International Journal of Geo-Information

MDPI

Article

A Spatial Regression Model for Predicting Prices of Short-Term Rentals in Athens, Greece

Polixeni Iliopoulou [1,*], Vassilios Krassanakis [1], Loukas-Moysis Misthos [1,2] and Christina Theodoridi [1]

[1] Department of Surveying and Geoinformatics Engineering, University of West Attica, Egaleo Park Campus, Ag. Spyridonos Str., Egaleo, 12243 Athens, Greece; krasvas@uniwa.gr (V.K.); lmmisthos@uniwa.gr (L.-M.M.)
[2] Department of Public and One Health, University of Thessaly, 43100 Karditsa, Greece
* Correspondence: piliop@uniwa.gr

Abstract: Short-term house rentals constitute a growing component of tourist accommodation in several countries and the determination of factors affecting rents is an important consideration in relevant studies. Short-term rentals have shown increasing trends in the city of Athens, Greece; however, this activity has not been adequately studied. In this paper, spatial data of Airbnb rentals in Athens are analyzed in order to indicate the factors which are important for the spatial variation of rents. Factors such as property capacity, host attributes and review characteristics are considered. In addition, several locational attributes are examined. Regression analysis techniques are used to predict the cost per night, according to various explanatory factors, while the results of two models are presented: ordinary least squares (OLS) and geographically weighted regression (GWR). The results of the OLS model indicate several factors determining the rent, including capacity and host characteristics, as well as locational attributes. The GWR model produces more accurate results with a smaller number of independent variables. For the residuals analysis several additional amenities were examined that resulted in a small impact on rents. The unexplained spatial variation of rents may be attributed to neighborhood characteristics, socioeconomic conditions and special characteristics of the rentals.

Keywords: short term house rentals; Airbnb; spatial analysis; ordinary least squares (OLS); spatial regression; Athens; geographically weighted regression (GWR)

check for updates

Citation: Iliopoulou, P.; Krassanakis, V.; Misthos, L.-M.; Theodoridi, C. A Spatial Regression Model for Predicting Prices of Short-Term Rentals in Athens, Greece. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 63. https://doi.org/10.3390/ijgi13030063

Academic Editors: Wolfgang Kainz and Jamal Jokar Arsanjani

Received: 11 December 2023
Revised: 2 February 2024
Accepted: 18 February 2024
Published: 20 February 2024

Copyright: © 2024 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/).

1. Introduction

Although there are several definitions of a sharing economy, it can be described as an economic activity of sharing resources among peers coordinated through online services [1]. There are various sectors in which services are provided in a sharing economy framework, and hospitality is one of the most important ones [2,3]. Hospitality platforms have grown very rapidly since 2008 and currently 10 million properties are listed in 120,000 cities [4]. The Airbnb platform is one of the leaders in the vacation rentals industry with over seven million listings in more than 100,000 countries [5,6].

The sharing economy in Greece started around 2010 and concerned houses for rent, as well as private transportation. Currently, sharing economy concerns primarily rentals for tourist accommodation. This type of sharing economy was related with the economic crisis which began in 2010 and the economic strains on households which were not able to pay off mortgages and in general cope with reduced income [7]. The first establishments were rooms in houses with no special amenities that were listed on the Airbnb platform. In 2010 there were only 132 listings in Greece, and almost half of them were in the region of Attica in which Athens, the capital of the country, is located. The number of Airbnb rentals rapidly increased especially after 2013, when tourism arrivals increased significantly. In 2018 the number of rentals in Greece was approximately 130,000 [8].

In terms of overnight stays, short-term rentals account for 2.8% in Greece, according to official data for the year 2022, but 7.6% correspond to the regional unit where Athens

belongs (Kentrikos Tomeas Athinon). Because of its archaeological sites and other tourist attractions the city of Athens has been one of the first regions in Greece to enter the short-term rentals market, targeting mostly visitors from abroad. The center of Athens ranks first, among the NUTS3 regions in terms of the overnight stays in short-term rentals [9,10].

Currently, according to AirDNA (accessed on 2 June 2023) [4], Athens attracts over 10,000 rentals, compared to only 33 rentals in 2010 [8]. In addition, data from insideairbnb.com (accessed on 2 September 2016 and 8 November 2023) [11] indicate a sharp increase of rentals after 2015, from approximately 2000 rentals in July 2015 to 12,350 in June 2023. (It is not possible to know the exact number of listings in the insideairbnb.com site since data concern several dates within the year. Furthermore, counts from airdna.co and insideairbnb.com are not fully comparable because the geographical breakdown for the city of Athens is different. It appears that insideairbnb.com includes data for several municipalities in the Greater Athens region and not only data for the municipality of Athens. In this work, the analysis concerns the municipality of Athens.) Airbnb was the first platform for short-term rentals in Greece, although other platforms such as Booking and Vrbo have entered this market in recent years. In Athens, according to http://airdna.co (accessed on 1 June 2023) [4], 79% of the rentals are listed in the Airbnb platform, 4% in Vrbo, and 17% in both platforms. In addition, a significant (but smaller compared to Airbnb) number of short-term rentals for Athens appear in http://booking.com (accessed on 1 June 2023) [12], although a possible overlap with other platforms cannot be calculated.

Because of its rapid growth, short-term rental activity has attracted research interest in recent years in many countries. Several aspects of short-term rental activity have been explored, such as the impact on long-term rents for residents, the impact on the neighborhoods hosting short-term rentals, the competition with the hotel sector and the factors influencing short-term rents [13–19]. However, in Greece, the number of studies on short-term rentals is very limited [7,8,20–22]. Two of these studies [7,22] Boutsioukis et al. [22] examine the Airbnb penetration in the country. Balabanidis et al. [7] also examine the effects of Airbnb activity in Athens; they present evidence that Airbnb in Athens causes a substantial increase of rents in several neighborhoods, resulting in the displacement of lower status social groups, including migrants. In addition, touristification processes can affect a neighborhood's character, social life, and social cohesion. On the other hand, Airbnb activity has positive effects on small businesses and individual professionals and it is considered to contribute to soft urban regeneration. In that respect, it seems to have a positive impact on both the urban environment and the economy. Iliopoulou and Stratakis [21] explore the spatial distribution of Aibnb rentals in 58 municipalities of the Greater Athens Region and suggest that the presence of hotels and the number of vacant houses are the most important factors for predicting the spatial penetration of Airbnb, while price per sq. m. of houses for sale is the most important factor for explaining the spatial distribution of rents. Athanassiou and Kotsi [20] provide information on the development and characteristics of the short-term accommodation sector in Greece, by examining several issues such as the size of the sector, its impact on the hotel sector and the regulatory framework.

The purpose of this study is to identify the factors affecting short-term rental listing prices. Price plays an important role in the shared economy, because it impacts a guest's accommodation selection and also has a significant impact on the host's profits. The studies which explore the price determinants of short-term rentals are rather limited in number, while in Greece this subject has not been adequately analyzed. Empirical results from other cities suggest a variation concerning the magnitude of factors determining rents [23]. Therefore, this study may contribute to the discussion on the range of factors that influence Airbnb accommodation prices, while the effect of individual characteristics on Airbnb rentals is of considerable interest to home owners, real estate brokers, developers and appraisers.

Studies for rent determination in several cities suggest a variety of factors, among which location and size are of great importance [15,23–28]. In all studies size characteristics are important, such as the number of bedrooms and beds, the number of bathrooms and the

maximum number of guests [23,25,27,28]. Size is related with the type of the rental, i.e., the entire house, independent or shared room. The type of the rental affects price not only in terms of capacity but also in terms of privacy [25]. Location concerns proximity to various points of interest (POIs) which will not necessarily be the same in different cities. In general, smaller distances from POIs are related to higher prices. In most studies the distance from the city center is important, although Perez-Sanchez et al. (2018) suggested that prices increased with distance from the historical center. The central points are defined for each city individually; for instance, it could be the historic city center or some landmark of economic or cultural importance [27–29]. Other POIs concern transportation, often distance from the nearest subway station [23,28,30]. Distance from tourist attractions is important, while the proximity to hotels has been examined as well [21,23,25,31]. Proximity to the coastline also increases rents in coastal Mediterranean cities [29,32]. The host's characteristics have been examined in the literature, for example, whether the host has good reviews and is characterized as a "superhost", and whether the host's identity has been verified. Also, the number of the host's listings seems to affect prices positively, indicating higher prices for commercial operation on Airbnb [23,27,30]. The number of reviews increases the visibility of the listing, while high review scores overall or on certain criteria, such as cleanliness, increase prices [24,25,27,28,33]. However, having a large number of reviews is related to lower rents in some cities [27,29,30,33,34]. Additional amenities, such as parking space and wireless internet, also increases the rent [27].

