indicator is based on the rook continuity. The other uses the continuity of queens. We constructed a spatial weight matrix using two different methods as the basis for the spatial measures.

The structure of the article is as follows. The second section, the third section and the fourth section respectively describe the problem, the problem to solve the problem and the purpose of the research. The fifth section introduces the characteristic pricing model and spatial econometric model. The sixth section is the analysis and discovery of the results. The seventh section summarizes the whole paper and puts forward two suggestions.

2. Problem Statement

Through the analysis of the methods to solve the problem of urban green space economic evaluation, it shows that this task is to comprehensively consider the spatial heterogeneity and spatial correlation of the urban system, and to comprehensively evaluate the impact of urban green space area on house price through the hedonic price method.

3. Research Questions

The theme of this study is to establish the economic index model of the characteristic price parameters of urban green space under the background of the transition to sustainable development, to provide the basis for the formation of an effective control mechanism and the improvement of the environmental efficiency of urban management decision-making.

4. Purpose of the Study

The aim of the study is to substantiate econometric models of hedonic assessment of urban green areas, which provide a solution to the urgent problem of integral assessment of their impact on the property

price, as well as to develop a mechanism for using these assessments in the urban management system in order to improve the environmental efficiency of management decisions.

5. Research Methods

5.1. Baseline hedonic pricing model

The basic methodology of the study is the hedonic pricing model, which is first brought up by Rosen in 1974. Rosen illustrated that each characteristics of the good could contribute to its prices (Rosen, 1974). Thus, the hedonic pricing model could be represented as:

$$P_i = f(A_i, D_i, E_i) \quad (1)$$

where the P_i represents the price of each property (i); the A_i represents the basic attributes of the properties, such as the areas of the properties, the number of bedrooms, the age of the property, etc.; the D_i expresses the location characteristics like the proximity to the nearest garden or park, transportation center, public places etc.; while the E_i represents the environmental attributes, such as the number of parks near the property, the areas of green land, the variety of the green species and so on. The basic intuition of the hedonic pricing method is maximum the consumer utility, which is the property's price in this model.

Statistically, the hedonic pricing model could be represented as:

$$P_i = \beta_0 + \beta_1 A_i + \beta_2 D_i + \beta_3 E_i + \epsilon \quad (2)$$

5.2. Model with spatial weight matrix

A spatial weight matrix is a matrix that reflects the interdependence of different geographic regions in space (Seya et al., 2013). The core concept to understand the relationship among districts is the distance-based spatial weights, which is most common used method in spatial econometrics. Euclidean distance, d_{ij} is the most familiar case of the distance-based spatial. $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, for two districts i and j , with separated coordinates (x_i, y_i) and (x_j, y_j) (Liberti et al., 2014). In our study we create a spatial weight matrix to describe the closest distance between each city i and neighbouring city j in the sample. We use two spatial weight metrics to represent such distances. The concept of contiguity weight means two spatial units being in actual contact along a boundary or a border (Chen, 2012). The contiguity weight usually can be distinguished into two categories: a rook contiguity and a queen contiguity. For the rook contiguity weights could be represented as:

$$w_{ij} = \begin{cases} 1, & l_{ij} > 0 \\ 0, & l_{ij} = 0 \end{cases} \quad (3)$$

With l_{ij} notes the length of shared boundary, between i and j .

While for the queen contiguity weights are defined by

$$w_{ij} = \begin{cases} 1, & bnd(i) \cap bnd(j) \neq \emptyset \\ 0, & bnd(i) \cap bnd(j) = \emptyset \end{cases} \quad (4)$$

$bud(i)$ represents the set of boundary points of unit i .

The spatial weight matrix represents as following:

$$W = \begin{pmatrix} 0 & w_{12} & \dots & w_{1n} \\ w_{21} & 0 & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & 0 \end{pmatrix} \quad (5)$$

with: $w_{ij} = \begin{cases} 1 & \text{if } j \in N_k(i) \text{ or } i \in N_k(j) \\ 0 & \text{otherwise} \end{cases}$

There are three basic spatial econometric models. Spatial autoregression (SAR) model can include spatially related dependent variables and spatially related error terms. The basic representation of SAR model is:

$$Y_n = \lambda W_n Y_n + \beta X_n + \varepsilon_n \quad (6)$$

W_n represents the spatial matrix. The term $W_n Y_n$ considered as “spatial lag”.

The spatial error model (SEM) model describes the spatial disturbance correlation and spatial total correlation. The SEM model is represented as:

$$\begin{aligned} Y_n &= \rho Y_n + \beta X_n + \mu \\ \mu &= \lambda W_n \mu + \varepsilon_n \end{aligned} \quad (7)$$

The spatial durbin model (SDM) is a combination of spatial lag model and spatial error term model, is a SAR model enhanced by adding spatial lag variable:

$$Y_n = \lambda W_n Y_n + \beta X_n + \theta W X_n + \varepsilon_n \quad (8)$$

$\theta W X_n$: exogenous interaction effect.

