

Article



# Influence of the Urban Green Spaces of Seville (Spain) on Housing Prices through the Hedonic Assessment Methodology and Geospatial Analysis

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Abstract: The city of Seville (Spain) is made up of a historical network of pre-existing city overlaps, which increase the economic and heritage value of certain urban areas. To date, green spaces are one of the most important variables in determining the economic value of housing. Thus, this paper uses the hedonic technique and geostatistical analysis with GIS as a methodological approach to infer the economic influence of urban green spaces on housing prices. Along with the traditional variables used to explain dwelling prices, the size of the green space has also been taken into account as an environmental variable affecting prices. The sample consists of 1000 observations collected from Seville. According to the findings, the most relevant variables depend on the hedonic model. Still, in general terms, a dwelling's selling price is related to basic explanatory variables such as living area, number of rooms, age, and number of baths. The green area per inhabitant present in a dwelling's district is also included as part of these basic explanatory variables. In conclusion, the hedonic linear model is the model that best fits housing prices where the values are similar to those obtained by kriging regardless of the district. Based on this research, each square meter of green space per inhabitant in a district raises the housing value by  $120.19 \notin/m^2$ .

Keywords: hedonic method; GIS; geospatial analysis; urban green space; housing prices

## 1. Introduction

Green spaces serve essential environmental and recreational functions [1]. Forest and urban vegetation, in edaphoclimatic terms, improve the environment in which they are found and serve as the foundation for the conservation of fauna and flora. Recreational activities with a basis in nature are becoming more popular and, while the effects are on a smaller scale, urban parks serve the same environmental and recreational functions as larger forests and green spaces.

Gardens and city parks play the primary environmental function of absorbing carbon dioxide (CO<sub>2</sub>) emissions. These emissions are primarily generated through the use of private vehicles in urban transportation. Moreover, emissions have increased significantly in recent decades. It is worth noting that, in Spain, each person in a large city emits 4.62 tonnes of CO<sub>2</sub> per year [2]. Given that one hectare of Mediterranean forest can absorb approximately four tonnes of CO<sup>2</sup> per year, a simple calculation leads us to conclude that we require more than one hectare of green space per inhabitant (inh) to offset the pollution generated by these emissions. The preservation of urban green spaces is thereby becoming increasingly important in order to combat the growing contamination of our cities.

Additional factors, such as acoustic isolation, should be included in the list of the environmental functions of urban green parks as some gardens serve as acoustic screens



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**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). between high-traffic roads and residential areas. Plants have individual and collective aesthetic value which contributes significantly to preserving a pleasant landscape in addition to serving as a link between residential, urban, and industrial areas. Many recreational activities (including children's play areas, landscape enjoyment, and sports) take place in city parks and gardens. The abundance of services provided by urban green spaces help to explain the impact of environmental variables on housing prices.

However, the benefits that vegetation brings to the urban environment have no (direct) economic value because they are intangible goods [3]. Subsequently, their economic valuation is a complex and time-consuming task. The difficulty of applying monetary value prevents these open spaces from being adequately accounted for in cost-benefit analyses of public urban planning policies. As a result, we risk seeing urban green space endowments fall below the social optimum.

Economic science has developed specific methods for capturing the monetary value of environmental assets. This value is sometimes indirectly determined by observing people's behaviour as in the travel cost method (TCM). Other methods, such as contingent valuation (CVM), determine an environmental asset's value by asking people how much they are willing to pay for its use or conservation. This final method is highly versatile and has been used to value different projects such as the valuation of mining heritage in Extremadura (Spain) [4], the assessment of landowner demand for forest amenities in Andalusia (Spain) [5], as well as the social and private costs of water for irrigation in San Vicente del Raspeig, (Spain) [6].

As has been proven in different recent studies, Geographic Information Systems (GIS) can help improve the understanding of urban green spaces worldwide (i.e., Africa [7], Europe [8–10], Asia [11], America [12,13], or Oceania [14]).