The methods employed to identify the most important factors contributing to rents are, in general, regression models. Regression models are widely used for estimating property values; in this form, they are also known as hedonic models [35–39]. Various forms of regression models have been developed, to optimally fit the data. For estimating property prices linear regression is commonly used, often with some log transformation of variables. Similar models have been used for estimating rents [40–42]. Therefore, it is expected that these models would be useful for predicting sharing economy rents, although rents refer to short-term rentals which have—to some extent—hotel characteristics. Regression models for predicting short-term rentals have been presented for several cities in the world [24,26,27,33]. Linear regression models (ordinary least square—OLS) are used in several studies [18,26,27,30], as are other forms of regression, such as quantile regression [31,32,43]. For problems where the spatial dimension is evident, such as the analysis of property values, spatial regression models have been developed. They are particularly useful when the results of OLS indicate violation of the basic assumptions of the method, mostly the independence of residuals. Provided that the location of the observations is available, spatial regression models can be implemented, often producing more accurate results compared to OLS. Spatial regression models are based on the measurement of spatial autocorrelation (the similarity of values in neighboring locations). In several studies of short-term rentals, spatial regression models together with various methods of spatial analysis are used. Indices measuring spatial autocorrelation are commonly used, while different spatial regression models, among them geographically weighted regression (GWR), are constructed [21,26,28,29,34,44,45]. When spatial regression is to be employed, it is typically preceded by an OLS regression in order to examine the independence of residuals.

The results of the analysis of short-term rentals in different cities indicate that certain models leave a considerable percentage of variability in rents unexplained. For example, Gibs et al. [24] analyzed data for Canada employing 15 variables describing general characteristics, amenity features, management features, review quantity and quality, as well as host characteristics in a hedonic price model which resulted to 52.7% explained variance. Lladós-Masllorens and Meseguer-Artola [25] performed regression analysis of Airbnb data for Madrid and Barcelona including location, host's characteristics, property attributes and quality signaling factors. In all variants of the model, around 50% of the price variability is explained. Tang et al. [26] in a study for ten tourism cities in USA analyzed fourteen variables describing site and situation attributes employing spatial regression models and

the explained variance ranged from 20.3% to 34.6%. Zhang et al. [28], in a study for Metro Nashville Tennessee, employed GLM and GWR models with five explanatory factors which resulted in a maximum of 30% explained variability in Airbnb prices. Tong [33], in a study for Barcelona and Madrid, presented a hedonic pricing model using weighted least squares and quantile regression after performing clustering on room types and attributes. Fourteen variables concerning the type of the listing, capacity, host attributes, reviews, location, number of photos and cancellation policy were incorporated into the model, resulting in a percentage of explained variance of around 70%. Perez-Sanchez et al. [32] in a study for four Spanish Mediterranean cities, performed OLS and quantile regression employing 18 independent variables grouped into four categories, i.e., accommodation characteristics, advertisement and host features, environmental characteristics and location characteristics, and the explained variance in the OLS model reached 64%. Chica-Olmo [29] introduced 21 variables in OLS and spatial regression models, and the explained variance reached a maximum of 46%. In this study, the price of the rental in terms of cost per night is examined relative to a series of factors concerning property characteristics and host attributes, as well as locational factors. Data on short-term rentals include listings from the Airbnb website, since this website is the most popular platform for short-term house rentals in Greece. In addition, data for Airbnb listings are available for certain dates from the http://insideairbnb.com/ site (accessed on 2 September 2016 and 8 November 2023) [11]. The study region is the municipality of Athens. Within the municipality of Athens, important differences exist in terms of the proximity to tourist attractions, transportation infrastructure, socioeconomic conditions, etc. Since rents are quite different within the study region, the purpose of this study is to explain the spatial variation in Airbnb rents.

It is expected that the characteristics of rentals which influence rents are to some extent similar to the ones used in hedonic pricing models for the valuation of dwellings. The housing characteristics can be grouped as structural, location and neighborhood characteristics [39]. Structural characteristics include size, age floor, type of property, parking. Location refers to distances from points of interest relevant to the study region. Neighborhood characteristics in particular, such as criminality, pollution and noise are important for Athens; however, there is very limited data available. According to Sirmans [38], of all these characteristics, size is of primary importance together with age, bedrooms, bathrooms, garage, swimming pool, fireplace and air conditioning. Given the hospitality nature of short-term rentals, apart from the housing characteristics, the host characteristics and the reviews are expected to be important factors that influence rents.

The research hypotheses are that the characteristics of rentals which influence Airbnb rents include capacity, location relative to POIs, host attributes and reviews. The size of the rental will affect the rents. Some attributes of rentals, such as the maximum number of guests or the number of bathrooms may indicate their size. Location appears to be important: especially proximity to major archaeological sites, which is expected to increase rents. A similar effect is expected for proximity to the city center and the subway stations which provide easy access to the center and the tourist attractions. In addition, it is anticipated that Airbnb rentals with higher rents will tend to be close to the hotel area in the city of Athens. Finally, if a host has consistently good reviews as well as credibility (host identity verification), it seems reasonable that prices will increase. Similarly, high review scores are expected to increase prices, while the number of reviews might have a negative impact. Additional amenities, such as parking space, are also expected to increase prices. In terms of statistical analysis, it is expected that a regression model is appropriate for explaining rents and since there is a clear spatial dimension in the Airbnb data, a spatial regression model should be more accurate.

After describing the study region and the data set, statistical analysis is presented in terms of descriptive statistics, correlation analysis and regression analysis. The factors contributing to rents constitute rental characteristics derived from the Airbnb platform, but also locational attributes, in terms of distances from points of interest (POIs). Two regression models are constructed, an OLS model and a GWR model. The results of the

OLS model indicate several factors that determine the rent, including capacity and host characteristics, as well as locational factors. The GWR model produces more accurate results when including only capacity and host characteristics. The GWR model explains to a quite significant degree the spatial variability of Airbnb rents, while the unexplained variance can be attributed to neighborhood characteristics, socioeconomic conditions or special characteristics of the properties. The results of the models are visualized in an interactive web platform.

2. Materials and Methods

2.1. The Study Region

The study region of this research study is the municipality of Athens, which is the capital of Greece. Figure 1 illustrates the study region, including the Airbnb rentals and two important POIs, i.e., Syntagma Square (the city center) and Acropolis. The present population is 637,798 inhabitants (2021), while there was a population decrease in the period 2011–2021. Although the hotel sector is well developed in Athens, short-term rentals have increased rapidly since 2010, when the first Airbnb listings appeared in Athens. An important characteristic of the municipality of Athens is the large percentage of vacant houses (31% according to data from the Hellenic Statistical Authority), which is attributed to the population movements away from the city center in previous decades [46]. Vacant houses combined with low house prices in certain areas close to the center have stimulated the transformation of many buildings in to Airbnb accommodation.

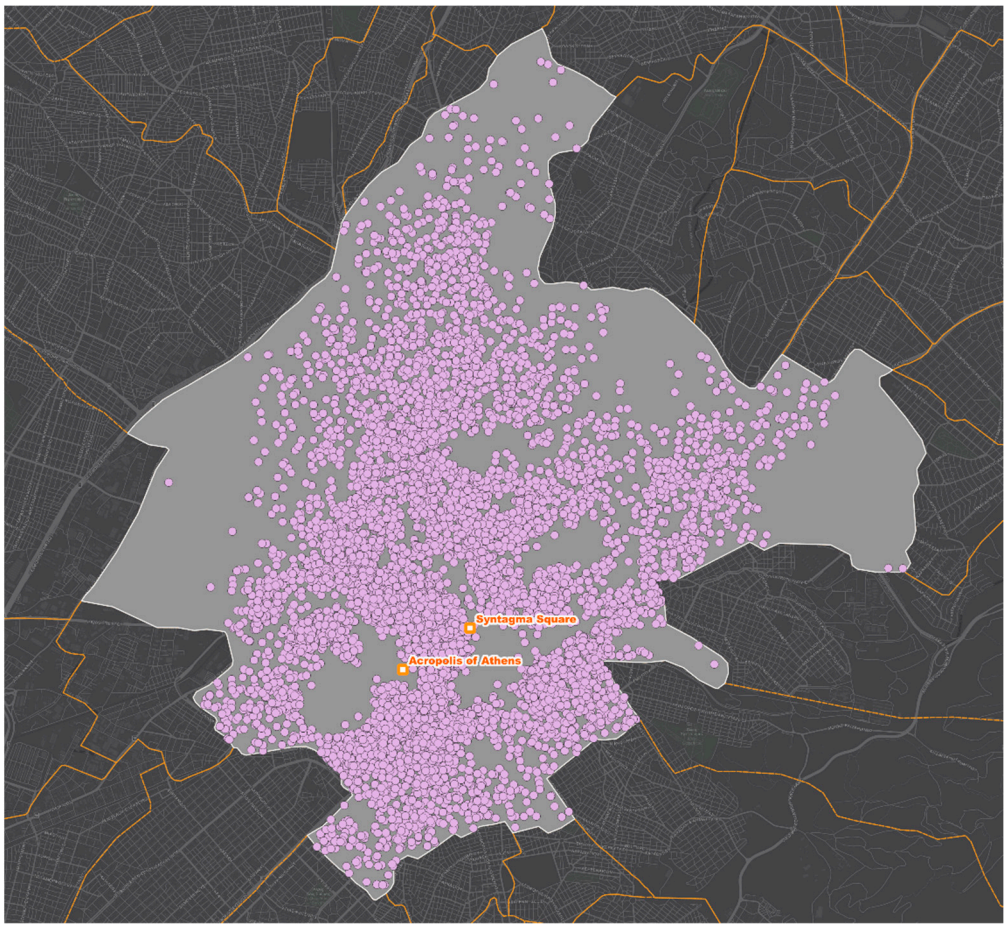

Figure 1. Map of the study region, the Airbnb rentals and two important POIs, i.e., Syntagma Square and Acropolis (elaboration from http://insideairbnb.com/, accessed on 24 September 2022).

