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Addressing regional tourism policy: Tools for sustainable destination management

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Abstract

Policymakers need to develop measures to counter overcrowding and relocate excess tourism in congested areas to others with fewer visitors. This article proposes a methodological framework consisting of a survey and statistical tools to a gain deeper understanding of tourist profiles and characteristics and determine how covariates affect the ratio of each group in the market. Spatial analysis is performed to determine regional cluster patterns and propose measures aimed at alleviating congested areas by redirecting tourism to other destinations with less pressure without losing the economic impact of tourism. The proposed methodology is applied to international tourists in Spain and reveals some relevant aspects of four international tourism profiles. The analysis confirms the existence of spatial dependence between Spanish regions, suggesting that the application of public policies in one region could have implications for neighbouring ones.

Keywords

Covariates, daily expenditure, latent class model, spatial statistics, stay length, regional development

Introduction

The Covid-19 pandemic has had a significant impact on tourism worldwide and not only affected tourist flows but also consumption (Armstrong and Read, 2021; Gibson, 2021; Škare et al., 2021). Thus, the primary mission of stakeholders should be to recover tourism activity (Zhang et al., 2021) given the changes that have occurred in both the tourism sector and tourist behaviour (Villacé-Molinero et al., 2021). These consumer patterns differ between individuals but are also affected by external economic, sociocultural, political, or health-related events, such as those experienced from 2019 onwards (Sigala, 2020; Škare et al., 2021). As the tourism market is remarkably heterogeneous, destinations should optimise their resources to better match tourism services supply and demand and thus obtain greater business profitability (Du et al., 2016; Hristov and Zehrer, 2019; Sigala, 2020). To achieve this, tools such as segmentation have been developed to provide tourist destinations competitive advantages through the efficient use of their limited resources (Barreal et al., 2021; Mckercher et al., 2022). The success of such tools lies in adapting destinations to the different segments identified (Botti and Peypoch,

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2013), which may partly alleviate problems arising from overtourism that affect destination sustainability (Dodds and Butler, 2019).

In addition to market segmentation strategies, it is of interest to study each region's territorial planning (Mohammed et al., 2019). Through these strategies, policymakers and tourism agents can influence overtourism by means of tools to diversify the offer across a country (Shoval, 2006) or exploit new resources and attractions to prevent the decline of a destination (Aguiló et al., 2005). These objectives can be achieved by renovating urban infrastructures and accommodation facilities, enhancing the environmental quality of rural villages, and diversifying the tourism offering (Aguiló et al., 2005). Geographical, spatial, and statistical analysis models are effective tools for territorial planning. They can support global decisions concerning the group and/or spatial behaviour of different tourist segments through the diversification of the tourism offer and the expansion of elements susceptible to demand throughout the territory (Li et al., 2015).

This research aims to determine different tourist segments based on their activity and analyse their spatial behaviour, thus allowing us to determine whether these segments behave heterogeneously throughout a territory. This information can be of use in policy planning aimed at improving tourism distribution throughout the country, thus taking advantage of the overcrowding of specific destinations.

To this end, this study examines the case of Spain as it is one of the main international tourist destinations worldwide (Vena-Oya et al., 2021a) and ranks second in number of international tourist arrivals (UNWTO, 2020). Due to the economic importance of the tourism sector in the country (12% of GDP), tourism is considered a strategic sector in the design of socioeconomic policies, with consequences at the territorial level. The main results highlight the economic (length of stay in days and expenditure per night) and spatiotemporal behaviour of the segments identified and reveal the deficiencies in tourism policies in different areas of Spain. Finally, a series of recommendations are made to address this problem.

Literature review

Tourism research involves several fields of inquiry and employs a variety of methodological frameworks to analyse tourism patterns, tourist behaviours, or market development. For the purposes of this research, it is, therefore, necessary to combine statistical techniques and economic theories, as well as review the previous literature on market segmentation and spatial planning.

Table 1. Examples of overtourism in Spain

City	Inhabitants	Tourists per year (2021)
Granada	240,000	2,500,000
Barcelona	1,620,000	4,500,000
Seville	690,000	2,500,000
Málaga	570,000	5,500,000

Source: National Statistics Institute (INE, 2023).

Prior to the literature review, it is important to provide some background about the situation of tourism in Spain; a country whose main sector of activity is tourism but which suffers from pressing problems of overtourism. Although overtourism can have positive impacts in regions as excess demand generates higher levels of income, it can also decrease tourist satisfaction, have negative effects on residents, or saturate city centres and public services (Castañeda et al., 2019; Mihalic and Kuščer, 2021). Some cities, such as Granada, which has less 300,000 inhabitants but receives receive more than 2,5 million visitors per year, are particularly affected by these problems (Vena-Oya et al., 2021b). More worrying is the case of Barcelona, where residents are rejecting overtourism and some areas of the city are becoming depopulated, as has occurred in other cities such as Venice (Goodwin, 2019). Despite attempts by these destinations to tackle this problem, the situation has only worsened (Dodds and Butler, 2019), thus affecting the sustainability of destinations, tourist satisfaction, and the relationship between tourists and residents (Vena-Oya et al., 2021b). To solve this problem, it is necessary to rethink tourism policies and propose others. Table 1 provides some examples of the situation of overtourism in major tourist destinations of Spain.

Tourism market segmentation

Several theories have attempted to explain the different manifestations of tourist behaviour. One theory that has gained interest in the wake of the pandemic is that tourists tend to minimise risk (in this case to their health) when planning their trip (Han et al., 2022), while other theories focus on tourists' personal values as the main precursor of their choices (Ahmad et al., 2020). However, the theory of planned behaviour

(TPB) developed by Ajzen (1991) is one of the most widely used to explain tourists' destination choice behaviour (Kim and Hwang, 2020). The TPB prioritises knowledge of tourist profiles based on their activities and subsequent segmentation (Álvarez et al., 2020), thus suggesting that tourists' choices are complex (Armitage and Conner, 2001). For this reason, analysing the type of tourists that visit a destination, segmenting them, and better adapting the tourism offer based on what they demand is key to maintaining the sustainability of destinations (Morales et al., 2015; Barreal et al., 2021). Azjen's TPB is also one of the most widely used theories to explain individuals' complex decision-making processes (Armitage and Conner, 2001). Thus, to better understand individuals' behaviour, it is necessary to consider sociodemographic aspects as well as cognitive and affective components that influence their decisions (Mercadé-Melé et al., 2021). For this purpose, segmentation emerges as an important marketing tool, as it allows identifying profiles of consumers that share common characteristics and characteristics that differentiate them from other groups (Du et al., 2016).

