Comprehensive evaluation of the tourism seasonality using a synthetic DP_2 indicator.

Abstract

Tourism plays an important role in the economic development of several regions over the world. Imbalances in the activity levels throughout the year will condition the positive effects generated by the sector given that work stability and economic flows are dependent upon it. The measurement of seasonality based on indicators that are built using individual variables offers only a partial picture of the situation, or even contradictory results subject to which data were taken as a reference. This paper proposes a new system to measure seasonality. It is based on a DP_2 synthetic indicator that includes both, supply and demand variables and is able to determine comprehensively how intense seasonality is. This method, which is replicable in any region, has been applied to the regions of Spain. It has been determined that the areas with a better annual stability are Madrid and the Canary Islands. This indicator also allows us to analyze the amount of information provided by each variable when constructing the indicator, as well as identifying the most relevant variables when explaining regional disparities.

Keywords: seasonality, sustainable development, synthetic indicator, Spain.

Introduction

Seasonality, understood as the uneven development of a certain economic activity throughout the year, is a characteristic present in a large number of sectors. Tourism might be affected to a larger extent than others (Cisneros-Martinez & Fernández-Morales, 2013). In the context of tourism, one of the most widely accepted definitions is that proposed by Butler (1994), who describes tourism seasonality as ‘a temporal imbalance in the phenomenon of tourism, [which] may be expressed in terms of dimensions of such elements as numbers of visitors, expenditure of visitors, traffic on highways and other forms of transportation, employment, and admissions to attractions’. This definition proposes several variables that can be taken as a reference in order to analyze the seasonality intensity. According to Martín et al. (2014), this implies that the variable of analysis selected to measure seasonality intensity will condition the results and that we will arrive to different rankings and, therefore, the variable we select conditions our conclusions too. If we take this into account, in order to improve the measurement of seasonality intensity, we need a system that allows us to synthetize the information provided by different variables that describe the phenomenon in an integrated and complete manner.

There are no synthetic indicators in the academic literature that analyze tourism seasonality in a comprehensive way. Thus, making it difficult to follow seasonality trends, to comprehend the size of the problem; and to analyze the success of public policies and business actions developed in order to reduce seasonality. To overcome this problem, a synthetic index is constructed using a set of partial indicators to quantify various aspects of tourism seasonality and aggregate them into a single item of data. The indicator proposed by this paper takes the Distance Method (DP_2) of Pena (1997) as a reference. A distance indicator initially designed to measure disparities in social welfare between areas (Zarzosa, 1996; Somarriba, 2008). Many contributions made by this methodology improve the measurement of seasonality in comparison with other indicators used previously. First of all, we do not face the problem of measuring seasonality with just one indicator. As shown before, the systems that do this only offer a partial picture that is conditioned by one side of the phenomenon instead of providing us with a global interpretation. Second of all, choosing this methodology to build synthetic indicators proves advantageous over other possible alternatives because DP_2 allows us to assign to each variable its relative weight in a non-arbitrary way at the same time that removes redundant information. The whole set of improvements made by this methodology is presented below.

Many authors have pointed out how important it is to widen the analysis of some of the aspects related with seasonality so that its measurement, description; and comprehension are enhanced. Higham & Hinch (2002) argue that although it is a well-known characteristic of tourism, it is also one of the less understood. Koenig-Lewis & Bischoff (2005) argued that research gaps still remain in terms of both defining a solid theoretical framework and the need to adopt a more demanding quantitative perspective. This assertion follows the line of this research since we offer a new perspective on the quantitative analysis of seasonality trends. We propose a methodology that gathers multiple manifestations of tourism seasonality from both, demand and supply points of view. As a result, the destinations or regions are ranked by their seasonality intensity.

The causes of tourism seasonality are varied and complex. This has drawn the attention of numerous researchers who have analyzed explanatory aspects of this tendency. One of the most widely accepted classifications on the causes of tourism seasonality is that proposed by Hylleberg (1992), which differentiates between three groups of determinants: calendar effects (festivals, dates of religious holidays), weather (number of sunshine hours, temperature) and timing decisions (fiscal years, school holidays, accounting periods, business holidays, etc.). Higham & Hinch (2002) indicate that some causes of seasonality derive from the very same restrictions imposed to the development of the tourist activity. In addition to these factors, other elements such as inertia or social pressure (Butler, 1994), that might have an influence on tourism seasonality have been described in the literature of this topic. Rosello et al. (2003) argued that the growth in tourists' income and the fall in relative prices tend to improve the distribution of holidays throughout the year.

The impacts of tourism seasonality encompass different dimensions that have intensified with the spread of mass tourism (Wall & Yan, 2003). The negative consequences of the seasonality refer to the effects generated during peak periods as well to those produced during times when the affluence is minimum. In the first case, repercussions derive from the overcrowding, whereas in the second one, from the underutilization. Altogether, problems caused by temporary imbalances arise in the tourist activity causing disorders in the economic development of cities and regions that chose tourism as a tool for economic growth. The impact of seasonality on regions where the tourist activity is developed can be broadly divided into economic, ecological, socio-cultural and employment effects. Economic effects imply that the coexistence of peak periods with periods of underutilization result in lower profits (Cuccia & Rizzo, 2011), as well as the inefficient use of resources and facilities (Georgantzas, 2003). During peak season, the maintenance of facilities and the quality of the services provided might be affected (Koc & Altinay, 2007). Moreover, as noted by Murphy

(1985), employees of the tourism sector have to save enough money in order to compensate the scarcity of activity at other times of the year.

Environmental effects are related to periods of high concentration of tourists rather than valley periods. Effects like disturbance of wildlife, the congestion of rural roads, the production of large volumes of waste and environmental degradation among others have been described (Grant et al., 1997). Sociocultural impacts, as the environmental ones, are stronger in the peak season; and their effects are as noticeable by visitors as by the locals. Within this category are included effects such as increases in the costs of services, heavy traffic and road congestion, lines for services; and lack of parking among others (Waitt, 2003; Kuvan & Akan, 2005). Besides these impacts, during periods with a high concentration of visitors extra staff must be hired to reinforce some public services. This might also cause a tax rise (Murphy, 1985). In the valley season, some commercial establishments might close. This will affect the overall experience of the tourists and the image of the destination (Flongfeldt, 2001) whereas during peak season, the quality of the services might be undermined (Butler, 1994).

