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Modeling the Potential for Rural Tourism Development via GWR and MGWR in the Context of the Analysis of the Rural Lodging Supply in Extremadura, Spain

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Abstract: The harmonious development of tourism activity in rural areas must be based on effective tourism plans adapted to the territory. To achieve this, it is necessary that the tourist potential of the area be taken into consideration. However, the tourist attraction capacity is not always considered, which has led to a significant increase in the number of rural lodgings. This has caused strong imbalances in Extremadura, Spain. On the basis of this premise, in this research study, we aim to determine whether there is an adjustment between the main factors that attract rural tourists to the study area. To determine this, we make use of different geostatistical procedures based on spatially weighted regression models (GWR and MGWR). A comparative study is conducted using these models, on the basis of which it is deduced that one type of regression offers advantages over the other. However, the results show that neither regression models can explain the presence of rural accommodation in places that do not meet the requirements demanded by tourists. This fact shows that the increase in the supply of rural accommodation follows unsuitable patterns in some cases, which translates into numerous problems, such as low occupancy levels. In this study, it is concluded that there is no strong relationship between the attractiveness of a territory and its volume of supply, highlighting the need to rethink tourism plans in order to adjust them relative to reality.

Keywords: tourism potential; rural tourism; rural accommodation; geographically weighted regression (GWR); multiscale geographically weighted regression (MGWR); Extremadura

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1. Introduction

The definition and interpretation of rural tourism are complex, and there is no consensus among experts [1], despite the many attempts that have been made in this direction [2,3]. Since the 1990s, there has been discussion of the criteria to be used to define this variety of tourism. Among them are location in rural areas, functionality, scale, and the character and pattern of the place [4]. Nevertheless, three decades later, the debate is still open. It is even possible to ask what a rural territory is or what its functionality is [5]—and these questions would find varied answers. The same is true of the concept of rural tourism, and even of rural tourists [6].

Tourism is considered to be a means of achieving the socioeconomic development of rural areas [7], wherein the attractiveness of these spaces is key to attracting tourists. It is common to find studies analyzing rural tourism from the point of view of the supply of lodging [8], from the perspective of demand [9], and even from the perspective of territorial aspects [10]. In addition, in most cases, statistical analyses are used to corroborate the initial hypotheses [11]. However, it is not common to find studies attempting to determine the relationship between the presence of tourist attractions and the supply of accommodation, especially when statistical criteria are applied that include the territorial criterion as a weighting measure [12].

The need to incorporate the territory into the analysis of the tourism system arises because tourist attractions and the supply of accommodation and complementary services, together with the tourists themselves and the trips they make, are susceptible to being represented in geographical space [13]. To understand a tourism system, it is necessary to understand the relationships that are established among all of its components, nuanced by their location. Therefore, it would be logical to think that analytical techniques need to be adapted to this reality [14]. Similarly, the incorporation of the neighborhood criterion and spatial relationships helps to understand tourism, since the spaces nearby affect and are modified by tourism activity, thus influencing and altering strictly statistical models [15,16].

Rural tourism, like any other form of tourism, is no stranger to the tendency to incorporate the territory into the different analyses. This implies resorting to complex analyses requiring the conceptualization of spatial relationships and distance criteria. Thus, different geostatistical techniques are beginning to be applied, which are responsible for analyzing and even predicting values of any attribute or set of attributes in space on the basis of modeling. [17–20]. This branch of statistics emerged in the 1960s, although specific techniques based on spatial correlation already existed two decades earlier. The literature has concluded that this technique can be applied for the recognition and estimation of natural phenomena on the basis of the formalism of random functions, allowing all situations to be treated in the same way [21]. This analytical capacity makes it possible to regionalize very diverse variables [22], since many of them can be spatially represented and, consequently, are candidates for the application of this type of systematic approach. Numerous authors have carried out studies on different facets of tourism using geostatistical techniques [23–27].

Spatial analysis seeks to uncover hidden spatial structures, such as associations between objects. It seeks to model geographic phenomena in order to reflect the nature and quality of components or methods applied in the tasks and transformations carried out in spatial analysis. In concrete terms, they analyze the data obtained in the appropriate programs using the functions required by existing knowledge of the problem, in order to define the methods of analysis [26]. This makes it possible to represent variability, from either a descriptive or predictive point of view, on the basis of multiple functionalities collecting algorithms created over time.

The innovations represented by this new means of statistically analyzing data, in which the spatial criterion is incorporated, have been very well received by geographers, who have been very involved in the well-known quantitative revolution fighting against idiographic conceptions of geography [27]. Since then, tourism research has made more frequent use of the group of techniques incorporating the modeling of spatial relationships. The aim of this is to derive models by means of a set of regressions. These start with an exploratory regression, with which those models which are feasible and consistent are investigated, on the basis of which a prior filtering with respect to the condition factor and/or collinearity, which are the major obstacles of regression. The literature supports the use of viable models by means of ordinary least squares (OLS) regression [28–30]. This technique seeks to simulate models in which a set of independent variables is capable of explaining a dependent variable. These models are usually subjected to another specific treatment that seeks to integrate the territorial component, using spatially weighted regression (GWR) [31–34] and multiscale geographically weighted regression (MGWR) [35–38]. The field has moved from a relatively simple regression model (OLS), in which a single function was obtained for all the cases analyzed, to another that provides a differentiated model function for each case (GWR). The latter emphasizes the relationship with the spatial proximities among observations, although it has evolved further, even assuming that functions may be different in each case, but also when considering the different relationships that may be established between the regressors and the cases analyzed (MGWR). The specialized literature corroborates the increasing application of statistical and geostatistical techniques in tourism studies [39–41]. This is evidence of the weight acquired by the territory in this type of analysis.

If there are numerous options for analyzing tourism at the technical level, a notable problem also arises when specific aspects of tourism are studied. Specifically, these techniques have sometimes been used to determine the ideal location in a territory [42]. Attempts have also been made to determine the optimal location of tourist services on the basis of comparison with the extensive use of Geographic Information Systems to determine the optimal location of investments [13,43].

Despite the important efforts that have been made, it has only been possible to obtain a satisfactory explanation for the location of rural lodgings in a small number of cases. This is because the locations of rural lodgings do not always obey the rules of logical coherence, implying that they will be found in those areas that best meet their ideal conditions, or suggested by adaption to demand. In fact, certain studies have suggested an apparent randomness in their distribution [44], since they are not always located in those areas that offer the greatest capacity to attract tourists.

This situation has worsened in recent decades due to the notable growth in the number of lodgings, which has been promoted by the regional government itself. On the other hand, tourism plans have never been developed on the basis of studies linking the tourist demand with the availability of accommodation in an effort to support a clear tourism policy. As a consequence of all of this, growth has been disorderly, and not always in line with the potential of an area to attract tourists.

This article proposes, as a starting hypothesis, that the volume of lodging supply does not adapt to the existence of major tourist resources sought by tourists [45], which will be demonstrated with the use of regressions.

The general objective is to derive explanatory and predictive models in which the most important factors in explaining the availability of accommodation are determined by the tourists themselves. To achieve this objective, we performed the following steps:

- Geostatistical models, specifically spatially weighted regressions (GWR) and multiscale geographically weighted regressions (MGWR), were used to determine the fit between the regressors (X_1, X_2..., X_n) and the predicted variable (Y). The former is understood to denote the types of tourism resources preferred by this type of demand. The latter, on the other hand, refers to the number of vacancies in rural tourism lodgings.
- The use of this type of technique (GWR and MGWR) requires a series of preliminary investigations, in the course of which collinearity is eliminated by means of exploratory regressions.
- The derivation of viable models enables the initial hypothesis to be corroborated or disproved.

2. Materials and Methods

2.1. Study Area

The study focuses on Extremadura, which is an autonomous community located in the interior of Spain. It is made up of two provinces, Cáceres and Badajoz, although rural tourism takes on greater dimensions in the former. It shares a border with Portugal, the oldest border in Europe [46]. It also borders with other autonomous communities within the country such as Castilla y León, Castilla-La Mancha, and Andalusia (Figure 1).

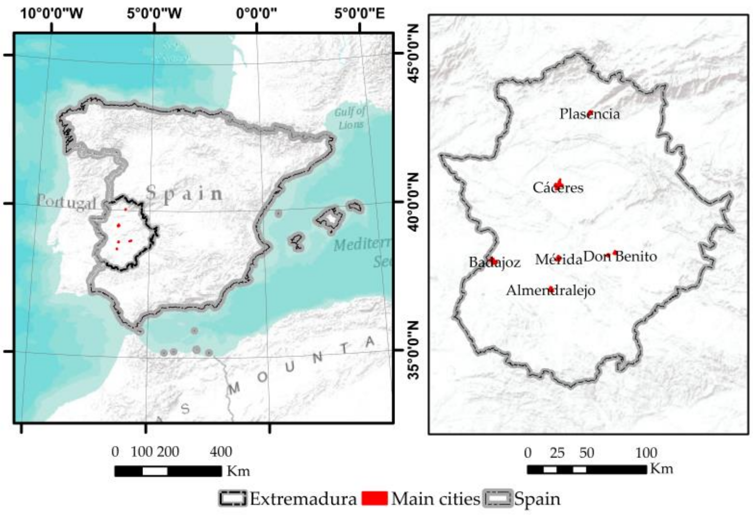


Figure 1. Location of Extremadura in the Iberian context.

This borderline position, far from the main socioeconomic centers of the country and marginalized from the main communication axes, has contributed to the scant development within its 41,634 km^2 area. As a result, it is sparsely populated, with only 1,054,776 inhabitants in 2022 [47]. As a result, it is one of the territories with the lowest demographic density, having a population density of 25.6 inhabitants/km^2.

The territory is dotted with a multitude of tourist resources with an important natural and cultural heritage, although it lacks the modality of sun and beach tourism [13,46–50]. Proof of this can be found in the numerous protected areas distributed throughout the territory [51], the bathing areas linked to rivers, and the significant volume of historical sites, as well as the areas and nuclei that have been listed as World Heritage sites by UNESCO [45].

Its tourist development has been poorly organized in rural areas, especially with respect to the variety of rural accommodation available. In addition, in recent years, there has been a real explosion of illegal supply, thanks to platforms such as Airbnb [52].

Rural lodging, according to Law 2/2011, of 31 January [53], regarding the development and modernization of tourism in Extremadura, must present special characteristics in terms of construction, type, and location in rural nuclei or in scattered developments located outside urban nuclei, and be dedicated to providing lodging, in return for economic consideration, to people who demand it, with or without the provision of other services. The law also clarifies that, for the purposes of said Law (6/2018), rural nuclei can be understood to be those with populations smaller than 20,000 inhabitants. This type of accommodation has experienced a peculiar increase since the beginning of this century, both in terms of lodging capacity and the number of visitors and overnight stays they make (Table 1). This can be deduced from a simple comparison, obtained from the survey of occupancy in rural tourism lodgings (EOTR) published by the National Institute of Statistics [54]. While in 2001 there were 104 establishments offering 939 bed places, in 2022, there were already 725 accommodations with an accommodation capacity of 5355 bed places.