If carried out effectively, segmentation can enable destination management organisations (DMOs) to implement more efficient marketing policies by better adapting supply to the demand of specific consumer groups (Molina-Gómez et al., 2021; Mercadé-Melé and Barreal, 2021). Additionally, the stakeholder theory helps to understand the relationships between individuals and groups seen as stakeholders (Freeman, 2010) to effectively manage relationships between DMOs and different interest groups (Hristov and Zehrer, 2019), where this connection is of particular importance for the leadership of organisations (Pechlaner et al., 2014). Thus, this article aims to shed light on the role of DMOs in tourism market segmentation considering stakeholder involvement and the adaptation of stakeholders to tourism demand. Destination leadership coupled with policies adapted to tourist typologies could help different stakeholders in a given area remain competitive (Hristov and Zehrer, 2019). With this knowledge, the visitor economy can coexist better with social inclusion and local development (Zehrer and Hallman, 2015). To this end, following Masiero and Law (2016) or Sánchez-Rivero et al. (2022), the length of stays (nights) and the price per night in hotels will be taken as the core segmentation criteria in tourist stays to identify tourist segments which are economically sustainable for destinations (Blancas et al., 2010). This problem is more acute in inland coastal areas and cultural destinations, where the average length of stays (De Menezes et al., 2008) and expenditure per tourist (Casteñeda et al., 2019) are lower than in other types of tourism, such as sun and beach tourism. Therefore, focusing efforts on attracting tourist segments with economically sustainable behaviour patterns is critical for destinations. With this in mind, this study poses the following research question:

> RQ1: Are there tourist segments that differ in terms of length of stay and expenditure per night in different areas of Spain? How do these variables affect the market composition?

Spatial tourism planning

Agglomerations in different industries have been of concern to scientists for more than 100 years (Lazzeretti et al., 2008), and the tourism sector has not escaped this concern (Mohammed et al., 2019). Factors that influence the location of industries in certain areas began to be analysed as early as the 1920s (Chhetri et al., 2017). In the tourism industry, agglomeration largely depends on the supply of each area. Specifically, as agglomeration increases in a region so will its dependence on tourism (Li et al., 2020). In this regard, policy-makers need to pay attention to potential spatial spillover and the effects of competition between cities (Kadiyali & Kosová, 2013; Li et al., 2016), in addition to the effects that overcrowded destinations can have on tourist satisfaction and the inconvenience it can cause to residents (McKinsey et al., 2017). The morphology of cities as well as the different strategies used to determine where to host and derive tourism play a key role in managing the phenomenon of overtourism and creating more sustainable cities (Bouchon and Rauscher, 2019). Some studies have addressed the problem of overtourism through the urban management of cities affected by this phenomenon (Bouchon and Rauscher, 2019; Goodwin, 2019) with a focus on correct planning management that leads destinations to implement these policies and ensures both the economic and social sustainability of the destination (Yrza and Filimonau, 2021). Other studies have proposed changes in destination planning to preserve the sustainability of the environment (Paunović and Jovanović, 2017). However, as indicated by authors such as Dodds and Butler (2019), most changes that cities are introducing in terms of urban management to put an end to this problem (i.e., Barcelona or Venice) are not achieving their purpose, so other actions are necessary to achieve sustainability in saturated destinations.

Therefore, one of the main aims of planning policies should be the diversification of tourist saturation (Shoval, 2006). Saturation usually occurs in city centres (inland destinations) and the most popular coastal destinations (Shoval, 2006; Wang and Nicolau, 2017). This overcrowding can be dispersed to specific points through hotel prices (Hall and Page, 2014) and by diverting demand to less crowded areas if there is a proper intra-urban transport system (Arbel and Pizam, 1977).

A further problem of tourism in Spain that affects the economic sustainability of the sector is that the occupancy rate varies considerably across the national territory (Urtasun and Gutiérrez, 2006). Such mass tourism has a negative effect on the quality of life (QOL) of both residents and tourists (Liang and Hui, 2016; Uysal et al., 2016; Choe et al., 2021), which is further accentuated in the so-called “micro tourist destinations” (Viu et al., 2008); the most widespread typology in Spain. The highest population density in Spain is found around large cities, which has led to rural depopulation towards urban centres and coasts (Fernández and Martínez, 2017) at a much higher rate than in Eurozone countries. In this regard, there is social consensus regarding the need for specific policies to address the current depopulation of rural areas in Southern Europe (Alamá-Sabater et al., 2021) with a view to sidestepping gentrification (Tulumello and Allegretti, 2021) and creating stable jobs in rural areas (Castillo et al., 2017).

In recent decades, rural areas of Spain have been adapted for tourism and improved their accessibility to promote tourism development (Fernández and Martínez, 2017; Aazami and Shanazi, 2020). Given that tourists are willing to sacrifice accessibility in exchange for lower prices (Wang and Nicolau, 2017) or less differentiation of the offer (Becerra et al., 2013), and considering that there are economically sustainable tourist segments (RQ1), the following research question is posed:

> RQ2: Can planning policies be developed to improve the spatial distribution of economically sustainable tourists?

Methodology

Figure 1 summarises the methodology, which involves four steps and employs different statistical and econometric tools to achieve the research goals. The first step consists of designing a questionnaire to be administered to tourists in order to collect primary information about their motivations, consumption, expenditure, and personal characteristics. In the second step, a latent class model with covariates is used to identify the main groups and analyse how their class membership probability changes depending on the selected exogenous variables. The model includes tourist preferences, motivations, and activities to determine the segments in line with the research objectives. According to the class, the models use the length of stay, daily expenditure, and season as covariates to obtain the probability of class membership depending on their values. Secondly, and depending on the groups chosen in the previous step, the statistically significant differences between the length of stay and expenditure classes are examined. For this aim, the confidence interval in pairs of groups is obtained to test if the interval shows significant differences in mean values between groups. Finally, the spatial correlation between Spanish province units is studied by considering tourists’ mean daily expenditure and length of stay in each group.

To promote the sector as being sustainable for the regional community, it is essential to reduce the impact of tourism on the environment and local lifestyle. The proposed framework can aid in designing a better national tourism policy by de-stressing areas that suffer overtourism by determining the demand profile and how changes in the status quo alter economic features. This can be achieved using the latent class model with covariates as it identifies clusters and changes in the probability of class membership if the market changes. Given the inhomogeneity between groups, a difference in means analysis is also performed to determine if the differences between groups are significant and the sign. In this sense, it is essential to promote the classes that have significant positive consequences to economic features. However, because the relations are trans-regional, the methodological structure also incorporates a spatial analysis to expand the knowledge from small-scale to involve the national tourism system and the interdependence patterns between regions.