Impacts on the job market have been widely described in the literature and they can affect both local business owners and employees residing in tourist destinations (Krakover, 2000). One of the main problems is the difficulties of hiring qualified staff (Murphy, 1985) given that seasonal job openings draw less qualified profiles (Mill & Morrison, 1998). Altogether, this might affect the quality of the service (Baum, 1999) since discontinuous employment makes it harder to design middle-term job training programs. From a positive point of view, however, seasonal jobs are very positive for people with discontinuous work needs, such as students, or to complement other areas of employment suffering from seasonality, for example, agriculture (Flongfeldt, 2001).

Several authors have highlighted the benefits of seasonality too. According to Hartmann (1986), it would not be correct to assess tourism seasonality solely in economic terms, since environmental and social factors must also be considered. Other authors have shown that seasonality has economic effects in terms of private and social costs, which often exceed the few benefits (Cuccia & Rizzo, 2011). Seasonality could bring some benefits because in the off-season communities could take a break, so to speak, from tourists (Andriotis, 2005). As Twining-Ward (1996) pointed out, destinations and residents can also benefit from low-demand seasons in a number of ways. The local population might need a period of rest so that the infrastructure can be repaired or upgraded. On a positive note, a season of low demand implies that the pressure on the environment is reduced and thus, a recovery is possible in the damaged environments.

In short, the impacts of tourism seasonality on the economic development of destinations are evident and of particular concern in developing areas that rely on tourism as a driver of economic growth. If seasonality is not managed properly, these effects will continue to occur, thus limiting the potential development of many regions. For this reason, it is necessary to gain insight into and measure and monitor these trends with a view to designing public or private policies and business strategies to contain the problem. This paper proposes a new system of seasonality measurement as an original contribution. This system overcomes the limitations that have been previously presented and reinforces objectivity in the aggregation of partial indicators. The study here developed begins with an exposition of the alternatives to measuring seasonality and continues with the description of this method's advantages. Later, we describe the statistical method that was used as well as its properties. Then, we show the results that were obtained after having applied the indicator to Spanish regions. The conclusions and discussion of the results within a public policy and business strategies framework are presented at the end. The application of this methodology to the different regions of Spain is justified by several reasons: the importance that tourism has in this country, the heterogeneity of its tourist product, which causes seasonality to be more intense in certain areas; and the vast bibliography that makes it possible to verify the legitimacy of the results. The ultimate aim of this work is proposing an original method of measurement of seasonality at the same time that we gain knowledge on its conditioning factors. This analysis can also be carried out in any other area.

To sum, this study makes the following contributions: the proposal of a methodology capable of measuring the intensity of seasonality that can be replicated in any other area. This methodology examines many variables representing different aspects of tourism seasonality. This makes it possible to measure it comprehensively since it is not conditioned upon a single variable. There are no synthetic indicators of seasonality as the one proposed here. This indicator is advantageous in comparison with other alternatives given that it determines the weights of the variables objectively, removes redundant information and avoids problems arisen from the aggregation of information expressed in different units. Moreover, this methodology allows for the analysis of the impact that each partial indicator has on the calculation of the synthetic indicator, as well as analyzing the partial indicators that are more relevant to the explanation of regional disparities. The results have brought to light new evidences that are consistent with previous studies on the most seasonal tourism models. This methodology also allows for the comparative monitoring of seasonality's intensity with other destinations, which helps to improve public policies and private business actions as well as analyzing their success or failure.

Measuring seasonality

There is not a general agreement on tourism seasonality when it comes down to deciding which methodology is more precise to measure or describe this phenomenon from a quantitative point of view, it is even possible to notice a lack of descriptive methodologies (Koenig-Lewis & Bischoff, 2005). Few researchers have proposed methodologies of measurement and comparison of seasonal trends (Koenig-Lewis & Bischoff, 2005). Many different measurement systems have been used without one being widely accepted.

In the academic bibliography on tourism seasonality, it is possible to find studies that follow different methodologies, and therefore, have different aims. One of the areas of analysis in the bibliography alludes to the estimation of seasonal factors, where it is common to use deviations proportional to moving averages by means of dummy variables in multi-linear regressions or any other method of analysis of temporary series. Nieto & Amate (2000), Pegg et al. (2012) and Cuccia & Rizzo (2011) give examples of these kind of studies. Other procedures used to study seasonality are the spectral analysis (Chan & Lim, 2011), seasonal long memory models and fractionally integrated time series models (Gil-Alana, 2010); and deterministic and stochastic studies (Chang & Liao, 2010; Alleyne, 2006; Koc & Altinay, 2007; Shen et al., 2009; Kulendran & Wong, 2005; Lim & McAleer, 2001, 2002).

One of the most accepted lines of work is focused on estimating concentration indexes, which offer a measurement of the annual degree of concentration of the tourist activity (Lundtorp, 2001; Wanhill, 1980; Fernández-Morales, 2003; Roselló et al., 2004). The Coefficient of Variation (CV), Theil Index (TI) or the Gini Index (GI) stand as examples. Among these alternatives, the GI has been used extensively in the academic literature to measure seasonality (Nastassios & Sitouras, 2004; Baum & Lundtorp, 2001; Koenig & Bischoff, 2003; Wanhill, 1980). The index is built using the following expression:

$$IG = 1 + \left(\frac{1}{n}\right) - \left(\frac{2}{(n^2.`x)}\right).(x_1 + 2x_2 + 3x_3 + \cdots .nx_{n1})$$

Where n is the number of observations (12 in the case of monthly data), $`x$ is the mean of the observations and $x_1, x_2, x_3 \ldots x_n$ are the individual observations in descending order of magnitude (Weaver & Oppermann, 2000). The values of this index range from 0 to 1, where (0) shows an equal distribution between the months of the year and (1) denotes the highest level of seasonal concentration.