Naturally, the growth in supply has occurred almost in parallel with that of quantitative indicators of demand, with an increase in the numbers of travelers and overnight stays of 791% between 2001 and 2022. However, both the average length of stay and the occupancy rate continue to show clear signs of improvement.

Perhaps the comparative analysis between supply and demand is more illustrative, especially when analyzing the situation existing throughout the period covered by the series analyzed. In this regard, it should be noted that, while in 2001 there were 70.9 overnight stays for each available vacancy throughout the year, in 2022, that figure was 66.2.

Table 1. Evolution of tourism magnitudes of rural accommodation.

	Travelers	Overnight Stay-Ciones	Estancia Half	Grade of Occupation	Degree of Occupation F/Week	Establishment Mientos	Places	Employment	Overnight Stays /Plaza
2001	30,192	66,548	2.09	23.31	NA	104	939	172	70.9
2005	65,815	146,220	2.13	18.88	NA	228	2668	397	54.8
2010	107,526	251,518	2.29	14.14	22.17	461	5496	719	45.8
2015	161,011	349,386	2.12	19.87	28.79	538	6515	795	53.6
2019	226,723	499,749	2.20	17.89	34.64	632	7609	1001	65,7
2020	110,065	271,571	2.47	13.42	22.17	466	5598	737	48,5
2021	184,975	433,665	2.34	15.51	28.04	664	7584	954	57.2
2022 *	238,897	533,431	2.19	17.26	31.70	725	8355	1153	66.2

* Provisional data. Source: Prepared by the authors on the basis of EOTR [54].

On the other hand, when observing the evolution of the ratio of overnight stays/places in this type of lodging, and taking the situation that existed in 2001 as a basis, it is clear that there has been a strong imbalance in growth for several consecutive years.

These data only corroborate the fact that, during the period analyzed, there has been significant growth, but it has been uncoordinated, lacking in foresight, and focused more on increasing the supply of accommodation than on reversing the situation with respect to demand, or facing the most pressing problems that constrain the sector, which include the low average length of stay and low occupancy rates.

2.2. Materials

This study is based on the creation of a database from several official sources that provide information with open access. These include the National Institute of Statistics [55], the Registry of Tourism Activities [56], and the Tourism Observatory [57], whereby the latter two belong to the Regional Government of Extremadura. All of these sources offer freely accessible information through their web portals related to the supply of accommodation and complementary services that make up the set of external variables considered.

All of the cartographic data used to obtain information related to internal variables and accessibility were obtained from the National Geographic Institute [58] and the Spatial Data Infrastructure of Extremadura [59], all of which was employed under a Creative Commons license.

These two data sources were complemented with the manual acquisition of data related to the location of the lodging and complementary offer, using a Garmin 62sc GPS.

The use of all of these sources made it possible to calculate and elaborate a database composed of 37 internal variables and 23 external variables for each of the 388 municipalities of Extremadura (Table 2). This database was used to carry out studies on the tourism potential of the territory, describing each of the variables used in detail [45].

Table 2. Variables included in the database.

Internal Variables Considered (Type, Subtype and Code)					
Type	**Subtype**	**Code**	**Type**	**Subtype**	**Code**
Relief	Mountains and their foothills	VI1	Summer thermal comfort	Average maximum temperature from June to September	VI22
	Saws	VI2	Others	Big game hunting + 1000 hectares.	VI23
	Piedemontes	VI3		Long-distance trails	VI24
	Lakesides and valleys	VI4		Short-distance trails	VI25
	Sedimentary basins/plains and peneplains	VI5		Local trails	VI26

Table 2. *Cont.*

Internal Variables Considered (Type, Subtype and Code)					
Type	**Subtype**	**Code**	**Type**	**Subtype**	**Code**
Hydrography	Rivers (up to 2 km)	VI6		Optimal visiting period (demand preferences)	VI27
	Reservoirs	VI7		Singularity (pairwise)	VI28
	Bathing areas	VI8		Attractiveness according to demand (questionnaire)	VI29
	Waterfalls	VI9		Proximity to main tourist attractions (EOH)	VI30
Protected natural areas	National Park	VI10		Proximity to tourist area (EOTR)	VI31
	Park or Nature Reserve	VI11		Population size	VI32
	Natural Monument	VI12		Vegetation species	VI33
	ZEPA ZEC	VI13 VI14		Geosites Viewpoints	VI34 VI35
Cultural/historical-artistic heritage	Distance to World Heritage City (time)	VI15		Observation points	VI36
	Historic-artistic site	VI16		Greenways	VI37
	Assets of Cultural Interest (Monuments)	VI17			
	Museums and collections Livestock trails at 2 km Castles Archaeological sites	VI18 VI19 VI20 VI21			
Considered external variables (type, subtype, and code)					
Type	**Subtype**	**Code**	**Type**	**Subtype**	**Code**
Hotel accommodation Accommodation (beds)	Hotel Hotel–Apartment Hostel Pension	VE1 VE2 VE3 VE4	**Others**	Activity companies (no.) Tourist guides (no.) Tourist offices Interpretation centers	VE13 VE14 VE15 VE16
Non-hotel accommodation (vacancies)	Tourist apartment	VE5		Wharfs	VE17
	Camping	VE6	**Accessibility**	Highway	VE18
Rural lodging (vacancies)	Rural hotel	VE7		National highway	VE19
	Rural house Rural apt.	VE8 VE9		Autonomous highway Main bus stations	VE20 VE21
Restoration	Three- and four-fork restaurants (seats)	VE10		Train stations	VE22
	One- and two-fork restaurants (seats)	VE11		Airport	VE23
	Café-bar (no.)	VE12			

Source: Sánchez-Martín, J.M. et al. [45].

2.3. Geostatistical Analysis

To perform the calculations required for the geostatistical techniques used throughout this research, the software ArcMap v. 10.8 and MGWR v. 2.2 were used.

Quantitative techniques offer important advantages, since they facilitate the analysis of considerable volumes of data and can be used to derive models, and even predicting values on the basis of them [30]. This is one of the major contributions of multiple regression, as well as the discovery of outliers [60]. However, they are not always able to capture the essence of tourism activities that nuance these relationships as a result of their transcending the territory. In fact, the role of geographical space is key [61,62], and is inherent to the field of tourism; although, given the complexity of this technique, it is necessary to calibrate the concept of distance very well as a key parameter for establishing the neighborhood criterion [63,64].

Any regression model is always subject to uncertainty due to the complexity of the algorithms used. Some authors claim that these formulas uncover the numerical complexity in determining the estimators. To do so, a matrix must be inverted, and not all matrices can be inverted (this is the case, for example, for singular matrices). There are two situations in which the calculations cannot be performed: when the number of observations is smaller than or equal to the number of independent variables; and when an independent variable is a linear combination of other(s) or is constant (collinearity) [65].

Although the regressions used (OLS, GWR, and MGWR) have common characteristics and objectives, they also exhibit marked differences, mainly due to the consideration of the neighborhood criterion. Ordinary least squares regression is perhaps that offering the simplest configuration, while at the same time, it has a long history in various scientific publications. Sometimes, it is used as a stand-alone technique, although in other situations it is used in conjunction with other methods of statistical analysis [66,67]. Its main objective is to obtain a suitable model with which to establish predictions on the basis of a previously defined set of independent variables.

The degree of accuracy in the configuration of the model is dependent on the independent variables influencing the explanation of the dependent variable, so it is necessary to be especially rigorous in the inclusion of regressors. Some authors insist on the need to check the possible existence of homoscedasticity or heteroscedasticity on the basis of the covariance matrix. In this sense, a predictive model would be understood as homoscedasticity when the error variance is constant in all cases. On the other hand, it would present heteroscedasticity in the opposite case; i.e., when the variance is different [68–70]. Moreover, interpretations tend to go beyond the actual configuration of the explanatory models to focus, in addition, on the important role played by the mismatches between the theoretical model and the real situation. These comprise the residuals [71].

The most frequent problems are the omission of explanatory variables, the existence of nonlinear relationships, the presence of outliers, multicollinearity, inconsistent variance in the residuals, etc.

The procedure followed in this research is based on the application of an exploratory regression model based on multiple ordinary least squares regressions. The aim is precisely to eliminate invalid models, because the values obtained either when calculating the F-Statistic or when subjecting the models to the Wald, Koenker, or Jarque–Bera tests exceeded the admissible limits.

The application of OLS regression results in a general model, which applies to all the cases used, and is based on the following formulation:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon$$

where:

$\boldsymbol{y_i}$ denotes the observed value of the dependent variable at point i;
$\boldsymbol{\beta_0}$ is the point of interception and constant value;
$\boldsymbol{\beta_n}$ is the regression coefficient or slope of the explanatory variable n at point i;
$\mathbf{x}_n$ is the value of variable n at point i; and
ε denotes the error of the regression equation.

The following requirements must be met for its application [72]:

- The model must be linear;
- The data used should not depend on any external factor;
- Explanatory variables should not be related to each other;
- The explanatory variables must have a negligible measurement error;
- The residuals must add up to 0; and
- The residuals must have homogeneous variance and follow a normal distribution.

Once the integrity of the chosen model has been verified, spatial autocorrelation is applied using the residuals obtained as a numerical variable, in such a way as to verify their randomness.

Once this randomness has been confirmed, the models are created, including the territorial aspect. The presence of some tourist resources favors not only the areas in which they are located, but also nearby areas.

The need to include distance as a parameter is key, according to the literature [73–77].

To address this context, spatially weighted regression (GWR) has emerged as a viable alternative for building models in which spatial relationships are effectively considered. This allows the construction of a model using explanatory variables, just like OLS. GWR specifies whether the kernel is constructed following a fixed distance, or whether it is allowed to vary in width depending on the density of the attribute under analysis [78,79]. It also makes it possible to determine the extent of the kernel, either by means of the Akaike corrected criterion (AICc), cross validation (CV), or the bandwidth parameter (Bandwidth Parameter).

In GWR, a separate equation is constructed for each entity by incorporating the dependent and explanatory variables of the entities that are in the bandwidth of each target entity. The following equation is used:

$$y_i = \beta_{i0} + \sum_{k=1}^{m} \beta_{ik} + x_{ik} + \varepsilon_i$$

where:

$\boldsymbol{y_i}$ is the dependent variable at location *i*;

$\boldsymbol{x_{ik}}$ is the k-th independent variable at location *i*;

$\boldsymbol{m}$ is the number of independent variables;

$\boldsymbol{\beta_{i0}}$ is the intercept parameter at location *i*;

$\boldsymbol{\beta_{ik}}$ is the local regression coefficient for the k-th independent variable at location *i*; and

$\boldsymbol{\varepsilon_i}$ is the random error at location *i* [62].

This allows the coefficients to continuously vary over the study area, and the set of coefficients can be estimated for any location, so that the coefficients can be mapped and the very existence of potential heterogeneity in their relationships can be questioned. In addition, this type of regression allows a point calibration to be performed relative to an "influence anomaly"; i.e., around each regression point at which closer observations have more influence on the estimation of the local set of coefficients than more distant observations [61,80].