2.2. Data

Data on short-term rentals in 2022 were extracted from the insideairbnb.com/ (accessed on 24 November 2022) website; these Airbnb data are a snapshot of the situation on 17 June 2022. Therefore, data refer to a particular date and they do not include all the available rentals over time. However, the selected day can be considered representative because it is a month within the peak of tourist arrivals in Athens with a large number of Airbnb listings. In terms of variables, a file named "summary information" and a detailed file including more information are both available at http://insideairbnb.com/ (accessed on 24 November 2022). In this study, the detailed file is used, containing a total of 76 columns in .csv format (comma separated values), most of them corresponding to individual variables. However, some of the columns contain detailed information about the property and the host characteristics, in text format. A smaller number of the above variables is considered useful for this analysis, according to the research hypotheses. In addition, five new variables were created in ArcMap 10.8, provided by ESRI®, which concern distances from POIs, i.e., the distances from: the city center (Syntagma Square), subway stations, museums and archaeological sites, hotels and the area including the monuments of Acropolis and the historical neighborhood of Plaka. Spatial data for some of the above POIs are publicly available, i.e., the metro stations (https://archive.data.gov.gr/dataset/arxeio-gewgrafikhs-apeikonishs-8esewn-sta8mwn-metro-kai-tram, accessed on 8 January 2023). The locations of hotels were derived from the official Greek hotels website (https://www.grhotels.gr/, accessed on 21 June 2021). A list of 267 hotels were recorded on this website and their addresses were located on Google Maps. A list of 27 museums and 12 archaeological sites in Athens was obtained from the Ministry of Culture (http://odysseus.culture.gr/, accessed on 15 June 2021) and they were located on Google Maps. Both maps were exported in ArcMap. Maps for the city center and the district of Acropolis and Plaka were created through digitization in ArcMap. Then, Euclidean distances of each listing from the five POIs were calculated in ArcMap.

The variables from the Airbnb data which are considered useful for statistical analysis and their description are presented in Table 1. In the same table, the locational variables are presented as well.

Table 1. Variables in the analysis of the Airbnb data set.

Variable	Description
price	Price in $
room type	Entire home or apartment/Private room/Shared room/Hotel
accommodates	The maximum capacity of the listing
bathrooms	The number of bathrooms
bedrooms	The number of bedrooms
beds	The number of beds
host_listings_count	The number of listings a host has
host_is_superhost	The host has consistently good reviews (true or false)
host_identity_verified	Identity verification with legal documents (true or false)
number_of_reviews	The number of reviews the listing has
review_scores_rating	Review score
distance from the city center	Distance from point feature (in meters)
distance from Acropolis and Plaka	Distance from polygon feature (in meters)
distance from subway station	Distance from the closest subway station (in meters)
distance from museums and archaeological sites	Distance from the closest point feature (in meters)
distance from hotels	Distance from the closest point feature (in meters)

Since the data were large, multifarious and hard to use manually, an additional task was the question of how to handle the data effectively. Thus, towards the automatization

of the process of data extraction, there was a significant endeavor to develop and implement programming techniques. More specifically, a Python script was written (Python, version 3.x) and executed in order to extract the examined variables and produce an appropriate output that could serve as an input to any geographic information system (e.g., ArcGIS or QGIS). The initial idea for developing the aforementioned script was to deliver a simple command-based software tool which is meant to enable the automatic extraction of the desired variables from the corresponding raw data file provided by the platform that was used. However, considering the existing inconsistencies among the raw data files referring to different periods, this script has to be adapted to each case in order to effectively support the process of extraction. Nevertheless, this approach consists a groundwork towards developing an integrated framework which could also involve more sophisticated data cleansing techniques.

The number of listings for the municipality of Athens in June 2022 was 10,258; however, only 9021 listings were included in this analysis. This is because data cleansing was necessary since, as also referred to above, there are several inconsistencies in the data set. A great number of hotel rooms in the data set, as well as other types, such as boats and RVs, were removed. Additionally, a great number of private or shared rooms were actually hotel rooms. For this reason, and because the great majority of the listings (88%) concern a certain type of property, i.e., an entire home or apartment, only this room type was included in the analysis. At a second stage some cases were excluded for various reasons: wrong geographic coordinates, missing values for price or unreasonable values for certain variables. Also, data transformation was necessary, mainly from text to number format (e.g., price, bathrooms, superhost).

2.3. Statistical Analysis and Regression Models

At first, it was necessary to describe the variables in the data set employing methods of descriptive statistics. Frequency distributions count the occurrence of each value of the variable, providing an overview of values which prevail in the data set. They can be directly calculated for qualitative variables or variables with a few discrete values, such as type, numbers of bathrooms and bedrooms, in this data set. For quantitative variables, descriptive statistics, such as the mean, median, minimum and maximum can be calculated. In this data set, frequencies are calculated for the type of the rental and host characteristics. Minimum and maximum values indicate the presence of outliers in the data set, therefore both the mean and the median are calculated for quantitative variables.

In order to build a linear regression model, it was necessary to explore the relationship among variables. A linear relationship was assumed between price and the explanatory factors. Pearson correlation coefficients measure the linear relationships among quantitative variables and indicate the variables that are useful for regression analysis, i.e., the variables with a high correlation with price [47]. In this study, correlation analysis is carried out in order to identify the variables that are significantly correlated with the price of the listing and can be used for building a regression model.

The purpose of regression analysis is to construct a mathematical model which will explain one variable, the dependent variable, based on one or more independent variables (or covariates) which constitute the explanatory factors. The main goal for creating a regression model is to predict the values of the dependent variable for cases with unknown values for the dependent variable but available data for the independent variables. Regression analysis is a family of models. The most basic one is linear regression. In this model, the dependent variable is a linear function of the independent variables.

The parameters defining the model are the constant of the equation and the regression coefficients. The regression coefficient for an independent variable represents the change in the value of the dependent variable for a unit of change of the independent variable. Since the regression model is about fitting an equation to the data, there is always some error. The error (residual) for each observation is the difference between the value of the dependent variable which is calculated by the model (predicted) and the value in the original data

set (observed). The method for calculating the linear model is the method of least squares which minimizes the sum of the squared residuals for all observations. Usually, the linear regression model is referred to as ordinary least squares (OLS) model [47].

In regression analysis, the results include the predicted values and the residuals for all observations, the parameters defining the equation, as well as diagnostics evaluating the goodness of fit of the model. Furthermore, the standardized regression coefficients (beta coefficients) are the regression coefficients without the different units of measurements of the independent variables. Beta coefficients enable the comparison of the independent variables in terms of their effect on the dependent variable. If the values for independent variables are known for an observation outside the initial data set, regression coefficients are applied on the values of the independent variables in order to predict the value of the dependent variable.

In applications of regression analysis for spatial data, the observations are certain geographic entities or features, mostly points or polygons (regions). The linear regression model is often called global, because the regression equation applies to the study region as a whole, while the data for all features have been used for the calculation of the parameters. The residuals are visualized in maps and it is possible to examine whether they follow some pattern, for example, whether they are spatially clustered.

Linear regression analysis is based on a series of assumptions [48]. One important assumption is the existence of a linear relationship between the dependent variable and each one of the independent variables. Correlation analysis is directly related to the goodness of fit of regression analysis and the squared Pearson correlation coefficient is the most common measure of the goodness of fit of the regression model, referred to as the coefficient of determination or R square (R^2). The coefficient of determination is a ratio of the explained variance over the unexplained variance of the dependent variable. The values of R^2 are between 0 and 1 and values close to 1 suggest an almost perfect model fit. The adjusted R^2 makes a correction according to the number of independent variables and it is useful for the comparison of different regression models.

Although several independent variables may have linear relationships with the dependent variable, not all of them are included in the analysis. The selection of variables takes into consideration possible strong correlation among the independent variables, i.e., multicollinearity. In that case, there is redundant information and the results may not be significant overall. If a large number of independent variables are available, certain methods have been developed for selecting the variables to be included in the analysis. In this way, some of the independent variables are excluded from the analysis in order to avoid multicollinearity and statistically insignificant regression coefficients.

