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Hedonic Pricing Models in Rural Tourism: Analyzing Factors Influencing Accommodation Pricing in Romania Using Geographically Weighted Regression

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Abstract: This study investigates the factors influencing pricing in Romanian rural tourism using a hedonic pricing model through a hybrid LASSO-OLS regression and geographically weighted regression (GWR). By analyzing data from 5028 unique accommodation units across 1170 local administrative units, we identify some key pricing determinants, including accommodation size, capacity, facilities, and environmental attributes. The results reveal that larger accommodations and those with higher guest capacities command higher prices. Luxurious facilities, such as massage services, pools, and fireplaces, significantly increase pricing, although the impact of such features varies by region, as do accommodation type and natural scenery, with agritouristic boarding houses and proximity to natural attractions like water bodies and forests being more valued in certain regions. These factors can aid rural entrepreneurs in optimizing pricing to enhance competitiveness and profitability.

Keywords: hedonic pricing; rural tourism; agritourism; geographically weighted regression

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1. Introduction

Hedonic pricing models operate on the assumption that various characteristics of a good or service influence their prices. Initially applied in real estate since the 70s, hedonic pricing has also been successfully used in tourism research, highlighting the most important factors that positively or negatively influence pricing [1–4].

The most significant research gaps regarding hedonic pricing remain the lack of representation in some areas and the limited methodological approaches previously employed to research those areas. In the case of Romania, one previous work analyzed the factors influencing the pricing of rural and urban areas in Brașov County, finding that rural areas in Brașov tend to be associated with higher prices compared to urban ones and that luxury facilities are one of the main drivers that allow businesses to increase prices [5]. Other examples of geographical areas studied from the perspective of the hedonic pricing models include the Algarve region of Spain, Malaga, Barcelona, Madrid and Seville in the same country, Cyprus, Nord-Pas-de-Calais in France, Halkidiki in Greece, as well as some rural areas of China and Thailand [6–14]. The most distinct methodological limitation of some previous studies is their relatively restricted measurement of the spatial dimension of the effects of the various variables on pricing [6,7,15–19].

With a focus on the Romanian rural tourism sector, this study aims to provide the groundwork for new approaches in pricing research by analyzing the factors influencing accommodation prices using both global (ordinary least squares) and local (geographically weighted regression) models for a large study area, as opposed to most of the previous works that focused on relatively small areas. From a theoretical perspective, we argue that satisfactory, albeit probably lower, model performance can be maintained even when dealing with such a vast area of study compared to articles focused on smaller regions. Future confirmatory research can attempt to replicate this approach. Furthermore, from a practical perspective, by employing these methods, the study provides useful insights into the pricing determinants in Romanian rural tourism, offering a more comprehensive view that can guide local entrepreneurs located in various areas around Romania in making informed investment decisions and enhancing their pricing strategies to maximize profitability and customer satisfaction.

This paper also deals with the issue of variable selection in hedonic pricing research by proposing an approach complementary to that of another recently published article in this field [8]. This paper proposes the usage of LASSO (least absolute shrinkage and selection operator) on an extensive database containing over 300 predictors. While a fair comparison of the LASSO model performance compared to stepwise regression or other variable-selection methods would be an interesting research result, this falls outside of the main aim of this paper. However, it is shown that usable results can be obtained through this method.

In short, the main objectives are to present the global and local effects of some variables that are important to pricing in the context of rural Romania, to show that a hedonic pricing model does not need to be limited to a relatively small research area and to present the results of the LASSO variable-selection strategy in the context of hedonic pricing.

In order to fulfill the aims described, this research paper contains a literature review section, where previous results are described and, based on those, the main research hypotheses are formulated; a materials and methods section, containing information aimed at ensuring the reproducibility of the research; results; discussion, where the results are compared with those found in the literature; and conclusions, providing an overview of the main findings.

2. Theoretical Background and Research Hypotheses

2.1. A Brief Retrospective of Pricing Research

Pricing has long been considered one of the most important elements of the marketing mix, directly influencing revenue and business profitability. [3]. Besides this vital function to the financial sustainability of commercial enterprises, pricing also plays a key role in market segmentation and positioning, helping businesses target specific customer groups effectively and build brand equity [20,21]. Historically, pricing research in the field of hospitality has not been a subject as widely debated as others, such as destination marketing or tourism forecasting [22,23].

However, recently, many academic papers and books describe the various pricing strategies within the general economic environment and the hospitality industry, from a business-oriented perspective, signifying the maturity of this field and, most significantly, the increasing levels of interest in research regarding pricing in the hospitality industry [23–27].

One of the most common and intuitive methods is cost-plus pricing, where businesses add a markup to the total costs of a product or service to ensure profitability [28]. This method is commonly associated in the context of the hospitality industry with the Hubbart formula, where the room rate is calculated starting from the expected return, to which operating costs are added and other types of income are subtracted; the result is then divided by the number of projected overnight stays [29]. Another commonly used method is the “rule of thumb”, which states that for every 1000 units in the construction costs, the average daily rate (or price) should be increased by one unit (in most cases referring to dollars) [30].

Another prevalent approach is value-based pricing, which sets prices primarily based on the perceived value provided to customers rather than the cost of production [31]. This method is aimed toward the maximum amount customers are willing to pay based on the product's benefits and uniqueness. Additionally, competition-driven pricing is another strategy employed by businesses, where market dynamics influence pricing decisions. In this approach, competitive pressures can compel organizations to either lower their prices to stay competitive or, conversely, allow them to raise prices when market conditions permit [23].

Another pricing strategy employed is dynamic pricing, often used in the hospitality and airline industries [32]. Dynamic pricing adjusts prices based on real-time supply and demand conditions. This strategy can utilize advanced algorithms and data analytics approaches to predict demand fluctuations and set prices that maximize revenue. For instance, hotels might increase their room rates during peak tourist seasons due to higher demand while lowering them during off-peak periods to attract more customers [33]. This approach enhances revenue and optimizes occupancy rates, making it a vital tool for businesses operating in highly volatile markets. From the perspective of statistical analysis of pricing in tourism, this approach is somewhat problematic for researchers, as it would require switching from a cross-sectional approach to a panel data one. So far, seasonal price variations are controlled for or analyzed in a simplified form by fitting separate regression models for high and low seasons, by adding dummy variables accounting for these variations or by selecting relatively small periods for data collection [6,34]. Other approaches might be challenging to implement, computationally expensive, or outside the scope of the research's usefulness, though future research may benefit from such approaches by employing panel data methods.

While each strategy reflects different priorities and market conditions, companies must often blend approaches to suit their specific operational and competitive contexts. Thus, by considering all the components described before, namely costs, customer value, and pressure from competitors, businesses can build pricing strategies appropriate to their needs and goals.

2.2. Hedonic Pricing Methodologies—General Characteristics

A noteworthy approach in pricing research is the usage of hedonic regression models in studies related to the hospitality industry. While initially used in real estate valuation, hedonic pricing has been successfully used in the context of tourism research [35–37]. These models operate on the assumption that the characteristics of a good or service are key determinants in setting prices that are acceptable to customers [6,38,39]. Such an approach assumes that observed prices are the sum of implicit prices of the product's component characteristics. This requires collecting extensive data on the goods or services and their prices and then analyzing how individual characteristics influence pricing. As such, this type of research tends to belong to the quantitative paradigm [40,41].