Therefore, GWR can be used to measure the inherent relationships around each regression point *i*, where each set of regression coefficients is estimated by weighted least squares using the following equation:

$$\hat{\beta}_i = \left(X^T W_i\, X\right)^{-1} X^T W_i y$$

where:

$\boldsymbol{X}$ is the matrix of the independent variables that intercepts with the first column;

$\boldsymbol{y}$ is the vector of the dependent variable;

$\boldsymbol{\hat{\beta}_i = \left(X^T W_i\, X\right)^{-1} X^T}$ is the vector of $m + 1$ local regression coefficients; and

W_i is the diagonal matrix denoting the geographic weighting of each observed data for regression point i [63,78].

This type of regression assumes that all the relationships of the independent variables that make up the model vary in space, but are always on the same spatial scale, which can influence the results. For this reason, an increasing number of specialists have opted for the application of multiscale geographically weighted regression (MGWR), as it allows the relationships established between the independent variable and the regressors to mutate at different spatial scales. This de facto implies that the distance used can vary according to the type of surfaces involved in the model [69].

Assuming that there are n observations, for observation i ∈ {1,2,...,n} at location $(u_i,\ v_y)$,

$$y_i = B_0(u_i\ ,\ v_i) \sum j\ B_{bwj}(u_i,\ v_y)\ x_{ij} + \varepsilon_i$$

where bwj in B_{bwj} indicates the bandwidth used for the calibration of the jth conditional relationship [81,82].

3. Results

The use of regression models has been proposed in the literature, since they have shown good ability to predict events. However, their use is not without certain problems arising from the interrelationships that may exist between the independent variables. [83,84].

To avoid one of the main pitfalls of regression models, namely multicollinearity, which has been extensively described in the literature [85], the first step is to clean up the variables by performing multiple exploratory regressions.

All of the internal variables, as well as those related to accessibility, described in Table 2, were taken. In addition, given the collinearity observed, it was decided to reduce this set of variables to only include those that prevailed in the course of preliminary refinements. A linear correlation matrix was used for this purpose. Even so, and to obtain the most plausible models, free of problems arising from multicollinearity, numerous exploratory multiple regressions were performed using the spatial statistics module integrated in ArcGIS v.10.8.

The dependent variable chosen was the number of vacancies in rural establishments in each of the 388 municipalities, and the independent variables were those related to relief, hydrography, the network of protected natural areas, the most important cultural attractions, vegetation, and accessibility.

A brief synopsis of the models created shows the enormous variety of possibilities and existing combinations (Table 3).

Table 3. Overall summary of the exploratory regressions performed.

Search Criteria	Cut	Testing	No. of Accepted	% Accepted
R^2 adjusted minimum	>0.3	261,800	44,362	16.94
Maximum coefficient p value	<0.05	261,800	1269	0.48
Maximum variance inflation factor	<5.0	261,800	242,401	92.59
Minimum p value of Jarque–Bera	>0.1	261,800	0	0
Minimal spatial autocorrelation	>0.1	42	38	90.48

Although the number of trials performed was high, this allowed the variables to be refined in consideration of their significance, the variance inflation factor (VIF), and the number of multicollinearity violations. Most of the proposed variables were demonstrated on the basis of their statistical significance to be acceptable values, as also suggested by their variance inflation factors (VIFs). Only proximity to the mountain (VI1) possessed a high value that exceeded the permitted threshold. However, this variable was still regarded as acceptable, since variables were only to be discarded when a value of 7.5 was exceeded.

To safeguard integrity and to be as non-inclusive as possible in the calculations, any problematic variables were omitted from the weighting matrix. In addition, models were sought that contemplated between three and fifteen explanatory variables, including as indispensable conditions that their adjusted R^2 exceeded a value of 0.3, their *p* coefficient was greater than 0.05, their variance inflation factor (VIF) was less than 5, and that their Jarque–Bera and spatial autocorrelation tests demonstrated minimum acceptable values of 0.1.

A total of 1269 different models containing between three and nine independent variables were obtained that were able to meet these conditions, since the inclusion of a greater number of regressors showed strong statistical tensions in the form of collinearity. A first consideration of the derived models indicated the reiteration of certain regressors, which appeared in many of the models. These included accessibility, measured with reference to proximity to the highway, and the presence of a park or nature reserve, vegetation, or mountains and reservoirs, as is evident from Table 4.

Table 4. Significance and variance inflation parameters and repetition of variables in the feasible models obtained.

Variable *	Significance	Percentages		Inflation Factor of Variance (VIF)	Violations	Repetitions	Models	% of Occurrence
		Negative	Positive					
1-9 VI1	21.84	36.13	63.87	6.58	19,399	389	1269	30.65%
VI2	11.45	95.48	4.52	3.11	0	326	1269	25.69%
VI3	23.11	0.88	99.12	2.37	0	308	1269	24.27%
VI4	6.88	77.95	22.05	1.64	0	244	1269	19.23%
VI5	50.03	100	0	1.97	0	272	1269	21.43%
VI7	17.99	90.26	9.74	1.4	0	388	1269	30.58%
VI8	95.75	0	100	2.24	0	252	1269	19.86%
VI10	3.97	9.22	90.78	1.95	0	172	1269	13.55%
VI11	100	0	100	1.31	0	513	1269	40.43%
VI12	0.59	50.15	49.85	1.49	0	18	1269	1.42%
VI13	36.2	0	100	1.19	0	535	1269	42.16%
VI15	22.13	52.03	47.97	2.47	0	301	1269	23.72%
VI16	100	0	100	1.96	0	307	1269	24.19%
VI17	27.93	19.12	80.88	1.63	0	444	1269	34.99%
VI28	100	0	100	2.27	0	51	1269	4.02%
VI33	43.27	0	100	1.35	0	586	1269	46.18%
VE18	48.22	99.77	0.23	3.16	0	702	1269	55.32%
VE19	12.82	3.47	96.53	1.62	0	222	1269	17.49%

* VI1: Mountains and their foothills; VI2: Sierras; VI3: Foothills; VI4: Lakesides and valleys; VI5: Sedimentary basins; plains and peneplains; VI6: Rivers (up to 2 km); VI7: Reservoirs; VI8: Bathing areas; VI28: Singularity (pairwise); VI10: National Park; VI11: Park or Nature Reserve; VI12: Natural Monument; VI33: Species of vegetation; VI15: Distance to World Heritage City (time); VI16: Historic-artistic site; VI17: Assets of Cultural Interest (Monuments); VE18: Highway; VE19: National Highway.

The detailed analysis of the different models showed a reality that was much better defined. The adjusted R^2 did not improve with the inclusion of a greater number of independent variables. This coefficient barely increased between the inclusion of models with three and the inclusion of models with nine regressors, so a detailed study of each of the models that exceeded the required explanation threshold (0.3) was necessary.

Under this restrictive assumption, several viable models were obtained due to the relationship between the number of independent variables and the adjusted R^2.

Specifically, model (1) and the alternative models (2) and (3), which employed four independent variables, when compared to the more complex model (4), which used five variables, and, finally, to the most complex model (5), which employed up to fifteen regressors, offered similar results in terms of explanation of variance, although further nuance can be observed on the basis of an analysis of the regressors of which they were composed (Table 5).

Table 5. Main parameters of the models and contribution of the regressors to the model configuration.

Model	R^2 Adj	AICc	JB	VIF	SA	Model
(1)	0.32	3849	0.00	1.46	0.37	+VI8 ** + VI11 *** + VI16 *** + VI28 ***
(2)	0.31	3856	0.00	1.59	0.69	−VI5 + VI11 *** + VI16 *** + VI28 ***
(3)	0.31	3856	0.00	1.11	0.47	+VI10 +VI11 *** + VI16 *** + VI28 ***
(4)	0.32	3850	0.00	1.51	0.40	+VI8 ** + VI10 + VI11 *** + VI16 *** + VI28 ***
(5)	0.32	3860	0.00	5.83	0.99	−VI1 ** − VI2 + VI3 − VI4 − VI5 + VI8 ** + VI10 * VI11 *** − VI12 + VI16 *** + VI17 + VI28 *** + VI33 − VE8 * + VE19

R^2 Adj.: Adjusted R^2; AICc: Adjusted Akaike Criterion; JB: Jarque–Bera; VIF: Variance Inflation Factor; SA: Spatial Autocorrelation. Significance of the model: * = 0.10; ** = 0.05; *** = 0.01.

Model (1) demonstrated an acceptable adjusted R^2, with a very low variance inflation factor and the lowest spatial autocorrelation. In addition, its coincidence with the variables forming the main core of the function is notable, with the only one that varies, the distance to bathing areas (VI8), being more significant than the alternatives, which were distances to sedimentary basins (VI5), which demonstrated a negative relationship, or to the national park, which was positive. However, model (4) exhibited very similar statistical characteristics, although it used five variables; therefore, it is necessary to compare the results offered by both models in order to determine which of them was more efficient. In addition, it is worth mentioning that the results obtained by the most complex model, which employed 15 independent variables, indicated an adjusted R^2 that was similar to that of the aforementioned model, while presenting very high values of variance inflation factor and spatial autocorrelation.

From the description above, it can be concluded that the most viable models required only four or five independent variables, and these were model (1) and (4).

It should be pointed out, with respect to the first model considered (1), that the results offered by the ordinary least squares regression (OLS) presented an R^2 value of 0.327, and when this was adjusted, it remained at 0.32. This demonstrates its robustness. In addition, the variance inflation factor (VIF) was very low, especially when considering that a maximum acceptable value of 7.5 was selected. Despite this, there may be certain risks when considering other complementary parameters (Table 6).

Table 6. Ordinary least squares regression results and diagnostics—model (1).

Variable	Coefficient	Std. Error	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	−33.16	5.171	−6.41	0.000000 *	7.38	−4.49	0.000012 *	——-
VI8	5.44	1.717	3.17	0.001659 *	2.40	2.27	0.023983 *	1.46
VI11	6.00	1.554	3.86	0.000140 *	2.26	2.66	0.008137 *	1.09
VI16	5.15	1.504	3.43	0.000694 *	1.38	3.75	0.000219 *	1.18
VI28	10.70	1.535	6.97	0.000000 *	1.84	5.81	0.000000 *	1.33

* An asterisk next to a number indicates a statistically significant *p*-value ($p < 0.01$).

The cartographic representation of the standardized residuals obtained detected nuclei that presented anomalies, appearing with residuals exceeding the mean by more than 2.5 times the standard deviation. Malpartida de Plasencia and Valencia de Alcántara stand out as notable examples of this, with their residuals far exceeding the estimates made, which was due to the presence of the Monfragüe National Park and the commitment to rural tourism in Valencia de Alcántara (Figure 2).

