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DETECTING DETERMINANTS IN TOURIST SEASONALITY OF GREECE: A BINARY LOGISTIC REGRESSION APPROACH

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Abstract
Tourism seasonality is a complex phenomenon ranked as one of the most important and timeless issues for regional and tourism development. This paper builds on binary logistic regression to examine the determinants of tourism seasonality. The proposed method classifies the tourism seasonality of the Greek prefectures into two groups (high seasonality, low seasonality), which are examined in terms of their natural, geographic, and infrastructure characteristics. The study aims to identify the key factors of tourism seasonality, on monthly data of tourism overnight stays for the year 2018, both for foreign and domestic visitors. The overall analysis proposes a useful tool for tourism management, and regional policy because it allows considering in common the different dimensions of the tourism seasonality phenomenon.
Keywords: tourism seasonality; regional development; seasonal classification; spatial distribution.

1. INTRODUCTION

Tourism seasonality is the unequal distribution of tourist demand, in a specific destination, during a year (Butler 2001; Batista et al. 2019). It is a complex global tourism phenomenon, with temporal, spatial, and socio-economic dimensions, which presents differences, both between countries and within countries (Tsiotas et al. 2020a). These dimensions of the phenomenon, which extend to the unequal distribution into the development process and, consequently, to economic and social imbalance, has to be addressed as a regional issue (Khan 2018; Polyzos 2019). Within the context of this complex phenomenon, tourism seasonality ranks as one of the most significant and timeless issues of regional and tourism development

(Cisneros-Martinez et al. 2017; Batista et al. 2019; Martin et al. 2019; Tsiotas et al. 2020a). The increase of both the competitiveness between tourism destinations and the contribution of the tourism sector to national gross domestic products (GDPs) make the further examination of the phenomenon even more important.

Tourism seasonality is approached by various methodologies depending on the geographical and socioeconomic framework of the considered destinations and the availability of temporal data (Ferrante et al. 2018; Martin et al. 2019; Tsiotas et al. 2020a), as the different dimensions of the phenomenon create complex interactions between many and various factors (Lee et al. 2008; Charles Edwards and Bell 2013). In literature, the main effects on tourism seasonality arise from natural (sea, forests, climate, weather), institutional (holiday period, travel patterns, planned cultural events, national days), and other socio-cultural factors, such as fashion and traditions (Butler 2001; Ruggieri 2015; Fernandez-Morales et al. 2016), religion, culture, sports (Lee et al. 2008; Rossello and Sanso 2017), the type of tourist product (Cuccia and Rizzo 2011), the market structure (Fernandez-Morales et al., 2016), the accessibility (Lundtorp et al. 1999; Erdem et al. 2019), and the configuration of local economies (Duro and Turrion-Prats 2019).

The scale, depth, and complexity of tourism seasonality are reflected in various negative effects such as the natural, economic, cultural, structured, and man-made environment (Martin et al. 2019; Polyzos 2019), the operation of tourism businesses (Cisneros-Martinez and Fernandez-Morales 2015; Corluca et al. 2016; Chen et al. 2017) and the intermediate companies (Polyzos, 2019). The sharp seasonal increase of the population in the tourist areas affects the living conditions of the local population and raises concerns about their attitude towards tourists (Pegg et al. 2012; Chen et al. 2017). Tourism and hotel businesses are burdened with high fixed costs to meet the operational needs during the peak period, which increases the average costs of business increase, and consequently, decreases the overall profitability (Cuccia και Rizzo 2011; Cisneros-Martinez and Fernandez-Morales 2015; Polyzos 2019). This result has an impact on finding human capital causing wider implications (Lundtorp 2001; Polyzos 2019), such as the internal migration (mainly of young people) of the local population during the year leading to spatial inequalities (Grobelna and Skrzewska 2019).

The contribution of each factor to the overall tourism seasonality differs from destination to destination (Lee et al. 2008). The phenomenon appears more intense in destinations with mass tourism, such as in the Mediterranean, where the summer aspects (natural factors) of the tourism product prevail (Corluka et al. 2016; Krabokoukis and Polyzos 2020b; Tsiotas et al. 2020a). In destinations with these characteristics, natural resources do not have the expected positive impacts on regional tourism competitiveness (Romao et al. 2017). European regions with more abundant natural resources are often developing unsustainable forms of mass tourism, with low value-added and little benefits for the host communities (Romao et al. 2017). From this perspective, results again the importance of temporal and spatial analysis of the phenomenon.