A conceptual correspondence between the pricing strategies mentioned previously and the hedonic regression assumptions can be drawn. As such, the factors researched in the hedonic regression models are the same or similar to those that drive customer value, allowing researchers to effectively model the price hikes that are present in the market for an added feature or the presence of an environmental factor [6,7]. This, in turn, can allow businesses to conduct cost/benefit analysis for possible feature upgrades.

Hedonic pricing can be used complementary with research on willingness to pay. The latter shifts the focus from the prices of goods toward consumer perceptions and the maximum prices they are willing to accept [42–45]. Ultimately, both these methods can provide businesses with a data-driven framework for setting a pricing policy appropriate to their situation. For hotel managers and destination marketers, understanding how features and attributes can influence prices allows for a more effective allocation of resources and can help in a cost-benefit analysis, leading to targeted investments in facilities or services that align with local market demands and maximize customer satisfaction and profitability.

Previous studies have reported that the key attributes affecting prices in accommodation establishments can be grouped into location or property-specific attributes [14,46,47].

Location-specific characteristics include proximity to natural attractions such as beaches, forests, rivers, and lakes, which attract tourists and allow businesses to charge higher prices. Water bodies' proximity was noted in a previous study focusing on Romania not to be an important predictor [48].

Land use is a topic that has been debated in some studies regarding the hedonic pricing model of the hospitality industry, especially in the context of ecotourism, rural tourism, or agritourism [47,49–51].

An article focusing on a hedonic pricing model for the Asturias region in Spain found that the presence of arable crops negatively impacts cottage prices. This negative perception is likely due to the environmental harm associated with arable crops, such as the use of fertilizers and pesticides and pollution from livestock feed production, which negatively influences the region's scenery. Grasslands positively influence cottage prices, with a 1% increase in grassland areas leading to a 0.4% price rise [52]. A similar situation was reported by an earlier study focusing on Belgium rural tourism, where the production of fodder crops in the vicinity of the accommodation units significantly reduced prices.

Another study focused on the pricing of German holiday apartments and cottages fonds that the presence of rivers, lakes, and wetlands significantly boosts the appeal of holiday accommodations [53]. Specifically, rentals near rivers and lakes are valued more highly, with a noticeable increase in price for both apartments and cottages. Wetlands also enhance the attractiveness of holiday apartments, indicating that rural tourists are willing to pay more for accommodations close to these natural features. Conversely, the study identifies a negative impact on rental prices due to the presence of arable land and forests within close proximity to holiday accommodations. Rentals surrounded by arable land or forests tend to be less expensive, reflecting tourists' preferences for open water features over agricultural or densely forested areas, similar to the situation in the Asturias [53].

Furthermore, proximity to man-made attractions such as museums or historical landmarks can also be of interest. In such cases, the relation between prices and proximity to a touristic attraction is positive [48].

In the case of a region of Nord-Pas-de-Calais, accommodation units can generally charge higher prices when they are near attractive public goods, especially tourist attractions, in both peak and off-peak seasons. Proximity to a beach significantly increases hotel rates during peak season, but this influence is not significant and even negative during off-peak season [10].

Property attributes can be described as facilities characteristic of the studied property itself. These facilities, such as swimming pools, fitness centers, spas, room types, room service, breakfast options, and overall property quality, can impact pricing.

Hotels with luxurious pools, hot tubs, saunas, and full-service spas generally charge more, depending on the studied area. A previous research utilizing data gathered from accommodation units from the Brasov county of Romania show that such features are crucial in determining pricing [5]. In some locations, mainly located in the colder climates, pool availability plays no role in pricing [15].

Hotel room size is a divisive factor in determining room rates. Generally, larger rooms typically command higher prices due to offering additional space and facilities, which are often perceived as more valuable by guests [13,54]. However, some disagreements over this exist, with some areas reporting a negative relation between room size and price [55].

Breakfast availability is another variable of interest in the literature One study that focused on Romania reported that breakfast availability had one of the most important effect on pricing, as did studies using data from Thailand and Sweden [13,18,48].

Some studies reported a direct relationship between property review scores and prices and a negative and significant one between the number of reviews and prices [12,17,56].

Customer ratings, particularly from platforms like TripAdvisor and Booking.com, generally have a significant positive effect on prices and customer willingness to pay, with Booking.com noted for its authenticity.

Another property-specific attribute mentioned in the literature as among the most important independent variables is the accommodation category, measured in most cases through the hotel star rating. Generally, higher star ratings correlate with higher prices. Studies either consider all categories or focus on high categories, consistently finding that higher ratings lead to greater price increases [7,10,18,48,57].

Accommodation unit type was also discussed in the literature. Accommodation types like tourist chalets and hotels can command higher prices than guest houses, according to previous research focused on Romania [48].

Based on the fact that the results in previous studies of other authors contain both elements that are contradictory and consistent between studied areas, we hypothesize that:

H1. *A mix of both location- and accommodation-specific attributes are important predictors of accommodation unit prices.*

H2. *The effect of location- and accommodation-specific attributes on prices varies significantly between studied areas, justifying the use of spatial models.*

H3. *The number of stars positively influences prices.*

H4. *Luxury facilities positively influence prices.*

Hedonic models usually focus on unique markets defined by distinct geographic images and utilize actual market data, not surveys [19]. Most research focusing on hedonic pricing models has used multiple linear regression (or its robust counterparts, such as the quantile regression [58]) applied to small touristic markets. Some authors have argued that results can vary significantly across regions, making it difficult to generalize findings [6,7]. Indeed, most of the research done in the field of tourism hedonic pricing usually features one geographical area, encompassing establishments located in urban, rural, or either area, thus keeping location-based attributes constant. However, the geographically weighted regression method allows the relationships between the variables to change over space, accommodating the idea that factors influencing hotel room rates might vary in different parts of a region [59,60]. Furthermore, the GWR or other spatial methods results can be mapped, providing a visual representation of how the influence of different factors changes across the region. As such, a growing number of papers also employed spatial methods, most notably the geographically weighted regression, spatial lag and spatial error models [7,16,61].

3. Materials and Methods

3.1. Romanian Rural Tourism—An Overview

Romanian rural tourism and agritourism significantly contribute to the economy and social rejuvenation of rural areas in Romania in a sustainable manner [62–65]. Those forms of tourism utilize the country's cultural heritage, diverse landscapes, and traditional way of life to attract visitors seeking authentic experiences [66–68]. Romania's rural areas offer attractive scenery, vast forests, and picturesque villages, ideal for hiking, bird-watching, and other outdoor activities [69,70]. This experience is complemented by local cuisine, featuring organic and locally sourced ingredients, and the opportunity to learn about traditional crafts and folklore [71,72].

From the perspective of agritourism, it should be noted that this field might be over-represented in official statistics. An objective analysis of the situation of Romanian agritourism can be limited by the data series provided by the National Institute of Statistics. The methodological observations from the series "TUR101C—Accommodation structures with tourist accommodation functions by types of structures, counties, and localities" mention that the data are collected from urban tourist guesthouses for the category of tourist guesthouses. In contrast, the category of agritouristic guesthouses includes both rural tourist guesthouses and actual agritouristic guesthouses [73].

However, another source of information, which only presents a cross-sectional analysis of the current situation of accommodation spaces and tourism reception structures, is the database offered by the Ministry of Entrepreneurship and Tourism called "Tourist reception structures with classified accommodation functions", which distinctly includes tourist guesthouses and agritourism guesthouses. This data source does not include arrivals and as such can be considered limited.

