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Assessment of the Spatial Variation of the Economic Benefits of Urban Green Spaces in a Highly Urbanized Area

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Abstract: Urban green spaces play a vital role in improving the quality of life and well-being of urban residents. However, their economic benefits in different spatial contexts within highly urbanized areas remain a critical yet understudied topic. This study delves into the economic value of urban green spaces in Cheongju City, Republic of Korea, and investigates the distance-decay features associated with the proximity of green spaces to residential properties. Two spatial econometric models were employed to address these questions: the spatially autoregressive (SAR) model and the generalized additive model (GAM). The SAR model was used to assess the economic benefits of urban green spaces, whereas the distance decay of these benefits was examined with the GAM. Empirical analyses revealed that small-sized parks or forests under 20 ha hold greater economic value when in proximity to residential areas compared to medium-sized parks or forests between 20 and 200 ha. Conversely, large parks or forests over 200 ha appeared to have a disamenity effect, negatively impacting property prices when in close proximity. The GAM's smooth functions illustrated that the distance-decay effect was shorter for small-sized green spaces and exhibited an inverted U-shape for large-sized ones, resulting in a negative benefit of proximity. Our findings suggest that urban green spaces have a positive impact on property prices, but this effect may not apply uniformly to large-sized parks or forests. Therefore, to enhance the residents' welfare, green infrastructure policies should prioritize the provision of accessible small- and/or medium-sized parks or forests near residential areas.

Keywords: distance decay; hedonic pricing; implicit economic values; spatial spillovers; urban green space

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1. Introduction

Urban green spaces play a crucial role in the sustainable development of cities, offering a wide range of economic, social, and environmental benefits [1]. These green spaces, which include parks, gardens, open spaces, greenways, and urban forests, provide opportunities for relaxation, recreation, and social interaction, contributing to the identity and social fabric of communities [2–4]. Moreover, they provide clean air, water, and soil, and stabilize urban temperatures and climates [5,6], promoting the sustainable development of the urban natural environment.

The diverse benefits offered by urban green spaces highlight their complex and multidimensional nature. Therefore, these spaces and their associated benefits are often classified to gain more granular insights into their value and the variables that determine these values. Baycan-Levent and Nijkamp [7] identified five types of green space values: ecological values, economic values, social values, planning values, and multidimensional values. These values collectively contribute to the well-being and economic prosperity of urban areas. The positive impact of urban green spaces on cities enhances their attractiveness to residents, workers, tourists, investors, and businesses, thereby improving the economic health of cities. Consequently, understanding the economic potential of urban green spaces has become a focal point in public policy and urban planning, with a primary emphasis on financing mechanisms for providing public goods and services.

The concept of urban green spaces as economic assets dates back to the early nineteenth century [8,9] and was based on the idea that residential properties close to green spaces tend to have higher market prices. This increase in property values boosts fiscal revenue through higher property taxes and other financial benefits, making it more feasible to finance public facilities and community improvements.

At the theoretical level, the influence of urban green spaces on residential property values is often explored through residential location models, which examine the structural role of natural amenities [10–12]. These models have confirmed a general preference towards living near natural amenities, and wealthier individuals typically outbid others to locate near these amenities. Consequently, the spatial distribution of housing prices reflects this process, with more expensive housing often being associated with amenity-rich areas, such as the urban core, green spaces, and coastlines [13,14]. However, the economic benefits generated by urban green spaces exhibit the characteristics of a public good, meaning that they are not adequately priced in the market. As a result, indirect, non-market valuation techniques are necessary to measure the economic benefits of urban green spaces [15].

Three main methods have been suggested to estimate the economic value of urban green spaces: contingent valuation, hedonic pricing, and travel cost methods [7,8,16–18]. The contingent valuation method involves surveying users to assess their willingness to pay for the benefits associated with urban green spaces. The hedonic price technique utilizes detailed property sales data and environmental characteristics to estimate the implicit prices of urban green space attributes. Finally, the travel cost method evaluates urban green spaces based on the explicit and implicit expenses incurred while traveling to them.

This study focused thematically on the economic value of urban green spaces and methodologically on the hedonic pricing technique. Out of the three quantitative methods mentioned above, the hedonic price modeling approach was selected to measure the economic value of urban green spaces in the city of Cheongju, a medium-sized city located in the central region of Korea. Moreover, two spatial econometric models were utilized to assess the value of urban green spaces using the hedonic pricing technique: the spatial autoregressive (SAR) model and the generalized additive model (GAM) with spatial gradient. The former was used as the baseline hedonic price model to estimate the economic impacts of urban green space on apartment prices, whereas the latter was used to identify the specific features of the distance-decay effect produced by each category of urban green spaces, focusing on their impact on property prices.

2. Models, Study Area, and Data

2.1. Models

2.1.1. Baseline Hedonic Price Model

One of the key objectives of this study was to measure the economic value of green spaces by quantifying their impact on the sales price of apartments sold in a highly urbanized area. Evaluating the impact of green areas on housing prices requires the consideration of spatial spillover effects. In spatial econometrics, two types of spatial spillover are considered: local spillovers and global spillovers. Local spillovers occur when the characteristics of neighboring entities influence the value of a particular entity at a given location. In this case, the spatially lagged independent variables capture the value of local spatial spillovers. On the other hand, global spatial spillovers represent long-run equilibrium effects where the level of an entity in one location affects the levels of entities in other locations and vice versa, creating endogenous interaction and feedback effects across different locations. Spatially lagged dependent variables provide a suitable means to capture the effect of global spatial spillovers. Thus, the SAR model, which contains spatially lagged dependent variables as endogenous variables, is the most appropriate type of spatial econometric model.