A fundamental issue in examining tourism seasonality is the measurement of the phenomenon. The most commonly used variables for measuring tourism seasonality are the number of visitors, arrivals, and overnight stays (Lundtorp et al. 2001; Porhallsdottir and Olafsson 2017). Fundamental measures, such as the seasonality range, seasonality ratio, and coefficient of seasonal variation, are used to measure tourism seasonality, but the complexity of the phenomenon leads to more composite indicators. These indicators are the Gini coefficient, the Theil index (Koenig-Lewis and Bischoff 2005), the Relative Seasonal Index - RSI (Lo Magno et al. 2017; Ferrante et al. 2018), and the synthetic index DP2 (Martin et al. 2019). The Gini coefficient and the Theil index cannot capture periodical (cyclical) structures (Lo Magno et al. 2017; Ferrante et al. 2018), are restricted to annual computations (Karamustafa and Ulama 2010), they provide restricted information about the spatial dimension of seasonality (Cisneros- Martinez and Fernandez-Morales 2014), and, are sensitive to the scale around the average (Duro and Turrion-Prats 2019). On the other hand, RSI and DP2 are more demanding in computations due to their complexity (Tsiotas et al. 2020a). The RSI is considered more reliable than the Gini coefficient (Lo Magno et al. 2017; Ferrante et al. 2018; Tsiotas et al. 2020a).

Although tourism seasonality is significant for regional development policies and appears significantly degree in Mediterranean countries, has not yet been studied in depth for the case of Greece. Previous studies, measured the tourism seasonality, in NUTS 2 level (regions) (Zacharatos et al. 2014), identified principal components in terms of their geographical and socioeconomic characteristics, in NUTS 3 level (prefectures) (Tsiotas et al. 2020a), and quantitatively detected the relations between tourism seasonality and saturation, in NUTS 3 (Tsiotas et al. 2020b). Aiming to serve this demand, this paper aims to detect the determinants of tourism seasonality in Greece by applying binary logistic regression to a set of tourism variables having regional configuration. The country ranked as 6th to the highest number in EE27 and 5th in Mediterranean countries (Worldbank 2020). For the year 2019, according to the Greek Tourism Confederation (SETE), the overall contribution of the tourism sector on GDP reached 20.8%, with total foreign arrivals (without the arrivals from cruises) at 31.3 million visitors and t 56% of these arrivals take place in July-August- September (SETE 2020). However, the productive base of the Greek economy is weak as it largely relies on the tourism sector (Polyzos and Tsiotas 2020). Greece is a coastal country, has more than 55km2 mountainous areas, more than 16,000 km of coastline, and more than 1,350 islands, islets, and rocky islands, of which over 230 are inhabited (Tsiotas 2017). The fact that Greek tourism is oriented to the summer months and at sea (3s) (Krabokoukis and Polyzos 2020a; Tstiotas et al. 2020a), beyond the spatial inequalities (Krabokoukis and Polyzos 2020b), leads traditionally significant tourism destinations such as Halkidiki, Heraklion, and the Dodecanese to tourism saturation (Polyzos and Minetos 2011; Polyzos et al. 2013; Papatheodorou and Arvanitis 2014; Tsiotas et al. 2020b). A further purpose of the paper is to examine the relationship between the coordinates of prefectures and the factors that have a high effect on tourism seasonality.

The remainder of this paper is organized as follows: Section 2 is a brief literature review on tourism seasonality, highlighting its temporal and spatial aspects. Section 3 describes the methodological framework of the study, the available data, and the available variables participating in the analysis. Section 4 presents the results of the analysis and discusses them within the context of regional science and tourism development. Finally, in Section 5, conclusions are given.

2. METHODOLOGICAL FRAMEWORK

The study aims to examine the effect of a set of tourism variables having a regional configuration to seasonality based on both foreign and domestic monthly overnight stays. To do so, the proposed methodology applies two binary logistic regressions, using as dependent variables the binaries variables, which define the Greek prefectures regarding their seasonality (high seasonality, low seasonality), which are based on foreign and domestic overnight stays separately. This technique is useful for situations in which is needed the predict the presence or absence of a characteristic or outcome based on the values of a set of the predictor variable (Norusis 2011). The methodological framework consists of 5 steps, as shown in Fig. 1.

