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Predictive Modelling for Sustainable Pilgrim Flow Management on the Camino de Santiago

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Abstract: When destinations are in a growth or maturity phase, two simultaneous debates usually arise: is there overtourism? and -if it exists- does it have negative consequences? The literature has been concerned with providing scientific answers to these questions analysing cases of urban and sun and sand destinations. The differential elements of rural destinations in relation to this topic have usually been neglected. This study presents a prediction instrument built specifically for a growing destination located - almost entirely - in a rural environment: El Camino de Santiago. Based on the information collected over the last 20 years by the Pilgrim's Welcome Office receiving more than 4 million pilgrims, this instrument is aimed at predicting the number of pilgrims who will pass through a series of hotspots -employing Seasonal Autoregressive Integrated Moving Average (SARIMA), and Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal Components (TBATS) models- to help control management of pilgrim flows and thus counteract the possible negative consequences of overtourism, optimising the experience for tourists, business owners, and residents of the hotspots.

Keywords: Overtourism; Predictive models; Management; El Camino de Santiago.

Modelización predictiva para la gestión sostenible del caudal peregrino en el Camino de Santiago

Resumen: Cuando los destinos se encuentran en fase de crecimiento o madurez, suelen surgir dos debates simultáneos: ¿existe sobreturismo? y -en caso de que exista- ¿tiene consecuencias negativas? La literatura se ha ocupado de dar respuestas científicas a estas preguntas analizando casos de destinos urbanos y de sol y playa. Los elementos diferenciales de los destinos rurales en relación con este tema han sido habitualmente desatendidos. Este estudio presenta un instrumento de predicción construido específicamente para un destino en crecimiento ubicado -casi en su totalidad- en un entorno rural: Camino de Santiago. A partir de la información recogida en los últimos 20 años por la Oficina de Acogida al Peregrino sobre más de 4 millones de peregrinos, este instrumento de predicción tiene como objetivo predecir el número de peregrinos que pasarán por una serie de *hotspots* -empleando la Media Móvil Autorregresiva Estacional Integrada (SARIMA)-, y *Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal Components (TBATS) models*- ayudando a la gestión del flujo de peregrinos y controlando así las posibles consecuencias negativas del sobreturismo, optimizando la experiencia de turistas, empresarios y residentes de los *hotspots*.

Palabras clave: Sobreturismo; Modelos predictivos; Gestión; Camino de Santiago.

1. Introduction

During the past few decades, "sustainability" and "overtourism" have been two of the most frequently discussed topics in tourism research. These concepts are often mentioned separately or together in many

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recent publications. When examined together, they are often seen as the cause (overtourism) and the effect (unsustainability). This proposition sparks controversy and encourages public debate when the issue is not thoroughly explored.

Those who advocate for the benefits of tourism often overlook the associated costs. On the other hand, some view every destination as a potential risk for long-term negative consequences due to tourism. Experts typically assess destinations based on their specific characteristics, focusing on established tourist destinations and emerging ones with high potential risk.

Very little research has been conducted on the issues associated with overtourism in rural destinations[1]. These areas are particularly sensitive in terms of environmental, economic, and socio-cultural sustainability. The perception of overcrowding in these areas is highly subjective and is based on tourists' expectations (Peron Lopez, 2008). Additionally, these destinations are at risk of becoming stagnant in hotspots.

This study aims to contribute to the understanding and management of overtourism in the context of emerging research. The goal is to develop a predictive tool specifically for a tourist destination located in a predominantly rural area. The chosen destination, the religious route known as Saint

James Way, has been identified as a victim of overtourism (Duque & Morère-Molinero, 2019), possibly due to a significant increase in visitors in recent decades2. This route culminates at the Cathedral of Santiago de Compostela3.

So, we aim to partially address the gap identified in the literature on overtourism in rural areas by focusing on a route with a potential risk of overcrowding.

More specifically, we present a predictive tool capable of analyzing the forecasted number of visitors at several hotspots, comparing it with the destination's maximum accommodation capacity, and thus assessing a maximum carrying capacity through thresholds that should not be exceeded by tourist arrivals. Our aim is to create a robust tool that can identify brief moments of overcrowding in advance and alert municipal authorities and businesses operating in hotspots of a popular touristic route, as is Saint James Way. This approach will enable authorities and business to respond effectively, preparing in advance to mitigate the negative impacts of overcrowding and promote more responsible and sustainable tourism practices.