Although this indicator is widely used in the academic literature, the description it provides is quite limited. To calculate the GI, variables such as the monthly number of tourist arrivals, the monthly number of overnight stays; or the number of bed places available are taken as a reference. Depending on the variable chosen, the results of the indicator will vary, which makes it harder to make decisions based on this. In order to overcome these limitations and offer a measurement of seasonality that captures several manifestations of this phenomenon, we propose an indicator that groups information from multiple variables. This indicator does not explain the reasons that lie behind seasonality, but instead it describes the phenomenon synthesizing imbalances by means of which this trend manifests itself. This paper proposes the calculation of the GI using multiple variables that describe the different manifestations of tourism seasonality; and their integration into an indicator that offers a comprehensive picture of the problem. This indicator will make it possible to compare regions more realistically, just like performing a more precise monitoring of the achievements in controlling the intensity of seasonality.

Choosing relevant indicators is one of the most sensitive aspects when studying seasonality (Ahas et al., 2005). In view of the bibliography on seasonality and the variables used in previous studies, we propose the estimation of GIs, which are calculated over the monthly number of overnight stays by domestic travelers, the monthly number of domestic travelers, the monthly number of overnight stays by foreign travelers, the monthly number of foreign travelers, the monthly number of bed places available in different types of accommodation, and the monthly number of employees in tourism activities. Besides these variables, other indicators are calculated over the monthly data for mean length of stay, degree of occupancy and degree of occupancy on weekends using the Coefficient of Variation (CV). These partial indicators of seasonality are calculated using the CV given that the GI must be constructed using cumulative variables and the previous ones are expressed in non-cumulative monthly ratios. After adding the aforementioned indicators, a more complete vision of the different manifestations of seasonality is offered from both the point of view of the supply of accommodations and the demand, which allows for the definition of a synthetic global indicator.

The CV measures the extent of a data series around an annual average as a percentage of that average. In the following formula, $\overline{x}$ stands for the mean of the 12 monthly observations and S denotes their standard deviation.

$$CV = \frac{S}{\overline{x}}$$

As shown before, using the CV to measure seasonality is quite frequent. Koenig-Lewis & Bischoff (2003) have shown, this is a particularly useful system for comparing the dispersion of data with different standard deviations and different mean. The CV takes into consideration redistributive changes in the data series and offers distributive neutrality, which is a useful characteristic in the measurement of seasonality and provides a measure not conditioned upon the position of the observations in a data series (Duro, 2016).

The DP_2 groups variables that show multiple manifestations of seasonality taking supply and demand variables into account. This indicator allows for the ranking of destinations according to their level of seasonality; and the monitoring of seasonal trends and comparison of destinations, which is very useful for destination planning and for public policy-making concerning tourism. Once the indicators are selected, the following step is selecting an appropriate aggregation method that is able to offer a synthetic indicator (Cuenca et al., 2010). Numerous alternative methods to aggregate indicators and create a composite indicator using linear or non-linear techniques have been proposed in the academic literature (Nardo & Saisana, 2008). During the variable-aggregation process, the most relevant aspects are those related to the assignment of the weights of the variables that form the indicator, the treatment of variables expressed in different units; and the aggregation of those variables into one single data (Somarriba & Pena, 2009; Ravaillon, 2010).

In this study, we propose the Distance Method (DP_2) as the methodology of aggregation of partial indicators. It was developed by Pena (1997) and in the last few years has received a growing attention and has been applied to different fields (Holgado et al., 2015; Martinez et al., 2016; Ray, 2014; Somarriba et al., 2015; Sánchez & Prada, 2015; Rodríguez et al., 2015b; Somarriba & Zarzosa, 2016; Canaviri, 2016). The main contributions of this method solve problems derived from the aggregation of variables expressed in different units, remove information that is duplicated and avoid arbitrariness when determining the weights of the variables that form the indicator (Somarriba & Pena, 2009; Somarriba et al., 2015; Murias et al., 2006). An important feature is the entry order of the information provided by each partial indicator. In this case, the order is obtained in accordance with the absolute values of the coefficients of linear correlation between the values of the indicators and the synthetic indicator (Somarriba & Zarzosa, 2016; Pena, 1977).

Main properties of the DP_2 method

The DP_2 method fulfills a number of properties that back up one of its main advantages: the weights associated to each variable are assigned non-arbitrarily. (Canaviri, 2016). Moreover, due to the fact that the DP_2 is built on the concept of 'distance', it belongs to the group of measurement systems based on axiomatic derivations. That is, it fulfills a number of requirements that are considered necessary to achieve the stated goal (Zarzosa & Somarriba, 2013). In addition to satisfying the conditions of distance in a metric space (triangular inequality, non-negativity and competitiveness) (Zarzosa, 2005; Somarriba & Pena, 2008; Pena, 1977), the DP_2 verifies ‘a set of properties required for a good indicator’ (Zarzosa & Somarriba, 2013). In particular, the DP_2 indicator fulfills the properties described next (Escobar, 2006; Rodríguez et al., 2012; Zarsosa y Somarriba, 2013; Rodriguez et al, 2018):

a) Existence and determination of the synthetic indicator for all partial indicators: considering the indicator-defining function, the indicator exists and takes a specific value, provided there is variance in each and every one of the components and that this is finite and not zero.

b) Monotony: in the face of positive changes in a partial indicator, the synthetic indicator also responds positively (if the rest of indicators do not vary). If the changes are negatives, it responds negatively.

c) Uniqueness quantification: given a group of simple indicators, the DP_2 method offers a single numeric data.

d) Invariance: the synthetic indicator remains invariable to changes at origin and/or scale in the measures of the components.