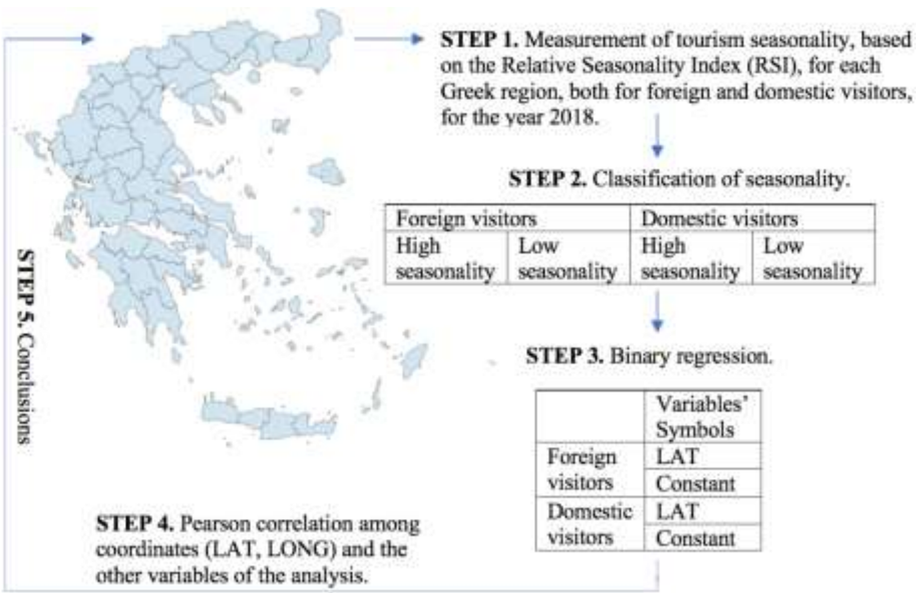

FIGURE 1 - THE CONCEPTUAL DIAGRAM ILLUSTRATING THE METHODOLOGICAL FRAMEWORK OF THE STUDY.

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At the first step, the values of the seasonal index computed on data referring to the monthly number of overnight stays, for both foreign and domestic visitors per prefecture (51 in total), for the year 2018 (ELSTAT, 2020a). To measure tourism seasonality in Greek prefectures, we applied the RSI which is a more suitable index related to Gini (Lo Magno et al. 2017; Ferrante et al. 2018; Tsiotas et al. 2018). The mathematical expression of RSI is described as follows:

$$S_R(\mu, C) = \frac{\sum_{i \in A} \sum_{j \in B} c_{ij} x_{ij}}{\mu \cdot max_{i \in M} \left\{ \sum_{j \in M} c_{ij} \right\}} \tag{1}$$

where x_i is the ith observation of variable x, μ represents the average value of the available observations, c represents the total cost for eliminating seasonality, A represents the set of high-season periods, B represents the set of low-season periods, and M represents the set of all possible observed time-patterns.

At the second step, a cluster analysis is applied for the classification of the RSI, which is based on the overnight stays, firstly of the foreign visitors, and secondly of the domestic visitors. Grouping and sorting data is a technique used to separate data set into subsets or clusters (Polyzos 2019). In our study, we want to separate the 51 prefectures in high seasonal and low seasonal prefectures, for foreign and domestic visitors separately. Given that the number of clusters is known, is applied K-means clustering, which attempts to identify relatively homogeneous groups of cases based on selected characteristics (Norusis 2011). Additionally, is used the Paired-Samples T-Test procedure to test the hypothesis of no difference between seasonality variables (RSI) of foreign and domestic visitors (Norusis 2011). At the third step, the clusters (high seasonality, low seasonality) resulted from the K-means clustering are used as categoric dependent variables in binary logistic regression, which is suited to models where the dependent variable is dichotomous (Norusis 2011). In this way, we reduce the dimensions of the issue under investigation and sustain only the major trends. This approach expanded to parade details on how some regional variables effects tourism seasonality that comes on the one hand, from foreign visitors, and on the other hand, from domestic visitors. At this step, 17 variables having a regional configuration, were tested (codes and names of the variables are shown see in the Appendix). Logistic regression is part of generalized linear models, treats the distribution in a probabilistic way, and expresses every dimension of the question as a probability (Polyzos and Minetos 2008). The general formula of binary logistic regression is shown in equation (2).