2. Literature review

Despite all the benefits that tourism brings, such as its contribution to the Gross Domestic Product (GDP) and employment of countries, as well as the cultural exchange between historically distant regions, improving both national and international relationships, it also has a downside. The unstoppable increase in global tourism, which has shifted from being a luxury item to a consumer good for a large part of the world's population, implies negative externalities in the long term, that have frequently been revealed in several locations worldwide in the last years, leading to the popularity of the term overtourism on the tourism literature. Overtourism is a situation in which locals feel that there are too many visitors and that tourists are negatively affecting their quality of life (Hansen, 2020; Seraphin et al., 2018). United Nation World Tourism Organization (UNWTO, 2018) defines overtourism as "the impact of tourism on a destination, or parts thereof that excessively influences the perceived quality of life of citizens and / or the quality of visitor's experiences negatively". The excessive influx of tourists in an area generates negative impacts, putting pressure on transportation infrastructure, causing damage to natural resources, and leading to discomfort among the resident population, as well as dissatisfaction among visitors.

Recent studies focused on the analysis of overtourism highlight among its effects those related to the loss of identity of destinations, the lack of authenticity perceived by tourists during the tourist experience, and the expulsion of residents from spaces saturated with tourists. In Spain, the term turismofobia (tourism phobia) has emerged to refer to the negative attitude of residents towards tourism due to the effects of overtourism. All are effects that point to the need for sustainable destination management (Colomb & Novy, 2016; Postma et al., 2018; UNWTO, 2018)

2.1. Overtourism in rural areas

Tourism has become one of the economic activities with the most sustained growth, as asserted by the UNWTO (2023). This subsector has become crucial for many economies, accounting for approximately 10% of global GDP and employment. The steady growth of this subsector after World War II was influenced by labor improvements that led to the creation of mass tourism phenomena after World

War II. Since then, a segment of the population in middle to high-income countries gradually gained access to international travel. This served as a policy promoting territorial equity among nations, as many low-income countries were able to boost their economic development through this economic activity (Cometta, 2021; Serdoura et al., 2009). This is because many developing countries are located in subtropical climates, prone to sun and beach tourism, which are typically targeted for vacations by countries with higher GDP per capita and colder climates in the northern hemisphere.

Despite tourism having faced several negative shocks, international tourism only experienced slight reductions for brief periods, such as in the early 1980s during the second oil crisis, following the 9/11 attacks, and after the 2008 economic crisis. However, the COVID-19 crisis has brought about a significant change in this trend. The global decline in international tourist arrivals fell by over 65% in 2021, 35% in 2022 and an estimation of 20% in 2023 (UNWTO, 2023) in comparison with pre-pandemic 2019. Tourism levels have yet to fully recover to those seen before 2019, prior to the health crisis caused by the COVID-19 pandemic in 2020, especially due to the restrictive measures taken by the Asian authorities, where the effects of their actions on foreign tourism can be observed nowadays (Avraham, 2021; Fan et al., 2023). The crisis incited both consumers of tourism products and the local population to reconsider their relationship with this economic activity. Residents in touristic areas are now more averse to accept the same level of tourism due to an increased perception of saturation. This perception is based on the comparison of the current situation with that experienced in 2020, where the actual overflow of tourist demand is perceived as a factor that decreases quality of life for the local population. Simultaneously, there's a perception of saturation among tourists who are less interested in traveling to destinations they perceive as overcrowded (Kainthola et al., 2021). Their tolerance for saturation has decreased since they spent over a year maintaining social distance due to the pandemic, leading them to perceive a place as more saturated compared to before, even if its objective characteristics remain unchanged.

The exacerbation of the overtourism sensation caused by the paradigm shift during the pandemic results in an increase in literature about this phenomenon in the last three years (Santos-Rojo et al., 2023). This issue, combined with factors such as gentrification of city centers or the oversaturation of certain touristic attractions like natural parks, theme parks, beaches, etc., has sparked interest in the scientific community. This was due to the discomforting situation occurring in these destinations, motivating authors to initiate studies on the effects of overtourism on both providers and consumers of tourism products, as well as the local population.

So, many authors have considered that the problem usually lies in the lack of demand, neglecting the study of what happens when demand significantly surpasses the supply of tourism goods and services, leading to most tourism articles to be focused on demand prediction, and failing to recognise that an excess on demand can be highly detrimental to business activity. An overdeveloped demand in an area can result in higher rents, lack of local customers, increased seasonality, among other issues, affecting both business, tourists and local residents (gentrification, abundance of tourist's oriented products, noise, crowded streets etc.) (UNWTO, 2018). From product suppliers' and local resident's perspective, overtourism presents an issue escalating the cost of serving each tourist beyond a certain optimal demand level, leading to increased labour costs, supply expenses, triggering a price spiral that does not translate into higher profit margins for business.