To formally represent the SAR model, a column vector y and a matrix X containing n sample observations of k variables are considered. The structural form of the SAR model with k explanatory variables is expressed by the following equation:

$$y = \alpha\iota_n + \rho W y + X\beta + \varepsilon,\ \varepsilon \sim N\left(0, \sigma^2 I_n\right) \tag{1}$$

where y is the $n \times 1$ dependent variable vector; X is the $n \times k$ matrix of explanatory variables, with the first column of ones excluded; ι_n is the $n \times 1$ vector of ones; α is the intercept coefficient; W is the $n \times n$ row-normalized spatial weight matrix representing the spatial structure of neighboring influences among the observations in y; ρ is the spatial autoregressive coefficient for the variable Wy, which denotes the endogenous interaction effects among the observations in y; β represents the regression coefficients in a $k \times 1$ vector; and ε is a white noise error assumed to follow a multivariate normal distribution, with a mean of zero and a constant scalar diagonal variance–covariance matrix $\sigma^2 I_n$ [19].

In the SAR model, the interpretation of the estimates of regression coefficients requires careful attention. It is incorrect to interpret the coefficient estimates of β in Equation (1) as if they are the coefficients of explanatory variables in ordinary least squares (OLS) models. In the SAR model, the spatially lagged variable y introduces spatial dynamics with a feedback effect between entities. This means that the short-run impact of the r-th explanatory variable x_r on the entity i's level y_i will also influence the level of other entities y_j, which, in turn, will affect y_i, and so on. Therefore, it is important to consider the additional effects exerted by the short-run impact of x_r on y through its impact on the level of y in other entities [20]. In this way, an exogenous shock to one entity will have a reverberating effect throughout the space, resulting in feedback among entities and flow through the space as a series of adjustments until a new stable equilibrium is achieved [20,21].

To properly estimate the equilibrium effect of explanatory variables in the SAR model, the expressions in Equation (1) can be manipulated to obtain a more condensed form of the equation:

$$\begin{gathered}(I - \rho W)y = \alpha\iota_n + X\beta + \varepsilon \\ y = (I - \rho W)^{-1}(\alpha\iota_n + X\beta) + (I - \rho W)^{-1}\varepsilon\end{gathered} \tag{2}$$

The expected value of y in Equation (2) is given by the following equation:

$$\begin{aligned}&E(y|X) = (I - \rho W)^{-1}(\alpha\iota_n + X\beta) \\ &\text{since } (I - \rho W)^{-1}E(\varepsilon) = 0.\end{aligned} \tag{3}$$

The partial derivatives of Equation (3) with respect to X are expressed as:

$$\begin{aligned}&\partial E(y|X)/\partial X = (I - \rho W)^{-1}(\beta \otimes I_n) \\ &= (I - \rho W)^{-1}\begin{bmatrix}(\beta_1 I_n) \\ (\beta_2 I_n) \\ \vdots \\ (\beta_k I_n)\end{bmatrix}\end{aligned} \tag{4}$$

For the i-th observation of the r-th explanatory variable x_{ir}, the relevant partial derivatives extracted from Equation (4) are expressed as follows:

$$\begin{bmatrix}\frac{\partial y_1}{\partial x_{1r}} & \cdots & \frac{\partial y_1}{\partial x_{nr}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial x_{1r}} & \cdots & \frac{\partial y_n}{\partial x_{nr}}\end{bmatrix} = (I - \rho W)^{-1}\begin{bmatrix}\beta_r & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_r\end{bmatrix} = \beta_r (I - \rho W)^{-1} \tag{5}$$

The elements of the $n \times n$ matrix of Equation (5) represent direct and indirect effects for the r-th explanatory variable in the SAR model. The main diagonal elements measure the direct effects of the r-th explanatory variable on the dependent variable. The average of the off-diagonal elements measures the indirect impact or global spatial spillovers, providing insights into how changes in an explanatory variable anywhere in the study area affect the value of the dependent variable [22–25]. Specifically, the own-partial derivative $\frac{\partial y_i}{\partial x_{ir}}$ $(i = 1, 2, \ldots, n)$ of the matrix $\beta_r(I - \rho W)^{-1}$ in Equation (5) represents the impact of a change in the i-th observation of variable x_r on the i-th observation of the dependent variable y. The average of the main diagonal elements is a summary measure of the average direct impact of the explanatory variable x_r. On the other hand, the non-zero off-diagonal cross-partial derivatives represent the existence of global spillovers. The average of column sums of the off-diagonals represents the average indirect impact on other entities, while the average of row sums measures the effect from other entities [26].

2.1.2. Generalized Additive Model with a Spatial Gradient

In this study, a GAM was adopted as the second model of hedonic pricing to investigate how the distance of urban green space from apartments influences housing prices. The GAM is typically used to examine the nonlinear impacts of covariates on the response variable [27]. In the context of hedonic pricing, the GAM provides a useful tool for testing the existence of a nonlinear relationship between housing prices and neighboring urban green spaces. The formal expression of the GAM is as follows:

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \sum_{j=k+1}^{p} f_j(x_{ij}) + \varepsilon_i \quad (6)$$

where y is the response variable, x_j is the j-th independent variable, β_0 is an intercept, β_j is the coefficient of x_j, f represents unspecified non-parametric smooth functions, and ε is an independently and identically distributed random error. In Equation (6), $\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}$ represents the parametric part related to the generalized linear model with k predictor variables. The term $\sum_{j=k+1}^{p} f_j(x_{ij})$ is the non-parametric part, which includes $p - k$ predictors.

Next, a smoothing function is used to summarize the trend of the dependent variable y as a function of one or more independent variables $(x_{k+1}, x_{k+2}, \ldots, x_p)$. Several different types of smoothing functions have been developed for data analysis, including local linear regression (loess), thin-plate regression splines, cubic regression splines, cyclic cubic regression splines, or P-splines [28]. Among these, smoothing splines are commonly used in GAM fitting due to their favorable mathematical properties [27,29]. Particularly, a smooth spline in GAMs can take two or more predictors as arguments [e.g., $f(x_5, x_7)$]. However, for illustration purposes, the spline functions in the non-parametric part of Equation (6) are denoted as taking one predictor as argument.