e) Homogeneity: the synthetic indicator is a grade 1 homogenous function in relation to the partial indicators.

f) Transitivity: given any three values of the synthetic indicator, if the first one is greater than the second and the second is greater than the third, it follows that the first is greater than the third. Since DP_2 is a numerical value, it verifies this property.

g) Exhaustiveness: the synthetic indicator should exploit completely the information provided by the partial indicators.

h) Additivity: the synthetic indicator linked to each territorial unit must confirm the previous properties. Furthermore, the difference between two synthetic indicators linked to two territorial units should be equal to the synthetic indicator obtained directly from the comparison of those two territorial units. To read a fully developed explanation of this property, refer to Zarzosa (1996).

i) Invariance compared to the base reference: if the base reference is the same for the two units and provided that for each variable it takes the maximum value or one which is higher, or the minimum value or one which is lower from the series of values in said variable (Zarsosa y Somarriba, 2013), the DP_2 distance between two units, calculated directly as well as through the difference between the two distances, does not vary, irrespective of the reference vector (Rodriguez et al, 2018).

j) Conformity: during the calculation of the DP_2, the entry order of the variables must be such that correlation coefficients in absolute terms between the resulting synthetic indicator and the simple indicators of which it is composed are ranked from highest to lowest. For further discussion on this property, see Zarzosa and Somarriba (2013).

k) Neutrality: the weight of each variable is determined in terms of the amount of useful information it provides. Zarzosa (1996) proves that the entry order of the variables into the DP_2 depends on their relative importance, measured in terms of linear correlation with the final synthetic indicator.

An alternative to this indicator could be the Data Envelopment Analysis (DEA), which is able to obtain similar goals (Murias et al., 2006; Shen et al., 2013; Carrillo & Jorge, 2016). However, this methodology is limited in some ways that the DP_2 is not, such as determining the weight of each variable in a subjective manner (Zarzosa & Somarriba, 2013). Equally, DEA does not fulfill the uniqueness and monotony properties needed to preserve variations in changes of origin and/or scale in units of measurement and to consider the interdependence of the indicators (Pena, 2009). The Principal Component Analysis could also be an alternative, but it does not solve some of the problems that have been presented, for instance, redundant information (Rodríguez & Salinas, 2012). This method does not fulfill mathematical properties of uniqueness, monotony, and most importantly, neutrality. Properties, that as shown, are fulfilled by DP2 (Pena, 2009). Moreover, the numerical results offered by the analysis of principal components lack quantitative interpretation that is provided by the DP_2 (Pena, 1977).

The DP_2 indicator is a cardinal measure that enables comparisons between units across space and/or time (Montero et al., 2010; Somarriba & Pena, 2008). Furthermore, DP_2 solves the heterogeneity problem in the measurement units of the variables (given that the partial indicators are expressed in abstract units) by dividing the indicator by the standard deviation (Ray, 2014; Montero et al., 2010). This measurement fulfills a variety of properties that guarantee that the weight of each variable is determined objectively and that the weighting has an economic interpretation (Rodríguez, 2014; Somarriba & Pena, 2009; Rodríguez & Salinas, 2012; Somarriba & Zarzosa, 2016; Rodríguez et al., 2015a).

The model

The calculation of the DP_2 for any destination/region *r*, is defined using the following expression (Pena, 1977; Zarzosa & Somarriba, 2013):

$$DP_2 = \sum_{i=1}^{n} \left\{ \left({}^{d_i}/_{\sigma_i} \right) \left(1 - R^2_{i,i-1,\ldots\ldots 1} \right) \right\}$$

where $d_i = d_i(r^*) = |x_{ri} - x_{*i}|$ with the reference base $X_* = (x_{*1}, x_{*2}, \ldots, x_{*n})$ where:

- n is the number of variables
- x_{ri} is the value of the variable i in region r
- σ_i is the standard deviation of variable i
- $R^2_{i,i-1,\ldots\ldots 1}$ is the coefficient of determination in the regression of X_i over $X_{i-1}, X_{i-2}, \ldots., X_1$, already included, where $R^2_1 = 0$

The coefficient of determination $R^2_{i,i-1,\ldots\ldots1}$measures the percentage of variance of each variable explained by the linear regression estimated using the preceding variables (Rodríguez, 2014; Pena, 2009). As a result, the factor $(1 - R^2_{i,i-1,\ldots\ldots1})$, which Pena calls "correction factor" (1977), avoids redundancy, leaving aside the information already provided by previous variables. So then, $\left(1 - R^2_{i,i-1,\ldots\ldots1}\right)$ expresses the part of the variance of X_i not explained by $X_{i-1}, X_{i-2}, \ldots., X_1$, the part already explained by the preceding indicator is obtained by multiplying each partial indicator by the corresponding coefficient of determination $R^2_{i,i-1,\ldots\ldots1}$ (Sánchez & Martos, 2014).

To assist with the interpretation of the results obtained from the DP_2 indicator, we use a hypothetical destination: an area that in the worst scenario possible has a synthetic indicator value of 0 (Zarzosa & Somarriba, 2013). This value shows a region with the most intense tourism seasonality. The results obtained for the rest of regions reflect the distance from each region to the region used as a reference (Ray, 2014; Rodríguez et al., 2012). A higher DP_2 value indicates, therefore, a favorable situation in which the distribution of activity throughout the year is homogeneous.

The order of entry of the partial indicators conditions the weight that is assigned to each one of them. This order is determined by an algorithm that reaches convergence and stabilizes to verify the condition of conformity with a non-random, neutral method for classification of variables (Rodriguez et al., 2018). The partial indicators are then ranked in a descending order, accordingly with their correlation to the first indicator, while irrelevant information is removed at the same time (Somarriba & Pena 2008). The differences in the i-th variable between a region and the reference region are therefore weighted by the percentage of new information (i.e., information not provided by other variables) that this variable provides (Zarzosa 2009; Chasco, 2014; Somarriba and Zarzosa, 2016).