5.3. Data

In our study, we choose forest cities as our research case. A national forest city is a city whose urban ecosystem is dominated by forest green vegetation and whose forest green space-related indicators can reach national standards. the title of "national forest city" was first awarded by the State Forestry Administration in November 2004. Up to now, 192 cities have been awarded the title of national forest city. In this study, 62 key forest cities were selected as research samples, and the forest green space data of these 62 cities were used for research. We also collected data on residential real estate transactions for these 62 cities between 2010 and 2018: a total of 558 real estate transactions (15 per year). In our model, various characteristics (floors, availability of infrastructure, etc.) were considered as factors influencing the price of housing properties, the most important control variable is the area of green spaces (Table 1).

Table 1. Descriptive statistics

Variable	Description	Obs	Mean	Std.Dev.	Min	Max
hp	Transaction prices yuan/m ²	558	9292	6152	2787	53941
agl	The areas of the green land	558	18063	24701	1461	148393
pGDP	GDP per capita	558	76331	30613	16057	189568
floor	Total number of floors the units have	558	17.49	5.023	6	25
hos	Total number of hospitals within 1000m	558	2.789	1.534	0	6
sch	Total number of schools within 1000m	558	4.018	1.784	1	9
old	Built year of the units	558	2008	4.328	2000	2018
ori	The direction of the unit (south=1 otherwise=0)	558	0.846	0.361	0	1
dec	Whether the unit is decorated (decorated=1otherwise=0)	558	0.376	0.485	0	1
trans	Total number of transport station within 1000m	558	3.849	1.954	1	9

6. Findings

6.1. Results of basic hedonic pricing modeling

Table 2 shows the results of the basic hedonic pricing modeling. To estimate the hedonic pricing models, we used three regression analysis methods: (1) the Ordinary Least Square; (2) the Fixed Effect and (3) the Random Effect. The results of all three methods using demonstrated a positive relationship between areas of green land and the property price. The results revealed that the areas of green land contribute to the house price with significant and robust effects, which are in accordance with previous studies. The OLS model ignores heteroscedasticity; the model variable pGDP measures the level of differentiation of GDP per capita between different cities. In contrast to studies where a similar variable was introduced into the OLS regression model in order to solve the problem of heteroscedasticity, in this study the pGDP variable was used to identify the level of statistical relationship between house price and green area., comparing with the fixed effect model and the random effect model, only one indicator – the built year of the property not represent a significant relationship. In Table 2 the results of fixed effect and random effect are similar.

Table 2. Results of OLS modeling, fixed effects, random effects

VARIABLES	(1)	(2)	(3)
	ols	Fe	re
	hp	Hp	hp
agl	0.0978*** (0.00855)	0.0536** (0.0228)	0.0826*** (0.0156)
pGDP	0.0603*** (0.00713)	0.0826*** (0.00698)	0.0781*** (0.00648)
floor	29.80 (38.54)	-24.95 (20.51)	-21.29 (20.59)
hos	181.8 (122.9)	-18.60 (68.40)	3.234 (68.30)
sch	745.5*** (110.7)	201.3*** (65.81)	225.2*** (65.68)
old	-32.56 (62.58)	-69.51** (32.22)	-71.63** (32.29)
ori	87.13 (499.1)	49.37 (246.3)	47.60 (248.1)
dec	-609.4 (561.5)	-31.68 (291.5)	-57.50 (292.6)
trans	-78.83 (92.60)	-50.55 (48.29)	-51.89 (48.53)
Constant	64,748 (125,458)	141,464** (64,530)	145,325** (64,693)
Observations	558	558	558
R-squared	0.532	0.370	0.368
Number of_ID		62	62

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.2. Results of spatial hedonic pricing modeling

Table 3 shows the results of spatial hedonic pricing modeling. The results also show a positive relationship between house price and GDP per capita. The areas of green land have a positive effect on the price of housing property. In SDM model, the results show that GDP per capita and green area in neighboring cities do not affect the price of downtown housing. The spatial spillover effect does not exist in the spatial correlation with the dependent variables. However, rho equal to 0.404 indicates statistical significance at a 95 percent confidence level, which means that home prices have spatially autocorrelation. Consequently, the cost of housing in one city will be influenced by the price of houses in nearby cities.