$$Prob(Y = 1) = \frac{e^{(a + a_1 X_1 + a_2 X_2 + \cdots + a_k X_k)}}{1 + e^{(a + a_1 X_1 + a_2 X_2 + \cdots + a_k X_k)}} \tag{2}$$

where Prob(Y=1) is the probability that Y is equal to 1 (that is, the probability of high seasonality), X1, X2, …, Xk are the independent variables and α, α1, α2, …, αk the regression coefficients. Within this context, the results of the regressions tabulate to configure seasonal and regional, spatial profiles of the clusters. The logic of logistic regression is based on the odds which are equal to $\frac{Prob}{1-Prob}$, where p is the probability of occurrence of a contingency. The expression Logit P(Y=1) in equation (3) shows the log of the odds of the probability that a destination is characterized by high seasonality (Y=1).

$$logit\big(Prob(Y=1)\big) = \log\left(\frac{Prob(Y=1)}{1-Prob(Y=1)}\right) \tag{3}$$

Two binary logistic regressions were applied to examine the effect of regional variables in the predicted value of dependent binary variables (high seasonal prefecture, low seasonal prefecture for each category of visitors). Using the ENTER algorithm (method), we observed that some variables weren't statistically significant, as their p-values were higher than 0.05. To solve it, in our analysis, we use the Backward stepwise Wald method, which is a removal testing, based on the probability of the Wald statistic (Norusis 2011).

At the fourth step of the methodological framework, a Pearson correlation analysis is applied to several regional variables to explore the linear associations between the coordinates of prefectures and the factors that have a high effect on tourism seasonality. Based on international literature, in the analysis, as independent variables, are used 16 regional variables refer to nature, infrastructure, and cultural resources, as shown in Table A1 of the Appendix. The results of the analysis, and the overall approach, are discussed at the fifth step of the methodological framework.

3. RESULTS AND DISCUSSION

The two clusters of seasonality (high seasonality, low seasonality) for both categories of visitors, resulted from the K-means classification, are shown in Table 1. The first thing that is highlighted is that foreign overnight stays seem to have higher seasonality (0.5514 and 0.2782) than domestic overnight stays (0.4471 and 0.1354) for both categories of prefectures (high season, low season).

TABLE 1 - CLASSIFICATION OF GREEK PREFECTURES INTO LOW AND HIGH SEASONAL PREFECTURES, PER VISITOR CATEGORY, USING K-MEANS CLUSTERING.

	Foreign Visitors		Domestic Visitors	
Cluster Name	Cluster Center	Number of Cases	Cluster Center	Number of Cases
Low Seasonal prefectures	0.2782	23	0.1354	31
High Seasonal prefectures	0.5514	28	0.4471	20
Total Prefectures		51		51

We proceed in a further test to examine the differences between foreign and domestic visitors. Table2 shows the results of the Paired-Samples T-Test for the RSI variables for foreigners and domestic visitors.

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Given that the Sig. (2-tailed) value is 0.000 (lower than 0.005), we reject the null hypothesis that there isn't a difference between the means of the variables. So, the test confirms that foreign overnight stays have higher seasonality than domestic.

TABLE 2 - PAIRED-SAMPLES T-TEST FOR THE SEASONALITY VARIABLES (RSI) OF FOREIGN AND DOMESTIC VISITORS.

	Paired-Samples T-Test		
Variables	**Mean**	**Std. Deviation**	**Sig. (2-tailed)**
RSI for foreign visitors	0.428198	0.1525473	0.000
RSI for domestic visitors	0.257634	0.1716938	
RSI for foreign visitors - RSI for domestic visitors	0.1705636	0.0153162	

Although most of the prefectures are classified in the same cluster (low seasonality, high seasonality) for both categories of visitors, some prefectures are classified in the high seasonality cluster for foreign visitors and in low seasonality for domestic visitors. These exceptions are the prefectures of Magnesia (23), Fthiotida (25), Evritania (28), Achaia (34), Aitoloakarnania (35), Chios (45), Heraklion (48), and Rethymno (50). As shown in Fig. 1, five of these prefectures are located in the center of Greece, and three on islands. The prefectures of Achaia (34), Heraklion (48), Aitoloakarnania (35), Magnesia (23), and Fthiotida (25) are classified as the prefectures with the largest population for the standards of the country (more than 150.000 inhabitants), and thus, domestic visits in these prefectures aren't purely for tourist purposes. This explains why the seasonality for domestic visitors in these destinations is low. The prefecture of Chios (45) has close values of RSI for foreign and domestic overnight stays of visitors (0.57 and 0.58, respectively). The prefecture of Evritania (28) has a higher seasonality index for domestic visitors than for foreign visitors. This prefecture is a winter destination for domestic visitors but almost unknown for foreign visitors, and the number of overnight stays is low.