To mirror this methodology and be able to study how intense seasonality is in other destinations, regions, or countries, it is necessary to count with monthly or quarterly data that illustrate each variable. Many statistical offices that are contingent upon public bodies provide that specific information, although we can also turn to private companies for data if the goal is to perform a small-scale study. In the case of cumulative data, the GI is calculated following the formula explained in this paper. On the contrary, if data are expressed in percentages, the CV must be used. The number of variables used to construct the indicator must always be higher than the number of destinations or regions to which the analysis is applied, being this a condition that must be fulfilled with no exception.

Other condition to be met in order to use the P_2 distance method is that every variable or partial indicator must be expressed in the same direction, or in other words, that an increase in any variable also represents an increase in the value of the synthetic indicator, and vice versa. In such a case, the partial indicators whose increase downgrades the goal to be measured, tourism seasonality in this case, must be multiplied by -1. This allows for the calculation of the DP_2 as distance to the minimum, in which each destination is compared with a fictitious destination that exhibits the lowest level of seasonality. In addition, the DP_2 can also be expressed as the distance to the maximum, in which each area is compared with other than suffers from the highest level of seasonality.

Once the partial indicators are expressed in the same direction, they are introduced into the model following the order determined by the absolute linear correlation coefficient between each partial indicator and the DP_2 synthetic indicator. Given that the synthetic indicator does not exist yet, Pena (1977) began by assuming that every variable were to be uncorrelated amongst themselves and, therefore, that the value of the Coefficient of Determination R^2 would equal zero and the factors of correction would have a value of 1. The result is the Frechet indicator, which represents the maximum value that the DP_2 synthetic indicator can assume for each destination.

Once the values of the DP_2 indicator have been calculated following Pena's initial solution, the entry order of the partial indicators is determined again in descending order in accordance with their Coefficients of Correlation with the DP_2, triggering a repetitive process. Once the DP_2 synthetic index is calculated after the first iteration, the entry order of the variables is determined once more in accordance with the values of the Coefficients of Correlation, which would result in new values of the DP_2, and so on until the indicator converges on a concrete value. More detailed explanations of this methodology are provided in the following studies: Zarzosa (1996, 1997), Pena (1977), Somarriba (2008).

Application to tourist regions of Spain

Tourism is considered to be one of the strategic sectors of the Spanish economy; in 2015 tourism accounted for 11.7% of the national GDP and directly supported 1.4 million jobs, more than any other sector in the economy (Exceltur, 2016). The activities linked with tourism have played an important role in the recovery of the economic crisis that has affected the country since 2007. In 2015, tourism contributed in 0.5 points to the growth of the GDP, with the overall Spanish figure being 2.5% and it was responsible for one out of seven work positions created that year. Worldwide, Spain ranked third in terms of international tourism receipts, generating USD 57 billion; a figure that is lower than the United States (USD 204.5 billion) and China (USD 114 billion) (Hosteltur, 2016).

The tourist offer in Spain is certainly heterogeneous, some regions rely solely on sun and beaches tourism and suffer from the seasonal limitations derived from the expected weather-dependent factor, whereas other zones have developed a type of tourism with less seasonal pressure, bound to the urban-cultural, congresses and events business offer. This heterogeneity in the shaping of the tourist product involves, therefore, different seasonality intensities, which requires a full tracking of the policies to be applied. Tourism seasonality in the regions of Spain has traditionally been measured using the GI, which is calculated annually according to number of arrivals by the National Institute of Statistics (INE), entity affiliated to the National Government. However, the measurement does not include the number of overnight stays or their annual distribution, which could compensate for variations in arrivals. Nor does it consider variations in prices, average length of stay or supply of bed places, etc. This limitation makes it difficult to track seasonal trends and the results obtained by the anti-seasonality policies implanted in each region.

This work examines tourism seasonality in the 17 regions of Spain, known as 'autonomous communities'. Given the aim of this study, it is first necessary to select a set of partial indicators that provide information on various aspects of tourism seasonality. To do so, we begin by calculating the estimated seasonal indicators for different variables in each of the regions: 1.GI for monthly arrivals of domestic travelers, 2. GI for monthly arrivals of foreign travelers, 3. GI for monthly overnight stays of domestic travelers, 4. GI for monthly overnight stays of foreign travelers, 5. GI for monthly number of employees in tourist accommodations, 6. GI for monthly number of bed places offered, 7. CV for average length of stay per month, 8. CV for monthly occupancy rate, 9. CV for weekend occupancy rate per month, 10. CV for monthly accommodation price index. The construction of this indicator needs to have into consideration that the number of observations (regions) needs to be higher than the number of variables. This will solve the problem of degrees of freedom in the DP_2 calculation (Somarriba & Pena, 2009; Escobar, 2008; Somarriba & Zarzosa, 2016; Murias et al., 2006). The results will be tested according to the partial references found in the aforementioned bibliography, so that their coherence may be validated. The validation of this method will allow its implementation to other situations, regions, cities or countries, providing the scientific community with a useful tool to measure seasonality trends.

Where possible, the data on domestic and foreign travelers has been analyzed separately, thus contributing additional information on the seasonality of the destination. The partial indicators have been calculated using monthly information provided by the INE, an organization that issues detailed information about the tourist activity developed in hotels, tourist apartments, rural accommodations and camping spots. This information allows us to obtain a complete image of the monthly evolution of this activity in Spain. The partial indicators related to variables 1-6 have been estimated by adding the information of each of the categories of establishments so that the monthly data reflects the total. As explained above, it is not possible to calculate the GI for variables 7-10 since the data cannot be aggregated but are expressed in means or indices. Therefore, the CV of the monthly data is provided as a reflection of seasonality in these cases. The data obtained from the partial indicators of tourism seasonality are shown in Table 1, providing a complete analysis of the seasonality in the Spanish regions. The heterogeneous Spanish tourist product involves conditions of seasonality very diverse. As can be observed, it is a complex task to draw conclusions regarding the problems and levels of seasonality in the regions because the ranking changes depending on the dimension considered.