The hedonic pricing method (HPM) is another model for assessing the monetary value of an environmental asset [15–17]. In this method the value is obtained indirectly through the environment's influence on the market price of another good. Similarly, the value of a particular dwelling can be inferred through geostatistical analysis of existing prices in the study area using a GIS. This paper uses these methodologies to assess the influence of urban green spaces on housing prices in the Andalusian capital, Seville (Spain) since it is a pioneer in urban sustainability [18]. The novelty of this research is conferred by the fact that a study of these characteristics had never before been undertaken in this city. A representative sample of this city's current real estate market was chosen. The data set includes the sale price and other key characteristics for 1000 residential dwellings. Traditional housing price determinants (i.e., size, number of rooms, and age) were considered, and the relative sizes of green areas were also considered as an environmental factor.

The rest of this manuscript is structured as follows: Section 2 defines the fundamentals with regard to the hedonic pricing method and the empirical models used in dwelling valuation; in Section 3 the study area is introduced; Section 4 deals with the materials and methods; Section 5 presents the results and discusses them; and finally, Section 6 outlines the conclusions of the research.

### 2. Fundamentals

#### 2.1. Hedonic Pricing Method (HPM)

According to Glumac et al. [19], some references specify that the origins of HPM may extend prior to the 1970s. Generally, the hedonic pricing method connects a good's market price to its characteristics. Thus, the monetary value of each characteristic can be calculated by observing the differences between the market prices of commodities with the same attributes. The initial hypothesis asserts that goods are made up of a diverse set of attributes or characteristics. As a consequence, when we engage with a good or service we can consider the price we might pay for it to be the sum of the prices we would pay for each of its characteristics; therefore, it can be inferred that an implicit price exists for

each of the attributes that define the whole good or service. For this reason, the price can be expressed as (Equation (1)):

$$P = f(x_i); i = 1, ..., n$$
 (1)

where "*P*" denotes the market price of the good and " $x_i$  (i = 1, ..., n)" indicates the characteristics it possesses. The partial derivatives of the price, with respect to the preceding variables [ $\delta(P)/\delta(x_i)$ ], provide information on the marginal willingness to pay for an additional unit of each characteristic; thus, the implicit price of each of them can be estimated. However, the hedonic theory does not provide a foundation for determining the functional form used. Li et al. [20] suggest linear, semilogarithmic, and double logarithmic forms instead of quadratic forms when some relevant explanatory variables are omitted.

In recent decades, the prices for a wide range of goods have been studied from a hedonic standpoint. The method's most common applications have been in the valuation of environmental externalities in real estate market analysis [21]. Given that housing is a multiattribute good, pricing is determined by a range of variables such as size, age, room number, number of baths, etc. When identical characteristics are shared, environmental factors such as green area surface, among others, may explain differences in market prices. The following is a formula for the price function (Equation (2)):

$$P = f(x_i, z); i = 1, ..., n$$
 (2)

where "*P*" is the household market price; " $x_i$  (i = 1, ..., n)" are structural characteristics (e.g., size, age, room number, number of baths), and "z" is the hedonic variable, i.e., environmental variable without a market price.

The method's essence is in ascertaining the portion of the price that can be accounted for by the hedonic variable. These datapoints are obtained by taking the partial derivative of the price concerning the variable "z" [ $\delta(P)/\delta(z)$ ], which gives us the marginal willingness to pay for an additional unit of the environmental asset, and thereby allows us to estimate its monetary value.

Many studies have been conducted using the hedonic approach to determine the relative value of environmental externalities [22] caused by air pollution and traffic, among other variables. For example, Lu [23] uses a data sample that includes 2996 listings in real estate databases; in which, the hedonic technique is applied to value south-facing houses in Shanghai city. Dumm et al. [24] mention more recent works on housing prices related to moral hazards associated with given residential properties. Moreover, Hong et al. [25] apply this methodology to evaluate the random forest approach in South Korean residential properties. Regarding the environmental externalities, Bherwani et al. [26] examined a set of methods used to appraise environmental externalities, and Mei et al. [22] estimated the economic value of domestic water pollution from shale gas.