In spite of these shortcomings, agritourism continues to raise interest from academics and rural business owners. The former pinpoint specific instances and strategies in which authentic agritourism has been successful in Romania or possible opportunities for the latter to develop this field [74,75].

Of particular interest is the development of guesthouses, which rose to prominence as one of the main types of accommodation units [76]. Table 1 shows the development of the number of guesthouses in rural areas compared to the total number of accommodation units in Romania.

Table 1. Rural guesthouses and the share of rural guesthouses in the total number of accommodation units in Romania (data sourced from the National Institute of Statistics [73]).

	Rural Guesthouses	Percentage of Rural Guesthouses among Total Number of Accommodation Units in Romania
2013	1598	26.2
2014	1665	27.2
2015	1918	28.1
2016	2028	29.2
2017	2556	32.3
2018	2821	33.4
2019	2800	33.3
2020	3022	35.1
2021	3460	37.8
2022	3484	38.2

Rural guesthouses represent a significant share of the total number of tourist accommodation units, increasing throughout the reported period. A slight decrease was reported in 2019, but this minor deviation from the norm was insignificant, as the strong growth trend resumed in 2020.

Considering that in this series, the numbers of rural tourist guesthouses and agritourism guesthouses are reported together, these values provide an overall picture of rural tourism rather than one specifically focused on agritourism.

A spatial distribution of rural guesthouses in Romania is shown in Figure 1.

The areas where rural guesthouses are most prevalent are located in the central and northern regions of Romania, with particular hotspots in the Brasov, Harghita, Suceava, Maramures, Cluj, and Bihor areas, as well as in Tulcea, the latter due to its proximity to the Danube Delta [77].

However, rural tourism is not limited to guesthouses and other types of chartered accommodation units, as online booking agencies and businesses associated with the concept of the sharing economy, such as Airbnb, have created a new niche of touristic offer, where owners can directly rent their home to tourists [78–80]. Those are a "force to be reckoned with" for conventional tourism, which led to some states adopting regulations regarding their operation [81–83]. Romania has, so far, allowed the "Airbnb-fication" of urban and rural spaces and the overall adoption of sharing economy services, including drive-sharing mobile applications [84–86]. As such, business owners in rural areas cannot ignore these new types of establishments and should formulate their pricing strategies accordingly or attempt to create mutually beneficial relationships [87].

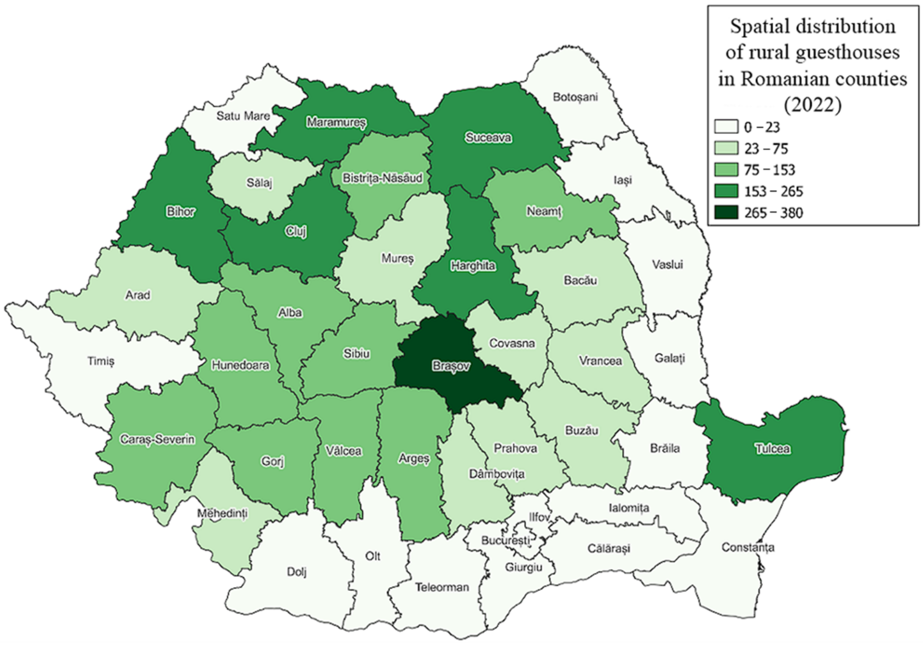

Figure 1. The spatial distribution of rural guesthouses in Romania.

3.2. Data and Methods

The first step in the research endeavor involved obtaining a list of villages and communes in Romania that reported touristic activities in the last three years. This information was compiled from the Tempo online database, which provided an adequate overview of rural areas engaged in tourism. This selection criterion ensured that the study focused on areas with recent and relevant tourism activities while maintaining relatively low computational and time costs. In this regard, a list of 1170 local administrative units was obtained.

Following this, a data scrapper was built using the R software environment (version 4.3.2), with the Rvest (version 1.0.4) and Selenider (version 0.4.0) packages to be used on Booking.com. This provided us with data on accommodation prices and attributes, including information on pricing, facilities, and other relevant features of accommodations in rural tourism destinations. All the data scraping techniques used were ascribed to netiquette (parallel processing was limited to 3 clusters, and a timeout of 5 s was employed to not disrupt normal website operations).

In this step, data on 5028 unique accommodation units were obtained, the vast majority with multiple room types, with 13.676 unique values. The room prices were calculated as an average for April–June 2024. This stage of the data collection phase took place from 5 April to 8 April 2024.

293 unique hotel features were obtained and subsequently transformed into dummy or discrete variables accordingly. The number of stars (ranging from 0, associated with accommodation units that are not chartered, to 5) were transformed into six dummy variables. To avoid the dummy variable trap (where dummy variables perfectly correlated with one another, leading to multicollinearity), the 0-star variable was not considered for modeling.

Other variables assessed were room size, the maximum number of guests in one room, review score, number of reviews, and type of accommodation units (hotel, villa, boarding house, agritouristic boarding house).

Touristic attractiveness was modeled using data from Google Maps. This dataset provided geographical locations, types, number of reviews and review scores, and other relevant attraction attributes that contribute to rural tourism destinations' desirability. In this case, the data was obtained through the googleway package (version 2.7.8) and with the Google Maps API. An attractivity score was obtained for each location by adding up the number of reviews for touristic attractions in a 5 km radius around each accommodation unit [88].

OSMLanduse Data was utilized to account for land use in the rural tourism destinations under study [89]. This dataset provided information on the distribution of different land use types (residential, water bodies, commercial and industrial, mines, dumps and construction sites, as well as arable land, pastures and forests) in a 5 km radius around each accommodation unit. Data processing for these variables was done using QGIS [90].

A hybrid approach combining LASSO (Least Absolute Shrinkage and Selection Operator) and OLS (ordinary least squares) regression techniques was utilized for variable selection in the hedonic pricing model [91]. First, variables that were highly correlated with one another were removed, and then LASSO regularization was used to shrink coefficients of less influential variables towards zero, the latter being removed from the model [92]. Following this, the surviving variables were fitted using the OLS regression.

This option was used due to the high interpretability of OLS regression coefficients while retaining the advantages of LASSO regularization in the context of feature selection, as compared to more classic feature-selection algorithms, such as stepwise regression [93]. While there is still an ongoing debate on the overall robustness of LASSO, in our case, as the number of variables obtained is considered quite large for the scope of the research, stepwise variable selection, backward or forward, would be disadvantageous from a computational perspective [94,95]. The package used for the LASSO is glmnet [96].