Table 1 near here

As indicated above, the aim of this work is to create a synthetic indicator to measure the level of seasonality in the Spanish regions, which allows for a complete comparison among them. A higher DP_2 value indicates a better position in the ranking of the set of variables (Somarriba et al., 2015). As regards the ranking of the regions, a higher value of the indicator implies less intense tourist seasonality in that region and hence a better result in its seasonal patterns. This situation shows a large distance to the 'least desired' theoretical setting (Murias et al., 2006). In this way, the base line would offer the result of a fictitious region that shows the worst possible scenario for all the partial indicators and therefore, we could assign it the value zero of this synthetic indicator (Zarzosa & Somarriba, 2013).

Table 2 shows the results of the DP_2 indicator of tourism seasonality. The inter-region distance (between the maximum and minimum values) is 8.05. Another way of expressing these differences is by using the opening coefficient (quotient between the maximum and minimum value), which yields a value of 69.62. The results show that the region of Madrid has the best situation regarding annual tourism stability, with a distance to the baseline of 8.17 (Table 2), followed by Castile-La Mancha (7.61), the Canary Islands (7.39) and Murcia (7.00). This classification does not always match with the one offered by all the partial indicators, hence the importance of having a summarizing indicator. Madrid exhibits excellent levels in most of the partial indicators, while remaining at a midpoint in terms of stability with regard to degree of occupancy, degree of weekend occupancy and cost of accommodation. This result is consistent with the literature on tourism seasonality given that the destinations with a lower level of seasonality are those with a tourist product that is profitable throughout the year (Palang et al., 2005; Ahas et al., 2005; Silm & Ahas, 2005). In this case, the tourist product of the region of Madrid is not based on season-dependent attractions, but is largely organized around the region's cultural and business offerings, as well as conferences and events. The case of the region that occupies the second position in the ranking, Castille-La Mancha, is slightly different. Tourism in this region is concentrated in cultural urban environments with an average potential, but whose power of attraction remains unchanged throughout the year. The case of the third region classified in the ranking, the Canary Islands, is also special. Because the region is located off the North African Atlantic coast, it has a highly appreciated tropical climate that makes this destination attractive throughout the year. The low seasonality of this region, as well as that of Madrid – both of which have designed their tourism models to modify anti-seasonal patterns – has already been reported in previous studies (Martin et al., 2014). These references support the legitimacy of the DP_2 indicator, since the exposed conclusions turn out to be coherent in relation to the bibliography on this topic. Anyway, the descriptive power of this indicator is expected to be greater.

The Balearic Islands, with an index of 0.11, is in the opposite situation (Table 2). This value places the region at a great distance from the first one in the ranking, as well as from the regions in the last positions. The region obtains the worst results in seven of the ten partial indicators proposed and occupies the second worst place in the remaining three. Like the Canary Islands, the region comprises a group of islands, but due to its geographical location (west of the Iberian Peninsula) the temperatures vary throughout the year and seasonality is high in the summer months, with a very high concentration of tourists. In line with Fernandez-Morales (2003) and Lundtorp et al. (2001), the results show that seasonality can create the conditions for anti-tourism phenomena, thus suggesting the need to properly manage off-season periods. In the case of the Balearic Islands, but also in other regions with negative results, such as Cantabria, Catalonia, Asturias, Galicia or Andalusia, the changes in temperature or the intensity of rains make it difficult to enjoy the destination and condition the landscape. These direct and indirect landscape values have been studied by several authors (Gustafson, 2002; Terkenli, 2005). Similar problems in these destinations have also been examined in previous studies (Duro, 2016; Martín et al., 2014) reinforcing even further the validity of this indicator. From the point of view of supply, the results are also consistent with previous partial studies. Tour operators are largely responsible for the fall in arrivals to coastal destinations, especially on the islands (Andriotis, 2005). Seasonal trends are more intense in regions with a well-established summer season (Koenig-Lewis and Bischoff, 2003), since in these regions, hotels and the hospitality industry or even the complementary offer do not find incentives to open during the off-season months because they are not as profitable as the summer months, which reinforces the process.

Table 2 near here

An analysis of the information provided by each variable and their discriminatory power.

In this section we present two analysis derived from the already proposed methodology, which are complementary to the estimation of the synthetic indicator. Specifically, we have analyzed the amount of information provided by each variable when constructing the synthetic indicator of seasonality and the discriminatory power of the same when explaining disparities among regions.

First, we analyze the impact each partial indicator has on the calculation of the synthetic indicator (Zarzosa, 2012). As shown before, the correction factor $\left(1 - R^2_{i,i-1,\ldots..1}\right)$ indicates the percentage of new information associated with each simple indicator (Zarzosa, 1997). The absolute value of the linear correlation coefficient is the measure used to hierarchize the simple indicators into the various iterations of the synthetic indicator calculations. The correction factors (Table 3) were obtained from the order defined by the linear correlation coefficients corresponding to the final iteration. Redundant information can be removed with this method (Somarriba & Zarzosa, 2016).

Based on the results obtained, the GI for monthly supply of bed places is the variable that contains the total useful (new) information, with a correction factor of 1 (Table 3). The GI variable for number of overnight stays of foreign tourists retains 29.9% of the information, while the GI variable for the number of foreign travelers contributes a similar level of new information (29.9%). These three variables – the first of which refers to the available accommodation and the other two to the international component of visitor flows – are therefore decisive in describing the level of seasonality of a destination. This conclusion is quite interesting because variables of supply and demand are essential for characterizing the seasonal intensity of a destination, thus justifying this comprehensive approach. At a second level, the variable referring to the coefficient of variation of the average length of stay gives 11.4% of the total information included in the synthetic indicator, followed closely by the GI variable for number of domestic travelers, which provides 10.07% of the information not incorporated in previous variables. These and the following variables have only a slight influence on the result of the final estimated index given that most of their information is contained in other variables. Finally, is must be pointed out that the selection criteria of the DP_2 only removes entirely a variable or partial indicator when it does not add new information to the construction of the synthetic indicator. In this case, no partial indicator has not been removed due to the fact that every variable offers new information not included in previous variables, even if the percentage of new information is not high.