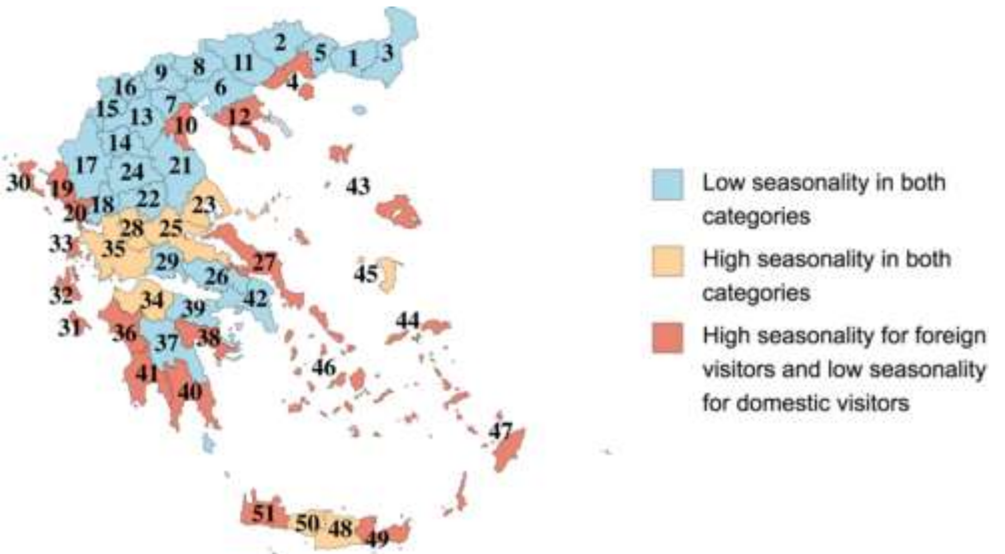

FIGURE 2 - GREEK PREFECTURES PER TOURISM SEASONALITY CATEGORY FOR FOREIGN AND DOMESTIC VISITORS, OF THE YEAR 2018 (NOMENCLATURE OF PREFECTURES SHOWN IN THE APPENDIX).

The binary variable (high seasonality, low seasonality) for each category of visitors are used separately as dependent bivariate variables in the two models of binary logistic regression. They get the value "1" if the prefecture is high seasonally and the value "0" when it is low seasonally. As independent variables examined variables that refer to physical (Duro and Turrion-Prats 2019) and other factors (Cuccia and Rizzo 2011; Rossello and Sanso 2017). During the analysis were tested in total 49 independent variables related to natural environment and infrastructures, but arose multicollinearity issues, and for the binary logistic regression, we kept the 16 of these variables, as shown in Table A1 of the Appendix.

From the application of binary logistic regressions, as it can be observed from Table 3, the two pseudo-R Squares measures Cox & Snell R Square, and Nagelkerke R Square, are high (relatively close to value 1) and show goodness-of-fit. The same results arise from the Hosmer-Lemeshow goodness-of-fit statistic, in Table 3. This goodness-of-fit statistic is based on grouping cases into deciles of risk and comparing the observed probability with the expected probability within each decile (Norusis 2011). Given that the p-values of both models for Hosmer-Lemeshow goodness-of-fit statistic are higher than 0.05, the goodness-of-fit test is not rejected, so models are adapted statistically enough to the data (Norusis 2011).

TABLE 3 - PSEUDO R-SQUARES OF BINARY LOGISTIC REGRESSION APPLIED TO THE BINARY VARIABLES (HIGH SEASONALITY, LOW SEASONALITY) AND SIXTEEN INDEPENDENT VARIABLES AS SHOWN IN TABLE A1, FOR FOREIGN AND DOMESTIC VISITORS.