The general formula for the OLS regression commonly used in hedonic pricing research is (1):

$$\text{lnPi} = \alpha + \beta 1 \times 1\text{i} + \beta 2 \times 2\text{i} + \ldots + \beta\text{k} \times \text{ki} + \varepsilon\text{i} \quad (1)$$

where lnPi is the natural logarithm of the price charged for the room, Xi is an attribute studied (an independent variable), α is the intercept value, and εi is the error term. The coefficient β reports the implicit price for the attribute.

Figure 2 shows the regression quantile-quantile plot. We see that the normality of residuals requirement for the OLS regression is acceptably followed, with some minor differences in the lower bounds associated with "thin tails". As the sample size is quite large (n = 13,676), we cannot reliably use the Shapiro-Wilk test to observe the normality of the residuals [97,98]. Heteroscedasticity was assessed using the Breusch-Pagan test, returning a value of 0.183, which shows that the variance of the results is constant.

Following the global model, a geographically weighted regression was fitted to the data. The GWR was modeled using the spgwr package (version 0.6-37), with a fixed bandwidth of 27.87 selected through cross-validation methods [99].The formula for the GWR, as compared to the OLS regression, adds a geographical (or coordinates) parameter as follows (2) [7]:

$$P(g) = \alpha(g) + \beta_1(g)X + \varepsilon \quad (2)$$

where g is the coordinates vector.

Adjusted R^2 and AIC values were analyzed to compare the two models. Dedicated statistical tests were used to assess the ability of the GWR model to fit the data compared to the OLS [60]. The AIC (Akaike Information Criterion) is used to compare models, in our case regressions, by estimating the prediction error of each model. As such, better models tend to have lower AIC [100].

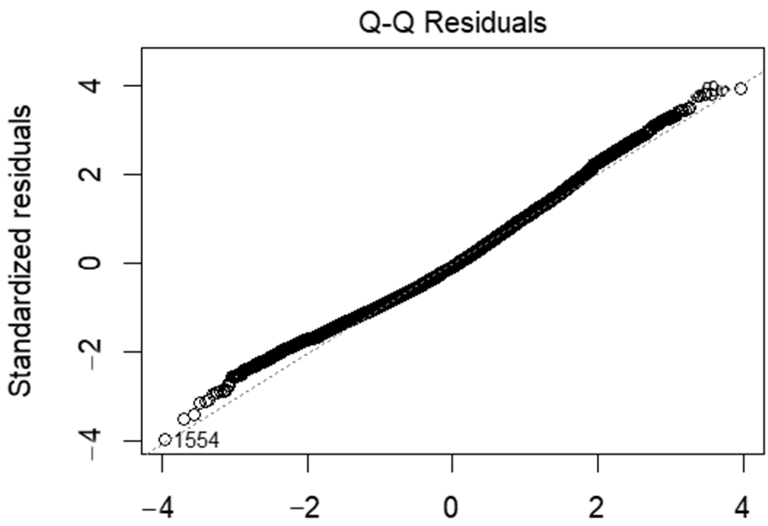

Figure 2. Quantile-quantile plot of the OLS regression.

4. Results

4.1. Descriptive Statistics

The unit of measurement (or variable type) mean value, standard deviation, median, and max values for the independent variables are reported in Table 2. Due to the fact that dummy variables can only take on two values (0 or 1), they are reported as such.

Table 2. Descriptive statistics.

Variable	Unit of Measurement or Variable Type	Mean	Std.Dev	Min	Median	Max
Size (log)	m^2 (log)	3.49	0.71	1.95	3.22	6.91
Number of reviews (log)	Number of reviews (log)	9	1.6	0	9.33	10
Maximum guests in a room	Number of guests	2.87	2.23	1	2	38
Bathroom accessories	Dummy variable	0.26	0.44	0	0	1
Entire place to rent	Dummy variable	0.12	0.32	0	0	1
Sauna	Dummy variable	0.42	0.89	0	0	1
Massage	Dummy variable	0.11	0.32	0	0	1
Pool	Dummy variable	0.2	0.4	0	0	1
Jacuzzi	Dummy variable	0.22	0.41	0	0	1
Elevator	Dummy variable	0.09	0.29	0	0	1
Breakfast	Dummy variable	0.23	0.4	0	0	1
Fireplace	Dummy variable	0.06	0.23	0	0	1
Smoke alarm	Dummy variable	0.41	0.49	0	0	1
Badminton	Dummy variable	0.16	0.36	0	0	1
Animals accepted	Dummy variable	0.08	0.28	0	0	1
Ironing services	Dummy variable	0.59	0.86	0	0	5
Aircon availability	Dummy variable	0.49	0.62	0	0	2
Agritouristic boarding house	Dummy variable	0.21	0.25	0	1	1
Cabin	Dummy variable	0.03	0.16	0	0	1
Villa	Dummy variable	0.03	0.16	0	0	1
5 stars	Dummy variable	0.16	0.37	0	0	1
4 stars	Dummy variable	0.08	0.12	0	0	1
Vegetation and forests % in a 5 km radius	Percentage of land use	38.53	26.31	0	37.95	96.13
Residences % in a 5 km radius	Percentage of land use	9.08	7.46	0	7.44	75.66
Water bodies % in a 5 km radius	Percentage of land use	2.4	5.52	0	0.19	36.22
Touristic attractivity (log)	Number of reviews for touristic attractions multiplied by review score (log)	5.3	2.36	0	5.45	14.3

4.2. Results of the Global Model (Multiple Linear Regression)

Table 3 shows the multiple linear regression (OLS) results on the variables selected using the LASSO method. This type of model treats the relationship between the dependent and independent variables as homogenous across the study area, a more straightforward approach compared to the geographically weighted regression model, but with lower predictive potential when the effects vary spatially. The percentage effect on the dependent was calculated by either exponentiating the coefficient, as is the case for most of the variables, or directly interpreting the coefficient as a percentile increase in the dependent variable for a 1% increase in the independent [101].

Table 3. Coefficients, variance inflation factor, estimates, effect on dependent, standard error, t- and *p*-value for the OLS regression.

Variable	VIF	Estimate	Effect on Dependent (%)	Std. Error	t Value	*p* Value
(Intercept)		2.795		0.02	131.083	<0.01
Size (log)	1.70	0.332	0.33	~0.000	39.888	<0.01
Number of reviews (log)	1.04	−0.019	−0.02	0.002	7.704	<0.01
Maximum guests in a room (log)	1.39	0.058	5.97	0.002	31.236	<0.01
Bathroom accessories	1.17	0.109	11.52	0.009	12.798	<0.01
Entire place to rent	1.54	0.070	7.25	0.014	10.185	<0.01
Sauna	1.82	0.027	13.54	0.005	4.355	<0.01
Massage	1.49	0.236	26.62	0.014	14.772	<0.01
Pool	1.19	0.143	15.37	0.010	13.147	<0.01
Jacuzzi	1.37	0.145	15.60	0.010	13.731	<0.01
Elevator	1.38	0.184	20.20	0.015	12.855	<0.01
Breakfast	1.22	0.276	7.90	0.010	26.286	<0.01
Fireplace	1.19	0.180	19.72	0.017	10.615	<0.01
Smoke alarm	1.22	0.095	9.97	0.008	11.042	<0.01
Badminton	1.10	0.126	13.43	0.011	12.042	<0.01
Animals accepted	1.24	0.112	11.85	0.015	9.039	<0.01
Ironing services	1.15	−0.050	−4.88	0.004	−9.98	<0.01
Aircon availability	1.41	0.062	6.40	0.007	9.904	<0.01
Agritouristic boarding house	1.11	0.166	18.06	0.016	9.558	<0.01
Cabin	1.08	0.169	18.41	0.024	7.544	<0.01
Villa	1.17	0.296	34.45	0.025	10.023	<0.01
5 stars	1.16	0.275	31.65	0.033	9.638	<0.01
4 stars	1.38	0.179	19.60	0.012	15.009	<0.01
Vegetation and forests % in a 5 km radius	1.07	0.009	0.90	~0.000	9.686	<0.01
Residences % in a 5 km radius	1.33	−0.008	−0.80	~0.000	−11.878	<0.01
Water bodies % in a 5 km radius	1.12	0.008	0.80	~0.000	10.007	<0.01
Touristic attractivity (log)	2.37	0.005	0.54	0.004	2.0759	0.058
	Multiple R^2: 0.5988, Adjusted R^2: 0.5879 F-statistic: 588.5 on 25 and 13,647 DF, *p*-value: <0.01					