The smooth is represented based on a set of functions called basis functions that collectively span a space of smooths containing the true smooth or a close approximation to it [30]. The j-th smooth function $f_j(x_j)$ can be represented as a weighted sum of d basis functions:

$$f_j(x_j) = \sum_{h=1}^{d} \omega_h B_h(x_j) \quad (7)$$

where $B_h(x_j)$ is the h-th basis function and ω_h denotes the weight applied to the h-th basis function [30].

The smooth spline f in Equation (7) is a piecewise-defined smooth curve comprised of sections of basis functions [30]. The points where the sections are joined together are known as knots. At the specified knots, the two sections of the smooth spline that meet have the same value, as well as the same first and second derivatives [30]. These properties ensure that the smooth curve is continuously differentiable at the knots. The number of knots affects the smoothness of the smooth spline: fewer knots result in smoother splines, while more knots can lead to overfitted splines.

When fitting the GAM, controlling the level of smoothness for the smooth spline is crucial. The optimal degree of smoothness can be determined by choosing the optimal number of knots, k, by sequentially removing knots. However, this approach is problematic, as a model based on $k-1$ evenly spaced knots will not generally be nested within a model based on k evenly spaced knots [27]. Alternatively, the basis dimension can be fixed at a size slightly larger than reasonably necessary while also incorporating a wiggliness penalty into the objective function that will be minimized to avoid fitting overly complex models [27,30–32].

The default wiggliness penalty used in GAMs is the second derivatives of the smooth spline of the spline at any infinitesimal point in the interval according to the predictor x_j [30]. The actual penalty term used is the integrated squared second derivatives of the spline function f expressed as follows:

$$\int (f'')^2 dx = \hat{\beta}^T S \hat{\beta} \tag{8}$$

where the right-hand side of Equation (8) is the penalty in quadratic form; $\hat{\beta}$ is the estimated weights of the basis functions of the smooth spline; and S is known as the penalty matrix [30,31].

Given the wiggliness penalty in Equation (8), the smooth function can be estimated by minimizing the penalized likelihood $\mathcal{L}_p(\hat{\beta})$:

$$\mathcal{L}_p(\hat{\beta}) = \mathcal{L}(\hat{\beta}) - \frac{1}{2}\lambda \hat{\beta}^T S \hat{\beta} \tag{9}$$

where λ is the smoothness parameter that controls the trade-off between the smoothness of the estimated f and fidelity to the data. As $\lambda \to \infty$, the penalty dominates $\mathcal{L}_p(\hat{\beta})$ and the wiggliness of the smooth spline tends to 0, resulting in a straight line, while $\lambda \to 0$ leads to an overfitted wiggly spline.

There are two main strategies through which λ in Equation (9) can be automatically determined during model fitting [30]. The first is to select a λ value such that it minimizes the prediction error of the model, such as Akaike's information criterion (AIC), cross-validation (CV), or generalized cross-validation (GCV). The second approach is to treat the smooth as a random effect, where λ is considered a variance parameter to be estimated using maximum likelihood (ML) or restricted maximum likelihood (REML) [28,33]. Several studies have shown that GCV, under certain circumstances, tends to generate under-smooth splines that are overly wiggly [30,34]. Better behavior has been reported for REML and ML smoothness selection, in that order. Therefore, REML smooth selection is generally preferred as a means of fitting GAMs [27].

2.2. Study Area and Data

The dataset for the analysis comprises transaction records of apartment units for the 2016–2018 period, selected from the city of Cheongju in Korea. Cheongju is the capital of Chungbuk Province and is located in the central part of Korea. In 2018, the city had a population of 851,328 residents living in 353,320 households spanning an area of 940.9 km^2, making it the largest and most densely populated city in Chungbuk Province, with a population density of 904.8 people per km^2 [35]. As of 2018, land use in Cheongju was categorized as follows: building sites (5.6%), roads (5.2%), industrial sites (2.3%), forest (50.3%), dry fields (9.6%), rice paddies (14.0%), and other uses (13.0%) [36].

Cheongju serves as the economic, political, and cultural center of Chungbuk Province, which comprises 11 municipalities and counties and had a population of 1,638,789 people as of 2018. In the same year, approximately 428,000 people were employed in Cheongju, accounting for approximately 60.0% of the total employment in Chungbuk Province. Additionally, from a total of 129,920 business enterprises in Chungbuk Province, 62,723 firms were located in Cheongju, accounting for approximately 48.3% of the total businesses in the province [35].

The cross-sectional sample of market transactions includes apartments located within a 5 km radius of the geographical center of Cheongju, a densely populated area with the majority of apartment buildings. For certain types of data such as detached houses, detailed addresses were not provided for personal information protection. Therefore, our analysis was conducted at the apartment level. When creating the final database for analysis, cases with incomplete information on relevant variables were also eliminated.

The variables in the sample include the nominal price per square meter of apartment units sold as the outcome variable and the structural characteristics of individual dwelling units, as well as the neighborhood and environmental characteristics surrounding the selected units. The sales prices of apartments were obtained from the Open Web Platform of Housing Sales Prices website (https://rt.molit.go.kr/, accessed on 3 March 2024), hosted by the Korea Ministry of Land, Infrastructure, and Transport. To ensure comparability, housing prices were adjusted for inflation to reflect their 2018 values. From February to March 2020, a total of 110 urban green spaces, including urban parks and forest areas, were mapped through field surveys and the interpretation of aerial photographs. The hedonic pricing approach is based on the crucial assumption that the utility that a household derives from housing consumption depends not only on the attributes of the housing unit itself but also on other goods and services, including the distances of the dwelling units to green space. Therefore, the incorporation of locational and environmental variables into the hedonic price model is justifiable as a means of exploring the neighborhood and environmental quality effects on property values.