	Cox & Snell R Square	**Nagelkerke R Square**	**Hosmer and Lemeshow Test**
Foreign visitors	0.635	0.850	0.890
Domestic visitors	0.572	0.775	0.986

In Table 4, there is the classification table of the two binary logistic regression. As it can be observed, for the model of foreign visitors, from the 20+3=23 high seasonality prefectures, 20 of them predicted correct (87.0%). The overall percentage of correct segregation for both models is satisfactory (88.2% and 86.3%). In the category of foreign visitors, the three prefectures with high seasonality that are not predicted correctly are Magnesia (23), Heraklion (48), Argolida (38), and the three with low seasonality that not predicted correctly are Trikala (24), Fokida (29), Attiki (42). Similarly, for the model of domestic visitors, prefectures Evritania (28), Achaia (34), Chios (45), and Rethymno (50) have high seasonality but predicted as low seasonality prefectures, while Pieria (10), Thesprotia (19), Argolida (38) have low seasonality but predicted as high seasonality. Most of these prefectures are located close to the center of the country.

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TABLE 4 - CLASSIFICATION TABLE OF MODELS' PREDICTIONS WITH DEPENDENT VARIABLES THE BINARY (HIGH SEASONALITY, LOW SEASONALITY) AND INDEPENDENT THE SIXTEEN EXAMINED VARIABLES AS SHOWN IN TABLE A1.

Observed			Category: High Seasonal	Category: Low Seasonal	Percentage Correct
Foreign visitors	Category	High Seasonal	20	3	87.0
		Low Seasonal	3	25	89.3
	Overall Percentage				88.2
Domestic visitors	Category	High Seasonal	27	4	87.1
		Low Seasonal	3	17	85.0
	Overall Percentage				86.3

a. The cut value is 0,500

Table 5 contains the estimates of the regression coefficients after the application of the Backward stepwise Wald procedure. The coefficients of column B refer to the accounting transformation of the dependent (binary) variable, while the coefficients of column Exp. (B) refer to the dependent (binary) variable. Otherwise, B coefficients are the values for the logistic regression equation for predicting the dependent variable from the independent variable. Logistic regression coefficients can be used to estimate odds ratios for each of the independent variables in the model (Norusis 2011). Exp. (B) are the odds ratios for the predictors are the exponentiation of the coefficients.

TABLE 5 - PARAMETER ESTIMATES FOR LOGITS FOR THE TWO MODELS WITH DEPENDENT VARIABLES THE BINARY (HIGH SEASONALITY, LOW SEASONALITY) AND INDEPENDENT THE SIXTEEN EXAMINED VARIABLES AS SHOWN IN TABLE A1.

	Variables' Symbols	B	Sig.	Exp. (B).
Foreign visitors	LAT	-3.664	0.003	0.026
	Constant	143.798	0.003	2.823E+62
Domestic visitors	LAT	-2.649	0.002	0.071
	Constant	101.937	0.002	1.866E+44

Of the total 16 variables applied in the Backward stepwise Wald method of the binary logistic regression in two models, the LAT variable is the only one that is used, is statistically significant, and negatively affects the dependent variables of both models. It appears that as the LAT value of a destination increases, probably reduces the chances of a destination with high seasonality. One decimal degree higher in the LAT variable multiplies the odds of higher seasonally prefecture by 0.026 (exp. -3.664) for the category of foreign visitors and 0.071 (exp. -2.649) for domestic visitors. As a general comment, and given that Greece is located north of the Equator and east of the Prime Meridian, as shown in Fig.3a, southern destinations appear to be characterized by higher seasonality indices. The constant term of the binary logistic regression is the expected value of the log-odds of seasonality category when all of the predictor variables equal zero, but is interesting in our analysis (Norusis 2011).