The analysis of the extreme cases considered when the standard deviation exceeded the mean by ±1.5 times offered an ambiguous perspective. On the one hand, there were towns with important internal factors for attracting tourism, but which did not offer rural lodging or, when they did so, this was very scarce, considering the attractiveness of the towns for tourism. On the other hand, there were nuclei in which the theoretical capacity of attraction for this type of tourism was low, or where there was a large amount of supply of the type of lodging under study. This situation was observed in some municipalities in the region of La Vera, one of the places with the greatest tradition of developing rural tourism. On the other hand, other municipalities in the same region, such as Jarandilla, possessed 268 beds, while the model estimated that there would be only 71. This situation was not exclusive to La Vera; it was also observed in other areas, such as Valle del Jerte and Valle del Ambroz. This was due to their locations in mountain areas and areas in which numerous bathing areas are located. Likewise, certain anomalies appeared in Baños de Montemayor, as a result of its famous spa, and Torrejón el Rubio, as a result of the presence of the Monfragüe National Park.

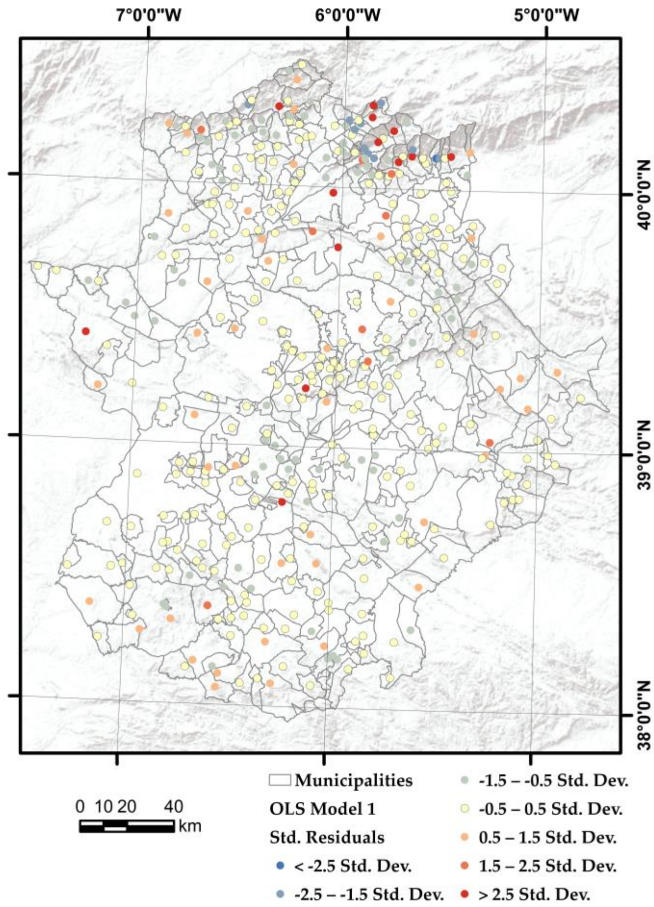


Figure 2. Distribution of standardized residuals. Model (1).

The derived model performed as expected in most cases; although, when there was a high-level resource, performance declined, and the model was not applicable. However, the question arises as to what had occurred in other cases to cause the constructed model not to fit. In this regard, one of the most evident coincidences between the models showing a negative bias in standard deviation with respect to the mean was small populations residing in these centers. This fact should logically prompt us to rethink tourism as another way of combating depopulation, if the necessary heritage is available to make the place in question attractive to tourists, thus allowing the generation of tourist products.

Since the aim is to construct a global model, it is necessary to rule out the spatial agglomeration of resources. To this end, a spatial autocorrelation must be carried out using Moran's global index. This was used to ensure the randomness of the residuals and to show that any explanatory variable referring to the distribution of rural lodging places had been omitted. The application of this index made it clear that the results obtained were random, since a value of 0.012 was obtained, implying, together with the probability of 0.55, that the null hypothesis cannot be rejected. Therefore, it is quite possible that the spatial distribution of entity values was a result of random spatial processes.

The results obtained using model (4), which had five regressors, possessed an R^2 of 0.33, which, when adjusted, remained at 0.321, also indicating its robustness. In addition, the variance inflation factor (VIF) was very low, considering that a maximum acceptable value of 7.5 was employed.

If using this model (Table 7), it is necessary to understand the existence of certain risks, as in the previous case.

Table 7. Ordinary least squares regression results and diagnostics—model (4).

Variable	Coefficient	Std. Error	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	−36.82	5.985	−6.15	0.000000 *	8.34	−4.41	0.000016 *	——-
VI8	5.06	1.745	2.90	0.003916 *	2.38	2.13	0.033719 *	1.51
VI10	2.18	1.797	1.21	0.225489	1.90	1.15	0.251148	1.05
VI11	6.25	1.566	3.99	0.000087 *	2.30	2.72	0.006785 *	1.10
VI16	5.16	1.503	3.43	0.000679 *	1.38	3.73	0.000231 *	1.18
VI28	10.70	1.535	6.97	0.000000 *	1.85	5.77	0.000000 *	1.33

* An asterisk next to a number indicates a statistically significant *p*-value ($p < 0.01$).

The territorial distribution of the standardized waste reflected slight nuances over the territory that had a very superficial effect, as well as slight nuances in the surroundings of Monfragüe National Park (Figure 3). Similarly, anomalies were observed in Valencia de Alcántara and Torrejón el Rubio, although they also stood out in some municipalities of La Vera, the Ambroz Valley, and the Jerte Valley.

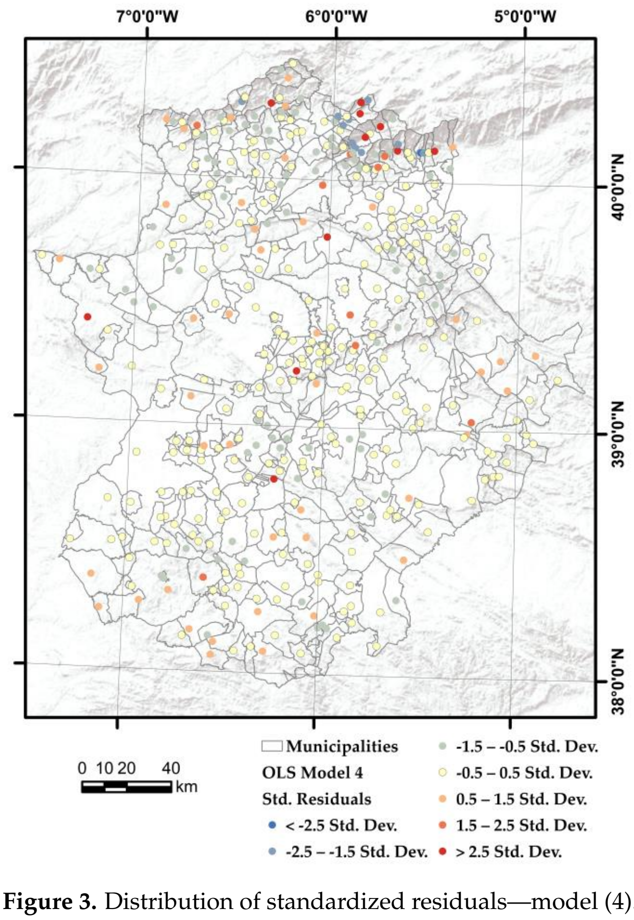


Figure 3. Distribution of standardized residuals—model (4).

When analyzing the database and taking the population centers into consideration that present extreme values where the standard deviation exceeds the mean by more than

±1.5 times, there was barely any significant change with respect to the previous model. Therefore, the spatial autocorrelation indicated by Moran's I (0.013) also implied that the null hypothesis could be accepted with a high degree of probability. On this basis, it could be concluded that the distribution of the residuals was random.

Despite the equality between the models analyzed, it could be observed that model (4) was more in line with reality. Therefore, it was taken as the preferred option for further analytical processes using spatially weighted regression.

Given the intended comparative nature, we chose to use the same variables, so that the differences could be identified, and the most problematic aspects when interpreting the results could be corroborated. It should also be noted that spatial regression allows the use of the fixed or adaptive kernel of the function, and even offers the option of selecting the method for obtaining the bandwidth using the Akaike-corrected criterion (AICc), cross-validation (CV), or bandwidth (BP) by selecting the distance or several neighbors.

All of these possibilities allow multiple methods with which to construct valid models or, at least, to surpass the effectiveness of OLS regression. Therefore, the following settings were applied:

- Kernel: adaptive; and
- Bandwidth: AICc, CV, and BP following the neighbor criterion.

This process, although it may seem complex, positively impacted our ability to identify the most effective options, considering that they were applied in a territory with a specific population distribution.

The results obtained showed that, whether employing Akaike criterion or cross-validation, the number of kernels used in the calculations was very high, which was not the case when a few reference neighbors were already specified. On the other hand, the coefficient of determination was similar to that achieved by OLS regression, especially when adjusted, provided that AICc or CV was applied. On the other hand, it was very high when the nearest neighbors were used, with an R^2 of 0.96 being obtained, and 0.89 when adjusted (Table 8).

Table 8. Main parameters of GWR according to bandwidth conceptualization.

Parameters	Conceptualization of Distance		
	AICc	**BP Neighbors**	**CV**
Residuals square	403,427	174	435,921
Effective number	25.9	5.5	12.2
Sigma	33.4	8.4	34.1
AICc	3841.8	118.3	3848.9
R^2	0.394	0.961	0.354
R^2 adjusted	0.353	0.890	0.326
Model configuration	Dependent variable: Rural lodging places	Independent variables: VI8–VI10–VI11–VI16–VI28	

The use of nearest neighbors was convincing when exclusively considering the values of the coefficient of determination. However, the condition number should not exceed a value of 30, demonstrating the presence of multicollinearity. This can be regarded as significant when considering that the elaboration of this type of regression culminates in predicted values being obtained for each kernel, and therefore, specific cases can be detected in which this statistical risk exists.

A comparison of the condition numbers obtained using the three conceptualizations of demand (Figure 4) corroborates that the use of bandwidth (BP) considering 15 neighbors should be discarded, due to the high value obtained for this parameter. Conversely, the condition number was low when using the Akaike-corrected criterion (AICc) and cross-validation (CV).