In terms of urban planning, some modern applications of the method have focused on the analysis of the effects of a shopping mall on housing prices [27], the effect of tourism activity on housing affordability [28], the impact of distance to green areas on property values [29], and air quality [30]. Other aspects that have been investigated include the use of genetic algorithms [31] and automated valuation models [32].

### 2.2. Empirical Models Used in Dwelling Valuation

As is well known, the relationship between the selling price and the housing characteristics (e.g., living area, number of rooms, age, number of baths) can take several functional forms [15].

If the price relationship linking housing characteristics is assumed to be linear [33], Equation (2) can be written as (Equation (3)):

$$P_{i} = \sum_{i=1}^{n} (b_{i} \cdot x_{i,j} + b_{z} \cdot z_{j} + \varepsilon_{j}); j = 1, \dots, T$$
(3)

where " $x_{i,j}$ ,  $z_j$  (i = 1,..., n; j = 1,..., T)" are variables describing housing "j"; the parameters " $b_i$ ,  $b_z$  (i = 1,..., n)" are the marginal willingness to pay for each attribute; " $\varepsilon_j$ " is the error term; and " $b_z$ " term is the marginal willingness to pay for an additional unit of the environmental good "z". It is crucial to specify that the willingness to pay for an additional unit remains constant under the linear specification, i.e., it is unaffected by the starting level of "z". This assumption is a significant constraint because, as Rosen points out, there are numerous reasons to believe that the relationship between the price and the environmental variable is nonlinear [34]. As a result, logarithmic specifications are frequently used, though linear models remain popular due to the ease of parameter interpretation.

A logarithmic model, on the other hand, allows us to measure the impact that changes in explanatory variables have on the dependent variable in relative terms [35]. Because the main variable explaining the price is the living area of the housing, the logarithmic model only includes this single variable. If the price equation (Equation (4)) takes the form shown below, where " $\alpha$ " and " $\beta$ " are parameters, "S" refers to the dwelling's living area, and "u" is the error term. Then the willingness to pay for an additional unit of living area is not constant because " $\delta(P)/\delta(S) \neq \beta$ ".

$$P = \alpha \cdot S^{\beta} \cdot e^{u} \tag{4}$$

Taking the logarithms in Equation (4), it is possible to obtain Equation (5):

$$\ln(P) = \ln(\alpha) + \beta \cdot \ln(S) + u \tag{5}$$

where " $\beta$ " is the elasticity of housing size–price according to Equation (6):

$$\beta = \frac{\partial \ln(P)}{\partial \ln(S)} = \frac{\left(\frac{\Delta(P)}{P}\right)}{\left(\frac{\Delta(S)}{S}\right)} \tag{6}$$

In another vein, according to Vásquez Sanijez [36], the formulation of a reciprocal model can provide helpful information on the real estate market. This specification was formulated by leaving "1/S" as the single explanatory variable. Equation (7) shows the relationship between the different variables that appear in this model:

$$P = \alpha + \beta \cdot \left(\frac{1}{S}\right) + \varepsilon \tag{7}$$

As can be seen from Equation (7), parameter " $\alpha$ " is the ceiling price at which a dwelling would be sold in this case because as "*S*" increases, "*P*" approaches " $\alpha$ ". In this equation " $\varepsilon$ " is the error term.