All previous statistical methods in the *R-Project* environment (R Core Team, 2019) are applied. The *PolCA* package (Linzer and Lewis, 2011) is used to develop the latent class model and the *stats* package (R Core Team, 2019) is used to obtain the confidence interval

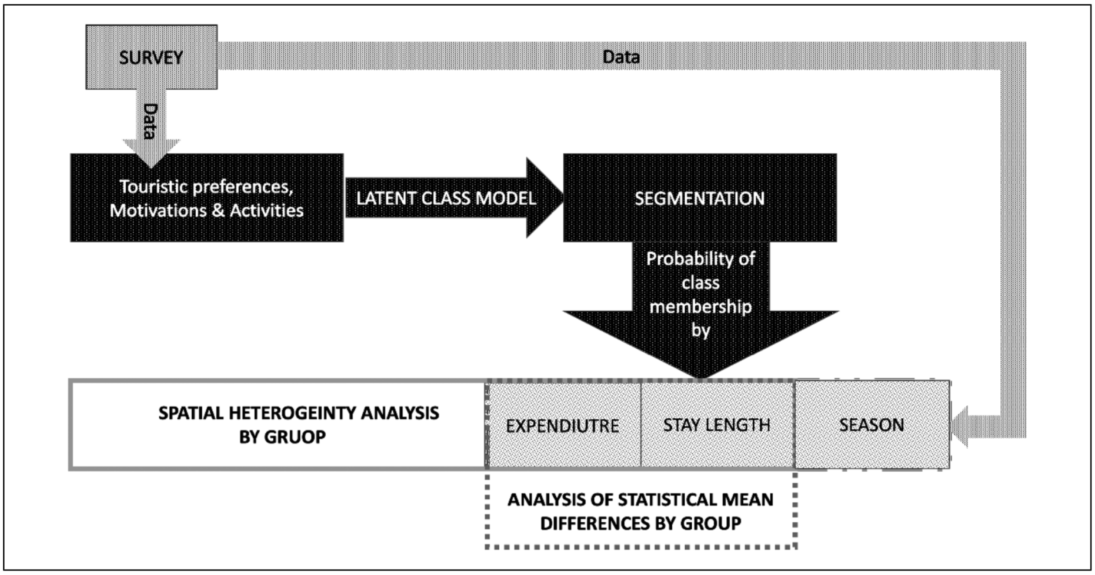

Figure 1. Flowchart of the methodological framework. Source: Own elaboration.

of the study variables. Other geographic information system (GIS) treatments and spatial statistics packages such as *maps* or *spdep* packages (Deckmyn, 2018) are also used.

Latent class analysis

As mentioned above, a latent class model (LCM) is used to determine groups or classes by multivariate categorical variables and describe the probability of class membership according to a set of covariates or exogenous variables. The LCM with covariates is not a novelty in the field of tourism and has been widely employed in the literature to analyse the tourism sector (Alegre et al., 2011; Biagi et al., 2016; Baños and Tovar, 2019). According to Weller et al. (2020), latent class analysis is adequate for identifying different subgroups in a sample and analysing their evolution towards exogenous variables. The authors also underline the functional outcomes provided by this method, as it allows researchers to design appropriate interventions according to their goals.

The LCM was developed from the latent structures proposed by Lazarsfeld (1950), which is employed in the theoretical framework of Hagenaars and McCutcheon (2002) and Linzer and Lewis (2011) to relate latent class models and finite mixture models (FMMs). The LCM employs a vector of categorical or manifest variables defined by J, each with a set of levels J_k. In this study, two main groups of manifest variables are proposed: one to describe the main travel characteristics, such as the selected accommodation or the number of companions, and another to depict activities, such as time spent on cultural or sports activities, among others. Each respondent presents an outcome defined by the variable j and its level k. Then, it presents an outcome defined by Y_{ijk}, which takes the value of 1 if respondent i selects the k^{th} option to i^{th} variable. If the respondent does not choose any level, the outcome is defined as $Y_{ijk} = 0$. The model has a finite number of groups according to the categorical variables ($r = 1,\ldots,R$), in which the outcome shows the proportion of respondents in category r (p_r) and the conditional probability of that one respondent in class r produces a reaction k on variable j (π_{jrk}). The LCM does not determine the number of classes; it considers some statistics that are described below. However, it has profound implications because a high-class number achieves better goodness of fit; meanwhile, the high number of groups causes over-fitted statistics or irrelevant groups with very low-class membership. It could cause several problems in defining and describing this type of class (Nylund et al., 2007; Masyn, 2013). Therefore, the objective should balance a good fit statistic and the relevance of the group.

The next step in the model is to define a set of external variables (Xi), also called covariates, to analyse how each variable influences the class membership ratio. By doing so, it is possible to determine how each variable affects the probability of being in one group or another. This information can be of use for policymakers or business managers because they know the variable influence to alter the grouping ratios, so they can act on it to achieve their organisational goals. In this case, the LCM with covariates involves the season as a dummy variable (winter, spring, summer and autumn), the stay length and the daily expenditure. Note that the regression model only considers intercept to consider the seasons. Equation (1) describes the functional form to estimate the proportion of respondents in each category considering the exogenous variables. A marginal increase in one independent variable implies an equilibrium change in class membership, remaining ceteris paribus.

$$p_{ri} = p_r(X_i; \beta) = \frac{e^{X_i \beta_r}}{\sum_{q=1}^{R} e^{X_i \beta_q}} \quad (1)$$

The present study also implements the Bayesian information criteria (BIC) and log-likelihood ratio as tools to set the model specification. The specification assumes from non-clustering to five different levels by considering season as an additive covariate and length of stay and daily expenditure as a multiplicative covariate. The minimum BIC and maximum log-likelihood ratio are the desirable scenarios, but it will also include the size of the proposed clustering levels. Therefore, this article considers the marginal reduction/increase of each statistic when the model increases one class and evaluates if all numbers of classes present a significant ratio in the sample.

Difference in means analysis

Considering the survey data and the LCM classification, statistical differences between groups are analysed using the analysis of variance method (Chambers et al., 1992). The statistical analysis establishes a null hypothesis of no significant differences between groups. In contrast, the alternative assumption considers that the difference between classes is notable. A condition for developing the model is that the data fit a normal distribution, which is determined by the Shapiro–Wilk test (Shapiro and Wilk, 1965). Given that a non-normal distribution is expected, the non-parametric Kruskal–Wallis test is performed to determine statistically significant differences between groups (Hollander and Wolfe, 1973). If the test detects statistical differences, the Wilcoxon test is used to establish if the differences between paired groups are statistically significant (Wilcoxon, 1945).

Spatial patterns analysis

Tourist preferences and decisions could present spatial inhomogeneity across Spanish regions. Therefore, it is essential to determine if spatial inhomogeneity exists and if specific clustering occurs around some geographical areas (Ripley, 2005). Some statistical tools can be used to achieve these goals. For this purpose, the Moran's I test was performed to analyse the global spatial autocorrelation of a selected variable in each LCM group (Griffith, 1980). In this case, the spatial patterns of the variables *daily expenditure per tourist* and *length of stay* were analysed. Equation 2 explains how to calculate the Moran's I test, where X is the value of the variable, N is the total observations recorded, ij denotes the different spatial units, and w is the spatial weight matrix. This statistical technique tests for the presence of spatial correlation in contrast to the null hypothesis of no spatial correlation.