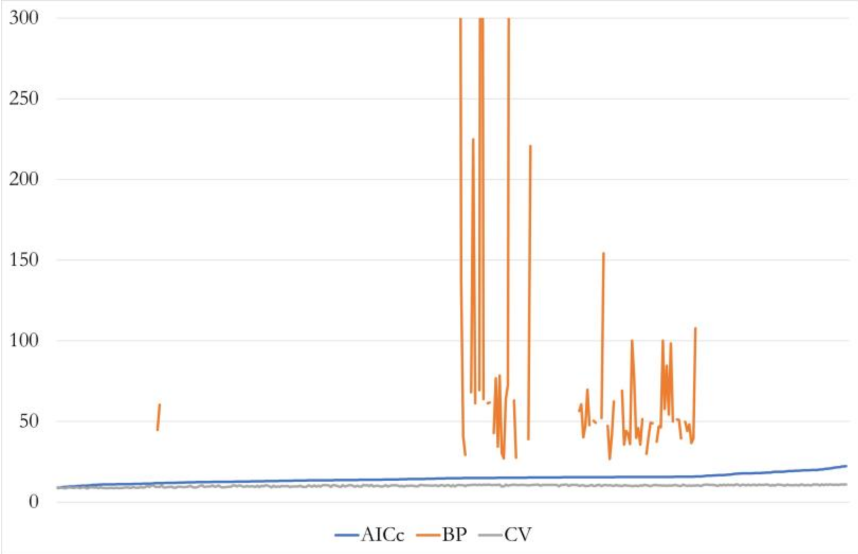
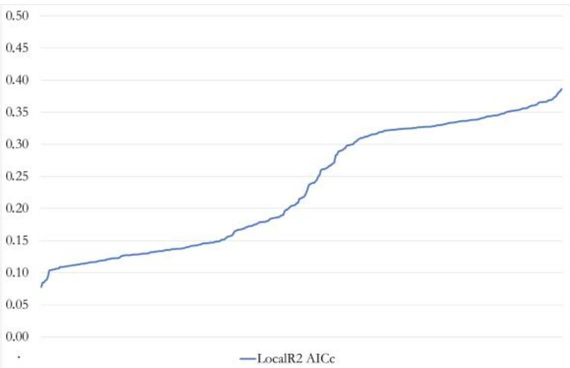


Figure 4. Condition numbers obtained according to different conceptualizations of distance.

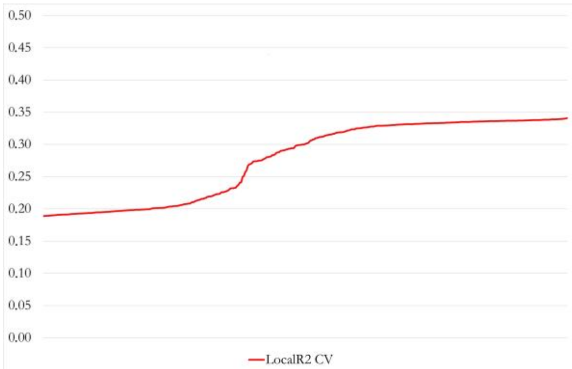
Although neither the model using AICc nor that using CV presented many cases in which the condition number exceeded the limit, it would be useful to analyze their significance coefficient in order to determine their goodness of fit.

In the first case, despite having an average R^2 value of 0.23, maximum values of up to 0.39 were obtained. Meanwhile, in the second case, the average was higher, at 0.28, reaching maximum values of 0.34. However, when values greater than 0.3 were selected, the number of municipalities meeting this requirement was 153 and 191, respectively.

The CV model obtained overall better and more homogeneous results, although the use of the AICc model enabled the establishment of a greater margin of adjustment in many cases (Figure 5a,b). Similarly, there was an apparent relationship between the values of R^2 obtained in both ways, as deduced from the correlation coefficient of 0.833, which is equivalent to a coincidence of 69.44%.



(**a**)



(**b**)

Figure 5. Local R^2 obtained with AICc (**a**) and CV (**b**).

The territorial distribution of the significance coefficients is relevant, since the greatest reliability was achieved precisely in those places with the greatest potential for the development of rural tourism, coinciding to a large extent with the north of Extremadura, defined by the INE as a tourist area, although it also extends to other areas. Mountain areas and bathing areas stand out as outstanding resources (Figure 6a,b).

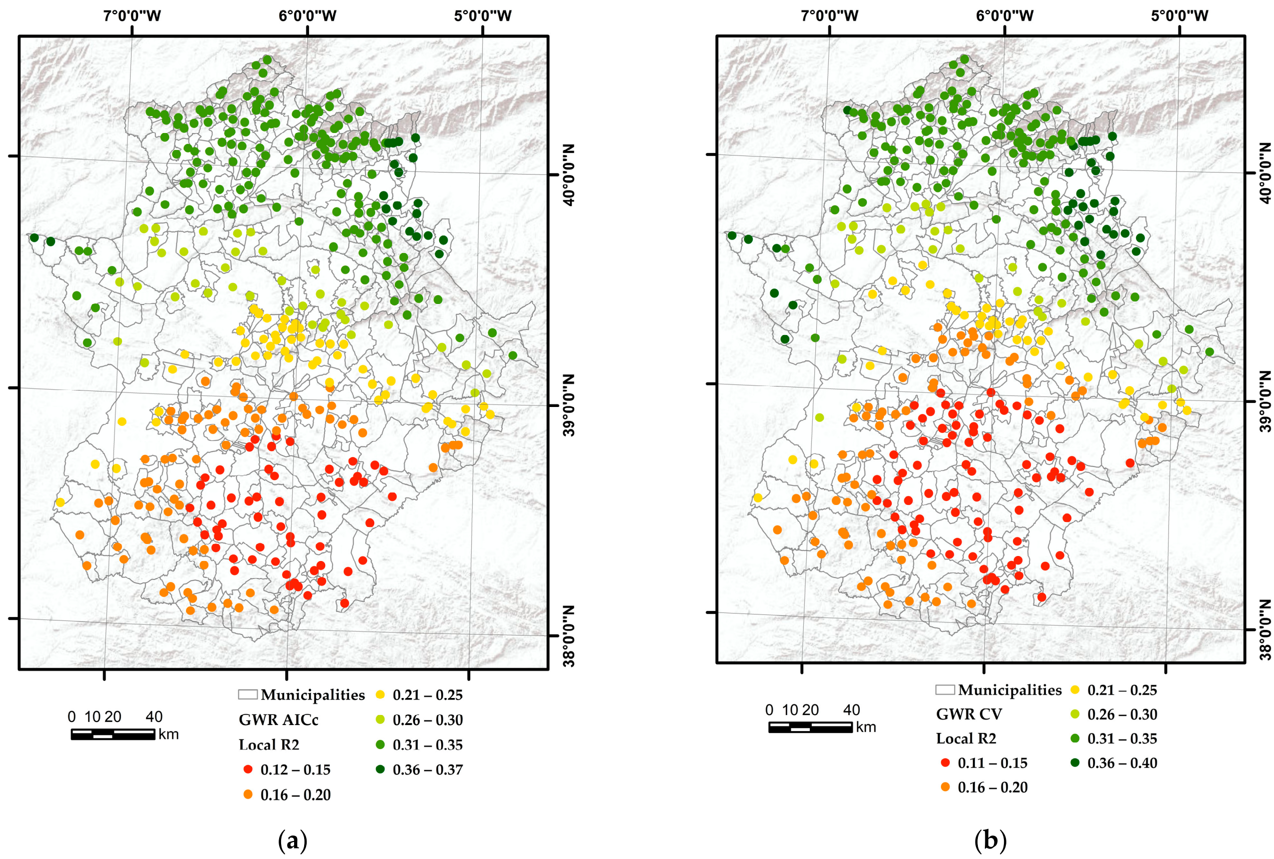


Figure 6. Distribution of R^2 employing the AICc (**a**) and CV (**b**) methods to obtain the bandwidth.

The spatial regression model obtained using the five independent variables defined through the OLS regression offered interesting performance in those areas possessing the greatest potential for rural tourism development. It was observed that a good part of the territory exceeded the significance coefficient, regardless of the method chosen to obtain the bandwidth used for the calculations.

There were subtle differences between the two methods for determining the bandwidth, depending on whether the AICc or CV criterion was applied. In the first case, there was a better fit with the existing potential for the development of rural tourism, since it did not include the large area of peneplain in the area surrounding the municipality of Cáceres and the surrounding areas. In the second case, on the other hand, this area was included, although it did not adjust to the known reality. Naturally, this fact does not imply that at any given time there is a lack of potential for the implementation of this activity, although it is necessary to be especially cautious and organize it around the available potential, in light of its consideration as a cultural or even ornithological activity during part of the year, with the observation of birds such as cranes or the Great Bustard being possible.

When analyzing the effectiveness of the local models constructed in accordance with both ways of obtaining the bandwidth used by the spatially weighted regression, it was observed that the standardized residuals were very similar (Figure 7). There was a high degree of coincidence, such that the decision as to the ideal method for the conceptualization of distance must be directly made on the basis of the adjustment observed in the territory. In this case, and in agreement with much of the literature, we opted for the use of AICc.

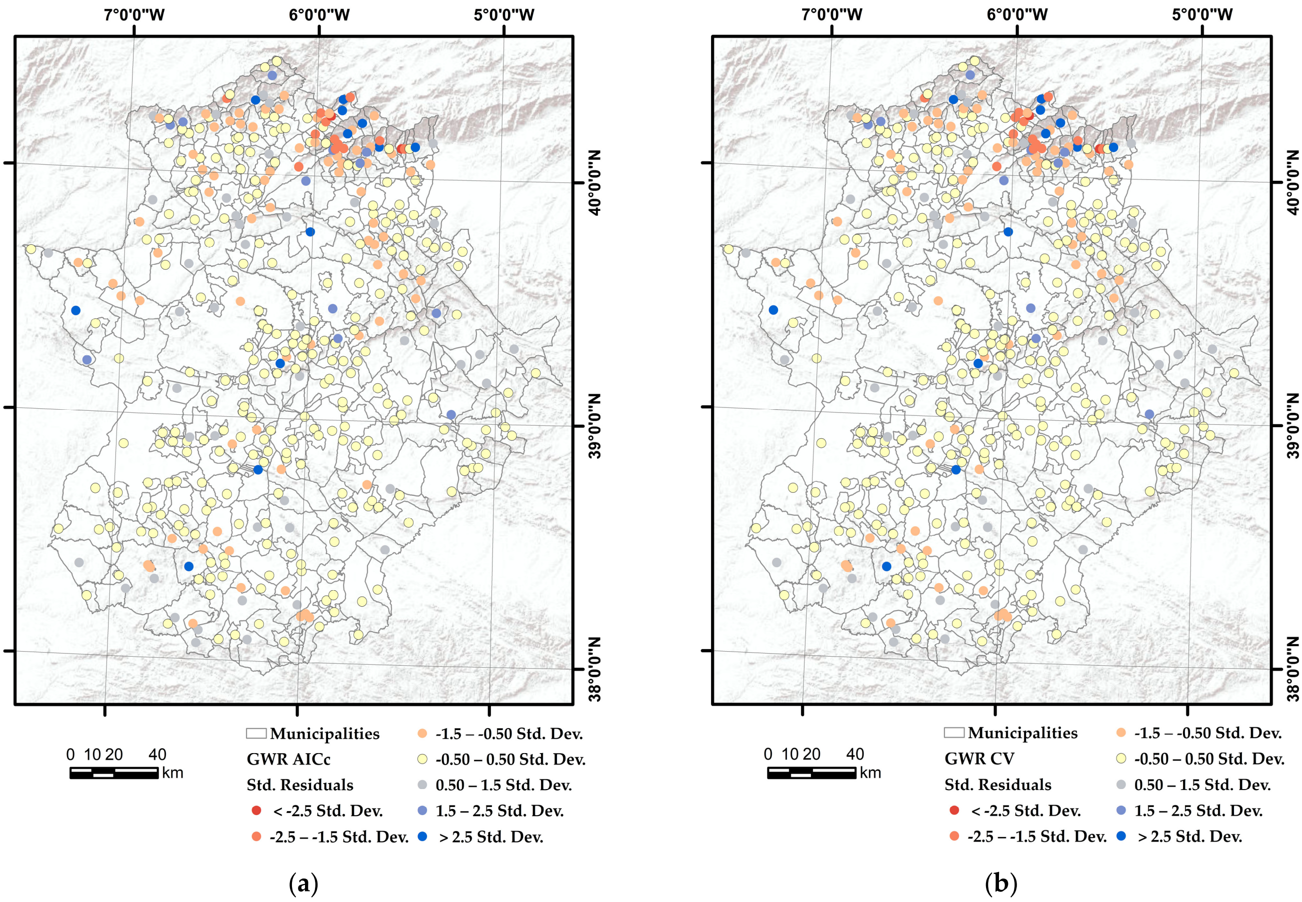


Figure 7. Distribution of standardized residuals obtained when using AICc (**a**) and CV (**b**) to obtain the bandwidth. Source: Own elaboration.