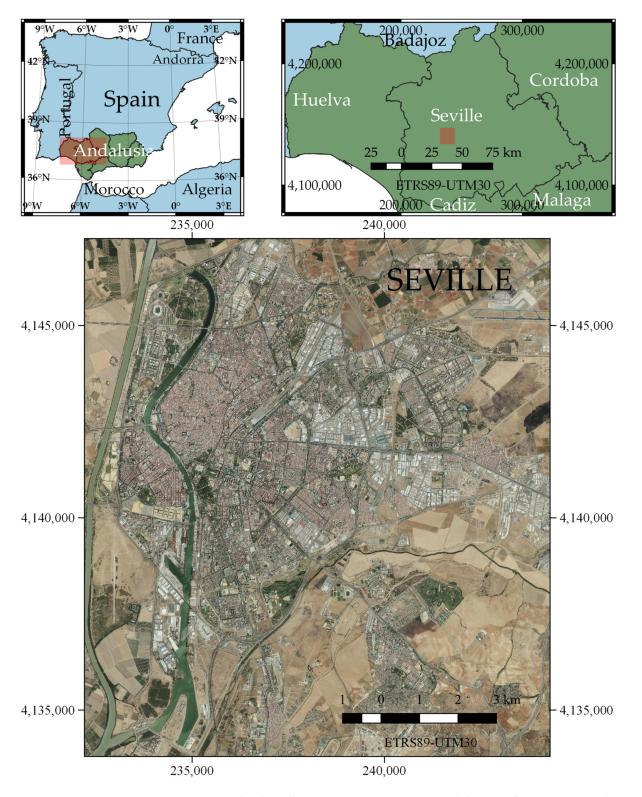
## 3. Study Area

As is well known, the city of Seville is the capital of the Autonomous Community of Andalusia, Spain (Figure 1), and as of January 2021, it comprised 684,234 inhabitants (www. ine.es (accessed on 4 November 2022)). It has been subject to continuous transformation throughout its history, thereby allowing it to adapt systematically to the passage of time while always maintaining the base of the pre-existing city.

Urban development policies in this city have given rise to a process of environmental sustainability focused on maintaining an adequate level of development while not endangering existing natural resources [37].Presently, the existence of a dual relationship between a city's functioning and its ecosystem's sustainability has resulted in a massive diversification of property offers with the added value of green areas positively influencing the final prices houses.

In recent years, the housing price evolution in Seville has had an interannual increase of 6.2% [38]. This fact has led to a slight stagnation in home sales, and therefore, to an increase in properties for sale with less demand. As a result, the average home sales price in Seville is reminiscent of the sales prices in the fourth quarter of 2012 when the

economic crisis of 2008–2014 brought about a price decrease of around 10% over 2008 rates. Nevertheless, the current economic situation brought about as a consequence of the war in Ukraine will cause this effect to translate into a progressive increase in the value of housing. This increase is likely to reach its maximum within one to two years.



**Figure 1.** Geographical Seville, Spain context. Source: Own elaboration from www.ign.es (accessed on 5 November 2022) and https://www.juntadeandalucia.es/institutodeestadisticaycartografia/DERA/ (accessed on 5 November 2022).

In the medium term, the consequences can be minimized through a set of local development policies aimed at sustainable development. Additionally, using the housing stock for sale may also have a mitigating effect. Under this course of action, green spaces will have to play an active role if the city government intends to maintain Seville's role as a sustainable urban centre on an international level.

# 4. Material and Methods

In this research, a total of 1000 observations of housing values in the Seville capital were collected during August of 2022 from Idealista S.A.U (www.idealista.com (accessed on 17 October 2022)). Figure 2 presents the flowchart of this research.

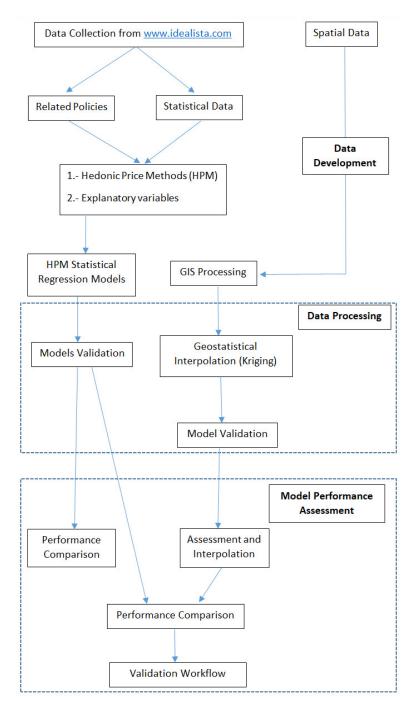


Figure 2. Flowchart of this research. www.idealista.com (accessed on 17 October 2022).

In order to facilitate and organize the data collection correctly, a decision was made to group observations according to zones corresponding to one or more districts of the city. To adequately select the sample "n" that was to be considered in each set of districts (Table 1), it was decided that stratified random sampling should be used (stratified random sampling is a technique used when clearly identifiable subgroups or subpopulations can be distinguished in the population).