The structural variables include the floor area, the floor level on which the apartment unit is located, and the age of the building. Using a geographic information system (GIS) approach, the locational attributes include the minimum road network distance (hereinafter referred to simply as "road distance") from dwelling units to neighborhood amenities such as bus stops, the provincial government office, educational facilities (kindergarten, elementary school, and high school), hospitals, and shopping centers. The environmental variables include the proximity to the nearest urban green spaces and the adjacent streets to the apartment building. Road distance to green spaces was used to quantify environmental amenities, whereas the Euclidean distance to neighboring streets was used as a proxy to assess street connectivity. This study expands on the established economic benefits of urban green spaces by examining the relationship between their size, proximity to residential areas, and economic impact. Urban forests and parks, which are major types of urban green spaces, were categorized into three size categories [37]: small-sized (1–20 ha), medium-sized (20–200 ha), and large-sized (>200 ha) green spaces. Figure 1 provides a map of the spatial distribution of green spaces and the locations of apartment buildings from which the individual dwelling units in the study sample were selected.

After excluding incomplete records, apartment units with no sales records, units sold before the year 2016, and outliers, a total of 1102 apartment units were selected as the final database for analysis in this study. Table 1 provides a list of the variables selected for analysis, along with their brief explanations and descriptive statistics. Spatial variables were obtained using ArcGIS Pro 3.1 [38].

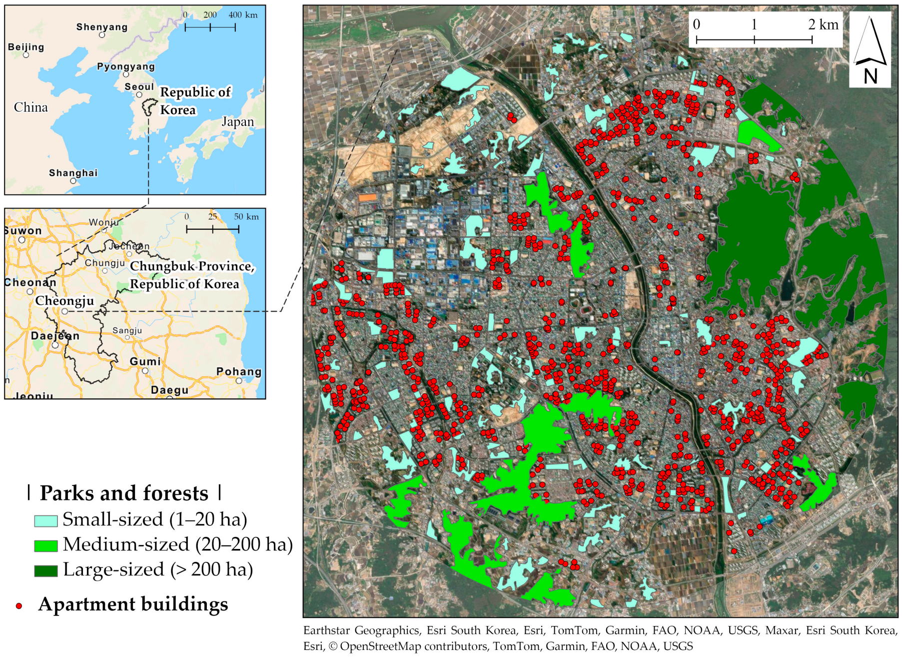

Figure 1. Map of parks and forests and the locations of apartment buildings in Cheongju City, Chungbuk Province, Republic of Korea, created using ArcGIS Pro 3.1 [38].

Table 1. Definitions and descriptive statistics of the variables.

Variable	Description	Unit	Mean	Std. Dev.
Dependent variable				
PRICE	Apartment selling price per m^2 (in 2018 price)	USD 7.69/m^2 (KRW 10,000/m^2)	217.19	77.41
Structural variables				
FLOORAREA	Total floor area	m^2	76.10	31.22
FLOOR	The floor on which the unit is situated		7.19	4.08
AGE	Building age (the period between the year the building was constructed and the year the property was sold)	Years	21.40	9.97
Locational variables				
DISBUSTOP	Road distance to nearest bus stop	m	244.89	121.97
DISPROVIN	Road distance to provincial government office	m	3799.00	1560.84
DISKINDER	Road distance to nearest kindergarten	m	557.05	333.26
DISELEMENT	Road distance to nearest elementary school	m	607.20	289.65
DISHIGH	Road distance to nearest high school	m	921.32	408.27
DISHOSPIT	Road distance to nearest general hospital	m	1570.79	626.86
DISHOPING	Road distance to nearest shopping center	m	1666.16	767.20
Environmental variables				
DISROAD	Euclidean distance to adjacent street	m	82.37	55.26
DISGREENSM	**Road distance to nearest small-sized green space**	**m**	**451.75**	**300.15**
DISGREENMD	**Road distance to nearest medium-sized green space**	**m**	**1481.42**	**946.42**
DISGREENLR	**Road distance to nearest large-sized green space**	**m**	**3331.16**	**1908.18**

3. Empirical Analysis, Results, and Discussion

3.1. SAR Model

The SAR model was used to evaluate the economic value of urban green spaces in Cheongju. The SAR model is appropriate when the errors of the OLS model are spatially autocorrelated. For this study, a global spatial spillover specification was considered more relevant than a local one. We first performed a Moran's I test to assess the spatial autocorrelation of the OLS model's errors. The Moran's I test results indicated a statistically significant spatial autocorrelation with an expected value of -0.010298 and a variance of 0.000254 (p-value < 2.2×10^{-16}). The spatial weight matrix W was constructed using the distance-based algorithm assuming that d < 300 m. In this case, d represents a distance threshold entered into the 'spdep' R package to construct the spatial weight matrix, W, given a matrix of data point coordinates. Its value was determined by iteratively running the codes until a statistically adequate SAR model was obtained. The Moran's I test indicates that the selling prices of apartments are spatially autocorrelated, suggesting that the price of an apartment is influenced by the prices of other adjacent apartments.