The residuals reflected another reality that is inherent to the tourism system of Extremadura itself, especially when dealing with this type of tourism. This is the lack of any correspondence, in many cases, between the tourist potential and the presence of rural accommodation. This fact appeared in a very marked way in the north of the province of Cáceres, where there were strong contrasts in the analyzed situations. It was common to find population centers that possess the attractions in the greatest demand by rural tourists, although they did not have the accommodation capacity calculated by the model to correspond to this.

There were also others in which the potential is not so high, essentially because they are more distant from the main attractions, but which had numerous rural lodging places. It was also observed that this imbalance was sometimes produced because they had accumulated a great supply of accommodation. Obviously, there were places in which both situations appeared, although such instances were the result of very specific facts. Among them, the indiscriminate creation of rural lodgings in places lacking notable tourist facilities stands out.

An analysis of the cases exhibiting extreme residual in one direction or another (Table 9) was performed in order to present their corresponding situation, although all municipalities could have been analyzed.

Table 9. Estimates of bed places in rural lodgings (extreme cases) following AICc.

Municipality	R^2	Places Real	Places Dear	Places Waste	Municipality	R^2	Places Real	Places Dear	Places Waste
Viandar de la Vera	0.35	0	91	−91	Jaraíz de la Vera	0.34	148	71	77
Gargantilla	0.33	8	92	−84	Acebo	0.32	143	66	77
Piornal	0.34	5	84	−79	Burguillos del Cerro	0.15	106	23	83
Guijo de Santa Bárbara	0.35	20	98	−78	Villanueva de la Vera	0.35	180	91	89
Talaveruela de la Vera	0.35	10	85	−75	Jerte	0.34	206	117	89
Segura de Toro	0.33	22	92	−70	Baños de Montemayor	0.34	157	67	90
Valdastillas	0.34	18	83	−65	Alange	0.11	104	8	96
Rebollar	0.34	16	80	−64	Pinofranqueado	0.33	168	61	107
Plasencia	0.33	19	77	−58	Montánchez	0.11	133	26	107
Descargamaría	0.33	8	64	−56	Torrejón el Rubio	0.30	137	19	118
Abadía	0.33	0	56	−56	Valencia de Alcantara	0.37	250	104	146
La Garganta	0.34	8	62	−54	Navaconcejo	0.34	294	124	170
Cabrero	0.34	6	57	−51	Hervás	0.34	269	93	176
Jarilla	0.33	18	68	−50	Jarandilla de la Vera	0.35	268	90	178

There were some nuclei that lacked places or had very few, although the model estimated that they would have many more on the basis of their possessing attractions demanded by tourists. In some cases, this is understandable; for example, Plasencia is a city with around 40,000 inhabitants, and the legislation itself prevents the installation of rural lodgings in its nucleus, although this can be undertaken in its wider municipal area. In other areas, the only possible explanation for the lack of this type of accommodation is their low demographic volume and the marked aging of their residents.

At the other end of the scale were the towns with the largest numbers of rural lodging places, although not all of them had the necessary attractions to support the practice of this activity. On the other hand, some very special attractions were on offer, as in the case of Alange, with a rich cultural and natural heritage in the vicinity, as well as reservoirs, etc., although these cannot compete with those in the northern areas of the region.

Similarly, there are municipalities in which it is difficult to determine a basis from the opinions of tourists, as is the case in Burguillos del Cerro. In these cases, it was observed that the derived model demonstrated considerably lower effectiveness, as reflected in the coefficient of determination. It was also observed that there were some municipalities with important attractions, although they had a very high volume of supply, which could possibly be considered pillars of the development of rural tourism in Extremadura, as in the cases of Navaconcejo, Hervás, and Jarandilla de la Vera. These sites are located in mountain areas, have bathing areas, and are close to natural areas. They are also well connected by roads. In view of this, it is possible to wonder whether there is not an oversupply in these towns, in contrast with the development possibilities of the surrounding municipalities.

The application of GWR makes it possible to better define the performance of the model created for each of the municipalities. They have a variable significance coefficient and adapt their diversity, surpassing the global regression model provided by OLS.

Recent literature has pointed out that the former assumes that the contribution of each regressor is similar in all cases, which implies excessive generalization [86–89]. For this reason, this regression was developed to also calculate the contribution of each variable in the model created for each of the cases analyzed, giving rise to multiscale regression, a derivation, or, more properly speaking, an evolution of geographically weighted regression (MGWR).

In order to compare the results and select the most appropriate type of regression, the same system of variables was applied as in the previous cases, although specific software specifically designed for this type of regression was used. Specifically, MGWR 2.2, developed at the Space Research Center (SPARC) of Arizona State University (USA), was used [90].

Following its application, the contribution of the selected variables was significant with 99% confidence. Similarly, the p-values ranged between 0.000 and 0.004 for four of the variables, the same as when GWR was applied (Table 10). These were proximity to bathing areas, to parks or nature reserves, to historical–artistic sites, and the uniqueness of the territory itself. Similarly, the independent variable that contributed least to the definition of the overall model was proximity to the national park.

Table 10. Overall summary of the regression.

Variable	Est.	SE	t(Est/SE)	*p*-Value
Intercept	0.000	0.042	0.000	1.000
VI8	0.149	0.051	2.903	0.004
VI10	0.052	0.043	1.214	0.225
VI11	0.176	0.044	3.990	0.000
VI16	0.156	0.045	3.432	0.001
VI28	0.336	0.048	6.972	0.000

The general results offered when using this variant of the spatially weighted regression represented a slight improvement on the overall coefficient of determination obtained when using GWR, with a value of 0.379, and 0.351 when adjusted. However, given the local nuance implicit to this type of regression, a comparative analysis of each of the 388 municipalities comprising it would be necessary.

The territorial distribution of the coefficient of local determination followed the general patterns marked by the spatially weighted regression, although slight improvements were detected in most cases (Figure 8). These were centered in mountain areas, such as in the Sierra de San Pedro, Sierras de Pela, and SW Badajoz, with increases in local R^2 that exceeded 0.05 units; i.e., an increase of five percentage points with respect to that obtained with GWR. The north of the province of Cáceres experienced more modest growth, with the model losing effectiveness in areas with less potential for the development of rural tourism, such as the area around the city of Cáceres, areas of Mérida, and the regions of Tierra de Barros and Campiña de Llerena. These areas are at low altitude and lack bathing areas.

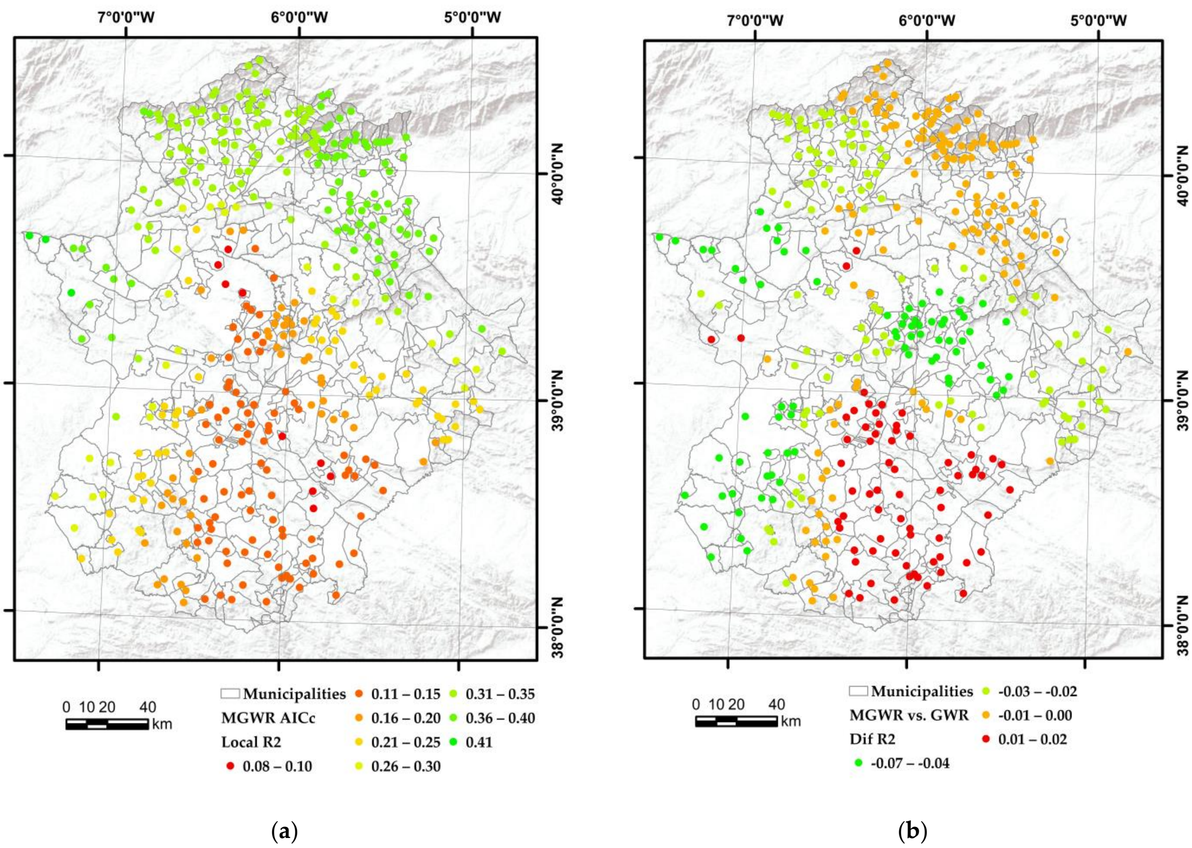


Figure 8. Distribution of R^2 obtained by MGWR (**a**) and differences between MGWR and GWR (**b**).

The improvements offered by MGWR over GWR are evident in most of the cases studied (Figure 9), as can be observed from the comparison between the determination coefficients obtained for the different methods.