In linear regression analysis, the dependent variable should follow the normal distribution. In the case of data expressing property values, it is often observed that the distribution of the dependent variable is right-skewed, because of the existence of extreme values. In the case of Airbnb data, some listings with very high rents might result in an asymmetry in the distribution of rents, therefore a logarithmic transformation of the dependent variable could be used [15,24,27,49].

Another important assumption of regression analysis is that the residuals are independent. Often, in the analysis of spatial data, the residuals are not independent, because of spatial autocorrelation, meaning that the values of the variables are similar in neighboring locations. For example, prices of Airbnb rentals are expected to be similar in neighboring locations. Therefore, the OLS regression model is mis-specified and, in order to obtain accurate results, spatial regression models that analyze spatial data in a GIS environment have been developed. Spatial autocorrelation is represented in several ways and it can take the form of a spatial weights matrix which indicates the neighboring locations for each target location according to contiguity or distance criteria. Measures of spatial autocorrelation, such as the Moran's I, can be used in order to detect the spatial dependency of the residuals [50].

Several spatial regression models have been developed and all of them take into consideration spatial autocorrelation for the estimation of the parameters. For example, it is possible to create an independent variable, which, for a given geographic entity (or feature), is calculated using the values of the dependent variable for all the neighboring features. Neighboring features are defined according to the way spatial autocorrelation is conceptualized through the generation of spatial weights. This new variable is a spatially lagged variable and, according to the model, it can be a weighted sum or a weighted average of the neighboring values [50].

Another popular model is the geographically weighted regression (GWR) model which suggests that the global model is not accurate for all features engaged in regression analysis. Therefore, a local model is more appropriate for cases similar to our research study, since it builds a separate regression model for every geographic entity, which in this study is for each rental. Consequently, the regression parameters are not the same in the whole study region, but they differ for each location [51]. The data employed in each equation are the dependent variable at the target location and the explanatory variables for all locations falling within a bandwidth, which defines the neighboring locations. Therefore, the data is not used from all locations, but only from locations defined by a spatial kernel. Spatial kernels can be fixed, i.e., with a fixed bandwidth—the same for each location—or adaptive with varying bandwidths, according to the density of points. If the points are dense in a part of the study region, the bandwidth is small and vice versa. In this way, the study region is divided into smaller parts according to the density of locations. It is not necessary, therefore, to divide the region into smaller subregions (using some boundaries, administrative or empirical) and calculate the OLS model separately, since the GWR model does this work using the density of the observations' locations. Moreover, the values of the locations within the bandwidth are weighted according to their distance from the target location. Another advantage of the GWR model is that the spatial variation of the regression coefficients allows the assessment of the importance of each independent variable in different locations [51]. The regression coefficients form through interpolation raster surfaces and at any given location within the study region, the coefficients can be extracted. In order to predict values for the dependent variable for observations outside of the original data set, the location of each observation and the corresponding values of the independent variables are required.

In this study, the OLS model was calculated by setting as dependent variable the rent (cost per night) and as independent variables several characteristics of the rentals as well as locational attributes. The OLS model stands alone as a model for predicting rents. But it is also used as a way to examine whether a spatial regression model is appropriate. If the residuals are randomly distributed in the geographic space, it is not necessary to proceed to a spatial regression model. However, if the OLS residuals are spatially dependent, the OLS model is mis-specified and a spatial regression model could remedy this problem. Furthermore, if a large number of independent variables are used, an OLS model can indicate the variables to be entered in a spatial regression model. For this purpose, in our research work, after testing the OLS residuals for spatial autocorrelation, a GWR model was calculated for the same dependent variable but taking into consideration a smaller number of independent variables. The variables from OLS were not all appropriate in a spatial context, because apart from standard multicollinearity, there is also the concept of spatial multicollinearity when the values of an independent variable cluster spatially. The results of the two models were compared in terms of the explanatory power and the independent variables entered. The independent variables for both models were initially the same, including a number of quantitative variables as well as some binary (or dummy) variables. However, after the variable selection, the independent variables in the two models were different. In this study, the stepwise elimination method was used for the selection of variables in the OLS model. In this method, the variable with the highest correlation is introduced first, followed by other variables with relatively high correlations. However, variables entered in earlier stages are re-checked to decide if they

are still significant [47]. The residuals of the OLS were mapped and spatial autocorrelation was measured using the Moran autocorrelation coefficient. If the result indicates spatial clustering, a GWR regression model can be constructed in order to obtain more accurate results. The selection of variables for the GWR model is the result of several trials with different sets of independent variables. In this study, non-spatial statistical analysis was carried out, employing SPSS v.27, while ArcMap 10.8 was used for GIS operations and spatial analysis.

Moreover, an interactive web platform was developed in order to visualize the spatial allocation of the used data, connect such locations with the corresponding parameters and results (see Section 3)—having been produced by the implementation of both regression models—as well as to disseminate the current work to the public. The analyzed data are represented as geospatial entities with point geometry on different well-known cartographic backgrounds, including OpenStreetMap (OSM), Wikimedia map, and those provided by Google (Roads, Traffic, Satellite, Terrain Hybrid, and Maps), and ERSI (Gray (dark)). Moreover, the position of two important POIs (Syntagma Square and Acropolis) and the municipalities' boundaries were added as well. The development of the platform was based on the utilization of open-source software. More precisely, QGIS software (Version 3.22.4) was used for the symbolization of the geospatial data, the QGIS plugin QuickMapServices (https://plugins.qgis.org/plugins/quick_map_services-accessed on 1 December 2023) for the incorporation of the different backgrounds from several services, and the QGIS plugin qgis2web (https://plugins.qgis.org/plugins/qgis2web-accessed on 1 December 2023) for the production of the interactive web map using Leaflet (https://leafletjs.com-accessed on 1 December 2023) JavaScript library. Finally, KompoZer software was utilized to finally refine the webpage. An overview of the developed web platform is illustrated in Figure 2. The platform is accessible to everyone over the internet as Supplementary Materials (https://athensrentals.uniwa.gr accessed on 1 December 2023).

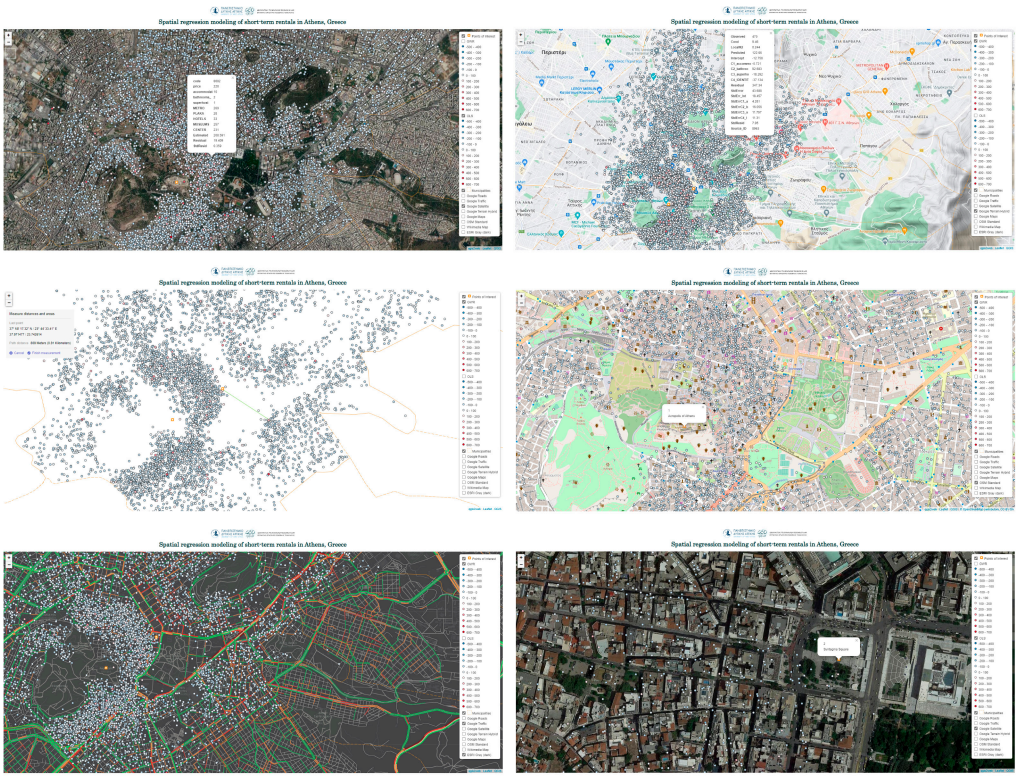

Figure 2. Overview of different aspects/snapshots of the web platform.

3. Results

3.1. Data Description

Frequency distributions were calculated for nominal data, i.e., host characteristics. The percentage of hosts with superhost status was 37.5%, while the percentage of hosts with identity verification is 79.3%.