District(s) of Seville Capital	n (Observations)	
Triana	73	
Torreblanca-Sevilla Este-Parque Alcosa	160	
Santa Justa-Miraflores-Cruz Roja-San Pablo-Santa Justa	92	
San Jerónimo-Pino Montano	111	
Prado de San Sebastián-Felipe II-Bueno		
Monrreal-La Palmera-Los	107	
Bermejales-Bellavista-Jardines de Hércules		
Nervión	79	
Macarena	114	
Los Remedios	39	
Cerro-Amate	138	
Centro	88	
Total	1000	

**Table 1.** Data grouping and observations using a set of districts (Own elaboration).

In each dwelling for sale the selected independent variables are specified in Table 2.

Table 2. Explanatory variables taken into account (Own elaboration).

Independent Variables	Specification	
Size (m <sup>2</sup> )	Property area in m <sup>2</sup>	
Rooms $(n^{\circ})$	Number of bedrooms	
Baths (n°)	Number of bathrooms	
Age (years)	Dwelling age in years	
Green area (m <sup>2</sup> /inh)	Green area in the set of districts presented in m <sup>2</sup> per inhabitant	
Property sale semester (dummy variable)	This variable will be equal to 1 when the property has been sold in a given period, otherwise its value will be 0	

In another vein, Table 3 gives the mean values of the explanatory variables.

Table 3. Mean values of the explanatory variables (Own elaboration).

Variables	Mean Value
Size (m <sup>2</sup> )	100
Rooms ( $n^{\circ}$ )	4.2
Baths (n°)	1.8
Age (years)	22.8
Green area (m <sup>2</sup> /inh)	17.14

From these explanatory variables the dependent variable  $(\text{€}/\text{m}^2)$  was derived by applying the HPM, which was then compared with values inferred for both the Logarithmic Model (LM) and the Reciprocal Model (RM).

On the other hand, in order to know how a property's situation affects the sale price, a geostatistical interpolation was carried out using a regression of Gaussian processes (Kriging) through an open-source geographic information system QGIS (www.qgis.org (accessed on 21 September 2022)). This was done with the aim of explaining the relationship between dwelling situation and housing price. A District Index (DI) was calculated as

the average price per  $m^2$  and was taken into account (Table 4) in accordance with Solano-Sánchez et al. [39]. Under the predefined hypothesis, a higher value per  $m^2$  in a district implies a higher dwelling value. This index was created by assigning one value to the city's most expensive district and then assigning a proportional value to the remaining zones. In order to be able to test and validate this study, a comparison of real price (www.idealista.com) versus estimated price for each HPM model will be conducted.

Table 4. District Index (DI) value for each set of districts (Own elaboration).

Set of Districts	€/m <sup>2</sup>	DI
Triana	2715.69	0.865
Torreblanca-Sevilla Este-Parque Alcosa	1207.94	0.385
Santa Justa-Miraflores-Cruz Roja-San Pablo-Santa Justa	1919.3	0.612
San Jerónimo-Pino Montano	1188.24	0.379
Prado de San Sebastián-Felipe II-Bueno Monrreal-La Palmera-Los Bermejales-Bellavista-Jardines de Hércules	2497.18	0.796
Nervión	2642.49	0.842
Macarena	1368.73	0.436
Los Remedios	2899.17	0.924
Cerro-Amate	1017.51	0.324
Centro	3137.89	1

Finally, a literature review was conducted to analyze the results obtained in this study and to carry out a coherent discussion concerning the works published to date.

# 5. Results and Discussion

Following the data analysis, it was discovered that including the green area  $(m^2/inh)$  variable in the price equation allowed for the estimation of the influence of environmental factors on dwelling market value. In order to find out if the HPM presents multicollinearity, it was decided that obtaining the Variance Inflation Factor (VIF) (Table 5) would be required. As is well known, if the VIF value for each independent variable is greater than ten then the multicollinearity is considered to be high.

**Table 5.** Independent variables and coefficients of linear HPM model (r = 0.85,  $R^2 = 0.721$ ,  $p \le 0.001$ ) (Own elaboration).