To sum up, studying the contributions made by each partial indicator of seasonality allows us to draw an additional conclusion: the variables that contribute the greatest amount of information to the measure of tourism seasonality are the GI for bed places offered in tourist accommodations, the GI for number of overnight stays by foreign travelers and the GI for number of foreign travelers.

Table 3 near here

The distances between the results of each region (according with the synthetic indicator of seasonality) are influenced by the discriminant capacity of each simple indicator within the set of regions as a whole (Zarzosa & Somarriba, 2013). A partial indicator might be useful for the construction of a seasonality indicator but not prove discriminant power within a specific series of regions. This might cause it not to have an impact on the distance between these regions. The Ivanovic Discrimination Coefficient (IDC) is used in order to analyze the partial indicators that are more relevant to the explanation of regional disparities. The resulting values of the IDC are in the range of 0-2 (Zarzosa & Somarriba, 2013), if a variable has the same value in every region, IDC is equal to 0, which indicates a null discriminant value between regions. On the contrary, if a partial indicator has a value other than zero for one region and in the remaining is equal to zero, the IDC takes a value of 2. This indicates that said variable has full discriminant power (Zarzosa, 1996), that is, when all but one of the values are zero.

Table 4 shows the IDC values corresponding to the variables, taking into account that the higher the coefficient value, the greater its contribution for evaluating differences in tourism seasonality between regions. The indicators that best explain the disparities in levels of tourism seasonality between regions are those related to annual differences in average length of stay, variation in prices, variation in bed places and variation in staff, all of which are indicators of supply. The importance of the accommodation supply in response to the different tourist seasons largely explains the disparities in seasonality between regions (Table 4).

Conclusions

Due to the important role that tourism plays in the development of many regions, the intra-annual stability of the sector is very relevant when proposing a consistent alternative of development, employment creation and a wise use of the resources. The imbalances produced throughout the year in the sector generate economic, social, working and environmental effects. Thus, the development of anti-seasonal policies requires precise and comprehensive instruments that are capable of measuring the intensity of this phenomenon across territories, as well as monitoring its trends.

In this study, a multidimensional synthetic indicator has been developed to track levels of tourism seasonality in a set of regions. The fact that depending on which variable of analysis we choose might affect the measurement of seasonality intensity makes it necessary to define a synthetic indicator that groups the information provided by several partial indicators of seasonality, which represents different manifestations of this phenomenon.

The results presented contribute to the comparative analysis of the Spanish regions, although the application of this methodology could embrace any group of countries, regions, destinations or cities. This analysis takes into consideration a wide group of variables, which allows for the creation of a multidimensional synthetic indicator able to offer an image of the seasonality intensity. This indicator makes possible to compare between regions or countries in a comprehensive manner.

The findings of the paper show a relatively high intensity of seasonal patterns in the Balearic Islands, Cantabria, Catalonia, Asturias, Galicia and Andalusia. These regions are greatly affected by their climate conditions, which in turn affect their capacity to exploit their tourism product to the fullest. For these tourist destinations, the creation of complementary tourist products is therefore recommendable. In contrast, regions such as Madrid and the Canary Islands enjoy excellent levels of seasonality and are able to exploit their tourism resources throughout the year, in line with the results of other studies, which endorses the power of this indicator.

The conclusions of this study must be considered cautiously. The calculations were performed taking one year into consideration. Therefore, it cannot be excluded that some destination suffered from a rare incident that altered its level of seasonality, like, for example, a big event. Nevertheless, general conclusions remain valid for two reasons. In the first place, because changes in the intensity of the seasonality come from changes in the tourism model, or in other words, in the very own structure of the destination, which happen slowly over time. In the second place, because the main conclusions about the seasonality level relative to the orientation of the destination are consistent with the literature on seasonality. This limitation of the paper specifically might lead to new research able to connect the intensity of seasonality either with the economic cycle, with the international openness of a country, with the events planning, etc.

Complementarily, this study offers information about which variables provide more information when defining a synthetic indicator of seasonality. Specifically, the results indicate that the GI for monthly supply of bed places is the variable that contributes most information to the indicator, followed by the GI for number of overnight stays by foreign tourists and the GI for number of foreign travelers. These three variables – the first of which refers to the available accommodation and the other two to the international component of visitor flows – are decisive in describing the level of seasonality of a destination. This conclusion is of interest, because supply and demand variables are key to characterizing seasonal intensity, thus justifying this comprehensive approach.

Lastly, the discriminant power that each partial indicator has in explaining the disparities between regions has been analyzed. Therefore, we can conclude which factors are more relevant when explaining disparities in the levels of seasonality between regions. The results show that the indicators that best explain differences between regions in levels of tourist seasonality are related to annual differences in average length of stay, variation in prices, variation in bed places and variation in staff; all of which are indicators of supply. The way in which the tourism industry changes the accommodation offer during the different months of the year explains to a large extent the difference in the levels of seasonal intensity among regions, a very helpful contribution of this indicator.

This approach to the measurement of tourism seasonality should be seen as a scientific contribution which seeks to provide a methodological basis that contributes to the analysis of a complex problem. Nonetheless, it also highlights important challenges for the regional development of tourist areas. The comprehensive analysis of tourism seasonality, such as that performed here, can contribute to the design of more appropriate public and private policies and serve to validate the results of those that have been implemented. The academic literature has pointed out multiple causes of seasonality as well as several lines of action to reduce it. This study brings to light the necessity to monitor the goals accomplished in reducing seasonality. This should be done not only considering one individual variable but a whole set of manifestations of the phenomenon. The results confirm the success of destinations based on tourist products that do not rely on a specific season because despite all the conditioning factors (like school or business holidays) that define tourism seasonality, destinations based on a tourist offer exploitable throughout the year obtain good results. Public policy-makers should take into consideration the way in which tourist destinations are configured and promoted.