The adjusted R^2 shows the percentage of the variance in the dependent variable explained by the independent variables. In this model, this value can be considered a sign that the model carries good explanatory power [102]. The variance inflation factors (VIF) calculated are low (below both recommended thresholds of 10 and 5). The VIF is useful in regression analysis as it allows the researchers to avoid multicollinearity (highly correlated independent variables) and to obtain useful results from the model. If two or more variables were highly correlated, the *p*-value of either would increase and be considered statistically insignificant, even if they are useful predictors [103].

A 1% increase in the size of the accommodation unit is associated with a 0.33% increase in price. This makes intuitive sense as larger accommodations typically command higher prices due to more space and potentially more facilities.

In the case of most independent variables, we observed positive effects, indicating that their presence increases the price of accommodation units. For instance, having a sauna increases prices by 13.54%, 4 and 5 stars increase prices by 19.60% and 31.65%, respectively, massage services by 26.62%, etc. These results suggest that customers are willing to pay more for properties that offer these facilities or features. Those effects are computed, all other variables being equal.

The impact of the number of stars on price can be even higher than those observed, as the number of services provided is also higher than those of lower-ranked units, and other factors can compound the effect.

In the case of land use features, the interpretation of the coefficient is that a one-unit increase or decrease in each variable leads to a one percent increase in the pricing of accommodation units. While the coefficient for these variables seems particularly low compared to others, it should be noted that most of the other variables are dummies, while these are percentages. As such, we can reasonably expect that accommodation units located in an area with a relatively high rate of land area occupied by vegetation or water bodies can charge a higher price for the rooms on offer. Conversely, high urbanization is associated with lower prices in the rural setting. Tourism attractivity, expressed as the natural logarithm of the total number of reviews for touristic attractions located in a 5 km radius around the accommodation units, multiplied by the review score, is also a significant factor in pricing, with a positive value.

Interestingly, the availability of ironing services has a negative effect on price (−4.88%). This could imply that properties offering ironing services may be perceived as less upscale or that this feature is provided as standard in high-price accommodations and is not advertised separately as such.

The number of reviews has a small but statistically significant effect on price, implying that while price is influenced by the volume of reviews a property receives, this variable's effect is relatively low. Several possible causes are suggested in the literature to explain this result. Firstly, suppose the number of reviews is treated as a proxy for touristic demand. In that case, lower-priced units attract more tourists, as can be expected considering the economic law of demand [104,105]. Secondly, a higher number of reviews can be associated with lower information asymmetry between tourists and operators, limiting the ability of the latter to overprice their products [104].

Accommodation unit type is also a significant factor in pricing. Cabins are associated with 18.41% more expensive in rural Romania. This is a substantial increase, suggesting that cabins are highly valued and can command higher prices likely due to their unique appeal, privacy, and possibly exclusive facilities such as scenic views or proximity to natural attractions.

Agritourism is associated with an 18.06% increase in accommodation prices. This type of accommodation appeals to travelers seeking authentic rural experiences and often includes activities like farm tours or local food experiences. The higher price reflects the added value of these unique experiences and cultural immersion. Booking.com labels the accommodation units that advertise themselves as practicing agritourism distinctly from other types of boarding houses. Further research may focus on the distinction between conventional and agritouristic boarding house pricing in rural Romania.

Villas demonstrate the highest effect among the three types of accommodation units analyzed, with a 34.45% increase in accommodation prices. Villas typically offer luxury facilities, spaciousness, and privacy, appealing to upscale travelers or groups looking for a premium experience. The substantial increase in price underscores the demand for high-end accommodations in rural Romania and the perceived value of villas in meeting those demands.

4.3. Results of the Local Models (Geographically Weighted Regression)

Table 4 shows the results of the geographically weighted regression model. This type of regression allows the coefficients for each variable to vary locally. In some areas, a specific variable might have a significant effect on the dependent variables, while in other areas, it is less important. For example, sea view can be a significant and useful predictor for prices in accommodation units on the seaside while being completely inconsequential for units far away from the sea. Table 4 indicates the minimal, 1st quantile, median, 3rd quantile, and max values for the coefficients calculated with the local models.

Table 4. Coefficients, variance inflation factor, estimates, effect on dependent, standard error, t- and *p*-value for the GWR regression.

	Min.	**1st Quantile**	**Median**	**3rd Quantile**	**Max.**
Intercept	0.112	2.623	2.761	2.980	4.257
Size (log)	0.111	0.280	0.319	0.363	0.651
Number of reviews (log)	−0.106	−0.030	−0.017	−0.006	0.127
Maximum guests in room	−0.064	0.048	0.061	0.073	0.147
Bathroom accessories	−0.227	0.026	0.084	0.153	0.657
Entire place to rent	−0.259	0.007	0.103	0.248	0.926
Sauna	−0.326	−0.016	0.002	0.061	1.030
Massage	−1.104	0.038	0.146	0.277	0.701
Pool	−0.317	0.080	0.131	0.168	0.444
Jacuzzi	−0.317	0.051	0.121	0.204	0.695
Elevator	−0.511	0.002	0.127	0.210	0.540
Breakfast	−1.423	0.201	0.258	0.297	0.556
Fireplace	−0.861	0.064	0.137	0.238	1.071
Smoke alarm	−0.144	0.038	0.074	0.117	0.378
Badminton	−1.020	0.053	0.110	0.149	0.607
Animals accepted	−0.593	0.028	0.106	0.186	0.882
Ironing services	−0.343	−0.072	−0.038	−0.008	0.180
Aircon availability	−0.450	0.044	0.083	0.128	0.382
Agritouristic boarding house	−0.106	0.122	0.175	0.285	1.148
Cabin	−4.396	−0.039	0.225	0.326	0.784
Villa	−1.042	0.152	0.224	0.301	1.167
4 stars	−1.293	0.147	0.269	0.466	1.330
5 stars	−0.51	0.067	0.162	0.280	0.662
Vegetation and forests % in a 5 km radius	−1.483	−0.003	0.006	0.010	0.418
Residences % in 5 km radius	−0.058	−0.019	−0.009	−0.003	0.038
Water bodies % in 5 km radius	−0.201	−0.037	−0.009	0.004	0.129
Quasi-global R^2: 0.683					

The size variable is the only variable to show consistently positive relations regardless of the geographical area of the accommodation units (local coefficients of 0.111 to 0.651). The maximum number of guests in a room exhibits primarily positive effects on pricing (−0.064 to 0.147). As such, we can infer that larger accommodations and higher guest capacity generally increase prices across the whole study area. Facilities like sauna (−0.326 to 1.030), and breakfast (−1.423 to 0.556) exhibit a wide range of impacts, with both negative and positive influences across the study area. More luxurious features, such as a pool (−0.317 to 0.444), fireplace (−0.861 to 1.071), and 5-star rating (−1.293 to 1.330), significantly enhance property values. However, the negative minimum values indicate potential oversupply or lack of demand in some areas.