Variables	Coefficients	Stand. Error	Student's t	Prob.	VIF
Constant	-120.443	14.795	-0.075	0.000	-
Size (m <sup>2</sup> )	30.032	0.039	1.7	0.000	1.622
Baths ( $n^{\circ}$ )	98.725	0.042	0.14	0.000	1.467
Age (years)	-53.31	1.42	-1.42	0.000	1.535
Green area (m²/inh)	11.145	0.87	0.872	0.000	1.020

Regarding the HPM model selected as the most satisfactory, it should be mentioned that the linear function form was found to be the most appropriate after performing the data analysis. Like the VIF, Table 4 also displays the independent variables' coefficients.

As for the logarithmic model, in addition to the VIF value, Table 6 provides the differences with respect to the linear model. Thus, the main difference is the dependence on the number of rooms (Rooms) variable in the logarithmic model. In contrast, under the linear model, the property's value depends on the dwelling area (Size) variable. This may be because of the relationship between both variables which causes the predominant variable to cancel the slave variable in the requisite model depending on the selected model.

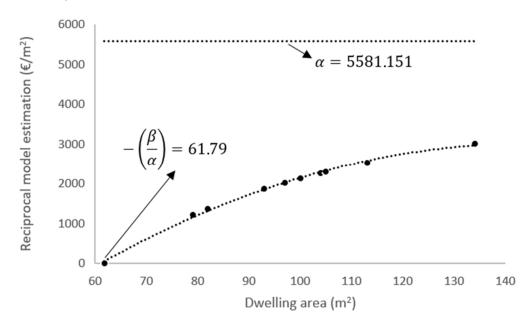
Variables	Coefficients	Stand. Error	Student's t	Prob.	VIF
Constant	6.56	1.49	4.36	0.000	-
Room	1.39	1.08	1.29	0.000	1.705
Baths $(n^{\circ})$	0.26	0.6	0.432	0.000	1.523
Age (years)	-0.365	0.205	-1.78	0.000	1.380
Green area (m <sup>2</sup> /inh)	-0.013	0.13	-0.1	0.000	1.000

**Table 6.** Independent variables and coefficients of the logarithmic HPM model (r = 0.816, R<sup>2</sup> = 0.667,  $p \le 0.001$ ) (Own elaboration).

If the reciprocal model is analyzed, Equation (8) is obtained (r = 0.647, R<sup>2</sup> = 0.42,  $p \le 0.05$ ):

$$P = 5581.151 - 344,864.49 \cdot \left(\frac{1}{S}\right) \tag{8}$$

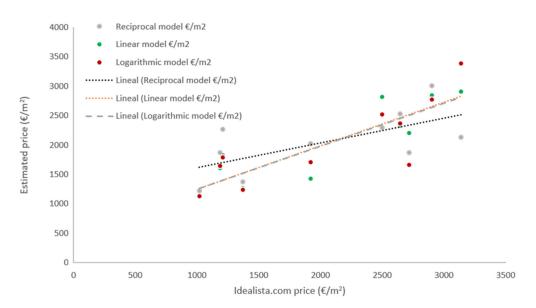
After the reciprocal model's price estimation (Figure 3) is represented, it can be observed that the price function shape in the limit, "*P*" trends towards " $\alpha$  = 5581.151". The term " $-(\beta/\alpha)$ " refers to the smallest amount of surface available in a dwelling (61.79 m<sup>2</sup> in this study).



**Figure 3.** Reciprocal model representation when " $\alpha > 0$ " and " $\beta < 0$ ". (Own elaboration).

If the three models are compared based on the coefficient of determination ( $R^2$ ), it can be said that a higher value of this coefficient implies a better estimate of the housing price. For this reason, the linear model explains 5.4% more of the predicted price than the logarithmic model and 30.1% more than the reciprocal model. On the other hand, the logarithmic model explains 24.7% more of the estimated price than the reciprocal model.