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \quad (2)$$

The spatial analysis requires defining the weight matrix previously as it should record the spatial relations one by one spatial unit depending on the contiguity set. Polygons or centroid contiguity are two different ways to define spatial patterns (Getis, 2007). The model considers the polygon contiguity to determine the spatial relationship between entities. At first, this assumption implies that the islands are not spatially connected with the peninsular regions. However, the spatial matrix was modified to include the Canary Islands among their provinces and the Balearic Islands with the cities of Barcelona and Valencia. This modification was necessary because visitors to these areas depend on ports and airports to travel to other regions of Spain, which are more expensive and limited than road or train options. Finally, the nearest connection is considered in these areas. The nearest polygon to each geographical unit in all directions (queen contiguity) is employed to consider the spatial relations in the weight matrix.

Following the previous methodology, spatial clustering is also used to determine the relation between similar/dissimilar units considering the proposed weight matrix. This analysis determines if the neighbourhood presents significant differences to each study unit, so it identifies hot/cold spots. The article avoids using the General

Getis-Ord (G) to identify these patterns because the positive results could be neutralised by false negative values (Songchitruksa and Zeng, 2010). However, the Local Getis-Ord (G_i*) indicates where the surrounded entities have similar values and determines a spatial cluster (Ord and Getis, 1995; Getis and Ord, 1996). The contiguity entities should also present high/low values as a significant hot/cold spot. Equation 3 defines this statistic for each entity i, which includes the data of remaining unit j; the weight matrix w_{ij}; the global standard deviation (S), and the mean ($\bar{X}$). Finally, Equation 4 typifies each local spatial autocorrelation result to compare each local result with the remaining ones.

$$G_i^* = \frac{\sum_{j=1}^{N} w_{ij}x_j - \bar{X}\sum_{j=1}^{N} w_{ij}}{S\sqrt{\frac{\sum_{j=1}^{N} w_{ij}^2 - \left(\sum_{j=1}^{N} w_{ij}\right)^2}{N-1}}} \tag{3}$$

$$Z_i = \frac{G_i^* - E[G]}{SD[G]} \tag{4}$$

The previous statistical results are easy to interpret: as the outcome becomes positive/negative and reaches an extreme value, the hotter/thecolder the spot is. In other words, the *z-score* falls in the null rejecting area depending on the confidence interval. The significance values α = (0.1,0.05,0.01,0.001) are considered to determine the relevance of the local result. For example, for the first alpha value (0.1), if the absolute value of the statistic is lower than 1.65, the existence of local clustering should be rejected. The same thing occurs with the remaining intervals, which depend on the considered range, and the existence of a spatial group with significance α can be accepted. All these spatial statistics will determine geographical patterns in the tourist segmentation and can aid in designing regional policies to promote specific segments or increase their economic expenditure.

Data and variables

This research applies a theoretical framework to analyse international tourism in Spain. To this end, surveys on foreign tourists' socioeconomic features, motivations to visit Spain, and consumption and expenditure behaviours during their stay conducted by the Spanish National Institute of Statistics were used (INE, 2021a). The surveys collect information in the major international arrivals facilities of the country using the same questionnaire (INE, 2022a). The INE provides the raw results and researchers can adapt the information to their goals. The INE also considers the statistical relevance of the sample, informs about the codification process, and provides detailed information about the classification items, among other important issues, to guarantee that the information is relevant and suitable for conducting tourism research (INE, 2022b). This study uses data from September 2015 to June 2019, which includes 318,765 valid inquiries. Other studies have also used secondary data for purposes of segmentation (Almedia et al., 2020), which are now accessible in real-time thanks to the evolution of virtual environments (Baye et al., 2006; Mohammed et al., 2019).

Although other research, like Tourspain (2018), have analysed segmentation using their own categorical variables. However, this method is not considered here because the selected features do not include information about tourist profiles and only focus on activities. Other authors, such as Alén et al. (2017) or Ramirez-Hurtado and Berbel-Pineda (2015), have used more variables to include sociodemographic characteristics, push and pull factors, and trip characteristics. However, they only analyse a specific segment in the tourism market.

In line with the study objectives, Table 2 shows the categorical data used to develop the LCM. Given that each variable presents different levels, the table defines factorial levels and each ratio in the variable, respectively. The variables can be classified into two main groups: the first group includes tourist profiles and the second group includes activities during the stay.

The survey is conducted throughout the year, so the results of questions related to expenditure should be examined at the same time of reference to be comparable between periods. Hence, expenditure is deflected taking into account the consumer price index (CPI) at 2008 prices (INE, 2021b). In addition, length of stay could condition expenditure, as longer stays may imply more expenses. Thus, these variables are converted to daily data to remove the effect of length of stay.

Results

The first part of the analysis involves the number of clusters considered in the LCM. Table A in the Appendix presents the log-likelihood ratio (LR), the Bayesian information criterion (BIC), and each class proportion by considering different

Table 2. Summary of categorical variables

Nationality	Benelux	Lv.1	11.29%	Sports	No	86.81%
	UK	Lv.2	21.15%		Yes	13.19%
	Germany	Lv.3	12.95%	Shows	No	89.67%
	France	Lv.4	12.42%		Yes	10.33%
	Other Europeans	Lv.5	28.59%	Parties	No	74.10%
	Other countries	Lv.6	13.60%		Yes	25.90%
Accommodation	Market accom.	Lv.1	67.88%	Shopping	No	37.93%
	Other non-market accom.	Lv.2	32.12%		Yes	62.07%
Travel type	Alone	Lv.1	33.60%	Museum	No	66.38%
	Couple	Lv.2	33.22%		Yes	33.62%
	Family and friends	Lv.3	33.18%	City Tour	No	45.25%
Main Motivation	Cultural and leisure	Lv.1	33.35%		Yes	54.75%
	Sun and beach	Lv.2	39.12%	Beach	No	44.55%
	Family	Lv.3	13.12%		Yes	55.45%
	Others	Lv.4	14.42%			

Source: Own elaboration based on INE data (2021a).

clustering levels. These results prompt the search for four different groups in the database because the LR and BIC show a high variation at the first levels. When the model considers five levels, the clustering presents the leading group and remains too small. A higher number of classes also generates undefined groups of little relevance to the research, thus indicating the overrating impact caused by adding classes to LK and BIC values (Nylund et al., 2007; Masyn, 2013).

These four groups present different tourist profiles and noteworthy contributions to global research. More specifically, Group 1 represents 45.46% of respondents with a Beach & Sun profile and Group 2 includes around 14.14% of respondents and who declare that their primary motivation for travelling to Spain is business or work. Group 3 includes nearly 21.92% of respondents that visit Spain mainly attracted by cultural activities. The last group comprises travellers who predominantly come to Spain to visit family and represents about 18.48% of respondents. Figure 2 includes more detailed information on the type of activity and tourism demands of each group. The plot shows the portion of each level in every internal variable by group.