One concept useful for stablishing hotspots that suffer from overtourism is the carrying capacity, where said regions suffer from this issue whenever they exceed certain thresholds. Tourism carrying capacity of a destination, defined by WTO as "the maximum number of people that may visit a tourist destination at the same time, without causing destruction of the physical, economic, and sociocultural environment and an unacceptable decrease in the quality of visitors' satisfaction" (WTO, 2004, p.20) is a key challenge for tourism marketers and managers alike. The concept arises from the perception that tourism cannot grow continuously in a particular region without causing irreversible damage to the local system (Cifuentes, 1992; Coccossis, 2001; Coccossis & Mexa, 2004; Mc Cool & Lime, 2001).

The definition of carrying capacity as the maximum number of tourists deemed acceptable for the fruition of destination by tourists (Cifuentes, 1992; Coccossis, 2001; Mc Cool & Lime, 2001) is closely related to the notion of crowding, which is often used to assess a destination's carrying capacity (Bo Shelby et al., 1989). The definition of carrying capacity implies various measurements (Cifuentes, 1992; Duque & Morère-Molinero, 2019; Getz, 1983; Santos Solla & Pena Cabrera, 2014): (1) physical carrying capacity, determined by measurements of the place, such as volume or surface area; (2) real carrying capacity, more restrictive than physical carrying capacity incorporating limits of arrivals without causing social, economic, or environmental issues;(3) effective carrying capacity, more restrictive than real carrying capacity incorporating limits on the maximum number of tourists that can be managed by businesses and public administration of the hotspot; and (4) perceptual carrying capacity, even more restrictive, defined as the negative evaluation of levels of use or encounters with other visitors (Boand Shelby & Heberlein, 1987). Therefore, the social, cultural, and natural heritage of tourist destinations is owned by the residents and desired by visitors. A high concentration of visitors in a point could become unsustainable because of its impact on the destination resources (Postman et al., 2018) and on the quality of life of the residents (Postman & Schmuck, 2017). Overtourism and sustainability may be in conflict (Milano, 2018). Many public administrations have adopted restrictive measures to avoid this conflict. However, several authors suggest that destination management should start with "effective measuring and monitoring of overtourism" (Asynchronously & Weber, 2020, p.3.) Why do rural destinations deserve separate consideration in a debate framed in these terms? There are clear reasons: (1) the sense of overcrowding is more pronounced; (2) people's perceptions are more subjective; (3) the impact of perceived overload is more detrimental (it contradicts visitors' expectations and disrupts their experiences).

Related to these impacts is the deterioration of the destination's image and identity, the decline of perceived authenticity, and -ultimately- the long-term sustainability of the destination. The exhaustion of residents, including those who depend on tourism for income, exacerbates these impacts. Image 1 shows a photograph captured in September 2023 at the entrance of a bar in the Ponte Maceira hotspot, illustrating the owners' attitude towards tourists frequenting their bar along Saint James Way.

Image 1: Blackboard displayed at the entrance of a bar located on the Saint James Way (Ponte Maceira)

Source: Courtesy of Roberto Samartim (2023)

2.2. Why Saint James Way?

As mentioned in the introduction, this route was selected as a case study because it is primarily located in rural areas and previous studies have identified it as a destination at risk of overtourism(Duque & Morère-Molinero, 2019; Fernandez & Rivera, 2018). Additionally, there are other significant factors:

- It encompasses valuable cultural and natural resources (the French Way -1993- and the four routes of the North Ways -2015- have been recognized by (United Nations Educational, Scientific and Cultural Organization: UNESCO as a World Heritage Site).
- It consists of various alternative routes (which will be detailed in Annex I), making it easier to manage flows through regulatory constraints or marketing activities.
- Its multiple stages allow for hotspot analysis.
- The economic importance of the route for the region, comprising 300 millions of euros in revenue each year since 2019 (Rodríguez, 2019).
- The significant increase in pilgrim arrivals to Santiago de Compostela following Saint James Way since the 1990s, from an average of 25,000 to 400,000 pilgrims in 2022 and 2023, is crucial for assessing the sustainability of the route (Pegregrino, 2023).
- The regional administration is inclined to use tourism policy instruments to protect this resource (as evidenced by the wording of the Law on the Protection of Routs, in 1996, and the Law of Cultural Heritage of Galicia, in 2016).
- There are initiatives to coordinate the various actors involved, such as the Jacobean Council or the Association of Municipalities of Saint James Way, although there is a lack of a common policy for coordinated management (Medina & Lois Gonzalez, 2017).
- Moreover, the Saint James Way is a pilgrimage route, and one of its main attractions is introspection and spirituality. Consequently, overcrowding of the route leads to a decline in the product quality according to the preferences of pilgrims, which can discourage them from returning or recommending the journey to family, friends, and others.