Environmental factors such as proximity to water bodies (−0.201 to 0.129) and vegetation and forests (−1.483 to 0.418) also play a role, reflecting the premium placed on natural surroundings in many areas. However, the range of effects is diverse, justifying the need to use the GWR method to obtain a more comprehensive overview of the impact of land use on the prices practiced in tourism.

Interestingly, variables like the presence of ironing services (−0.343 to 0.180) and air conditioning (−0.450 to 0.382) show mixed effects, perhaps reflecting varying preferences or climatic conditions across different regions.

Of particular note is the range of effects of the accommodation type. While in the OLS method, cabins were shown to be associated with positive influences on prices, the GWR shows an entirely different image, where this variable's minimum local coefficient value is −4.396. Agritouristic boarding houses and villas fared better, as both were associated with significantly higher minimal values and mostly positive impacts on price. The number of stars also exhibits spatial differences for both variables.

The number of reviews (log) (−0.106 to 0.127) generally has a small negative impact, possibly due to high review counts signaling older, less desirable properties. Alternatively, low prices might be associated with higher numbers of reviews due to their increased accessibility, as reviews on Booking can only be given by guests who stayed in the location.

Figure 3 indicates the GWR's local R^2 values, which show good explanatory power for many areas in rural Romania. The Central and Western Regions (e.g., Cluj, Sibiu, Timis) contain a mix of values in the 0.5–0.9 R^2 range, indicating moderate to high levels of model fit. The northern areas of Romania are similar to the central regions regarding the R^2 value but with a higher concentration of yellow and light yellow dots, indicating moderate fit. Hunedoara, Sibiu, and Vâlcea have the lowest fit values while retaining a moderately good model fit. Therefore, the GWR model can be considered an appropriate way to assess the factors influencing pricing in rural Romania.

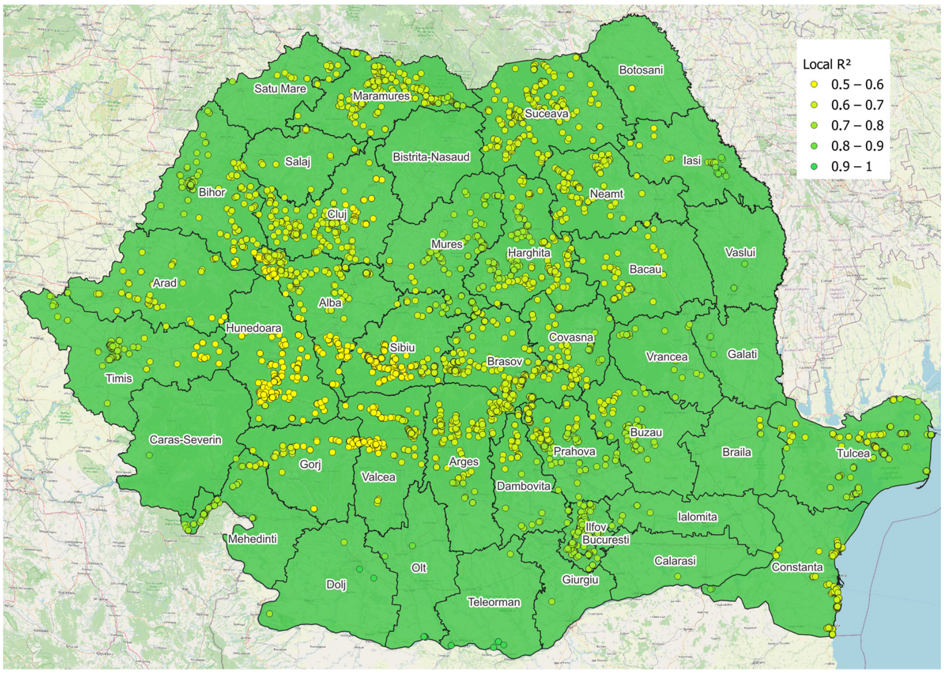

Figure 3. Local R^2 of the GWR model.

Furthermore, in order to assess the usefulness of the GWR model over the OLS, several approaches exist in the literature. In our case, we utilized the test proposed by Brunsdon, Fotheringham & Charlton [60]. For this test, the *p*-value is below the 0.01 threshold, with an F value = 1.45, *p*-value < 2.2×10^{-16}. As such, the GWR brings statistically significant improvement in the model's ability to match observed values compared to the OLS. The AIC for the OLS was 16,231.28, while for the GWR, the AIC value was 11,786.83, suggesting that the GWR offers a better fit.

Figure 4 shows the spatial distributions of the coefficients for size. The central and some southern regions appear to have a higher concentration of green data points (belonging to Q3 and Q4), indicating higher coefficient values for size in these areas. In these areas, size plays a significant role in setting prices of accommodation units.

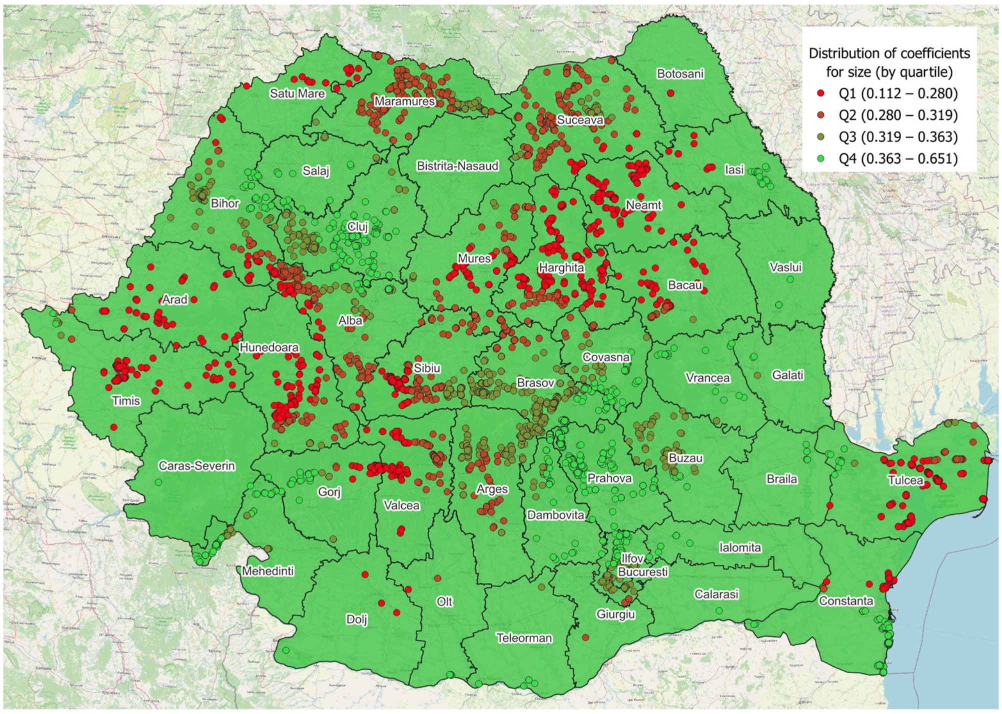

Figure 4. Spatial distribution of coefficients for size.