For scale variables descriptive statistics were calculated (a and b in Table 2). The results indicate that some variables such as the number of host listings, the number of bedrooms and beds, as well as the review score rating have a large number of missing values in the data set and if they were included in regression analysis the number of cases would be significantly reduced.

Table 2. Descriptive statistics.

a. Descriptive Statistics: Price, Size Characteristics, Host Listings and Reviews.

		Price ($)	Accomodates	Bathrooms	Bedrooms	Beds	Number of Host Listings	Number of Reviews
N	**Valid**	9021	9021	9013	8254	8936	7566	9021
	Missing	0	0	8	767	85	1455	0
Mean		83.85	3.93	1.20	1.52	2.16	25.26	47.44
Median		64.00	4.00	1.00	1.00	2.00	4.00	15
Minimum		10	1	1	1	1	1	0
Maximum		900	16	10	10	16	748	778

b. Descriptive statistics: review score and distances from POIs (in meters).

		Review Score	Subway Distance (m)	Acropolis-Plaka Distance (m)	Hotels Distance (m)	Museums—Archaeological Sites Distance (m)	City Center Distance (m)
N	**Valid**	7719	9021	9021	9021	9021	9021
	Missing	1302	0	0	0	0	0
Mean		4.74	447.60	1228.01	217.48	709.82	1674.13
Median		4.86	381.00	945.00	137.00	509.00	1524.00
Minimum		0	1	0	2	4	29
Maximum		5	1882	6173	1805	4753	6155

In Figure 3 the spatial distribution of rents is presented. Rents at each point can be found in the interactive platform https://athensrentals.uniwa.gr (accessed on 1 December 2023) by selecting OLS. Rents (in $) are under the name "price".

3.2. Correlation and Regression Analysis

The correlation coefficients were calculated in order to explore linear relationships. Table 3 displays the Pearson correlation coefficients regarding the correlation of the "price" variable with the rest of the variables considered for analysis.

Table 3. Pearson correlation coefficients with "price".

Variable	Pearson Correlation Coefficient	Significance
accommodates	0.463	0.000
bathrooms	0.533	0.000
number of reviews	−0.045	0.000
subway distance	−0.148	0.000
Acropolis-Plaka distance	−0.276	0.000
hotel distance	−0.158	0.000
museums—archaeological sites distance	−0.259	0.000
city center distance	−0.270	0.001

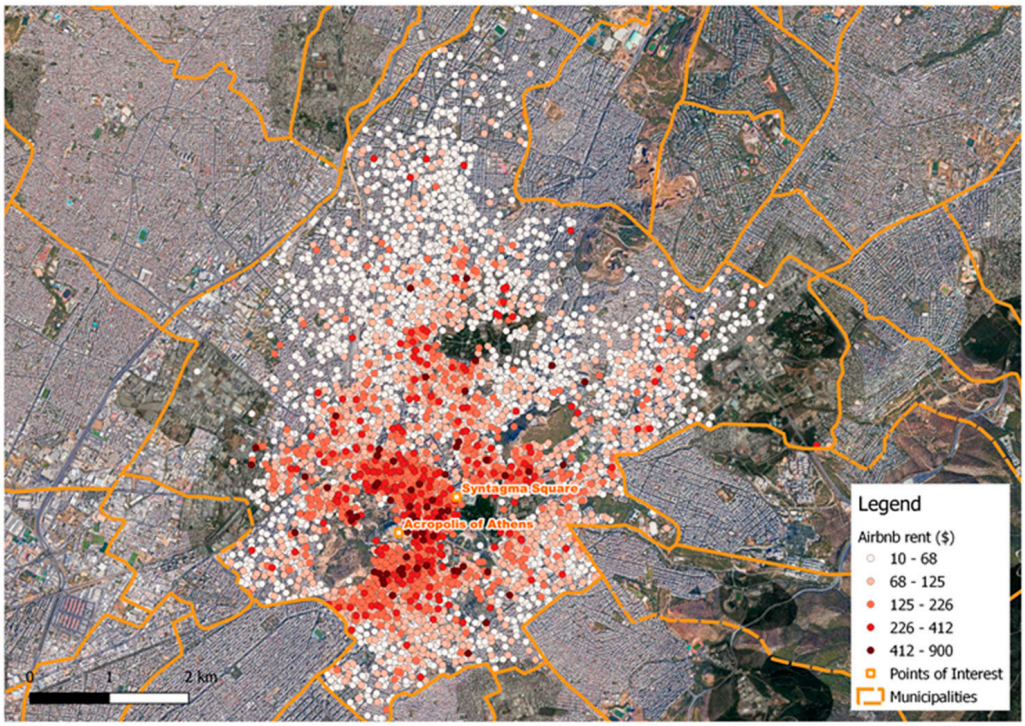

Figure 3. Price of Airbnb rentals (Elaboration from http://insideairbnb.com/, accessed on 24 September 2022).

After the correlation analysis, a linear regression model (OLS) was produced, having as dependent variable the price of the rental (cost per night) and as independent variables the capacity and locational characteristics of Table 3. In addition, two binary variables were introduced, concerning the host, i.e., the status of superhost and the verification of the host's identity. However, the number of reviews was excluded from regression analysis because the coefficient is very low. The OLS model can be calculated with conventional statistical analysis software, but also in a GIS environment. The difference is that when using statistical analysis software for the OLS model, it is easier to address multicollinearity problems and select independent variables which are not correlated with each other. In this study, the stepwise method was used for the selection of independent variables available in SPSS v.28. Initially, nine variables were introduced as independent variables, i.e., accommodates, bathrooms, superhost, host identity verification, and the five locational variables. After variable selection, eight independent variables were included in the OLS model. Two variables concern the size of the rental, i.e., accommodates and the number of bathrooms. One variable (superhost) represents host characteristics and five variables are distances from POIs, i.e., Acropolis and Plaka, the nearest subway station, museums and archaeological sites, hotels and the city center. The results of the OLS regression model are presented in Table 4. In this table, the standardized beta coefficients provide information about the relative importance of the independent variables. As a measure of the goodness of fit of the model, the adjusted R^2 was used, which has a value of 0.385. An additional trial was carried out with the addition of the variable "review score", because it was considered important for the determination of "price". In that case, all ten variables remain in the model and the adjusted R^2 increased to 0.42; however, only 7713 cases were used, due to missing values.

Table 4. Ordinary least squares (OLS) regression model with dependent variable "price" (SPSS).

Variables	Coefficients	Sig.	Standardized Coefficients (Beta)
Constant	15.119	0.000	-
accommodates	8.057	0.000	0.228
bathrooms	55.860	0.000	0.387
host is superhost	4.626	0.000	0.032
city center distance	−0.014	0.000	−0.185
Acropolis and Plaka distance	−0.012	0.000	−0.182
subway distance	−0.014	0.000	−0.056
museums—archaeological sites distance	0.013	0.000	0.126
hotels distance	0.010	0.003	0.032

Several procedures can be followed for improving the model's fit, as mentioned above. It is common to transform the values of the dependent and/or the independent variables using mathematical transformations [15,24,27,49]. In this study, running linear regression with a log-linear model increased the adjusted R^2 from 0.385 to 0.409. On the other hand, if data with a spatial reference were used, it would be possible to build spatial regression models. These models require a GIS environment, because then the location of the observations could be mapped and it would also be possible to measure spatial autocorrelation [21,26,28,44,45].

The residuals for the OLS regression are shown in Figure 4. Positive residuals indicate underestimation of prices and negative residuals overestimation. If spatial autocorrelation is detected, the OLS model is mis-specified and a spatial regression model is more appropriate. The residuals of the OLS model were tested for spatial autocorrelation using the Moran's I spatial autocorrelation coefficient. The coefficient indicated that the residuals are clustered at the 0.000 significance level. Therefore, an improvement of the model is expected when taking into consideration the spatial autocorrelation in the data. Initially, nine independent variables (as in the case of OLS) were introduced into a GWR model in ArcMap v.10.8, yet this model was not operational because local multicollinearity was detected [52,53]. After several trials, all variables representing distances from POIs were excluded and the GWR model was calculated with only four variables; two variables expressing the capacity of the rental (accommodates and bathrooms) and two variables concerning the host (superhost and identity verification). An adaptive kernel was applied in all versions of the model. The adjusted R^2 was equal to 0.536, showing a substantial increase relative to OLS. In Table 5, the diagnostics of OLS and GWR are compared including the Akaike information criterion [54]. The map of the residuals from the GWR procedure is presented in Figure 5. No regression coefficients were reported for the GWR model, since they were different for each point [51].

The residuals of the OLS and the GWR models were presented in the developed interactive web platform. The platform involves the municipalities' boundaries of Athens region and supports the exploration of the point spatial data. By default, the platform visualizes the residuals produced in both regression models using a common numerical and color scale in order to allow their comparison. Furthermore, the platform involves graphic tools that enable users to measure distances, as well as to interactively search locations (including specific POIs) on the backgrounds.