In addition to spatial autocorrelation, another key issue in spatial regression is heteroscedasticity, which refers to the violation of the assumption that residuals have equal variance at each level of the predictor variables. The Breusch–Pagan test was used to check for heteroscedasticity. The test statistic under the null hypothesis of no heteroscedasticity was 58.443 (degrees of freedom (df) = 14; p-value = 2.2×10^{-7}). Therefore, the test confirms the presence of heteroscedasticity in the OLS model's errors.

To simultaneously address spatial autocorrelation and heteroscedasticity, we used the SHAC (spatial heteroscedasticity and autocorrelation consistent) estimator to further examine the outcomes of the SAR model [39–43]. The SHAC estimator, which was first proposed by Kelejian and Prucha [41,42], is an extension of HAC estimators that have been extensively researched in the field of time series analysis. It is a non-parametric method of estimating a variance–covariance matrix for a vector of sample moments within the context of instrumental variable estimation. The model incorporates the natural log of the selling prices of apartments as the dependent variable and the structural, locational, and environmental attributes as explanatory variables. The SHAC estimation was conducted with the 'spdep' R package for spatial econometric analysis [44]. The results of the SHAC estimator are summarized in Table 2.

Table 2. Results of the estimation of the SAR model.

Variable	Coeff.	Std. Error	t-Value	p-Value	
Wy	0.086802	0.046722	1.8578	0.063192	•
(Intercept)	5.148492	0.255860	20.1223	0.000000	***
FLOORAREA	−0.000596	0.000197	−3.0294	0.002450	**
FLOOR	0.017397	0.001762	9.8760	0.000000	***
AGE	−0.021964	0.001069	−20.5490	0.000000	***
DISBUSTOP	−0.000132	0.000047	−2.8397	0.004515	**
DISPROVIN	0.000037	0.000007	5.1946	0.000000	***
DISKINDER	0.000011	0.000025	0.4303	0.666945	
DISELEMENT	−0.000026	0.000028	−0.9358	0.349394	
DISHIGH	−0.000090	0.000016	−5.6653	0.000000	***
DISHOSPIT	0.000022	0.000010	2.0999	0.035739	*
DISHOPING	0.000045	0.000009	4.9963	0.000000	***
DISROAD	−0.000271	0.000108	2.5158	0.011876	*
DISGREENSM	**−0.000034**	**0.000020**	**−1.6777**	**0.093397**	•
DISGREENMD	**−0.000014**	**0.000006**	**−2.4892**	**0.012802**	*
DISGREENLR	**0.000009**	**0.000005**	**1.9282**	**0.053825**	•
Residuals:					
Minimum	1st quartile	Median	3rd quartile	Maximum	
−0.970288	−0.086318	0.017733	0.104464	0.614417	
$\hat{\sigma}^2 = 0.02909$					

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1 ' ' 1.

As shown in Table 2, the estimated coefficient (ρ =0.0868) of the spatially lagged dependent variable (Wy) was statistically significant (p-value = 0.0632) at the 0.1 significance level, indicating that the SAR model effectively controls for spatial dependence of apartment prices. Most of the estimated coefficients were statistically significant at various significance levels (0.001–0.1), except for two variables related to distances to amenities: DISKINDER and DISELEMENT.

The estimated coefficients exhibit consistent relationships between the physical characteristics of apartments and sales prices [45]. However, in contrast to a previous study [46], the coefficient of the floor area of apartments (FLOORAREA) was negative, suggesting that as the total floor area of an apartment unit increases, the selling price per square meter decreases. This negative value reflects the diminishing marginal utility of additional unit space and may be attributed to the cost advantage arising due to economies of scale in the construction industry.

In contrast, the impacts of proximity to parks and forests on apartment prices are mixed. Specifically, out of the three explanatory variables representing distances from apartments to the nearest parks or forests, proximity to small-sized urban green spaces (DISGREENSM) and proximity to medium-sized green spaces (DISGREENMD) have a positive impact, whereas proximity to large-sized green spaces (DISGREENLR) has a negative impact. For small- and medium-sized parks or forests, the shorter the distance to the nearest parks and forests, the higher the apartment prices, as in other studies [47,48]. In contrast, proximity to large-scale parks or forests tended to decrease the selling prices of apartments. These results support the occurrence of a distance-decay effect (i.e., the declining effect of physical distance to green space on apartment prices) for the explanatory variables DISGREENSM and DISGREENMD.

Contrary to the two aforementioned distance-to-urban-green-space variables, in the case of the DISGREENLR variable, a decreasing distance from an apartment to the nearest large urban green spaces lowers its own price as well as that of other properties and vice versa. The positive distance effect of DISGREENLR on apartment prices might be due to restrictive land use and building regulations in the areas adjacent to large mountainous urban green spaces over 200 ha, most of which are the oldest parts of Cheongju, thereby comprising a large proportion of age-old properties. Stringent land use and building regulations are known to have a pervasive effect on local house values by influencing housing construction [49]. In this context, in the present study, strict regulations on age-old deteriorated properties near large-sized urban green spaces tended to have a strong constraining effect on the housing supply. Increased urban forest presence mostly had a positive impact on housing prices [50]; however, stringent zoning restrictions near large-sized urban green spaces, particularly those with mountainous terrain, may limit infrastructure development and thus potentially housing price growth in the vicinity.

When interpreting the coefficients of the explanatory variables, they were treated as if they were estimates of an OLS model. That is, β in Equation (1) was interpreted like the coefficient estimates of a multiple linear regression model. However, interpreting β in such a way is not correct when the spatially lagged endogenous variable Wy is included in the model. This is because they only represent the immediate short-run (or direct) impact of the corresponding explanatory variables on apartment prices.