Northern and western regions show more red and brown dots (Q1 and Q2), indicating lower coefficients, where other factors are more important.

There is a noticeable variation in the distribution of coefficient values across different regions, with no single region dominating in terms of highest or lowest values.

Figure 5 shows the spatial distribution of the coefficients for agritouristic boarding houses. Three quartiles contain exclusively positive data, suggesting that agritourism generates higher prices than other types of accommodation units. The highest values are consistently placed around the Maramureș and Satu Mare counties in the Northern part of Romania, while the same happens on the seaside in Tulcea and Constanța. This is indicative that those are areas where agritourism development is especially advantageous for local entrepreneurs. Agritourism carries a significant and positive influence on prices across Romania.

Figure 6 shows the coefficients for swimming pool availability throughout rural Romania. While agritourism positively affected the pricing of accommodations in Maramureș and Satu Mare, the same can not be said about swimming pools. As such, we can conclude that this region is more suited towards tourism in traditional farmhouses; additionally, this could be due to harsher weather conditions and colder climates, making outdoor swimming pools less viable or less used. Additionally, some bias regarding the impact of this feature can be caused by the data collection method, which focused on the period between April and June 2024 (off-season). However, prices in other regions are positively influenced by swimming pools, as is the case for some central and southern areas.

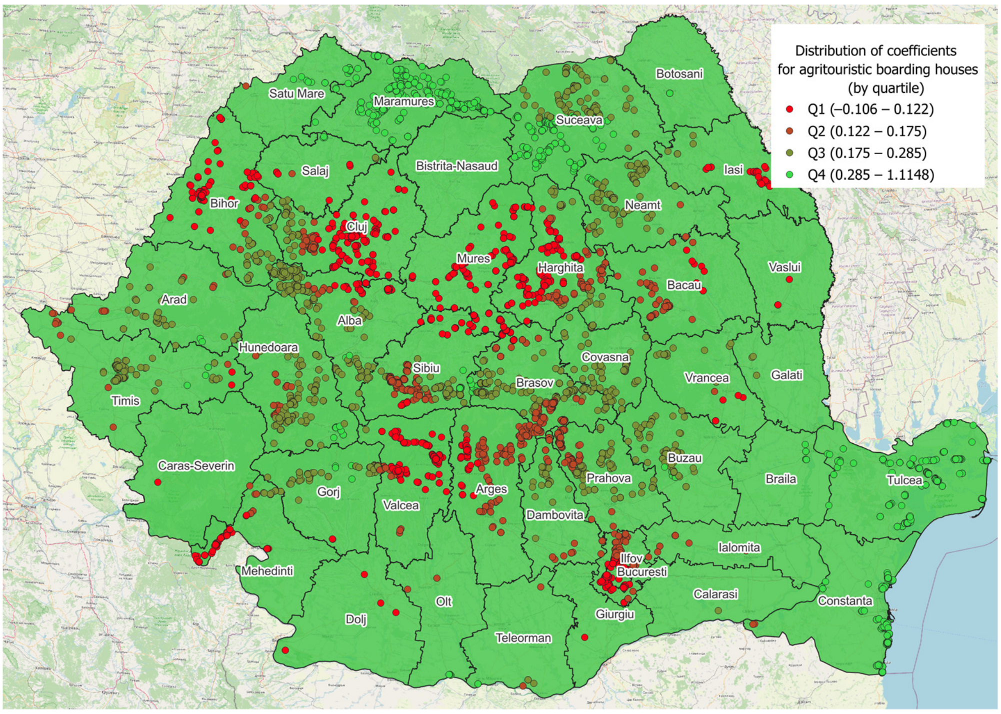

Figure 5. Spatial distribution of coefficients for agritouristic boarding houses.

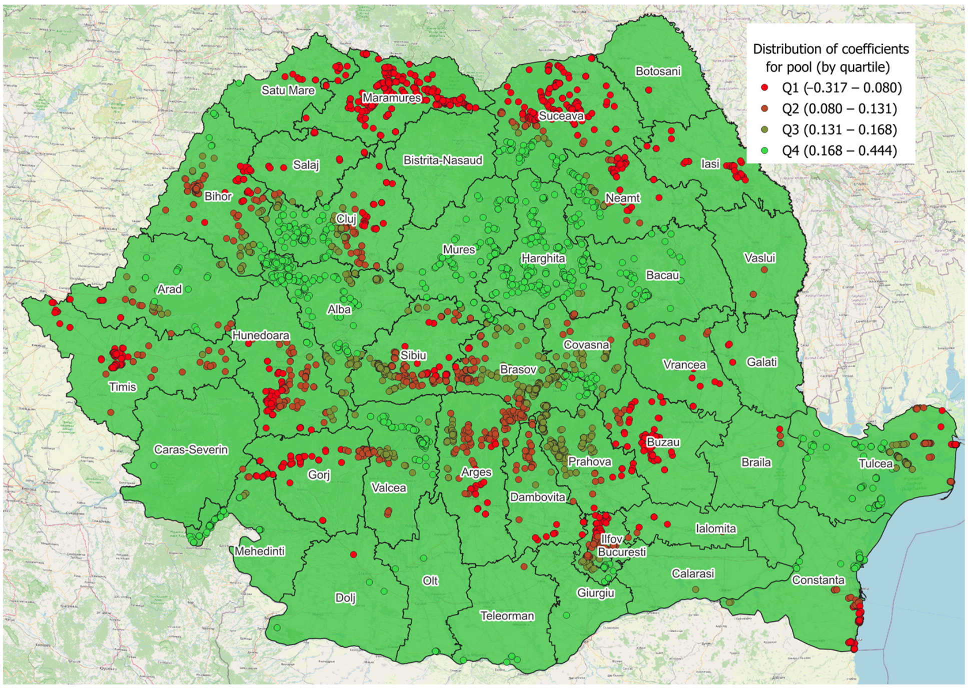

Figure 6. Spatial distribution of coefficient for swimming pool availability.

Regional differences in the impact of sauna facilities availability on hotel prices are highlighted in Figure 7. Significant disparities are present in this case, with sauna facilities more valued in the south and north-east, whereas their impact is less pronounced in the central and north-west regions.

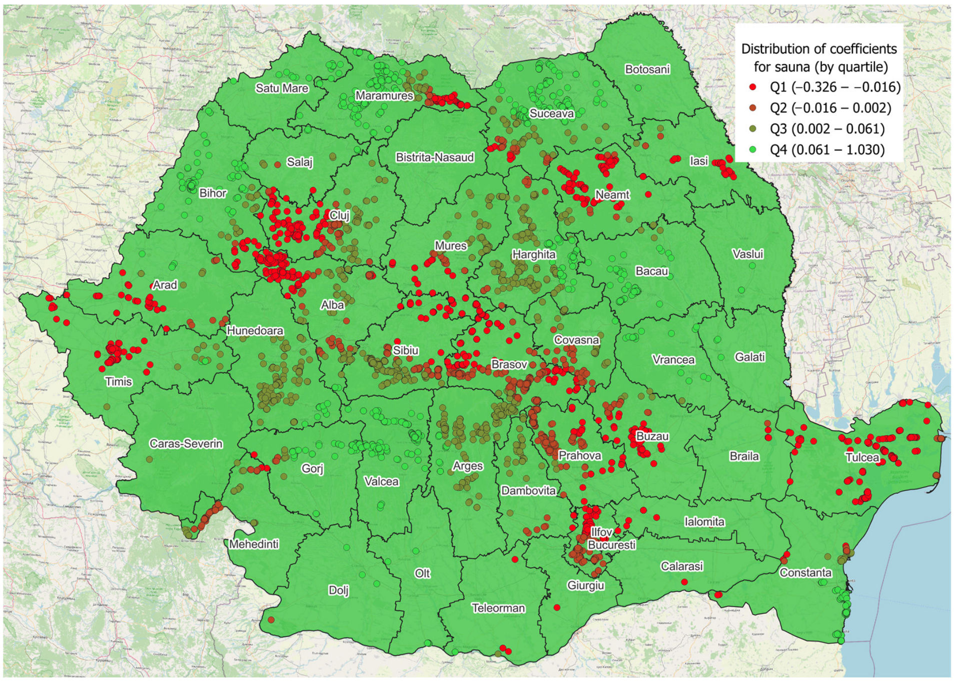

Figure 7. Spatial distribution of coefficient for sauna availability.