In order to analyze the residuals, additional information was extracted from the Airbnb data set. This information was included in the columns "Description" and "Amenities" and was available in text format. Five variables were extracted by writing a Python script (Python, version 3.x) combined with GIS operations: Wi-Fi, parking, view, pool and yard. The extraction of this information was not very reliable, since the wording for the same amenity might have been different throughout the listings, while for some variables the provision of the amenity is questionable. For example, Wi-Fi was written in different ways, while parking was often not within the property, but it was mentioned as free parking in the street or as paid parking. The results indicated that 26% of the listings

in this data set had the availability of Wi-Fi or Ethernet, 15% of the rentals indicated availability of parking space of all sorts, 12% had a view, mostly to Acropolis but also to the city, 4.9% had a yard, and only 18 rentals had a pool (0.2%). New calculation of regression analysis (OLS and GWR) indicated a small improvement of both models, if parking and Wi-Fi are included as independent variables, with the adjusted R^2 increasing by 1.5–2%. Furthermore, in another trial, all independent variables expressing distances from POIs were transformed to binary variables, i.e., less than 500 m and over 500 m (since 500 m can be considered as a walking distance), but there was no improvement of both OLS and GWR models.

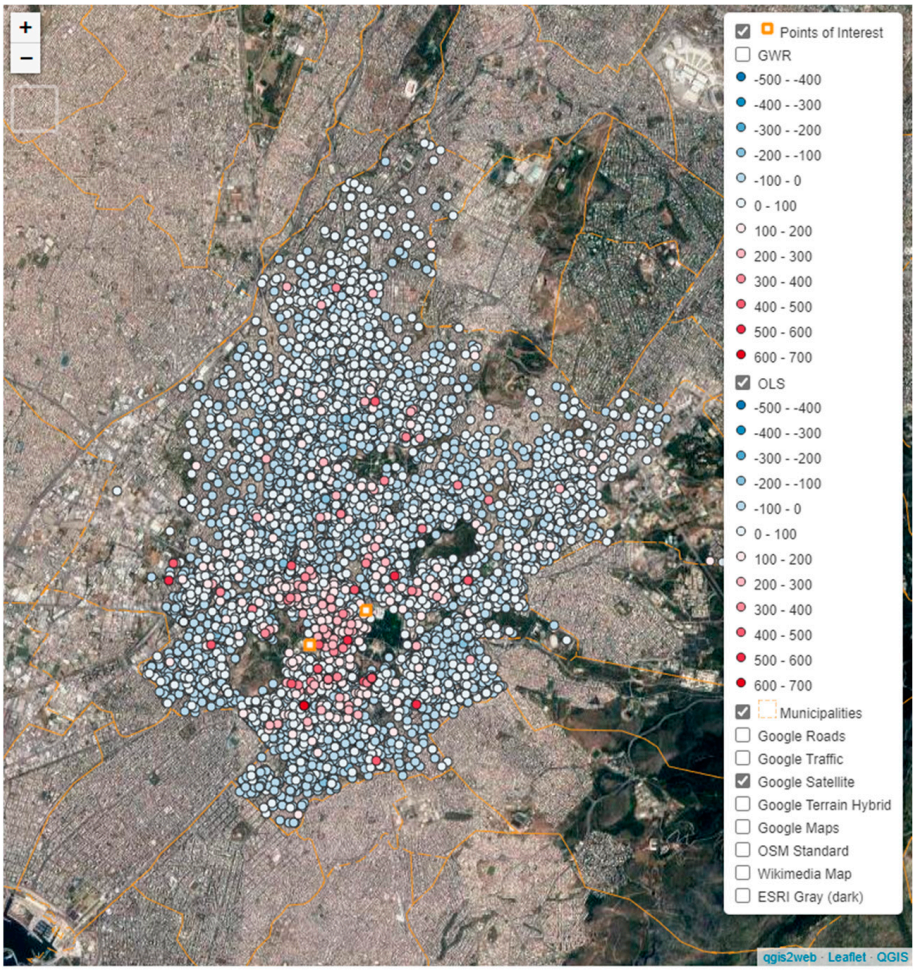

Figure 4. Ordinary least squares (OLS). Regression: residuals.

Table 5. Comparison of OLS and GWR models.

Model	Adj. R^2	AIC
OLS	0.385	97,509.19
GWR	0.536	95,675.74

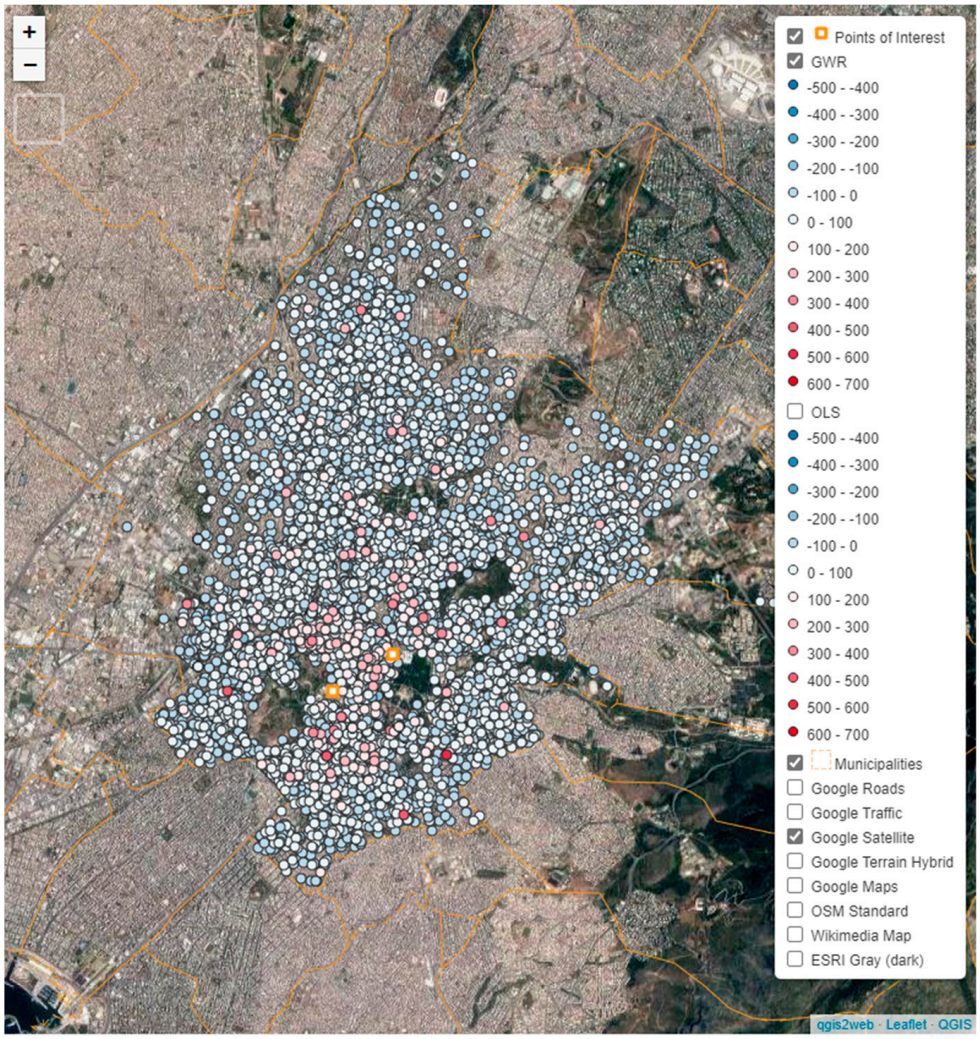

Figure 5. Geographically weighted regression (GWR): residuals.

4. Discussion

The results of the descriptive statistics indicate a great variation in the data. The mean price is 84$, although the median price is much lower (64$), since some of the listings are very expensive. The mean and median values are also quite different for the number of host listings, the number of reviews and some of the variables measuring distances from POIs. The mean distances from Acropolis-Plaka and the city center are significantly larger than the distances from the rest of the POIs. The minimum and maximum values suggest a great variability in the values of all variables.

Correlation analysis indicates that price has moderate positive correlations with the variables representing the capacity of the rental, while the coefficients with the variables measuring distances from POIs are all negative, as expected, but rather low. This is possibly due to the fact that distance is important if it is a walking distance; therefore, after some threshold the relationship is not linear. In addition, Euclidean distance was used; if distances along the road network were calculated, it is possible that the correlation would be stronger. At the first stages of designing the current research study, the potential to implement urban distance was examined. Since the road network in central Athens is very dense while, at the same time, building blocks are quite small, it was not expected to improve the results significantly. In addition, our experience with geographically weighted regression with numerous applications to property values in the Athens region [55,56], suggests that distances from POIs are not finally entered in this model. This is due to the fact that GWR incorporates distances anyway. Therefore, improvement of the results

might be expected only for the OLS model. Finally, the correlation of the number of reviews with price is negative and very weak. The negative sign agrees with results from studies in other cities [29,30,33,34]. This can be attributed to the fact that guests prefer cheaper rentals, since the purpose of renting short-term accommodation is to reduce costs. Therefore, cheaper listings tend to receive more bookings and consequently more reviews, resulting in an inverse relation of the number of reviews with price [27]. In OLS regression, nine variables were initially introduced. After the variable selection procedure, eight variables remained in the analysis as independent variables. The factors influencing rents are capacity (accommodates and bathrooms), location (all five distances from POIS) and host (superhost) characteristics, supporting the research hypotheses of this study. The beta coefficients, however, indicate that the most important factors are those expressing size (bathrooms and accommodates). Distances from the city center and from Acropolis and Plaka are also important.