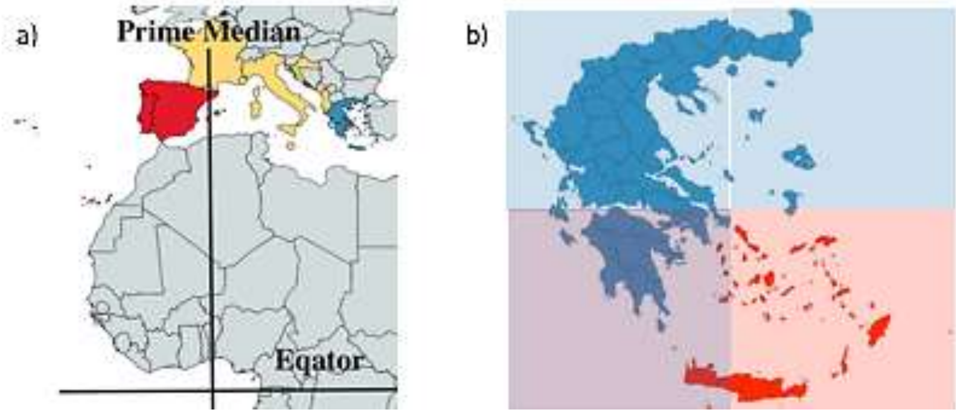

FIGURE 3 - A) THE GEOGRAPHIC POSITION OF GREECE (SHOWN IN BLUE COLOR) AND OTHER EUROPEAN MEDITERRANEAN COUNTRIES ABOUT THE EQUATOR AND THE FIRST MEDIAN. B) THE SPATIAL CONCENTRATION OF THE INDEPENDENT VARIABLES OF THE MODELS, AS DERIVED FROM THE PEARSON CORRELATION INDEX VALUES.

Table 6 shows the values of the Pearson correlation coefficient for comparisons of geographical variables (LAT, LONG) with the independent variables of the models, specifying their spatial distribution.

TABLE 6 - PEARSON CORRELATION AMONG COORDINATES (LAT, LONG) AND OTHER VARIABLES OF THE ANALYSIS.

REGIONAL VARIABLES	LATITUDE	LONGITUDE
FORESTS	0.513**	-
MOUNTAIN AREA	-	-
MOUNT ACTIVITIES	-	-
SKI CENTERS	0.317*	-
BEACHES	-0.462**	0.467**
BEACHES LENGTH	-0.358**	0.490**
SAND BEACHES LENGTH	-0.385**	-
BLUE FLAG	-0.352**	0.430**
PORTS	-0.375**	0.388**
HOTELS	-0.474**	0.370**
CAMPING	-	-
ROOMS	-0.282*	-
ANC MONUMENTS	-0.346*	-
CULTURAL RESOURCES	-0.464**	-

*Correlation is significant at the 0.01 level (2-tailed).

**Correlation is significant at the 0.05 level (2-tailed).

We observe that the variables FORESTS, SKI CENTERS are positively correlated with LAT, which means that as the LAT values increase (northern), so do these variables, and are placed at the top of Fig. 2b (blue area). In contrast, variables SAND BEACHES LENGTH, ROOMS, ANCIENT MONUMENTS, CULTURAL RESOURCES are negatively correlated with LAT and placed at the bottom of Fig. 2b (red areas). Lastly, variables BEACHES, LENGTH OF BEACHES, BLUE FLAG, PORTS, HOTELS are in

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common in Latitude and Longitude columns of Table 6, and are negatively correlated with LAT, and positively correlated with LONG. That means that as the LAT values increase (northern), the values of these variables decrease, while as the LONG values increases (eastern), the values are also increased (the reddest area at the bottom and right of the Fig. 3b). In this quartile, there is the most intense tourist activity in the country (Polyzos 2019; Tsiotas et al. 2020a) and explain these relations. Additionally, in this area, there is a large number of islands, and thus there is a large number of beaches and ports. The placement of the total hotel variable in this quadrant is interesting and confirmed by data, as for the year 2017, 40.53% of the total hotel beds were in the regions of Chania (51), Rethymno (50), Heraklion (48), Lasithi (49), and the Dodecanese (47) (SETE 2020), which are included in this quadrant.

4. CONCLUSIONS

This paper provided a methodological framework for identifying the determinants of tourism seasonality and assessing their contribution to this phenomenon. The proposed method applied K-means clustering to classify, according to the RSI index, tourism seasonality of the Greek prefectures, for the year 2018, both for foreign and domestic visitors. As was shown, the overnight stays from foreign visitors had higher seasonality than the stays of domestic visitors. Furthermore, the majority of Greek prefectures are classified in the same cluster (high seasonality, low seasonality) despite the category of visitors. The resulting groups (high seasonality, low seasonality) were examined in terms of their natural, geographic, and infrastructure characteristics to identify the determinants of the phenomenon by applying binary logistic regression. The analysis, after the examination of a data set of variables, resulted that latitude (LAT) is a major determinant of tourism seasonality. As the LAT value of a destination is increased, we probably reduce the chances of a high seasonality destination, and thus southern destinations are characterized by higher seasonality. In a further analysis, was applied a Pearson correlation among the coordinates (LAT, LONG), and the examined variables to draw more conclusions regarding the geographical location. The prefectures that are located in northern Greece (lower seasonality) show a positive correlation to the variables of the proportion of the forests' area to the total area of the prefecture (FORESTS) and the number of ski centers in each prefecture (SKI CENTERS). In contrast, southern (higher seasonality) and eastern prefectures show a positive correlation to variables refers to beaches (BEACHES, BEACHES LENGTH, BLUE FLAG), to the number of ports (PORTS), and hotels (HOTELS). The proposed methodology develops an integrated framework dealing with complexity describing socioeconomic research and particularly the seasonality in tourism.