The results of Duque & Morère-Molinero (2019) on the perceptual carrying capacity of the busiest route of the Saint James Way (The French Way) warn that a significant number of tourists are beginning to perceive symptoms of overcrowding that could lead them to abandon the route and avoid re-visiting. The weight of the imaginary with which tourists arrive on the road is very strong and positive, but it begins to weaken with the experience itself.

So, overtourism may reach a point of no return when demand spirals downward, leading to the failure of long-term investments in public or private infrastructures with extended amortization periods. This possibility increases uncertainty within the tourism sector, discouraging investors from making the necessary long-term investments for the area. To better understand the analysis, a brief description of this destination is provided in Appendix I.

2.3. Touristic demand prediction

Since the 1960s (Armstrong, 1972; Gray, 1966; Guthrie, 1961) there has been a growing trend on the utilization of demand prediction techniques within the field of tourism (Li et al., 2005; Liu et al., 2019). These techniques are aimed at preparing providers of touristic products and services for a fluctuating demand in an industry with limited budget margins, making it challenging for business to be profitable (Witt & Witt, 1995).

The need for tourism prediction arises from a characteristic of tourism, as is the lack of a stock that can be accumulated, unlike other products. Consequently, anything not offered to potential customers on a given day results in lost revenue. Inadequate prediction of tourism demand can lead to a series of issues, whether by excess or insufficiency as noticed by Frechtling (2001). On excess of demand, tourism satisfaction may decline due to overtourism at destinations, environmental degradation, transport issues, inflation or decrease in service quality. In opposition, on insufficiency of demand, excessive expending on infrastructure and wages may occur, combined with long-term financial problems.

The necessity to predict tourism demand, together with the significant advancement of these techniques, has not resulted in widespread usage of this methodologies across businesses within the sector. Instead, such methodologies have largely been confined to major tourism companies and national statistical institutes (Liu et al., 2019; Uysal & Crompton, 1985; Witt & Witt, 1995). There are multiple reasons why small businesses struggle to improve their demand prediction capabilities, starting with the lack of granularity in data (Liu et al., 2019; Yang et al., 2014), as tourism data often covers large geographical areas and is collected infrequently. Furthermore, there's a lack of data analysis capability by these companies, a factor that has only gained importance with the rise of Big Data. Consequently, these business are unable to benefit from precise tourism predictions when establishing their financial plans or management accounting strategies.

The tourist demand modeling through the prediction and measurement of the total number of tourists arriving at or departing from a specific destination has been developed using varied methodologies (Li et al., 2005; Song & Li, 2008; Uysal & Crompton, 1985; Witt & Witt, 1995; Yang et al., 2019):

Econometric: aimed to predict tourist arrivals using explanatory variables such as exchange rates, various measures of regional income, population, price levels, real interest rates, and elasticity of substitute products. In the event of incorporating spatial variables such as distance, they were referred to as gravitational models. In addition to the classic linear or logistic regression models, models such as VAR (Vector Autoregressive Models), AIDS (Almost Ideal Demand Systems), and ECM (Error Correction Model) belong to this category. VAR and AIDS, address issues related to the endogeneity of variables (Witt & Witt, 1995), while ECM, ensures the cointegration of variables (Algieri, 2006; Wooldridge, 2016).

Time series: designed to predict the number of tourists arriving at a specific destination or departing from a particular origin, based on their past data and error terms, with a particular focus on seasonality. The most used methods to calculate these types of models are SARIMA (Seasonal Autoregressive Integrated Moving Average) and GARCH (Generalized, Autoregressive Conditional Heteroscedasticity), with the first focusing on the number of tourists and the second analyzing the variability of the number of tourists. Advancements on these techniques have led to more refined models in recent years, such as BATS or TBATS, that guarantee greater flexibility (de Livera et al., 2011) than SARIMA and GARCH.