Additionally, the Chow test [40] was used to ensure the models' stability. It should be noted though that the Chow test has its origin in economics. Nevertheless, it has also been applied to other fields such as renewable energies [41], flood risk assessment [42], and spatiotemporal disease diffusion [43]. In this study, the results revealed that no structural changes occurred exclusively in the parameters of either the linear or logarithmic models. This can be seen in Figure 4, which compares the real price (from www.idealista.com (accessed on 18 October 2022)) to the estimated price for each model used. As can be seen, Figure 4 allows for the simulation of hypotheses that facilitate the validity of the study to be tested.



**Figure 4.** Comparison of real (www.idealista.com (accessed on 17 October 2022)) versus estimated prices for each HPM model. (Own elaboration).

When the models' degree of fit is perfect, they should appear as point clouds in a diagonal line starting at the origin (1017.51; 1119.94 in this study), as shown in Figure 4. In this case, the estimated values for linear and logarithmic models indicate that the linear form is a good fit. However, the reciprocal model presents a trend line that does not coincide with the indicated origin. For this reason, the model does not have as much stability as the linear and logarithmic ones.

Furthermore, with regard to the kriging, Figure 5 shows the geostatistical price interpolation for the city of Seville. As is well known, in order to perform predictions using kriging the forecasting system must be geometrically defined at some point. This means that we must establish the neighbourhood of the data that will intervene in the approximation. It is possible to use all the dwelling prices (assuming a global neighbourhood) and a set of data (considering a local neighbourhood) in the estimation. In practice, only house prices within a predefined circumference or ellipse centred on the estimated point are used. Obviously, the proximity of the data for each point to be valued will differ, thereby necessitating a different kriging equations system for each point on the map at which a prediction is desired. On the other hand, this method allows for the synthetic representation of housing price estimates in the form of a colour map. This representation is generated by performing predictions on the nodes of a regular mesh. In this manuscript the housing price has been estimated at each node of a 10-m-sided regular mesh.

The map in Figure 5 displays how the more valuable areas coincide with those closest to the city centre. The least valued areas, on the other hand, are primarily in the districts of San Jerónimo-Pino Montano, Torreblanca-Sevilla Este-Parque Alcosa, and Cerro-Amate. This is primarily due to a shift in buyer preferences following the COVID-19 pandemic. Following confinement the percentage increase in the preference for housing (new or used) with a balcony was around 80% [44]. As a result, the average percentage decrease in housing prices was 5% across the districts, except for the Centro district which is dominated by homes with small balconies and a communal roof terrace. In order to compare the kriging values in terms of  $\notin/m^2$  with those of the analyzed models, Table 7 lists the average values per district corresponding to the centroid established in the geospatial analysis.

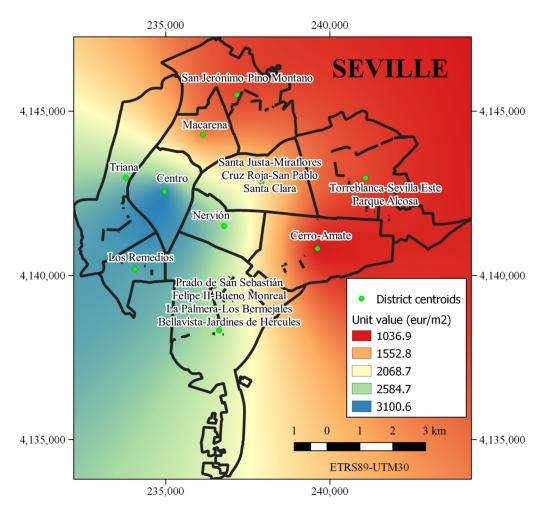


Figure 5. Dwelling price map estimated by ordinary kriging. (Own elaboration).

**Table 7.** Comparison of the average housing price  $(\ell/m^2)$  in each district's centroid is calculated by linear, logarithmic, and reciprocal models to those obtained by kriging. (Own elaboration).