In a spatially dependent housing market, the implicit price of an amenity (or disamenity) reflects not only the market transaction of a particular apartment unit but also the spatial spillovers of the same effect that diffuses from neighboring properties [14]. Hence, the long-run equilibrium or indirect impacts of the explanatory variables on apartment prices must also be estimated. The equilibrium effects, represented by the averages of the off-diagonal elements in Equation (5), account for feedback effects that arise due to impacts passing through neighboring apartments and back to the apartment unit that initiated the change. Table 3 outlines the estimated direct and indirect impacts of the explanatory variables in the SAR model on apartment prices.

The primary purpose of this study was to assess the economic values generated by urban parks or forests in Cheongju. Therefore, particular attention was given to the direct and indirect impacts of the three explanatory variables DISGREENSM, DISGREENMD, and DISGREENLR on apartment prices. For the variable DISGREENSM, the direct, indirect, and total impacts were -0.000034, -0.000003, and -0.000037, respectively. The average total impact of 0.000037 was approximately 8.1% higher than the direct impact of 0.000034. Next, the impact values were expressed as the absolute value (i.e., the negative sign was omitted) of the coefficient estimates of proximity to urban green spaces variables. This result indicates that the total impact of the DISGREENSM variable on the per square meter price of apartments expressed as the natural log of the selling price (0.000037) increases with a unit decrease in distance to the nearest small-sized parks or forests. Then, the antilog of the total impact, USD 7.692592/m^2, represents the economic value generated by a unit decrease in distance to the nearest small-sized parks or forests. This economic value was derived from the conversion of the antilog of the total impact into USD: exp(0.000037) $\times$ KRW 10,000/m^2 $\div$ KRW 1300/USD = 7.692592 USD/m^2.

Table 3. Results of the estimated direct and indirect impacts.

Variable	Direct	Indirect	Total
FLOORAREA	−0.000596	−0.000056	−0.000653
FLOOR	0.017415	0.001635	0.019051
AGE	−0.021987	−0.002064	−0.024052
DISBUSTOP	−0.000133	−0.000012	−0.000145
DISPROVIN	0.000037	0.000003	0.000041
DISKINDER	0.000011	0.000001	0.000012
DISELEMENT	−0.000026	−0.000002	−0.000028
DISHIGH	−0.000090	−0.000008	−0.000098
DISHOSPIT	0.000022	0.000002	0.000024
DISHOPING	0.000045	0.000004	0.000049
DISROAD	−0.000271	−0.000025	−0.000297
DISGREENSM	**−0.000034**	**−0.000003**	**−0.000037**
DISGREENMD	**−0.000014**	**−0.000001**	**−0.000015**
DISGREENLR	**0.000009**	**0.000001**	**0.000010**

The proximity to the nearest medium-sized urban green spaces (DISGREENMD) was shown to yield a direct impact of −0.000014, an indirect impact of −0.000001, and a total impact of −0.000015, indicating that the total impact was 6.7% higher than the direct impact. This means that proximity to medium-sized green spaces exerts a far greater impact on the prices of apartments compared to the impact of other apartment prices. Specifically, the value of the direct impact, 0.000014, was 14 times higher than that of the indirect impact, 0.000001. The arithmetic economic value of the total impact, 0.000015, was USD 7.692423/m^2. This arithmetic value was not substantially different from that of the proximity to the nearest small-sized parks or forests. Thus, the economic values of urban green space measured on the arithmetic scale were barely different between small-sized and medium-sized parks or forests, although they were discernible when expressed as logarithmic values.

Finally, proximity to the nearest large urban green areas (DISGREENLR) negatively affected apartment selling prices in equilibrium. The strength of the impact of this variable was weak compared with that of the small- and medium-sized parks or forests. In the log scale, the sizes of direct, indirect, and total impacts were 0.00009, 0.000001, and 0.000010, respectively. Compared to the other explanatory variables (DISGREENSM and DISGREENMD), the three impact categories of the DISGREENLR variable were notably small.

Another useful way to illustrate the variation in equilibrium effects is to investigate the impact of a change across all different apartment units and examine the distribution of the apartment unit-specific estimates. Figure 2 displays histograms of the estimated total impacts for the three proximity-to-green-space variables: DISGREENSM, DISGREENMD, and DISGREENLR. In the histograms, the vertical axis represents the number of apartment units, and the horizontal axis indicates the range of total impact for individual apartments in the dataset.

As illustrated in Figure 2, the frequency distributions of total impact for DISGREENSM and DISGREENMD are slightly skewed to the right. The positive-skewed distribution indicates that for DISGREENSM and DISGREENMD, the mean total impact values are positioned to the right of the medians. In the histograms, each bar covers one-twentieth of the range between the maximum and minimum values of total impact, and the height of each bar indicates the number of apartment units in each impact range. For both variables, a large portion of apartments exert a middle range of total impact on apartment prices. In contrast, the distribution of the total impact values for the DISGREENLR variable appeared bumpy and heterogeneous. That is, the heights of the bars are quite irregular, forming a jagged shape, but the data were not randomly distributed.

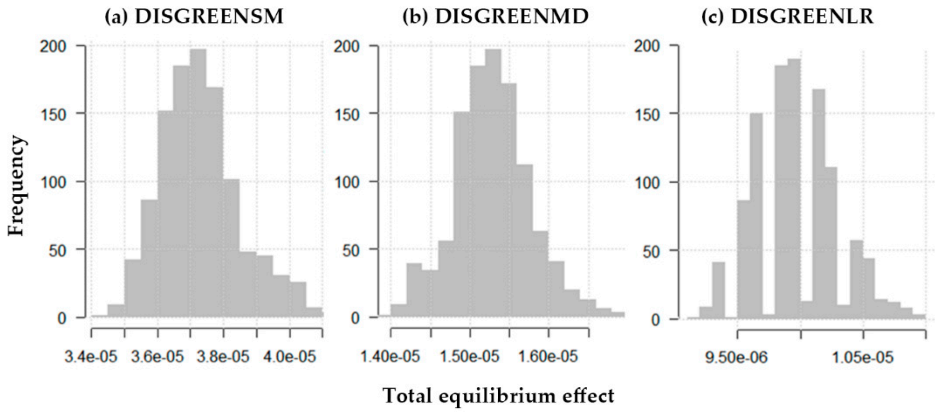

Figure 2. Histograms of the total impacts for DISGREENSM, DISGREENMD, and DISGREENLR.