Machine leaning: A group of techniques designed to predict a variety of dependent variables, such techniques may include both time series models and explanatory variables. Despite the development of regression trees or ensembles, SVM (Support Vector Machine), and neural networks before the 80s (McCulloch & Pitts, 1943; Rosenblatt, 1958), the new computational capabilities achieved in the last decades have allowed their utilization, due to the diminishing computational cost associated with them in mid 90s (Cortes & Vapnik, 1995; Hochreiter & Schmidhuber, 1997).

To predict the saturation of hotspots on Saint James Way, we will use a time series model, such as TBATS (de Livera et al., 2011) and SARIMA as benchmark, where the first has demonstrated its predictive capability in the fields of engineering (Karabiber & Xydis, 2019), biomedicine (Kuchcik, 2021; Talkhi et al., 2021) or economics (Hassani et al., 2015; Silva et al., 2019) dealing with highly granular data, applied in our article in the touristic context, while the second model is widely used as a standard time series model.

3. Methodology

In this research we employ a definition of carrying capacity, where we consider that a specific hotspot faces issues of surpassing their ability to manage tourists when more than a certain level of the total hotel accommodations in the destination are occupied, following the effective carrying capacity measure. This criterion allows for a practical and relatively straightforward assessment of overtourism, enabling us to detect instances where a substantial portion of the available hotel space is utilized, signifying a potential strain on the destination's capacity to handle visitors. In this case, a threshold of 30% is selected for illustrative purposes, as the organization implementing the predictive system must establish a threshold for each hotspot, correlating the perceived level of saturation with the specific threshold metric. We will measure the effective carrying capacity of the hotspots, explaining the method for obtaining daily data for each of the hotspots and make predictions for 1 month, in order to verify which of the two time series methods makes fewer mistakes, being a candidate to implement in an early anomaly alert system.

3.1. Data

The dataset used comes from the questionnaires that pilgrims must complete to obtain the official credential of Saint James Way. This credential is issued by the Pilgrim's Welcome Office, registering that they have completed more than 100km on foot, 150km on horseback, or 200km on a bicycle on one of the certified routes. The dataset collects the characteristics of the pilgrims who receive the credential, as well as the arrival time, the name of the initial stage, and the chosen route of the Saint James Way undertaken by the pilgrims. Once we filter out the pilgrims who have completed a route of Saint James

Way with less than 10,000 arrivals in the last 20 years,we have at our disposal 4 million pilgrims arriving to Santiago de Compostela from January 2003 to August 2023. By aggregating pilgrim surveys, we can count the number of pilgrims arriving in the city of Santiago de Compostela for each day of the year.

3.2. Variables

The analysis is based on daily data for each hotspot along the route for two variables: arrivals and accommodations.

3.2.1. Arrivals

One of the main variables we will use in our analysis is the number of people passing through each stage of Saint James Way. Table 1 shows the last stages of the 7 main routes to reach Santiago de Compostela, along with the distance in days to the city.

Table 1: Name and number of stages to reach Santiago de Compostela by each way

Number of stages from Santiago de Compost ela	French Way	Portugue se Way	Coastal Way	Primitive Way	English Way	Silver Way	North Way
1	O Pedrouzo	Padrón	Padrón	O Pedrouzo	Sigüeiro	Ponte Ulla	O Pedrouzo
2	Arzúa	Caldas de Reis	Caldas de Reis	Arzúa	Hospital de Bruma	Silleda	Arzúa
3	Palas de Rei	Pontevedra	Pontevedra	Melide	Betanzos	O Castro	Sobrado
4	Portomarin	Redondela	Redondela	San Romao	Pontedeume	Cea	Baamonde
5	Sarria	Tui	Vigo	Lugo	Ferrol	Ourense	Vilaiba
6	Triacastela		Baiona	O Cádavo		Xunqueira de Ambia	Lourenza
7	O Cebreiro		A Guarda	A Fonsagrada			

3.2.2. Accommodations

Each of the stages has a specific number of hotel accommodations, which are distributed among tourist hostels, apartments, campgrounds, hotels, guesthouses, rural tourism, tourist-use homes, and tourist apartments. In Table 2, we present the number of accommodations available in each of the last stages of Saint James Way (Galicia, 2023).