It is also important to show that importance of the supply variables (dependent upon the hotel industry) when explaining the different seasonality levels. This implies that a big portion of the problem derives from the way in which the business sector reacts to the possibility of a reduction in the flows of visitors, which triggers a feedback problem. In this sense, public and private sector should work together to define anti-seasonality policies, such as attracting temporarily complementary tourist segments, adapting hotel infrastructures to said tourists, planning events or even, adjusting prices throughout the year in order to keep the flow of visitors stable. Finally, the importance of international tourism has on the definition of the level of seasonality is enormous. This is something that should push the public and business sectors to work towards the diversification of markets that are a source of tourists and increase the percentage of international arrivals that can supplement temporarily national arrivals.

In sum, and taking the results of this paper as a reference, we give some final directions in detail. Public authorities, altogether with the private sector must work to define anti-seasonality policies that contribute to developing a homogeneous tourist activity throughout the year in order to avoid underutilization and peak periods. The negative effects associated with situations of high levels of seasonality have been described. This paper has presented some conclusions that must be taken in consideration when defining public policies capable of reducing seasonality in destinations. The destinations with a tourist product dependent upon the weather should define complementary products oriented to other types of visitor. The complementary products should be able to make up temporarily for the lack of traditional visitors. The important role that foreign tourists play in reducing seasonality has been proven. Therefore, one of the main goals should be the diversification of international sources markets, particularly those capable of complementing the national flows in off-peak periods. The public sector should work hand in hand with the private sector by means of incentives to create new tourist products and promote them internationally, but most of all, to avoid a decrease in the supply of accommodations at off-peak periods. Lastly, it is important to monitor continuously how intense seasonality becomes, so that it is possible to point at the most successful strategies and avoid the ones that work poorly. To do so, we recommend a system of partial indicators such as the one that has been proposed here. Using a synthetic indicator to aggregate them will help both, the business sector and policy-makers to perform a more intuitive and comprehensive monitoring.

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Tables

Table 1. Partial indicators of tourism seasonality in the regions of Spain for 2015

	GI Bed places	GI Domestic travelers	GI Foreign travelers	GI Overnights Domestic	GI Overnights foreign	GI Staff	CV Stay	CV Occupancy	CV Weekend occupancy	CV Prices
Andalusia	0.099	0.196	0.216	0.310	0.231	0.140	0.120	139.496	116.840	11.627
Aragon	0.072	0.140	0.324	0.196	0.360	0.061	0.024	37.185	41.007	51.847
Asturias	0.175	0.321	0.457	0.443	0.492	0.125	0.107	231.750	231.738	23.765
Balearic Islands	0.460	0.395	0.537	0.471	0.556	0.473	1.062	376.286	332.225	75.422
Canary Islands	0.009	0.233	0.059	0.266	0.061	0.014	0.204	33.771	19.768	5.759
Cantabria	0.276	0.378	0.509	0.497	0.557	0.205	0.196	189.666	168.415	6.803
Castile and León	0.083	0.163	0.332	0.193	0.301	0.043	0.003	57.612	67.285	2.806
Castile-La Mancha	0.040	0.108	0.206	0.150	0.198	0.039	0.007	16.883	30.785	2.829
Catalonia	0.254	0.226	0.294	0.356	0.421	0.170	0.467	163.061	128.935	104.385
Valenciana	0.069	0.225	0.200	0.343	0.164	0.103	0.150	161.138	152.693	18.765
Extremadura	0.076	0.165	0.260	0.194	0.270	0.056	0.008	41.227	55.418	15.657
Galicia	0.157	0.301	0.406	0.374	0.403	0.139	0.023	161.005	166.228	6.030
Madrid	0.005	0.040	0.124	0.045	0.123	0.011	0.001	43.642	53.049	15.923
Murcia	0.049	0.158	0.164	0.297	0.077	0.100	0.152	76.632	70.963	11.584
Navarre	0.088	0.197	0.412	0.269	0.384	0.061	0.026	131.633	141.899	16.269
Basque Country	0.049	0.130	0.316	0.196	0.332	0.051	0.015	215.613	179.249	61.220
La Rioja	0.049	0.174	0.356	0.251	0.336	0.050	0.023	71.311	86.605	13.720

Source: own elaboration based on data from the National Institute of Statistics of Spain (INE).

Table 2. Synthetic indicator of tourism seasonality for the regions of Spain. Relative ranking of regions according to DP_2 for 2015.

Regions	DP2
Madrid	8.17
Castile-La Mancha	7.61
Canary Islands	7.39
Murcia	7.00
La Rioja	6.89
Extremadura	6.88
Aragon	6.81
Castile and León	6.79
Basque Country	6.44
Valencia	6.20
Navarre	6.19
Andalusia	6.09
Galicia	5.03
Asturias	4.37
Catalonia	3.88
Cantabria	3.29
Balearic Islands	0.11

Source: own elaboration based on data from the National Institute of Statistics of Spain (INE).

Table 3. Correction factors and Ivanovic's Discrimination Coefficient. 2015

Variable	Correction factor	Correction factor (Ranking)	Ivanovic's Discrimination Coefficient	IDC (Ranking)
GI Bed places	1.00	1	0.08	3
GI Overnights foreigners	0.39	2	0.04	7
GI Foreign travelers	0.38	3	0.04	8
VAR Stay	0.11	4	0.11	1
GI Domestic travelers	0.10	5	0.04	9
VAR Prices	0.09	6	0.08	2
VAR Occupancy	0.08	7	0.07	5
GI Staff	0.07	8	0.08	4
VAR Weekend occupancy	0.02	9	0.06	6
GI Overnights domestic	0.02	10	0.04	10

Source: own elaboration based on data from the National Institute of Statistics of Spain (INE).