As the figure shows, determining international tourist profiles requires much more than simply considering their primary motivation to visit Spain. These findings answer RQ1 and confirm that Spain has different international tourist clusters. These clusters are summarised in what follows:

- Sun and beach (45.46%). This is the most significant class and mainly involves activities related to shopping and city tours. The tourists in this class mostly come from European countries and travel in couples or groups. They usually book market accommodations.
- Business (14.14%). This is the smallest class and does not usually demand typical tourist activities. The members of this class regularly travel alone and come from all regions of the world. They demand hotels, apartments, and other market accommodations.
- Cultural (21.92%). This is the most international group as it includes travellers from many non-European countries. In addition, the members engage in more activities than the previous classes. They demand city tours, shows, parties, museums, and shopping at a higher than average rate for Spain.
- Family visit (18.48%). The members of this class are family and friends who travel to Spain for holidays and do not typically use hospitality services. They regularly go shopping and to parties. Sun & Beach tourism or city tours are not common in this group.

Table B and Figure A in the Appendix show the LCM result with covariates in which all coefficients are relevant. The results indicate the probability of class membership throughout the season, daily expenditure, and length of stay. The Sun & Beach class presents high seasonality with excellent rates in the spring and summer. This class displays a mid-low expenditure level with a great variety in length of stay. The business class has lower seasonality effects with high expenditures and short stays as determinants

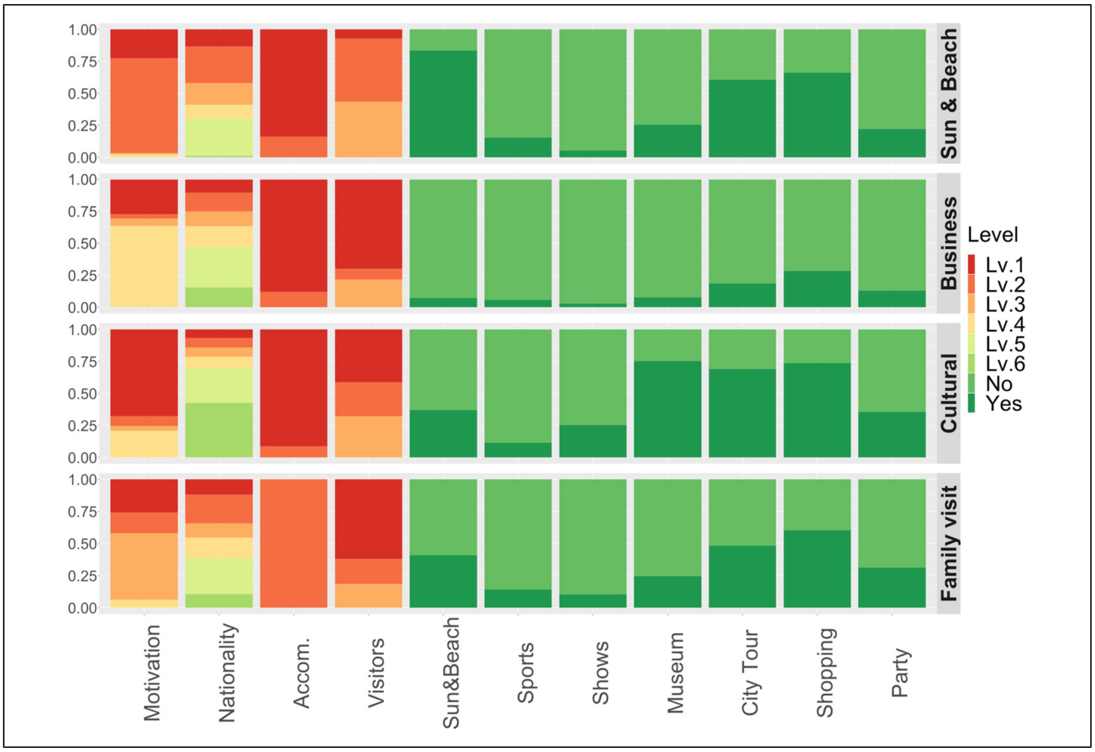

Figure 2. LCM results. Source: Own elaboration.

of membership rate. Family visit shows different seasonal patterns that increase class membership probability during the autumn and winter; however, the expenditure in this group is low and stays are long. Finally, cultural tourists show no significant differences between periods, have a high level of expenditure and stay for extended lengths of time.

The groups exhibit different patterns, thus indicating that not all international tourists are the same or have identical needs. However, it is important to determine whether these differences are statistically significant. To confirm this, Table C in the Appendix reports the 95% confidence interval of mean differences between each class and the corresponding p-values of the tests. Significant differences are found between all groups for expenditure and length of stay. This finding supports the relevance of segmentation for analysing expenditure levels between different classes of international tourists and the need to adapt the tourism offering according to the clustering result, including differences in expenditure. Based on this information, the tourist industry could adapt, readjust, or accommodate their strategies according to differences in the segment revenues. The analysis is similar for length of stay as the significant differences between all the groups indicate. The hospitality sector could also use this information to tailor its offer to the different demand profiles and length of stay requirements. For example, an accommodation firm could adapt its market to the business class. However, they should expect shorter stays with high revenues, which implies high volatility in their earnings between high and low seasonal demands.

The rate of respondents by class is different across regional entities. The first row in the maps shown in Figure 3 depict this heterogeneity and highlight the relevance of certain areas depending on the specific classes. As expected, coastal areas and islands present the highest ratios of international tourists with sun and beach motivations. Business tourists primarily travel to the mainland regions with Madrid, the Basque Country, or Teruel being the regions with higher values. Provinces like Madrid, Barcelona, Salamanca, and Seville have a high concentration of international tourists with cultural motivations. Finally, family visits are relevant in the mainland areas and do not belong to any specific previous market segment.

Following the classification obtained in the clustering, the spatial description of the covariates was mapped by Spanish regions. The remaining maps in Figure 3 outline the spatial