Since the residuals of the OLS model were found to be spatially clustered, a spatial regression model was calculated. The GWR model included only capacity (accommodates and bathrooms) and host characteristics (superhost, host identity verification). No variables expressing distances from POIs were finally included, because spatial collinearity was detected. The GWR model results in a much higher R^2 and a lower value of the Akaike information criterion, relative to OLS. Both measures suggest a better fit of the model. Therefore, the GWR model produced a better fit with a smaller number of variables, which is a result that is also observed in other studies for Athens [55,56].

Despite this improvement, the results of the GWR model indicate that some variables are probably missing from the analysis. Several studies [15–28] report quite low coefficients of determination with similar data. As indicated in the introduction, in several studies the coefficient of determination is much lower than 50%. In this study, the explained variance of the GWR model is among the highest in the literature. The choice to include in the analysis only entire homes or apartments, together with data cleansing, probably results in improved model fit. Concerning the unexplained variation in prices, it can be attributed to special characteristics of Airbnb rentals, beyond the independent variables used, for example luxury characteristics or the condition as indicated in the pictures of the property. In addition, the quality of the neighborhood, in terms of city planning or criminal activity, for example, should be taken into consideration, although in the case of Athens there is a lack of relevant data. Data availability is also a constraint concerning the socioeconomic differences within the study region, at least in terms of recent data. Previous research in the Greater Athens Region suggests that higher prices of Airbnb rentals are correlated with areas of higher socioeconomic status [21]. For example, a relationship between short-term rental price and educational level is reported for Athens, and other cities as well [7,57]. Another limitation is that it is difficult to analyze the hosts' behavior in setting their own prices, according to social and psychological factors which may be important. Finally, it is probably useful to distinguish business operations as opposed to part-time hosts.

5. Conclusions

Although studies concerning the factors influencing rents are not very common, the topic of this article has been examined in other cities. Even so, the topic has not been adequately explored in the literature, and in Greece the relevant studies have not been undertaken. Since there are many differences among cities and countries in terms of their socioeconomic characteristics, the tourism sector and the way that short-term rentals are regulated, this study can be used for comparisons with other cities and contribute to the discussion on the range of factors that influence Airbnb accommodation prices. Concerning the methodology, several studies in the literature employ regression methods to analyze Airbnb data with variations in the methodology, i.e., the data and variables used as well as different regression models.

In this study, several characteristics of Airbnb rentals were analyzed, regarding 15 rental characteristics. A linear regression model was constructed, incorporating variables

expressing capacity, distances from POIs and host attributes. The variables with the greatest influence are the number of bathrooms and the maximum number of guests (accommodates), while distances from the city center and Akropolis-Plaka have a smaller impact. Since the residuals of OLS are spatially clustered, a spatial regression was calculated which suggests that capacity (bathrooms and accommodates) and host characteristics (superhost status and host identity verification) are important for Airbnb prices. These findings support the research hypotheses and agree with studies for cities in other countries. The GWR model produces more accurate results, although the unexplained variance suggests that more variables should be included.

Future research would first concentrate on the rentals with high residuals and analyze the neighborhood characteristics and the amenities they offer. In addition, replacing Euclidean distances with distances along the road network might improve the results of the OLS model. On the other hand, programming techniques should be used for easier manipulation of the data and the extraction of additional information. Finally, in this study, as in other similar studies, only the supply side is analyzed. The demand side is not taken into consideration, i.e., what are the characteristics and the preferences of the guests according to which the decisions as to the location and the price of the accommodation are taken.

The findings from the present research study may contribute to the debate regarding Airbnb rents, while they can help hosts optimize the pricing of their listings, increasing in this way their occupancy rates and maximizing their revenues. In addition, real estate brokers and appraisers can benefit for property appraisal purposes, since short-term rents are an important factor for estimating property values. Generalization of this study is possible for urban areas in Greece and other countries, in terms of the rental characteristics and the regression models. However, it is expected that analysis for rural areas or island tourist destinations will produce different results.

Supplementary Materials: The following supporting information can be downloaded at: https://athensrentals.uniwa.gr (accessed on 1 December 2023, ordinary least squares (OLS) regression, and geographically weighted regression (GWR) residuals.

Author Contributions: Conceptualization, Polixeni Iliopoulou; methodology, Polixeni Iliopoulou and Vassilios Krassanakis; software, Polixeni Iliopoulou, Vassilios Krassanakis and Loukas-Moysis Misthos; formal analysis, Polixeni Iliopoulou and Loukas-Moysis Misthos; investigation, Polixeni Iliopoulou and Christina Theodoridi; data curation, Polixeni Iliopoulou and Christina Theodoridi; writing—original draft preparation, Polixeni Iliopoulou, Vassilios Krassanakis and Loukas-Moysis Misthos; writing—review and editing, Vassilios Krassanakis and Loukas-Moysis Misthos; visualization, Vassilios Krassanakis and Loukas-Moysis Misthos. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request. Open data used in this study are extracted from the websites: http://insideairbnb.com/ (accessed on 24 November 2022), https://www.data.gov.gr/ (accessed on 8 January 2023) and https://www.statistics.gr (accessed on 8 December 2023).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Hamari, J.; Sjöklint, M.; Ukkonen, A. The sharing economy: Why people participate in collaborative consumption. *J. Assoc. Inf. Sci. Technol.* **2015**, *67*, 2047–2059. [CrossRef]
2. Daglis, T. Sharing Economy. *Encyclopedia* **2022**, *2*, 1322–1332. [CrossRef]
3. Puschmann, T.; Alt, R. Sharing economy. *Bus. Inf. Syst. Eng.* **2016**, *58*, 93–99. [CrossRef]
4. AirDNA. AirDNA MarketMinder. Available online: https://app.airdna.co/data/gr/65?tab=performance (accessed on 2 June 2023).
5. Adamiak, C. Current state and development of Airbnb accommodation offer in 167 countries. *Curr. Issues Tour.* **2022**, *25*, 3131–3149. [CrossRef]