Table 2: Number of accommodations per stage of Saint James Way

Stage	Accommodations
A Guarda	2.632
Arzúa	2.652
Baamonde	360
Baiona	6.231
O Cádavo	265
Caldas de Reis	1.597
O Cebreiro	1.005
A Fonsagrada	586
A Gudiña	242
Laza	334
Lourenzá	996
Lugo	3.891
Melide	1.242
O Pedrouzo	1.891
Ourense	2.992
Padrón	1.563
Ponte Ulla	301
Pontevedra	3.523
Redondela	1.606
Ribadeo	2.986
San Romao	1.671
Sarria	2.817
Sobrado	255
Triacastela	898
Tui	2.031
Vigo	10.922
Vilalba	744
Xunqueira de Ambía	77

3.2.3. How to obtain daily data for each hotspot

The database collects the daily arrival of pilgrims to the city of Santiago de Compostela, as well as their starting point and the specific "Way" or route they have undertaken to reach the city.

To assess the number of pilgrims passing through each hotspot along Saint James Way, we make two assumptions:

- Pilgrims complete one stage per day. This assumption is less restrictive than it seems because, even when they could take breaks or divide the journey over several days throughout the year, pilgrims who do this usually opt for such an approach when the distance they are going to cover is very long. To support this assumption, it is worth noting that there is a portion of pilgrims who pre-book accommodation, restaurants, or luggage transportation services several days in advance. Additionally, predicting only the final stages of the journey, minimize any potential error.

- Pilgrims complete the entire path they claim to have selected. In other words, they do not undertake any significant diversions along the path that would place the end of the stage in a different location than the established by the official routes. To support this assumption, it's worth noting that all routes, with the except for the Portuguese Way or the Coastal Portuguese Way, do not cross areas with adequate accommodation services for tourists and have a lower level of infrastructure. Consequently, most pilgrims follow the path as defined with minimal variance.

Thus, knowing the arrival day of the pilgrims and the number of stages between the start of Saint James Way and the end, it is possible to deduce where the pilgrims were passing by several days before reaching Santiago de Compostela. To do this, we will subtract the number of stages between the starting point and Santiago de Compostela, and we will know which day it was when the pilgrims passed through a hotspot. A prediction will be performed on each time series, obtained for each hotspot within 7 days of Santiago de Compostela, using TBATS and SARIMA models.

3.3. Models

In this section, we will provide an explanation on the method of estimation of both models for time series forecasting TBATS and SARIMA.

3.3.1. TBATS

Following the original article by de Livera et al. (2011), TBATS (Trigonometric seasonality, Box- Cox transformation, ARMA errors, Trend and Seasonal Components) is a time series forecasting method for series with complex seasonality. It has its roots in the traditional approach of exponential smoothing (Holt, 2004; Winters, 1960), introducing Box-Cox transformations (Box & Cox, 1964) to account for the possibility of non-linearity, ARMA errors, as well as seasonal patterns in a trigonometric form based on Fourier series (Gardner, 1985). That we can write as follows:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega}, & \omega \neq 0 \\ \log y_t, & \omega = 0 \end{cases} \tag{1}$$

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \tag{2}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t \tag{3}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t \tag{4}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{5}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t \tag{6}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1}^{(i)} \sin \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos \lambda_j^{(i)} + \gamma_2^{(i)} d_t \tag{7}$$

$$\lambda_j^{(i)} = \frac{2\pi j}{m_i} \tag{8}$$

$$d_t = \sum_{i=1}^{p} \phi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{9}$$

Where $y_t^{(\omega)}$ is the Box-Cox transformation with the parameter ω, l_t is the level component of the series and b_t is the trend component at time t. The α, β, $\gamma_1^{(i)}$ and $\gamma_2^{(i)}$ coefficients are the smoothing parameters. Describing $s_{j,t}^{(i)}$ as the stochastic level of the ith seasonal component and $s^*_{j,t}{}^{(i)}$ as the stochastic growth in the level of the ith seasonal component. Being m_i the periods of the ith seasonal cycles and ϕ the damping parameter, d_t representing the ARMA process for residuals, φ_i and θ_i the ARMA(p,q) coefficients and ε_t a Gaussian white-noise process with zero mean and constant variance σ^2.

3.3.2. SARIMA

The SARIMA or Seasonal Autoregressive Integrated Moving Average model is an extension of the ARIMA model, incorporating seasonal components in both its autoregressive and moving average parts (Box & Cox, 1964; Hamilton, 1994; Verbeek, 2004). These models are the most commonly used in the macroeconomic analysis of time series, employed due to their predictive capability with this type of data, demonstrating their ability to forecast phenomena that evolve over time such as consumption (Silva et al., 2019), tourism (Park et al., 2017) or prices (Hassani et al., 2015; Karabiber & Xydis, 2019).