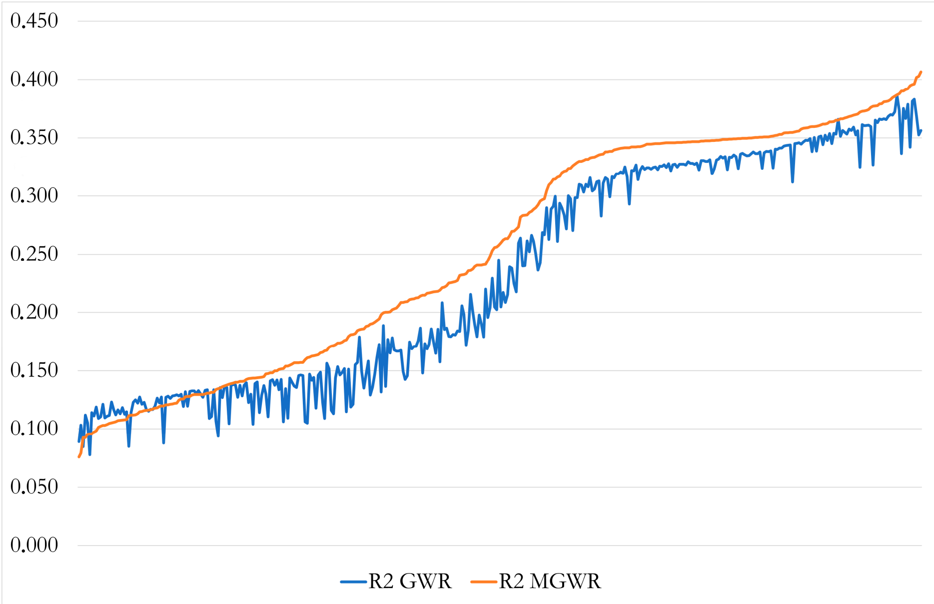


Figure 9. Comparison of local R^2 obtained by GWR and MGWR, conceptualized using AICc.

The improvement in the coefficients of determination did not follow a pattern defined by the volume of vacancies, but by the configuration of MGWR itself, where the contribution of each regressor is different for each observation (Figure 10). The beta coefficients, which precisely show which regressors are fundamental for the overall explanatory power of the model, were calculated for each regressor. The singularity of the territory (VI28), conceived of as being related to altitude and slope, contributed the most to the configuration of the regression equations derived for each village. This fact was very relevant in some population centers, where the contribution of this variable exceeded 50%. Next in importance was the distance to parks and nature reserves, as well as to historical–artistic sites and bathing areas. However, the distance to Monfragüe National Park did not make a particularly decisive contribution, perhaps because it attracts hikers rather than tourists.

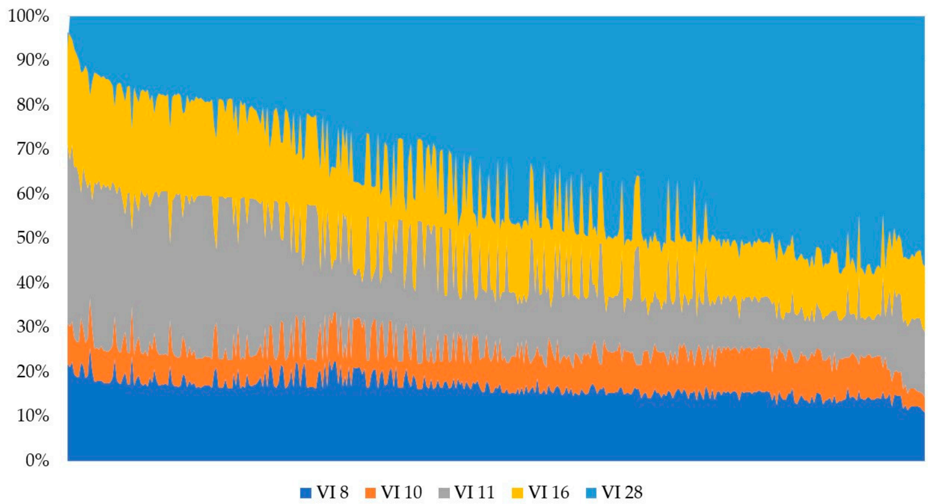


Figure 10. Beta coefficients of the regressors.

The territorial distribution of the beta coefficients (Figure 11) reflects the existence of an area in which the contribution of the regressors is more balanced because it has several interacting tourism resources, as is the case in the northern part of Extremadura. Other areas have a contribution for which a single regressor appears in the majority, reflecting that the resources offered are limited, at least in terms of quantity.

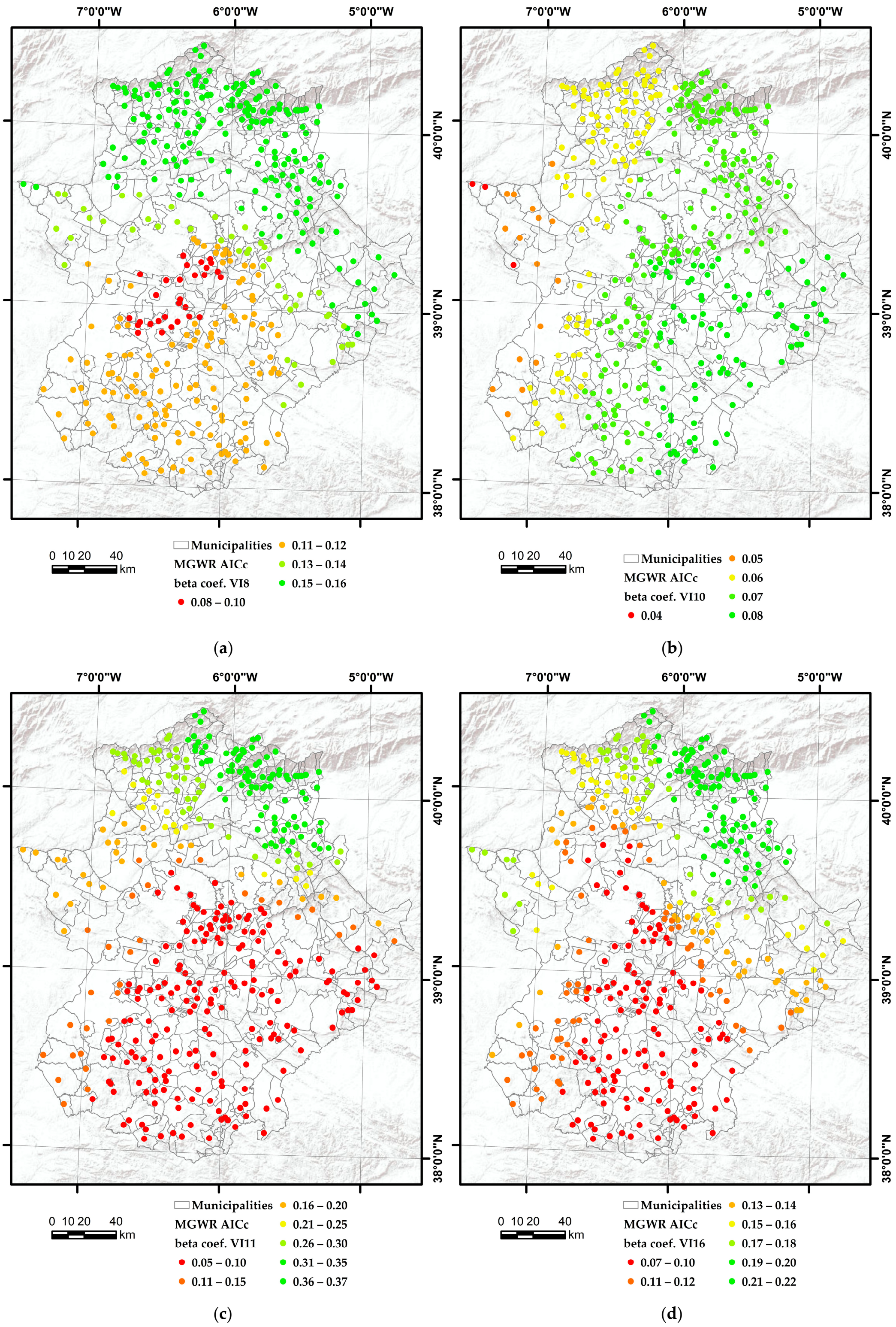
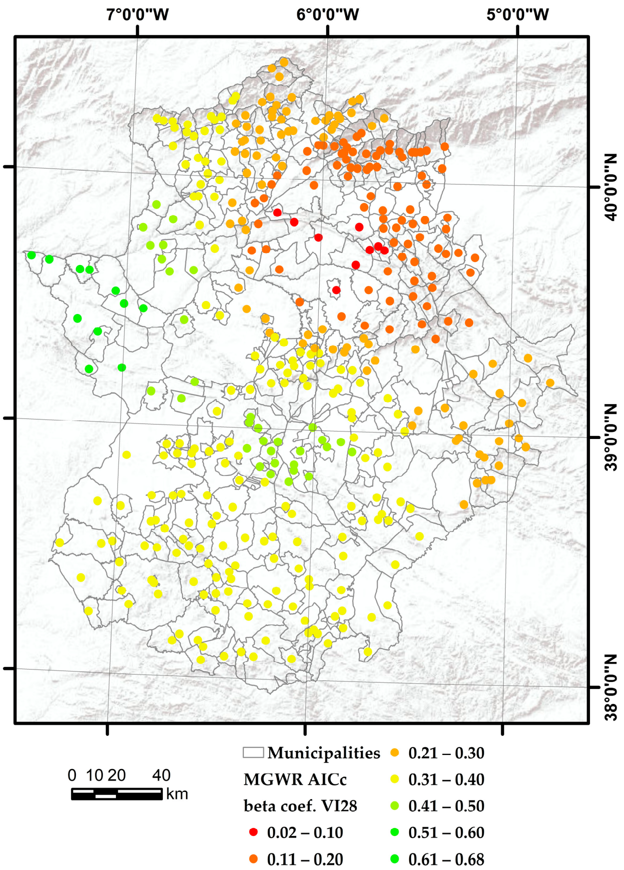


Figure 11. *Cont.*



(**e**)

Figure 11. Territorial distribution of beta coefficients according to the regressors VI8 (**a**), VI10 (**b**), VI11 (**c**), VI16 (**d**), VI28 (**e**).

The regressions conducted reflect the impossibility of deriving models that offer remarkably high coefficients of significance. It can be deduced from this that the distribution of the supply of rural lodgings is not adapted to what most tourists demand.

4. Discussion

The planning of tourism activities becomes complex when aiming for a balance between public policies, rural tourism, and sustainability itself [91]. For this reason, it is worth asking whether the adequacy of the supply of accommodation for a given attraction has been considered. Thus, the relationship between the preferences expressed by tourists regarding such resources and the facilities available to them should be direct and strong. It is logical that the areas that bring these attractions together in higher concentrations should be those with the greatest accommodation capacity [13]. At the same time, the literature has analyzed the impact of accommodation on attractions [92,93]. There is a symbiotic relationship between attractions and the supply of accommodation. In fact, the location of accommodation is justified by tourists' inclinations [94].