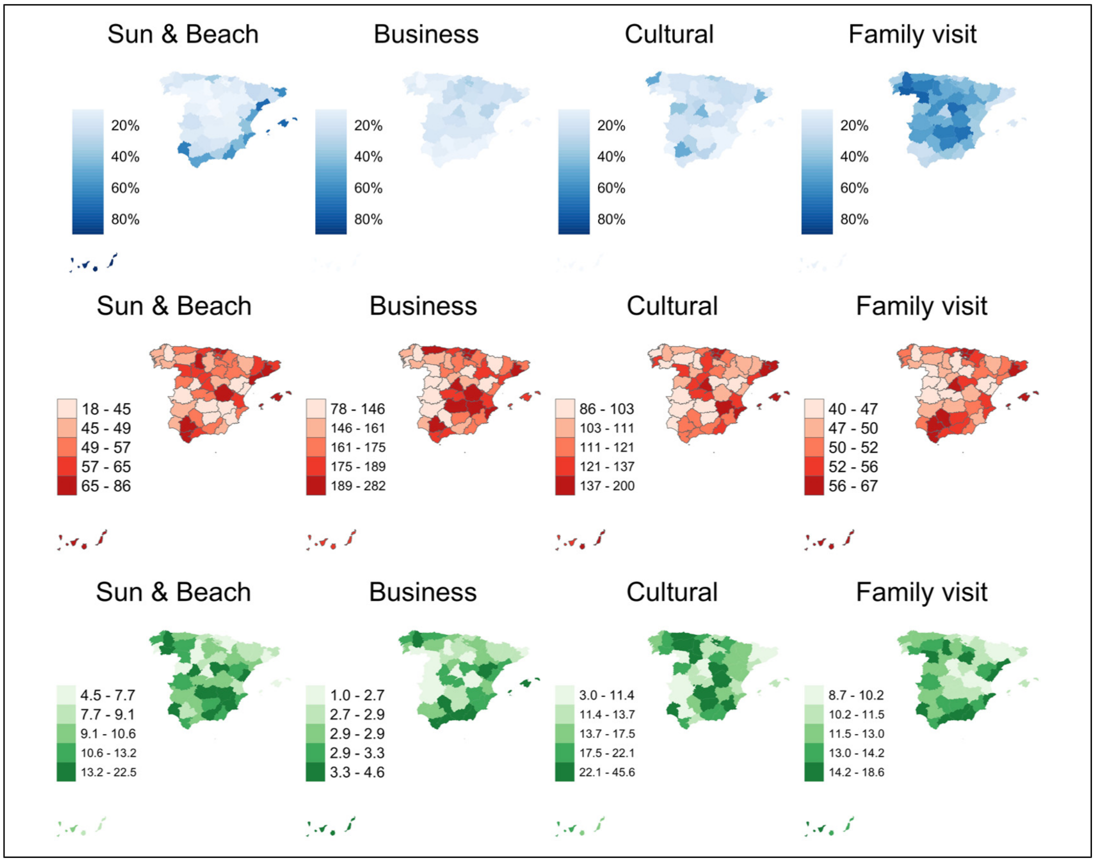

Figure 3. Response rate (blue maps) and mean values of daily expenditure (red maps) and length of stay (green maps) by class per Spanish region. Source: Own elaboration.

patterns by class for daily expenditure and length of stay. As can be seen, expenditure is high in the islands, some Mediterranean regions, the Basque Country, and among Sun & Beach visitors. By contrast, Extremadura and most of the region of Castilla-Leon show the lowest daily expenditure, regardless of class. The opposite occurs in the Basque Country, Madrid, and Barcelona, which show the highest values for all classes. Seville is noteworthy, as it ranks first in all classes except for the cultural segment, which is one of the most important segments in the sector because the city celebrates relevant international cultural events, such as Holy Week or the April Fair.

For all classes, the length of stay is shorter in Madrid and coastal areas of the Basque Country. The remaining regions have different implications depending on the class. For example, Sun and beach tourists remain for longer stays in the south-eastern regions than in some inland provinces or northern regions. Stays by members in the business class stays are longer in areas of southeast Andalusia, Lugo, Teruel, or the Balearic Islands compared with Extremadura or Castilla-Leon. As regards the cultural tourism segment, stays are generally heterogeneous, with the exception of Asturias, northern Castilla-Leon, Murcia, and some areas in Castilla-La Mancha, where stays are longer. This contrasts with other influential cultural areas, such as Seville, Madrid, or Barcelona. Although these destinations primarily attract international tourism, stays are shorter in these areas. Finally, family visits are associated with more overnight stays in coastal rather than inland destinations; a pattern that links the weather and proximity to the sea as a factor to spend more time with relatives and friends.

Moran's I statistic helps to determine the spatial autocorrelation. Figures B and C in the Appendix provide each result for both study variables by cluster classification using 1 to 5 spatial lags. The figures also provide the confidence interval of the Moran's I results; the extreme values should include zero to reject the spatial autocorrelation. The results show that the spatial patterns mainly involve one lag to achieve higher spatial dependence. This consideration is

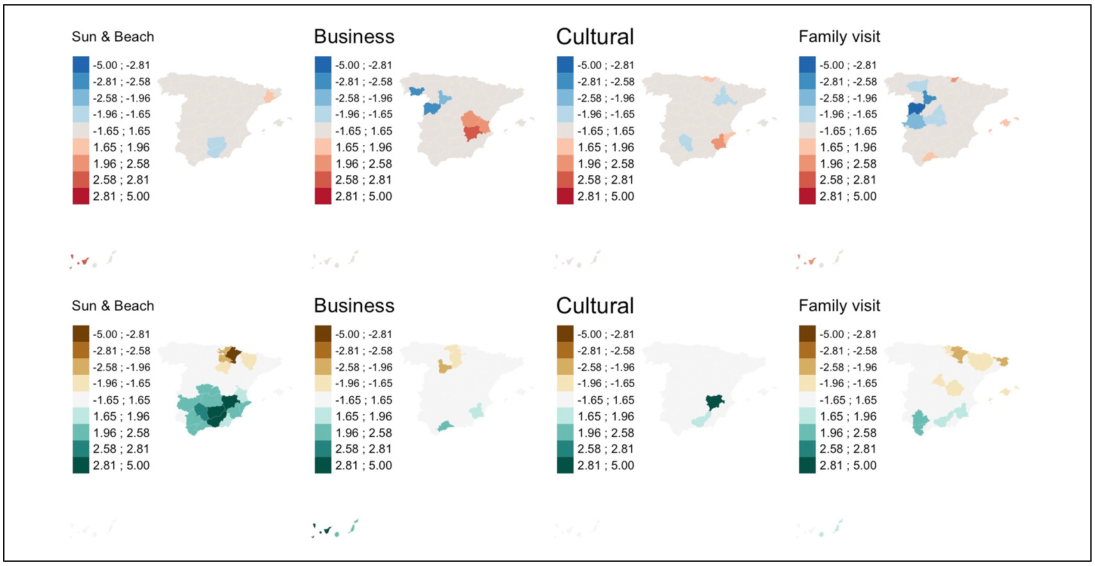

Figure 4. Spatial cluster: daily expenditure and length of stay. Source: Own elaboration.

not valid for two segments in relation to length of stay: Class 1, which achieves a better result to 3 lags, and Class 3, which does not present any valid results. These results support the use of spatial patterns for market segmentation and to adapt the tourism offers to the specific demands depending on the features of each.

The regional spatial clustering of daily expenditure and length of stay was analysed considering a direct contiguity matrix by Spanish regions with 1 and 3 lags. Therefore, Figure 4 plots the local Getis-Ord results for each variable and depicts some relevant spatial inhomogeneity patterns. Specifically, daily expenditure shows significant cold spots in Granada, Jaén, Ourense, Salamanca, Valladolid, Cáceres, Leon, Zamora, Córdoba, Madrid, and Toledo for some segmentation classes. These provinces do not have the opportunity to absorb extra income by attracting the tourists that visit contiguous provinces because these are low-income tourists. These regions should consider specific international programmes to increase international tourist expenditure. The opposite occurs in Barcelona, Tenerife, Valencia, Cuenca, Albacete, Vizcaya, Gipuzkoa, Murcia, Alicante, and Málaga, all of which are significant hot spots characterised by high daily expenditure by international tourists. Therefore, these areas could implement advertising campaigns to promote their tourist attractions in contiguous provinces to engage tourists with previous high expenditure levels. The results highlight significant differences between classes because all areas show a combination of hot and cold spots for the different international tourism segments. This suggests that public or sectoral administrations should consider measures to increase daily expenditure in the surrounding areas to foment sharing between segments.