Set of District(s)	Kriging (€/m²)	Reciprocal Model (€/m²)	Linear Model (€/m²)	Logarithmic Model (€/m <sup>2</sup> )
Triana	2715.69	1872.93	2206.78	1659.61
Torreblanca-Sevilla Este-Parque Alcosa	1207.94	2265.14	1829.18	1787.60
Santa Justa-Miraflores-Cruz Roja-San Pablo-Santa Justa	1919.3	2025.84	1429.27	1708.55
San Jerónimo-Pino Montano	1188.24	1872.93	1608.77	1641.63
Prado de San Sebastián-Felipe II-Bueno Monrreal-La Palmera-Los Bermejales-Bellavista-Jardines de Hércules	2497.18	2296.73	2815.51	2522.79
Nervión	2642.49	2529.25	2332.77	2368.58
Macarena	1368.73	1375.48	1265.74	1240.19
Los Remedios	2899.17	3007.53	2844.85	2776.72
Cerro-Amate	1017.51	1215.78	1119.94	1132.06
Centro	3137.89	2132.50	2903.91	3390.32

Based on the findings of this study, it is clear that the dependent variables considered in the models used are consistent with previous studies [3,45–50] in terms of distance to the city centre.

Finally, in order to know the influence of urban green spaces on housing prices in the Andalusian capital given the results of the geostatistical analysis, it has been possible to observe that each square meter of green space per inhabitant increases the dwelling value by  $120.19 \notin /m^2$ .

#### 6. Conclusions

In this study, a hedonic price function of housing was calculated in which the sale price was related to the endowments of urban green areas in the city. Along with a set of conventional explanatory variables, one environmental variable, the green area's size (in m<sup>2</sup>/inh), was included on the right-hand side of the regression. The results show that the statistically significant variables are model dependent. In this regard, the variables considered in the linear model were dwelling size, number of bathrooms, housing age, and green area per inhabitant. Alternatively, the logarithmic model used the number of rooms, bathrooms, dwelling age, and green area per inhabitant as dependent variables. The only explanatory variable in the reciprocal model was the size of the living area.

Additionally, it should be noted that housing covered by official protection regulations [51,52] is significantly less expensive than housing sold in free market conditions. This fact demonstrates the effectiveness of public policies that encourage home ownership. A reciprocal model allowed us to calculate the minimum living area (61.79 m<sup>2</sup>) that housing options in the sample areas tend to have.

In terms of environmental variables, only the size  $(m^2/inh)$  of the green area is significant in this study. According to estimates, each square meter of green space per inhabitant in the district raises the housing value by 120.19  $\epsilon/m^2$ . Although the size of the green area effect is small, it has important policy implications for urban planning because it appears to indicate that providing numerous small green areas throughout the city is preferable to a few large parks.

Moreover, concerning the geostatistical analysis (kriging) performed using a GIG, this study suggests that using the kriging method for mass appraisal may be of interest. Continuous maps of housing prices can be obtained using this method, thereby providing appraisers with an overall view of pricing.

Under the assumption of quasistationarity, the ordinary kriging method produced slightly better results than the detrending method. Nevertheless, among the available geostatistical methods, cokriging could provide the best results in crossvalidation [53]. The reason is that the multivariate method allows us to use isotopic (original sample) and heterotopic (original sample plus second sample) forms of data. This method also allows us to perform house price valuations when the only available characteristic is location. The regression model (HPM models used in this work), on the other hand, can only work with isotopic data and, in order to derive housing prices, the characteristics of the houses must be known. Another interesting difference between cokriging and regression models is that multicollinearity among explanatory variables is desirable in the former but not in the latter.

In addition, the linear HPM model produced the best values for the ratio between estimated and observed values. Comparatively, the reciprocal HPM model was the worst in this regard.

Furthermore, it is worth pointing out that the methodology used in this study could be a key tool for city governors in that it can facilitate sustainable planning and design of all existing cities around the world. It could even be very useful for those professionals who, in the course of purchasing and selling of real estate, need to know the influence of green spaces on housing prices in order to offer clients the right property based on their economic possibilities.

Finally, future studies could be aimed at finding out what influence exists at the level of the autonomous community or even at the national level. Given the observations of this study, it follows that periurban green areas must have a significant influence on the prices of dwellings isolated from the main urban nucleus. Even those dwellings belonging to the city which are close to peri-urban parks may also be subject to these influences.

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