In this study, tourist attractions and the preferences of tourists were taken as a reference forming a basis on which to explain the location of the supply of rural lodging. However, while the analysis carried out highlighted the existence of areas in which there was a concentration of this type of lodging in line with the presence of attractions demanded by tourists, on the other hand, there were other areas in which no such concentration was detected, perhaps because they do not have all of the resources demanded by travelers, although they may have some [13,42].

These paradoxical situations favor the interpretation that the analysis of the main tourism parameters related to supply depicts a situation, since the generality does not present territorial dispersion [16]. In addition, given the manner in which tourism is conceived, which is highly biased towards economic considerations, aspects representing important qualitative considerations, such as those related to the demand preferences, the opinions of tourists, etc., are not considered. In this context, Geographic Information Systems have been used to analyze distribution patterns and models [44,45].

Categorical affirmations are frequently heard that cast rural tourism in the role of the savior of the rural environment. It is argued that there has been a notable increase in the number of tourists, that territories bring together large numbers of tourist resources, etc. Nevertheless, no scientific vision is offered justifying these affirmations. On the contrary, aspects are omitted, as reflected in the scant consideration given to our heritage when establishing tourism plans and the proposition of rigorous tourism policies. Many aspects, such as increases in supply or demand, have also been analyzed in a manner that remains open to debate, since these factors are usually studied in isolation, ignoring considerations related to non-economistic disciplines [16].

Aspects such as tourist satisfaction, the impacts generated by tourism in the social and environmental spheres, the situation of businessmen, etc., are rarely mentioned. From all of this is derived the increasingly widespread opinion that only those aspects that benefit the communicator are reported, and that scientific rigor is not being attended to with the necessary objectivity. In this sense, in this study, tourism analysis was approached from a neutral position on the basis of the preferences of tourists. They are the ones who should decide on their tastes, and offerings should be available in which their expectations are met [95].

The tourism plans developed in Extremadura have not taken into consideration opinions on the demand side in the generation of tourism products. Not even in the last one [96], which is still in force, which were the preferences of tourists analyzed with the aim of promoting tourism policies. The increase in the supply of rural accommodation has been encouraged without considering the presence of tourist attractions that might generate tourist demand. All of this has resulted in a mismatch between one part of the supply and the tourist potential that the territory actually possesses, thereby multiplying inequalities. There has been a significant proliferation of rural lodgings in recent decades, although, until relatively recently, real tourism products had not been built to give them meaning.

The main problem is that the link between heritage and the supply of lodgings is not always ideal, since heritage corresponds to the potential of a territory to support tourism development. This hypothesis was corroborated by the different geostatistical methods used in this study, since in no case was a sufficiently high coefficient of determination threshold exceeded, on the basis of which it could be deduced that rural lodgings are primarily present in areas possessing the attractions demanded by tourists.

Numerous authors have applied diverse geostatistical techniques when analyzing tourism activity in multiple different regards [97,98], including the ideal location of accommodation [99].

The application of these techniques shows that there are areas in which accommodation is concentrated in a manner that does not coincide with more than a few resources, leaving aside the enormous heritage boasted by Extremadura. If the number of resources in this territory is known, then the implementation of specific and innovative tourism products could be facilitated. However, only part of this heritage has been converted into tourism resources, since rural tourism is closely linked to nature, although it is not the only thing present in the rural environment. There are important cultural treasures in the form of monuments, many of which have been declared BIC or have been registered, but which have not been promoted, despite attempts having been made to create products oriented towards cultural itineraries, even within these areas. This lack of use is confused, in many cases, with low valuation, leading people with few scruples to become dedicated to their shearing and destruction, something that could be reversed if they were valued with regard to tourism. It makes no sense that in the 21st century, there are black or red heritage listings, something that contravenes the very principles of sustainability and sustainable development, as referred to by the powers that be.

These circumstances have prompted a debate on the discrepancy between the potential of the territory to develop tourism and its current use. It has been shown that tourists possess numerous different motivations for visiting Extremadura [57] and its rural environment, but they only visit very specific places, generally corresponding to authentic rural tourism destinations. There are other areas that possess rural offerings and heritage, but have never been put to good use for the purposes of tourism. It will suffice to point out, as an example, one of the most common landscapes in the region, the dehesa, which was recognized over two decades ago as being one of the areas with the greatest projections for the practice of rural tourism in its broadest sense, but the conversion of which into a destination has still not been translated into reality [96,100]. In many cases, demand trends are not considered when creating tourism products or planning the location of accommodation.

In view of this situation, we aimed to determine the suitability of the location of lodging by resorting to the preferences on the demand side. This complements other studies carried out in this area [98], which tried to determine whether the location of accommodation was random or whether it followed some logic.

Satisfactory explanatory models could not be achieved through the application of regressions with different orientations and formulations, despite multiple refinements and tests. In fact, while the OLS-based models were not very good, the situation did not improve much when using more complex techniques such as GWR and MGWR. Despite this, the latter two geostatistical techniques have been demonstrated to offer important results due to their local analytical character. In fact, the use of MGWR allows the derivation of a larger number models, with a superior performance in some places, particularly with respect to those areas with the greatest potential for the development of an activity.

For all of these reasons, it was concluded that it is not possible to derive complete explanatory models. Even when applying local multiscale models (MGWR), it was not possible to draw logical conclusions for more than a part of the area analyzed. This shows that the location of accommodation not obeying the criteria set by tourists required the introduction of serious alterations to the models. It is precisely these sources of accommodation and these municipalities that are of greatest concern, since, although they do not possess the attractions demanded by tourists, they do have other heritage objects. This heritage should be enhanced in order to create tourism products that are based on cultural and natural heritage. In fact, it has been shown that certain places can serve as a basis for the creation of tourist itineraries [50,99].

The application of this research should focus on two aspects. On the one hand, this research demonstrates the need to adapt the location of accommodation to the preferences expressed by tourists. To this end, the suitability of geostatistical techniques should be considered, specifically MGWR, with which results were obtained that were better than those obtained using GWR and OLS. On the other hand, alternatives to accommodation located outside those areas possessing resources preferred by tourists need to be found. This will require the creation of alternatives on the basis of the presence of other resources and on the tourism potential offered by the territory [45].

Along the same lines, it is possible to affirm that the most favored areas are those within close proximity to mountain areas, and that also offer bathing areas, which is a normal activity during the summer, when the temperatures in Extremadura can surpass 40 degrees centigrade. Cultural heritage and good accessibility are also advantageous. However, there are many other attractions scattered throughout the territory that give it potential for the development of specific tourism products [45].

Therefore, this research can be considered by the regional administration when discussing the need to adapt supply to demand. It can also be used to better plan the location of future accommodation and the creation of tourism products in those places that have supply, but do not have the fundamental attractions that tourists want. Demand feedback and mismatches between tourist tastes and product supply should also be taken into account in the development of tourism plans. As has been demonstrated using a variety of different techniques, there is a very clear division in certain areas that have rural lodgings, but lack the main attractions desired by the demand. This is reflected with a poor degree of consistency in the models. However, such areas do have specific attractions that could serve as a basis for the generation of specific products. This could solve, to a great extent, the low occupancy of lodgings located in places with little potential or the strength of which is dependent on some natural, cultural, or other element.

The main recommendation that can be made following the elaboration of this study is that it is necessary for the administrations to carry out the effective planning of the offer on the basis of the criteria established by the demand. This requires an in-depth knowledge of the tastes and preferences of tourists, using different techniques to deduce the tourism potential of the territory.

Despite our best efforts, the study presented may possess certain limitations due to problems arising from the use of regressions. The literature always insists on the possibility of error occurring as a result of collinearity, although all possible precautions have been taken. Similarly, it must be recognized that the techniques used employed Euclidean distance, rather than real distances or displacement times, to construct the neighborhood criterion.

On the other hand, two new lines of research have emerged. First, we will insist on the further development of models based on MGWR, although with a focus on those areas with the highest occupancy rates. This will make it possible to derive models that are better adjusted to the preferences of tourists. In this way, it will be possible to better understand the real adjustment required between supply and demand in these areas. Secondly, an attempt will be made to determine the capacity of territories in which establishments with lower occupancy rates can be found, taking as a reference the creation of tourism products on the basis of their potential. It may be possible to resort to other statistical or geostatistical models in an effort to precisely determine these factors.

5. Conclusions

The research carried out allows us to conclude the following interesting aspects.

It emphasizes that Extremadura can be considered a natural paradise, in which cultural heritage has played an important role in its development. However, it is possible that too many territories find themselves unable to access their value in the form of tourist resources and products. The raw materials are present, but they are only used in very specific areas.

Positive and negative evaluations can be made of the evolution of extent of tourist offerings since the beginning of the century. With respect to the former, it can be observed that the region is increasingly being visited, and more overnight stays are being registered in rural accommodation. On the other hand, with respect to the latter, the average length of stay has hardly increased, and occupancy rates are very worrying, since there is a significant degree of seasonality, etc. However, this analysis becomes even worse when comparing the initial situation with the final one, also taking into consideration the occurrence of a serious economic crisis in the intervening years. On the other hand, territorial analysis shows the existence of few areas in which tourism can be considered an important activity, as is the case for the main tourist points and for zones recognized by the INE.

Despite the existence of numerous methodologies for evaluating tourism potential, these have never been applied to plans, not even to tourism policies, thereby resulting in a total lack of knowledge about the tourism development capacity of the territory. Moreover, it is worrying that the study of heritage or tourism resources has been omitted from plans, when it should have been the basis sustaining the activity. It follows that the tourism plans are biased, and that the lodging plan that has been created does not have the best relationship with the surrounding attractions.

At a technical level, it is noteworthy that the application of different types of regression analysis corroborates the lack of adaptation between the accommodation capacity of the territory and its attractiveness. This is less noticeable when performing the analysis using OLS, since only numerical relationships are considered. However, analyzing the territorial component using other types of regression makes it possible to derive local models that are adapted to each observation unit. In this respect, MGWR outperforms GWR, obtaining somewhat better models that are always derived on the basis of the preferences expressed by tourists.

Given the variety of techniques used, the models offer different results, although GWR and MGWR do show superior efficacy, especially the latter. It is true that the main predictor variables coincide in all cases, with slight differences in the explanation for these variances. In addition, their performance is better in places that are more attractive according to the demand criterion, corresponding to the northern part of the area analyzed. The relief and bathing areas are concentrated most highly in this region, and it has acceptable accessibility. It is also noteworthy that the model constructed with MGWR assigns little relevance to the presence of the National Park, which is in line with the results obtained using the other techniques.

As we have seen, resorting to complex techniques of these types favors the creation of models, the localization of adjustments to the territory, and the possible search for solutions. It should be noted that the models work better in some places than in others, and it is precisely in those areas where the models work less well that emphasis should be placed, especially when there is an existing lodging plan that does not have sufficient attractions to produce demand. This situation should be corrected by creating tourism products that focus on the potential reasons for the attractiveness of these areas. In view of the above, the initial hypothesis is confirmed; i.e., it is corroborated that the distribution of lodgings is not always adapted to the attractiveness of the territory.

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