Table 3. Results of SDM modeling

VARIABLES	(1)	(2)	(3)	(4)
	sdm Main	Wx	Spatial	Variance
lpGDP	0.267*** (0.0884)	-0.111 (0.0918)		
sagl	0.122*** (0.0354)	0.0848 (0.0928)		
floor	-0.000521 (0.000872)	-0.00103 (0.00152)		
hos	0.00467 (0.00325)	-0.000321 (0.00583)		
sch	0.0128*** (0.00317)	0.0177*** (0.00607)		
old	-0.00264* (0.00142)	-0.00124** (0.000492)		
ori	0.00341 (0.00867)	0.00824 (0.0158)		
dec	0.00935 (0.0142)	0.0130 (0.0190)		
trans	-0.00239 (0.00245)	-0.00132 (0.00348)		
rho			0.404*** (0.0652)	
lgt_theta				-2.201*** (0.117)
sigma2_e				0.00869*** (0.00135)
Constant	11.29*** (2.988)			
Observations	558	558	558	558
R-squared	0.443	0.443	0.443	0.443
Number of _ID	62	62	62	62

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The results of these three spatial econometric models indicate that firstly, spatial autocorrelation exists in the prices of housing property. The prices of one city housing property are affected by the prices in neighbor cities. Secondly, the area of urban green space has no spatial autocorrelation, which means the area of urban green space in one city cannot be influenced by such area in the nearby cities. Thirdly, even though there is no spatial autocorrelation in area of urban green space, the spatial spillover effect still exists in spatial hedonic pricing model.

6.3. The value of green land in the city

Calculating the economic value of urban green space is the most important part of this paper. The results of the calculation based on the results of the baseline model using the OLS method are that the economic value of urban green space in 62 forest cities is 53 yuan/m², the results of the calculation using the fixed-effects model are 31.8 yuan/m², and the results of the calculation using the random-effects model are 42.5 yuan/m². This result is a basic judgment for understanding the value of urban green space and can

provide some reference for policy makers in policy implementation and formulation. However, the OLS results do not reflect well the spatial correlation among forest cities, nor do they avoid the errors brought by spatial heterogeneity on the estimation results. Therefore, we first used fixed effects and random effects to eliminate the problem of spatial heterogeneity. According to the results of the Hausman test, the fixed-effects model is the better model after comparison.

6.4. Spatial spillover effects in hedonic pricing model

In order to better analyze the effect of spatial dependence among forest cities on urban green space valuation, we constructed SAR, SEM and SDM models respectively. Comparison of the results of constructing three spatial econometric models, SAR, SEM and SDM, showed that the SDM model was the best regression model (Table 3). Green space area and GDP per capita had a significant positive effect on housing costs in forest cities. However, based on the simulation results, we could not characterize the direct and indirect effects of these independent variables. According to the results, the size of green space has a greater impact on housing prices than GDP per capita. The coefficient of housing prices for the size of urban green spaces is 0.342 higher than the coefficient of GDP per capita. there are several reasons for this situation. First, the government has adopted a series of policy measures aimed at improving the environmental efficiency of green space development management decisions in forest cities. Second, residents of forest cities are more aware than other citizens of the benefits of having green space in the urban environment. According to our calculations, their willingness to pay for the expansion of urban green space is 32 yuan/ m^2 . The third reason is that there are some positive externalities associated with the development of urban green space. Consistent with our expectations the SDM results also reflect a significant positive spatial correlation between forest cities. From this we can analyze that green space resources in one city have environmental spillover effects and can bring positive externalities to neighboring cities. Comparing the OLS results, we can see that the urban green space valuation after considering the spatial correlation is lower at 32 yuan/ m^2 than the OLS result of 53 yuan/ m^2 . This also reflects the fact that urban green space has a spillover effect on other neighboring cities, thus reducing the city's original valuation of urban green space.

7. Conclusion

In this study, we get the basic value of urban green space. Through the recognition of the economic value of urban green space, we can pay more attention to urban green space from the perspective of economy and ecological environment. It is beneficial for us to better combine urban green space development with urban economic and social development in the process of urban sustainable development. Another important finding of this study is the spatial spillover effect of urban green space between different cities, that is, there is a positive correlation between the green space resources of a city and its neighboring cities. When we pay attention to the forest city, we find that the residents of the forest city have a higher understanding of the value of urban green space, even higher than their own understanding of the economy itself. This reflects that forest city can promote the formation of urban citizens' cognition of green space ecological value. In this study, we add the spatial weight matrix as an explanatory variable to improve the

spatial correlation of different urban green space resources. By comparing OLS model, we not only avoid the problem of spatial heterogeneity, but also further analyze the spatial correlation. It is concluded that urban green space has spillover effect on forest city. The green space resources of a city will have an impact on the surrounding cities. This spatial correlation further affects the value evaluation of urban green space resources. Although our research sample is innovative, 62 Chinese forest cities are selected, but this choice also brings some shortcomings, that is, the deviation of sample selection. In the future research, we can add non forest cities in the sample to reduce the bias of sample selection, to make the research more accurate.

Finally, we can make some suggestions for improving urban policies through this study. First, based on the value of urban green space we can see the need to expand the area of urban green space, not only to improve the quality of urban ecological environment, but also to improve the sustainability of urban economic and social development. Secondly, through the analysis of spatial model, urban green space generates spillover effects and positive externalities among adjacent cities. Therefore, it is necessary to strengthen inter-city cooperation, not only to promote the ecological environment progress of one's own city, but also to bring positive effects to neighboring cities, gradually forming a sustainable urban cluster.

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