Following Guisán (1997) notation, we can write the SARIMA model as follows:

$$\phi(B)\phi_S(B^s)(1-B)^d(1-B^S)^D Y_t = \theta(B)\theta_S(B^S)u_t \tag{10}$$

Where:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \tag{11}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{12}$$

$$\phi_S(B^S) = 1 - \phi_{s1} B^S - \phi_{s2} B^{2S} - \cdots - \phi_{sP} B^{PS} \tag{13}$$

$$\theta_S(B^S) = 1 - \theta_{s1} B^S - \theta_{s2} B^{2S} - \cdots - \theta_{sQ} B^{QS} \tag{14}$$

Where Y_t is the time series at time t, B the backshift operator that makes the series stationary, $\phi(B)$ non-seasonal autoregressive operator, $\theta(B)$ non-seasonal moving average operator, p, d, q represent the non-seasonal AR, differencing and MA orders, respectively, $\phi_s(B^S)$ seasonal autoregressive operator, $\theta_s(B^S)$ seasonal moving average operator, P, D, Q represent the seasonal AR, differencing and MA orders, respectively, and u_t the random noise.

4. Results

We present and analyze the one-month predictions with out of sample forecast, using TBATS and SARIMA methods for three main hotspots. TBATS, known for handling seasonality, trends, and holidays, is compared against the widely used SARIMA method. The aim is to evaluate their accuracy for three specific hotspots, determining their suitability for an early anomaly alert system.

Table 3: Prediction metrics

		TBATS			SARIMA	
	Sarria	Arzúa	Redondela	Sarria	Arzúa	Redondela
Alpha	.359	.009	.625	-		
Beta	-.016	Null	.0002	-		
Damping parameter	.800	Null	1	-		
Gamma one	1.7e-4 2.8e-4	5e-5 -8e-5	-1.06e-4 -7.97e-4	-		
Gamma two	-2.1e-4 -1e-4	-9e-5 6e-5	-1.37e-4 -3.05e-5	-		
AR	4	3	5	1,7,365	1,7,365	1,7,365
MA	3	1	1	1	1	1
MAE	272	319	123	525	216	112
MSE	109.495	160.825	22.299	334.119	82.739	21.316
RMSE	331	401	149	578	288	146
MAPE	28.7 %	25.7 %	24.1%	51.04%	17.6%	18.6%

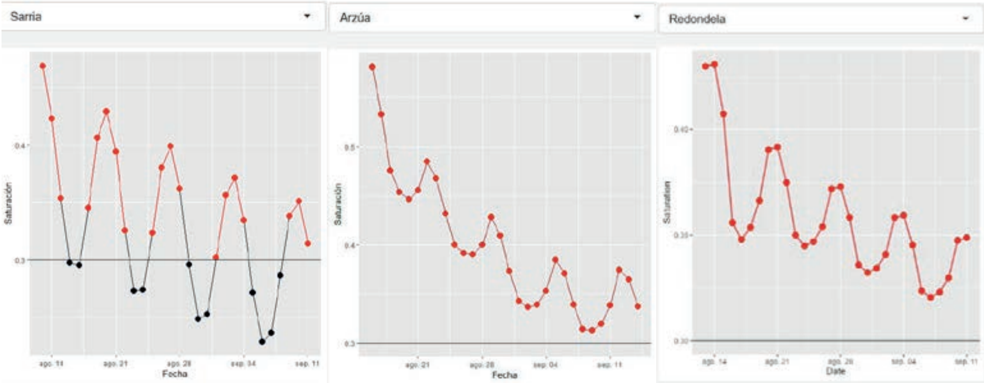
Analyzing the prediction metrics from Table 3 reveals two key observations. Firstly, concerning Arzúa and Redondela, the TBATS prediction performs moderately worse than the SARIMA model based on metrics such as MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error), where all the metrics metrics show, are based on the difference between predictions and actual values. So, accurate models will have lower values, regardless of units of the metrics, with the best models having values closer to zero. However, a different trend emerges with Sarria, where the TBATS model shows superiority over SARIMA across all previously mentioned metrics due to their lower values. Furthermore, it becomes evident that the TBATS-based method exhibits greater consistency in its results. All three estimations demonstrate similar levels of accuracy, conversely, the SARIMA models vary significantly in performance, with two models displaying high accuracy and one considerably underperforming. This consistency in TBATS's performance across the different hotspots underscores its reliability, despite its comparative weaknesses in certain instances, while SARIMA's varying performance raises questions about its consistency and overall reliability across different datasets and hotspots.