The previous figure also plots the spatial outliers and hot/cold spots for length of stay using the Getis-Ord statistics. As can be seen, there are significant differences between northern and southern Spain. The Basque Country provinces, La Rioja, Soria, Navarra, Huesca, Madrid, Cuenca, and Balearic Islands present cold spots, thus indicating shorter stays by tourists. Together, these areas cannot encourage longer stays. This finding contrasts with destinations in the south of Spain, such as the provinces of Andalusia except for Huelva, and Badajoz, Murcia, Alicante, Valencia, Albacete, Ciudad Real, Toledo, and the Canary Islands. Together, these regions present a hot spot where measures can be taken to promote more extended stays.

These previous considerations have partially answered RQ2. However, further considerations will be made in the discussion section as well as some recommendations for developing better planning policies to achieve a suitable spatial disturbance of international tourism in Spain and increase the economic sustainability of Spanish destination.

Discussion and conclusions

The methodology applied in this work is an innovative proposal to integrate different statistical tools to plan a more sustainable tourism strategy. These statistical methods have never been used in compendium to address issues affecting tourism. The information provided can serve as a guide to partially solve these significant problems by identifying economically profitable segments and their geographical dispersion. To this end, it proposes a model for selecting segments based on the characteristics expressed by tourists in a questionnaire, which can be adapted depending on the researcher's needs. The same questionnaire should include variables whose effect on the grouping is to be analysed. The study proposes expenditure and length of stay as covariates, but the research could examine other variables depending on the specific objectives. Segmentation is essential to identify the different groups of demand to support strategic decisions and to adapt the supply of goods and services according to the characteristics of the group members. On the other hand, the covariates could provide essential information on possible market changes and how they could affect tourists' expenditure or length of stay.

The other methodological approach of the study aimed to understand how the spatial dependence of covariates behaves and observe how alterations affect neighbouring areas or regions. This information can be used to achieve sustainable development by directing tourist flows to less crowded areas to decongest more highly saturated ones (Iqbal et al., 2022). Such measures could favour a balance between areas with excess demand and those with low demand, which would help these regions' economic development without affecting the sector's national impact. These two aspects of the study converge because through knowledge of the demands of tourists and where they are, it is possible to modify the supply in other locations to mobilise tourists to these less saturated areas. This is in line with other authors such as Castañeda et al. (2019) or Mihalic and Kuščer (2021), who have pointed to the importance of alleviating congestion in highly saturated areas to improve the quality of service in these destinations and increase tourist satisfaction (Castañeda et al., 2019).

This study has focused on Spain and international tourists. However, the proposed model can applied in other contexts and areas that want to implement sustainable planning policies. The model can also be of great help in the territorial planning of tourism and redistribution of the wealth it generates as it identifies economically sustainable segments (RQ1) and proposes the redistribution of tourism flows through a valid regional policy (RQ2). This redistribution should satisfy tourists' demands for more sustainable tourism (Merli et al., 2018), improve the quality of life of residents in overcrowded tourist areas (Liang and Hui, 2016), and encourage the relocation of tourism to less frequented destinations, which can boost the economic growth of these areas in a sustainable way (Mohammed et al., 2019). Moreover, this redistribution of tourism may be a solution to the serious problems of overtourism suffered by many cities, such as Barcelona or Venice, where the coexistence of residents and tourism is already unsustainable (Goodwin, 2019).

As concerns the results, the first part of the article identifies four significant segments and how external factors affect market composition, in this case, the tourists' level of expenditure and length of stay (Škare et al., 2021). Through the segmentation of international tourism, economically sustainable tourist profiles can be identified to take different actions aimed at achieving a marketing mix of them (Blancas et al., 2010). The results in the second part demonstrate the spatial heterogeneity in the covariates of study, such that modifying one covariate in a province implies alterations in the neighbouring province. This can bring benefits to neighbouring areas that are less saturated by tourism and more dependent on other activities, such as agriculture (Alamá-Sabater et al., 2021), as these areas can take advantage of tourist spillovers.

Furthermore, the proposed approach can help to establish different tourism planning policies for each region. Thus, for example, in the regions of northern Spain, the main problem is the low number of overnight stays, which could be solved with an appropriate policy to promote types of tourism with a higher average number of days of stay, such as sun and beach tourism (Botti and Peypoch, 2013). On the other hand, in the destinations of southern Spain, the results show a strong spatial dependence on sun and beach tourism (see Figure 4). This is an interesting result if the aim is to develop a policy to promote less visited destinations by transferring resources from overcrowded to less congested areas (Eugenio-Martín and Inchausti-Sintes, 2016); for example, by offering attractive secondary activities in areas with low tourist demand but close to the coast.

The proposed methodology can also be effective in understanding the behaviour of different types of tourists according to external variables.

For example, as Figure 4 shows, stimulating spending in inland areas of the country positively affects spending in neighbouring provinces. This is in line with De Menezes et al. (2008), who found that inland tourists prefer short overnight stays and visit several destinations on the same trip. Moreover, if a stable level of overnight stays is maintained in these inland regions, it can complement agricultural activity (the predominant sector in these areas; Castillo et al., 2017; Hernández-Mogollón et al., 2019).

Finally, regarding the limitations of the study, although the proposed methodology can support decision-making in tourism environments, its application is limited by the availability of data and the mobility of tourists, which means that we cannot capture the effect of Covid-19 in this study. The leading destination statement in the survey used here does not consider local mobility or the link between the destination and primary motivations or activities. Therefore, further research should consider other questionnaires to reflect this dispersion of movements and how they might spatially affect the tourist typology, taking into account the effect of the Covid-19 pandemic. It would also be of interest to measure the probability of registration according to decomposed variables of expenditure items or type of stay.

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Appendix

Table A. Model selection.

				Number of class				
Loglikelihood	BIC	Dif. loglikelihood	Dif. BIC	1	2	3	4	5
−2775071	5550371	-	-	100%	-	-	-	-
−2659966	5320478	0.0415	0.0414	46.03%	53.97%	-	-	-
−2585164	5171190	0.0281	0.0281	49.56%	27.42%	23.02%	-	-
−2544135	5089448	0.0159	0.0158	39.17%	23.88%	21.19%	15.76%	-
−2509924	5021344	0.0134	0.0134	39.11%	22.12%	15.03%	13.91%	9.83%

Table B. Output of LCM with covariates.