6. Airbnb. 2024. Available online: https://news.airbnb.com/about-us/ (accessed on 25 January 2024).
7. Balampanidis, D.; Maloutas, T.; Papatzani, E.; Pettas, D. Informal urban regeneration as a way out of the crisis? Airbnb in Athens and its effects on space and society. *Urban Res. Pract.* **2021**, *14*, 223–242. [CrossRef]
8. Athanassiou, E.; Kotsi, A. The Sharing economy in Greece: Developments in short-term real estate rentals. *Greek Econ. Outlook* **2018**, *37*, 49–54. (In Greek)
9. Hellenic Statistical Authority. Hotels, Rooms for Rent and Tourist Campsites/2021. 2022. Available online: https://www.statistics.gr/en/statistics/-/publication/STO12/2022 (accessed on 8 December 2023).
10. Eurostat. Tourism. 2022. Available online: https://ec.europa.eu/eurostat/web/tourism/database (accessed on 2 July 2023).
11. Inside Airbnb. Available online: http://insideairbnb.com/get-the-data (accessed on 8 November 2023).
12. Booking. Available online: http://www.booking.com (accessed on 1 June 2023).
13. Ayouba, K.; Breuillé, M.-L.; Grivault, C.; Le Gallo, J. Does Airbnb Disrupt the Private Rental Market? An Empirical Analysis for French Cities. *Int. Reg. Sci. Rev.* **2020**, *43*, 76–104. [CrossRef]
14. Benítez-Aurioles, B.; Tussyadiah, I. What Airbnb does to the housing market. *Ann. Tour. Res.* **2020**, *90*, 103108. [CrossRef]
15. Chang, C.; Li, S. Study of Price Determinants of Sharing Economy-Based Accommodation Services: Evidence from Airbnb.com. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 584–601. [CrossRef]
16. Coyle, D.; Yeung, T.Y.-C. Understanding AirBnB in Fourteen European Cities. Jean-Jacques Laffont Digit. *Chair Work. Pap.* **2016**, *7088*, 1–33.
17. Fang, B.; Ye, Q.; Law, R. Effect of sharing economy on tourism industry employment. *Ann. Tour. Res.* **2016**, *57*, 264–267. [CrossRef]
18. Todd, J.; Musah, A.; Cheshire, J. Assessing the impacts of Airbnb listings on London house prices. *Environ. Plan. B Urban Anal. City Sci.* **2022**, *49*, 206–222. [CrossRef]
19. Zervas, G.; Proserpio, D.; Byers, J.W. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *J. Mark. Res.* **2017**, *54*, 687–705. [CrossRef]
20. Athanassiou, E.; Kotsi, A. Short-Term Accommodation Rentals in Greece. Center of Planning and Economic Research. 2022. Available online: https://www.kepe.gr/prosfates-dimosieyseis/ektheseis/ek_83_gr/ (accessed on 1 November 2023). (In Greek).
21. Iliopoulou, P.; Stratakis, P. Spatial Analysis of Airbnb in the Greater Athesn Region, Greece. In Proceedings of the 12th International Conference of the Hellenic Geographical Society (ICHGS), Innovative Geographies II, Mapping and Modeling Our World, Athens, Greece, 1–4 November 2019; Available online: https://www.researchgate.net/publication/337151452_SPATIAL_ANALYSIS_OF_AIRBNB_IN_THE_GREATER_ATHENS_REGION_GREECE (accessed on 1 December 2023).
22. Boutsioukis, G.; Fasianos, A.; Petrohilos-Andrianos, Y. The spatial distribution of short-term rental listings in Greece: A regional graphic. *Reg. Stud. Reg. Sci.* **2019**, *6*, 455–459. [CrossRef]
23. Gyódi, K.; Nawaro, Ł. Determinants of Airbnb prices in European cities: A spatial econometrics approach. *Tour. Manag.* **2021**, *86*, 104319. [CrossRef]
24. Gibbs, C.; Guttentag, D.; Gretzel, U.; Morton, J.; Goodwill, A. Pricing in the sharing economy: A hedonic pricing model applied to Airbnb listings. *J. Travel Tour. Mark.* **2018**, *35*, 46–56. [CrossRef]
25. Lladós-Masllorens, J.; Meseguer-Artola, A. Price Determinants of Tourist Accommodation Rental: Airbnb in Barcelona and Madrid. In *Research & Innovation Forum*; Visvizi, A., Lytras, M.D., Eds.; Springer International Publishing: Berlin/Heidelberg, Germany, 2019; pp. 549–556.
26. Tang, L.; Kim, J.; Wang, X. Estimating spatial effects on peer-to-peer accommodation prices: Towards an innovative hedonic model approach. *Int. J. Hosp. Manag.* **2019**, *81*, 43–53. [CrossRef]
27. Wang, D.; Nicolau, J.L. Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. *Int. J. Hosp. Manag.* **2017**, *62*, 120–131. [CrossRef]
28. Zhang, Z.; Chen, R.J.C.; Han, L.D.; Yang, L. Key Factors Affecting the Price of Airbnb Listings: A Geographically Weighted Approach. *Sustainability* **2017**, *9*, 1635. [CrossRef]
29. Chica-Olmo, J.; González-Morales, J.G.; Zafra-Gómez, J.L. Effects of location on Airbnb apartment pricing in Málaga. *Tour. Manag.* **2020**, *77*, 103981. [CrossRef]
30. Deboosere, R.; Kerrigan, D.J.; Wachsmuth, D.; El-Geneidy, A. Location, location and professionalization: A multilevel hedonic analysis of Airbnb listing prices and revenue. *Reg. Stud. Reg. Sci.* **2019**, *6*, 143–156. [CrossRef]
31. Dudás, G.; Kovalcsik, T.; Vida, G.; Boros, L.; Nagy, G. Price determinants of Airbnb listing prices in Lake Balaton Touristic Region. *Eur. J. Tour. Res.* **2020**, *24*, 2410. [CrossRef]
32. Perez-Sanchez, V.R.; Serrano-Estrada, L.; Marti, P.; Mora-Garcia, R.-T. The What, Where, and Why of Airbnb Price Determinants. *Sustainability* **2018**, *10*, 4596. [CrossRef]
33. Tong, B.; Gunter, U. Hedonic pricing and the sharing economy: How profile characteristics affect Airbnb accommodation prices in Barcelona, Madrid, and Seville. *Curr. Issues Tour.* **2022**, *25*, 3309–3328. [CrossRef]
34. Lawani, A.; Reed, M.R.; Mark, T.; Zheng, Y. Reviews and price on online platforms: Evidence from sentiment analysis of Airbnb reviews in Boston. *Reg. Sci. Urban Econ.* **2019**, *75*, 22–34. [CrossRef]
35. Bhattacharjee, A.; Castro, E.; Marques, J. Spatial Interactions in Hedonic Pricing Models: The Urban Housing Market of Aveiro, Portugal. *Spat. Econ. Anal.* **2012**, *7*, 133–167. [CrossRef]
36. Efthymiou, D.; Antoniou, C. How Do Transport Infrastructure and Policies Affect House Prices and Rents? Evidence from Athens, Greece. *Transp. Res. Part A Policy Pract.* **2013**, *52*, 1–22. [CrossRef]

37. Goodman, A.C. Hedonic prices, price indices and housing markets. *J. Hous. Res.* **1978**, *3*, 25–42. [CrossRef]
38. Sirmans, G.S.; MacDonald, L.; Macpherson, D.A.; Zietz, E.N. The Value of Housing Characteristics: A Meta Analysis. *J. Real Estate Financ. Econ.* **2006**, *33*, 215–240. [CrossRef]
39. Xiao, Y. *Urban Morphology and Housing Market; Springer Geography*; Springer: Singapore, 2017; ISBN 978-981-10-2761-1.
40. Brunauer, W.A.; Lang, S.; Wechselberger, P.; Bienert, S. Additive Hedonic Regression Models with Spatial Scaling Factors: An Application for Rents in Vienna. *J. Real Estate Financ. Econ.* **2010**, *41*, 390–411. [CrossRef]
41. Hoesli, M.; Thion, B.; Watkins, C. A hedonic investigation of the rental value of apartments in central Bordeaux. *J. Prop. Res.* **1997**, *14*, 15–26. [CrossRef]
42. Löchl, M.; Axhausen, K.W. Modeling hedonic residential rents for land use and transport simulation while considering spatial effects. *J. Transp. Land Use* **2010**, *3*, 39–63. [CrossRef]
43. Zietz, J.; Zietz, E.M.; Sirmans, G.S. Determinants of House Prices: A Quantile Regression Approach. *J. Real Estate Financ. Econ.* **2008**, *37*, 317–333. [CrossRef]
44. Adamiak, C.; Szyda, B.; Dubownik, A.; García-Álvarez, D. Airbnb Offer in Spain—Spatial Analysis of the Pattern and Determinants of Its Distribution. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 155. [CrossRef]
45. Gutiérrez, J.; García-Palomares, J.C.; Romanillos, G.; Salas-Olmedo, M.H. The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tour. Manag.* **2017**, *62*, 278–291. [CrossRef]
46. Maloutas, T.; Spyrellis, S.N. Vacant Houses, in Social Atlas. 2016. Available online: https://www.athenssocialatlas.gr/en/article/vacant-houses/ (accessed on 10 February 2024).
47. Rogerson, P.A. *Statistical Methods for Geography*, 4th ed.; SAGE: Newcastle upon Tyne, UK, 2015.
48. Draper, N.R.; Smith, H. *Applied Regression Analysis*; John Wiley & Sons: Hoboken, NJ, USA, 1998.
49. Osborne, J. Improving your data transformations: Applying Box-Cox transformations as a best practice. *Pract. Assess Res. Eval.* **2010**, *15*, 12.
50. Anselin, L.; Rey, S.J. *Modern Spatial Econometrics in Practice: A Guide to GeoDa, GeoDaSpace and PySAL*; GeoDa Press LLC: Chicago, IL, USA, 2014.
51. Fotheringham, A.S.; Brunsdon, C.; Charlton, M. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*; John Wiley & Sons: Hoboken, NJ, USA, 2002.
52. Brunsdon, C.; Charlton, M.; Harris, P. Living with Collinearity in Local Regression Models. In Proceedings of the Accuracy 2012—10th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, Florianópolis, SC, Brazil, 10–13 July 2012.
53. Wheeler, D.C. Diagnostic Tools and a Remedial Method for Collinearity in Geographically Weighted Regression. *Environ. Plan. A Econ. Space* **2007**, *39*, 2464–2481. [CrossRef]
54. Portet, S. A primer on model selection using the Akaike Information Criterion. *Infect. Dis. Model.* **2020**, *5*, 111–128. [CrossRef]
55. Iliopoulou, P.; Feloni, E. Spatial Modelling and Geovisualization of House Prices in the Greater Athens Region, Greece. *Geographies* **2022**, *2*, 111–131. [CrossRef]
56. Iliopoulou, P.; Stratakis, P. Spatial Analysis of Housing Prices in the Athens Region, Greece. *RELAND Int. J. Real Estate Land Plan.* **2018**, *1*, 304–313.
57. Schor, J.B. Does the sharing economy increase inequality within the eighty percent? Findings from a qualitative study of platform providers. *Camb. J. Reg. Econ. Soc.* **2017**, *10*, 263–279. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.