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Appendix

TABLE A1 - THE SOCIOECONOMIC AND GEOGRAPHICAL VARIABLES PARTICIPATING IN THE ANALYSIS

Code	Variable's Symbol	Description	Source
SE.1	LAT	The latitude of the geographical center of the region.	(Google, 2020)
SE.2	LONG	The latitude of the geographical center of the region.	(Google, 2020)
SE.3	RSI	The Relative Seasonal Index of each prefecture computed according to relation (2)	(own elaboration)
SE.4	FORESTS	The proportion of the forests' area to the total area of the prefecture.	(ELSTAT, 2020c)
SE.5	MOUNTAIN AREA	The proportion of the mountain areas to the total area of the prefecture.	(ELSTAT, 2020c)
SE.6	MOUNT ACTIVITIES	The number of mount activities (walking paths, mount sports, climb fields, etc.) in each prefecture.	(ELSTAT, 2020c)
SE.7	SKI CENTERS	The number ski centers in each prefecture.	(ELSTAT, 2020c)
SE.8	BEACHES	The number organized beaches in each prefecture.	(ELSTAT, 2020b)
SE.9	BEACHES LENGTH	The length of beaches in each prefecture.	(ELSTAT, 2020c)
SE.10	SAND BEACHES LENGTH	The length of sand beaches in each prefecture.	(ELSTAT, 2020c)
SE.11	BLUE FLAG	The number of beaches granted a blue flag in each prefecture.	(ELSTAT, 2020b)
SE.12	PORTS	The number of ports included in each prefecture.	(ELSTAT, 2020b)
SE.13	HOTELS	The number of hotels in each prefecture.	(ELSTAT, 2020b)
SE.14	CAMPING	The number of camping sites in each prefecture.	(ELSTAT, 2020b)
SE.15	ROOMS	The number of rooms to let (non-hotel accommodation) in each prefecture.	(ELSTAT, 2020b)
SE.16	ANC MONUMENTS	The number ancient monuments sites in each prefecture.	(ELSTAT, 2020b)
SE.17	CULTURAL RESOURCES	The number of cultural resources sites in each prefecture.	(ELSTAT, 2020c)

*. All variables have length 51, including scores corresponding to the Greek prefectures

TABLE A2 - THE SEASONAL VARIABLES PARTICIPATING IN THE ANALYSIS CORRESPOND TO THE 51 GREEK PREFECTURES

Variable Code	Prefecture	Var. Code	Prefecture	Var. Code	Prefecture	Var. Code	Prefecture
1	RODOPI	14	GREVENA	27	EVIA	40	LAKONIA
2	DRAMA	15	KASTORIA	28	EVRYTANIA	41	MESEENIA
3	EVROS	16	FLORINA	29	FOKIDA	42	ATTIKI
4	KAVALA	17	IOANNINA	30	KERKYRA	43	LESVOS
5	XANTHI	18	ARTA	31	ZAKEENTHOS	44	SAMOS
6	THESSALONIKI	19	THESPOTIA	32	KEFALONIA	45	CHIOS
7	HMATHIA	20	PREVEZA	33	LEFKADA	46	CYCLADES
8	KILKIS	21	LARISSA	34	ACHAIA	47	DODECANESE
9	PELLA	22	KARDITSA	35	AITOLOAKARNANIA	48	HERAKLION
10	PIERIA	23	MAGNESIA	36	HELEIA	49	LASITHI
11	SERRES	24	TRIKALA	37	ARKADIA	50	RETHYMNO
12	CHALKIDIKI	25	FTHIOTIDA	38	ARGOLIDA	51	CHANIA
13	KOZANI	26	VIOTIA	39	KORINTHIA		