	Coefficient	Std. error	*t*-value	Pr(>t)
2/1				
Intercept	−0149	0023	−6573	>0001
Summer	−0989	0019	−51,672	>0001
Autumn	−1477	0022	−67,905	>0001
Winter	−0401	0018	−21,655	>0001
Daily expenditure	0018	0000	87,322	>0001
Stay length	−0617	0007	−92,325	>0001
Daily expenditure * stay length	0001	>0001	22,739	>0001
3/1				
Intercept	−2380	0018	−130,631	>0001
Summer	−0709	0016	−43,422	>0001
Autumn	−1071	0017	−63,345	>0001
Winter	−0399	0016	−24,322	>0001
Daily expenditure	0018	0000	100,237	>0001
Stay length	0008	0001	6611	>0001
Daily expenditure * stay length	0001	0000	24,619	>0001
4/1				
Intercept	0415	0019	21,851	>0001
Summer	−0966	0015	−65,632	>0001
Autumn	−1370	0015	−89,236	>0001
Winter	−0546	0014	−37,707	>0001
Daily expenditure	−0009	>0001	−35,653	>0001
Stay length	0012	0001	11,740	>0001
Daily expenditure * stay length	>0001	>0001	2477	>0001

Table C. Mean differences by group.

		2-1	3-1	4-1	3-2	4-2	4-3
Daily expenditure	Lower	122,170	72,291	−12,424	−51,597	−136,321	−85,973
	Upper	124,794	74,419	−10,362	−48,657	−133,429	−83,522
	p.Adj	>0001	>0001	>0001	>0001	>0001	>0001
Stay length	Lower	−6441	1616	2499	7814	8695	0704
	Upper	−6069	1918	2791	8230	9105	1051
	p.Adj	>0001	>0001	>0001	>0001	>0001	>0001

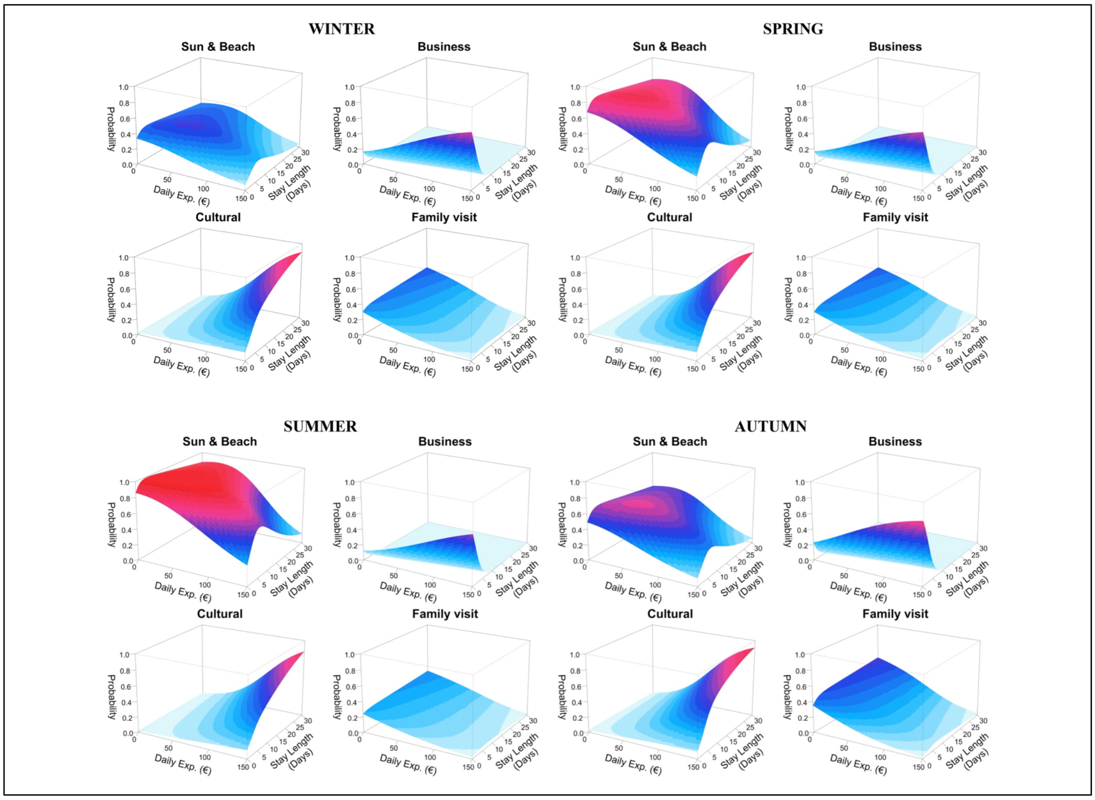

Figure A. Probability membership by class and season. Source: Own elaboration.

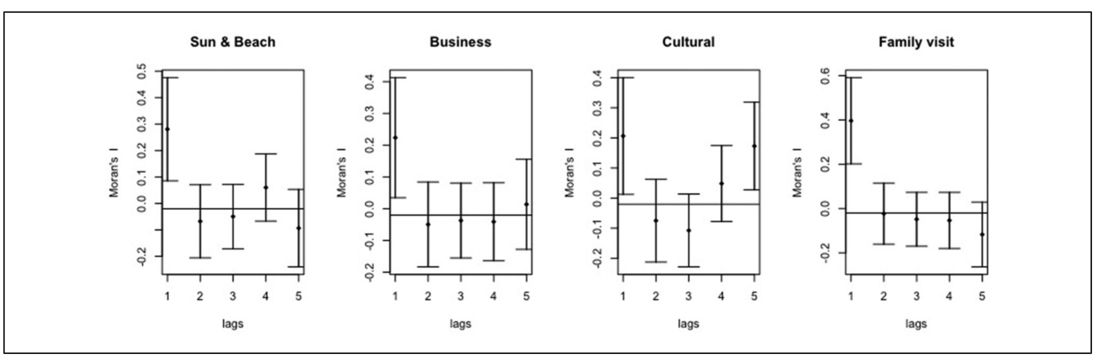

Figure B. Correlogram for daily expenditure. Source: Own elaboration.

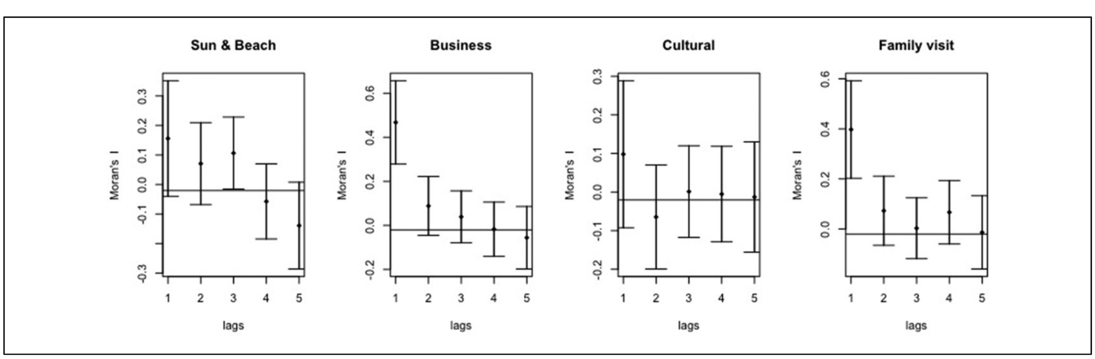

Figure C. Correlogram for length of stay. Source: Own elaboration.