Compared to previous research examining the situation in Brasov County, we find evidence that sauna and pool facilities have weaker effects [5]. Possible causes may be changing customer preferences and the fact that the current research utilizes a different methodology, with local models assessing only rural areas, instead of a global model applied to a region with both urban and rural areas.

5. Discussion

The hedonic pricing model analysis described in this paper provides significant insights into the factors influencing accommodation prices in Romanian rural tourism from a general and a localized viewpoint, through the OLS and the GWR approaches. The results indicate that specific attributes and facilities have a pronounced impact on pricing, aligning with the theoretical underpinnings and previous research in the field. Indeed, most results are consistent with earlier works, suggesting that hedonic pricing models do not need to be limited by strict geographical limits. Instead, researchers should consider the typology of the market studied rather than just its size when deciding to investigate. Those are evidence supporting Hypotheses H1 and H2: both location- and accommodation-specific attributes are important predictors of accommodation unit prices, and the effect of location- and accommodation-specific attributes on prices varies significantly between studied areas, justifying the use of spatial models. The evidence counters the null hypotheses associated with H1 and H2, namely that location and accommodation attributes are not significant factors influencing prices and that no spatial component is present in the relationship between the dependent and independent variables studied.

H3, stating that the number of stars positively influences prices, should be analyzed in the context of the spatial model. As such, while the global model would lead us to the conclusion that generally, a higher number of stars would lead to higher prices, we notice from the results of the local models that this varies significantly by location. This is a useful consideration for future studies in order to uncover the causes of this behavior. While the result of the global model is consistent with the literature, the local models present interesting results that conflict with the literature [7,10,18,48,57]. Possible causes include the proliferation of accommodations that are not chartered by the authorities, but that nevertheless practice touristic activities. In such cases, the quality differences that are quantified by the number of stars are not accurately represented.

This is similar to the case of H4, which states that luxury facilities positively influence prices. While the global model confirms that massage services, pools, saunas, jacuzzis, elevators and fireplaces show substantial positive impacts on pricing, the local models show that some areas do not follow this trend. Generally, these facilities are often seen as luxurious or enhancing the overall guest experience, thereby justifying higher room rates; however, the variability in their impact across different regions suggests that their value might be context-dependent, influenced by local preferences and the availability of alternatives. The literature presents some cases where such variables have limited effect, such as in the case of pools during off-season in colder climates [15].

Proximity to natural scenery is important in determining accommodation prices. Properties located near water bodies, forests, or other natural scenic environments tend to charge higher prices, reflecting the importance placed on natural surroundings. However, the diverse range of impacts observed for these environmental factors suggests that the attractiveness of such features can vary widely, possibly due to differences in local tourism approaches or the availability of alternative attractions. Regarding the impact of the presence of water bodies, the literature shows some contradictory results, where a previous study focusing on Romania highlights a negative relationship, while data from Germany shows positive relationships. Our research shows that the global model generally associated water bodies with higher prices; however, this relationship exhibits spatial variability as evidenced by the local models. This might suggest a non-linear component to the relationship, that up to a certain point, the presence of water bodies positively influences prices, then after reaching a certain threshold, the relationship reverses.

A similar situation occurs with forests. In the case of this land use class, the general trend runs counter to the literature, showing a positive relationship. However, the local models show that a nuanced approach is needed to examine the impact of this variable and that the effects vary spatially.

The percentage of arable land was not selected as a significant variable. However, it should be noted that there are important differences between the agricultural production methods practiced in Romania and in the countries in Western Europe mentioned in the literature, the former being less mechanized and intensive [106], whereas the later are more mechanized and utilize practices that are not associated with the possible tourists' idea of rural living. This can also be related to the fact that in the case of Romania, agritouristic boarding houses manage to fare better in terms of price compared to boarding houses from other countries, where chalets are more appreciated. While the direct impact of agricultural land use on Romanian accommodation unit prices might be negligible, the indirect impact of agriculture, mediated through agritourism, seems to play a significant part.

Our findings suggest that at least in some areas of rural Romania, agritouristic boarding houses charge higher prices than villas and cabins. A direct comparison with previous works exploring the factors influencing pricing in Romania is not possible, as they took into consideration conventional guesthouses as a variable [5,48]. Even so, this paper shows that agritourism has a positive effect, while previous works show that conventional guesthouses tend to charge lower prices. This is of particular interest to rural entrepreneurs, who can focus more on agritourism.

Touristic attractivity, as expressed through the proxy of Google Maps reviews, also seems to play a role in the formation of prices, consistent with the literature, where the proximity to touristic attractions exhibits positive effects on prices [10,48].

The mixed effects of variables like the number of reviews and the presence of ironing services offer some insights into market dynamics and customer preferences. While higher numbers of reviews generally correlate with slightly lower prices, possibly due to older properties or competitive pricing strategies to attract more guests, the negative impact of ironing services might indicate a perception of these features as standard rather than premium. This finding aligns with the broader literature, which suggests that while facilities are essential, their perceived value can vary significantly based on customer expectations and market norms [5,15]. In such cases, it may be wiser for businesses to inspect regularly the current market conditions and attempt to supply the facilities that are most in demand.

Room size shows consistent and positive effects on prices, both in the global and local models, joining other works in the literature reporting the same [13,54].

Future works can attempt to explain the differences in pricing between those regions or integrate other spatial characteristics to improve the model. Furthermore, to assess the variation in price between off-season and high-season, approaches blending GWR and panel data analysis might prove fruitful, if perhaps difficult to implement. A future research project can attempt to compare a specific type of tourism, such as agritourism, between regions of Romania or between Romania and another country.

6. Conclusions

Pricing is a fundamental issue in tourism research, and attempts to model the impact of various factors on it have been made previously, with varying degrees of acuity and different scopes, generally targeting markets in small geographical boundaries. This valid approach can provide useful, targeted information regarding the studied area. However, we show that a more generalized approach is possible and can generate interesting results.

The advantages of our approach include the large scope of the studied area with adequate model performance; the focus on rural forms of tourism, which are becoming increasingly important for the sustainable development of those areas; the usage of the LASSO method for model selection, which has considerable advantages over other approaches and finally, the contribution to the growing corpus of research on hedonic pricing.

The impact of our research can be viewed through the lens of providing a managerial toolbox helpful for entrepreneurs in rural areas, helping them understand the factors that matter in pricing and allowing them to make smart investments in facilities that generate value to the accommodation units.

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