The results of the empirical estimation of the SAR model were examined with special emphasis on the equilibrium impact on apartment prices obtained based on the three proximity-to-green-space variables (DISGREENSM, DISGREENMD, and DISGREENLR). Our findings support the presence of a distance-decay or reversed distance-decay effect with respect to the distance of an apartment to the nearest urban green spaces [14,51]. Votsis [14] has shown that the impact of green infrastructure on apartment prices depends on the type and location of green infrastructure. The findings of this study further revealed that the implicit economic value of the parks or forests in Cheongju varied depending on the size of the green space. Specifically, a property's proximity to urban green spaces serves as an economic amenity (for small- or medium-sized parks or forests) or a disamenity (for large-scale parks or forests).

3.2. GAM

As illustrated in Equation (6), a GAM was fitted to examine the shape of the relationship between the proximity of apartments to neighboring urban green spaces and apartment prices. As with the SAR model, our analyses were primarily focused on the features of spatial decay for the three variables DISGREENSM, DISGREENMD, and DISGREENLR. In the empirical GAM in Equation (6), the linear (parametric) portion consisted of three variables—FLOORAREA, FLOOR, and AGE, whereas the non-parametric portion comprised the remaining eleven predictors, including the three proximity-to-green-space variables. Similar to the SAR model, the response variable was the log-scaled apartment selling prices. Table 4 summarizes the estimation results of the GAM.

Table 4 shows the overall goodness-of-fit statistics of the GAM. The model explains a notable amount of variance in apartment selling prices, with an adjusted R^2 of 0.813. On the other hand, the GCV score, an estimate of the mean square prediction error based on a leave-one-out cross-validation estimation process [52], was quite low (0.025). This score is used to assess smooth functions, with lower values being indicative of a better fit. The high R^2 value coupled with the low GCV score observed herein suggests that the GAM accurately described the dataset.

In addition to the measures of the model's overall performance, Table 4 presents the test results for the significance of the parametric and non-parametric terms of the GAM. Interestingly, our analyses highlighted the importance of all parametric terms (i.e., FLOORAREA, FLOOR, and AGE), as their coefficients were statistically significant. This was validated by the fact that the p-values for the coefficient estimates of these variables were less than 0.05.

Table 4. Results of the estimation of the GAM.

A. Parametric coefficients					
Variable	Coeff.	Std. error	*t*-value	*p*-value	
(Intercept)	5.727103	0.031545	181.555	0.000000	***
FLOORAREA	−0.000673	0.000189	−3.544	0.000414	***
FLOOR	0.018206	0.001997	9.115	0.000000	***
AGE	−0.022872	0.000825	−27.725	0.000000	***
B. Approximate significance of smooth terms					
Smooth term	EDF [(1)]	Ref. DF [(2)]	*F*-value	*p*-value	
s(DISBUSTOP)	7.401	8.371	1.525	0.142935	
s(DISPROVIN)	45.195	47.862	2.524	0.000000	***
s(DISKINDER)	7.093	7.999	5.113	0.000002	***
s(DISELEMENT)	6.592	7.596	2.448	0.012865	*
s(DISHIGH)	8.421	8.858	4.458	0.000009	***
s(DISHOSPIT)	1.385	1.675	2.223	0.137499	
s(DISHOPING)	14.980	17.175	2.415	0.000000	***
s(DISROAD)	4.511	5.578	2.757	0.014079	*
s(DISGREENSM)	8.891	8.891	2.701	**0.003640**	**
s(DISGREENMD)	6.340	7.479	2.724	**0.007506**	**
s(DISGREENLR)	25.348	30.745	2.113	**0.000368**	***
R-sq.(adj) = 0.813 Deviance explained = 83.7%					
GCV = 0.025496 Scale est. = 0.024245 *n* = 1102					

[(1)] EDF = effective degrees of freedom; [(2)] Ref. DF = reference number of degrees of freedom. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1 ' ' 1.

Regarding the non-parametric terms, the nine terms, except for DISBUSTOP and DISHOSPIT, appeared to be statistically significant in accounting for apartment prices. This finding was evidenced by the assessment of the effective degrees of freedom (EDF) for the smooth terms in the GAM, which was further examined via a special F-test to evaluate the significance of the smooth. The EDF of a smooth is the sum of the effective degrees of freedom of all basis functions that constitute that smooth [53]. The effective freedom of a basis function is the proportion of the original weight of that basis function that is retained after penalization [27,29]. Given that the main objective of this study was to evaluate the economic value of urban parks or forests, we primarily focused on the smooth terms corresponding to the three proximity-to-green-space variables, DISGREENSM, DISGREENMD, and DISGREENLR, among other variables. As shown in Table 4, the F-statistics for the smooth functions for these three variables were significant (p-value < 0.05 for each smooth). This result confirmed that the estimated smooth functions corresponding to these variables accurately reflect a non-linear relationship between the relevant predictor variables and apartment prices.

Upon confirming the non-linear relationships between the smooth functions and apartment prices, we next sought to investigate the specific features of the average estimated distance-decay effect of these variables. The forms of the fit were visualized by plotting the apartment price effect by smooth term. Figure 3 displays the graphical representation of the estimated distance-decay effect for the three proximity-to-green-space variables.

Panels (a), (b), and (c) in Figure 3 show the distance-decay effect of the smooth functions for proximity to small-sized, medium-sized, and large parks or forests, respectively. As illustrated in Panel (a), the effect of the proximity to the nearest small-sized parks or forests tended to taper, with apartment prices declining up to a certain distance from the apartment sites (about 200 m), after which the distance effect can be positive or negative depending on the distance. Panel (b) shows that the proximity to medium-sized green spaces exhibits a sustained distance-decay effect within an average distance of approximately 1500 m, after which a positive distance effect was observed. In contrast, Panel (c) shows that proximity to large-scale green spaces results in an increasing effect on apartment prices up to approximately 1500 m, beyond which the effect becomes highly irregular.

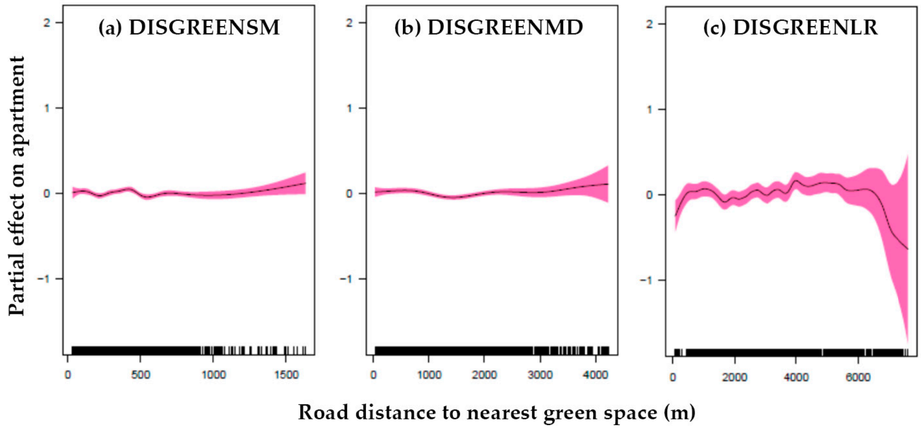

Figure 3. Smooth effects for the DISGREENSM, DISGREENMD, and DISGREENLR variables. The plots above show the partial effects of the three selected predictors on apartment prices. The tick marks on the *x*-axis are observed data points of distance. The *y*-axis represents the partial effect of each variable on apartment prices. The areas shaded in red indicate the 95% confidence bands.

As shown in Figure 3, the average estimated distance effect for urban-green-space proximity varies depending on the green space size. A distance-decay effect was identified for the DISGREENSM and DISGREENMD variables but there were differences in the distance ranges at which the effect was observable. The average distance-decay effect of the proximity to smaller parks or forests on apartment prices dissipates faster than that of proximity to medium-sized ones. In contrast, the distance effect of the DISGREENLR variable was very different from that of the previous two variables, exhibiting a reversed or inverted U shape.

The results of the empirical analysis using the GAM indicate that the economic values of green spaces in Cheongju vary based on their size and proximity to apartments. Specifically, small- and medium-sized parks or forests have positive economic values, whereas large green spaces have a negative impact on apartment prices. The distance-decay effect or reversed effect was observed for all three sizes of green spaces, but there were size-dependent variations in the range of distance within which the effect was sustained. These findings align with the results presented by Łaszkiewicz et al. [51], who observed that different sizes of green spaces exert different effects on property prices. Further research is needed to explore the underlying reasons for the negative impact of large-sized green spaces and identify strategies to mitigate the impact, potentially through improved urban planning and land management.

4. Conclusions

This study sought to measure the implicit benefit of urban green spaces in Cheongju, as well as to identify how the benefit associated with proximity to these green spaces decays as the distance from apartment properties increases. To address these questions, two spatial econometric models were generated: the SAR model was used to measure the economic benefit of urban green spaces, whereas a GAM was used to investigate the spatial distribution of distance decay.

Our findings provide strong evidence of the occurrence of the proximity principle in the study site, whereby proximity to urban green spaces influences the value of nearby properties, as demonstrated by other studies (e.g., [47,54]). Specifically, we found that a unit increase in distance from a small- or medium-sized park or forest decreases apartment prices, whereas the distance to large parks or forests had a positive effect on apartment prices. Additionally, small-sized parks or forests appeared to increase the value of surrounding properties more markedly than their medium-sized counterparts. These results imply that distance-decay functions are not constant but rather influenced by the size of the green space [51]. Interestingly, proximity to a large park or forest was shown to be a source of disamenity, as increased proximity to these green spaces decreased property prices. In other words, the presence of large-sized green spaces did not translate to higher apartment prices, with this negative effect on property prices dissipating with increased distance due to the distance-decay effect.

Additionally, we identified variations in the spatial ranges within which the distance-decay effect was valid depending on the sizes of the urban green spaces. Particularly, visualizing the smooth functions of the GAM revealed that the distance-decay effect of small-sized parks or forests dissipated within a markedly narrower distance range compared to medium-sized parks or forests. In other words, the impact of smaller parks seems to be more localized, potentially due to factors like usability or safety perception [55]. In the case of large-sized parks or forests, the smooth function exhibited an inverted U-shaped curve, resulting in a negative effect on property prices. However, the smooth functions for all three categories of urban green spaces generally exhibited wiggly and undulating trends, indicating complex non-linear patterns that require further investigation.

Collectively, our findings suggest that urban green spaces in Cheongju are likely to produce an economically beneficial impact on property prices, but this principle might not apply to large-sized parks or forests. Therefore, to enhance the welfare of city residents, green infrastructure policy should prioritize the provision of small- and/or medium-sized parks or forests accessible from residential properties. This study's distance-decay-based approach, employing spatial econometrics, can be effectively applied in other regions and countries to optimize green space and urban planning, ensuring residents benefit from proximity to valuable urban green spaces. To comprehensively assess the environmental impacts, future analyses should incorporate diverse environmental factors like air quality and noise pollution, as well as accessibility and the distribution of green spaces and other infrastructure. This approach is expected to not only increase property values but also improve the overall quality of life of residents.

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