We conducted predictions for the hotspots mentioned in section 3.2.3. and we present in Figure 1, an illustration of saturation prediction for the three main hotspots. The daily saturation estimation is highlighted in red, when the model forecasts arrivals exceed 30% of the total accommodation capacity.

How does the saturation early warning system work?

The operational early warning system works in several steps: Initially, pilgrim arrival data is collected at the Pilgrim's Office, while at the same time we update the maximum available hotel accommodations whenever possible. Subsequently, the daily data for each hotspot along Saint James Way is computed with the system depicted in section 3.2.3. Following this, we undertake evaluation of a series of time series analysis models, validated for their effectiveness in predicting daily data within this dataset. We generate predictions based on these models, extending beyond a two-week period. If the forecasted saturation exceeds a threshold known to cause issues for the local community, hostel operators, and tourists, proactive measures are enacted, thus, when the system anticipates such anomalies, notifications are promptly transmitted to the respective hotspots, allowing them to take necessary actions deemed essential to manage the situation effectively. This proactive approach aims to ensure quick interventions, promoting a smoother and more sustainable pilgrimage experience along the route while mitigating potential disruptions for both residents and visiting pilgrims.

Figure 1: Example of three hotspots with saturation (daily arrivals >30% of Total accommodation capacity)



5. Discussion and conclusions

The value of the methodology lies not only in its novelty but also in the logic implicit in the selection of daily data for each hotspot as the basis for estimation. Daily prediction is ideal for managing a tourist route, as it enables the fine tuning of the business and policy-makers that manage the supply touristic goods and services for each hotspot. The robustness of the estimates is ensured by checking the accuracy and consistency of the results obtained using two different models: TBATS and SARIMA. Through a evaluation of the predictive accuracy and consistency of both models, it was established that the TBATS model exhibited superior performance in forecasting visitor numbers within these hotspots, as its higher consistency in predicting the number of pilgrim

passing through each hotspot showed as more suitable for the predictive tool. However, we observed varying outcomes regarding the performance of TBATS and SARIMA models across different contexts. Similar to our results Talkhi et al. (2021) concluded that TBATS outperformed SARIMA in their analysis on the forecasting of deaths caused by Covid-19, while Hassani et al. (2015) also found TBATS to outperform SARIMA predicting gold prices, whereas Silva et al. (2019) noted that both models exhibited similar performance predicting the google trend of the term Burberry, while Kuchcik (2021) reported satisfactory results by utilizing TBATS, indicating its effectiveness at predicting Universal Thermal Climate Index. On the contrary, Karabiber & Xydis (2019) found that SARIMA outperformed TBATS predicting electricity prices. These diverse findings underscore the importance of considering specific contexts and datasets when determining the efficacy of forecasting models.

The study contributes to addressing the gap in literature regarding overtourism in rural destinations by providing a prediction tool based on historical data. This tool offers valuable insights to both public and private organizations, aiding in decision-making processes aimed at mitigating overtourism. The predictive model developed proves to be an effective tool for analyzing visitor numbers within hotspots, enabling the creation of a proactive system to anticipate potential saturation in advance. By alerting relevant municipal authorities and businesses promptly, interventions and management strategies can be implemented swiftly and effectively.

Further contributions of the research goes beyond what has been called “smart solutions”, which have proven unsmart in avoiding the unsustainability of destinations (García-Hernández et al., 2019). The integration of this prediction with qualitative analysis of the perceptual carrying capacity -such as the research developed by Duque & Morère-Molinero (2019) specifically for the route of Saint James Way known as the French Way- is a valuable ad hoc scientific tool that truly has the potential to support informed decisions.

6. Implications

We propose a practical example of the application of the early warning system developed for municipal authorities. This system would trigger an alert mechanism when the prediction of arrivals of pilgrims surpassed predefined thresholds at specific hotspots. These alerts would be directed the people responsible for managing the respective hotspots, facilitating proactive measures to ease potential saturation issues.

In the future we aim to collaborate with different economic agents to implement our predictive system along with their respective analytic tools, integrating both to improve the understanding of tourism. The system predictive system will alert potential overcrowding issues, aiding policymakers in proactive management.

In a broader sense, this research contribute to transferring the debate on overtourism/sustainability to the real situation of one destination in different spaces and moments. The ideological debate on the compatibility of the rights of residents and visitors becomes sterile when relevant information for decision-making is available.

Should this transfer to the society be achieved, we would have attained one of the most significant goals of research in the social sciences: contributing to decision-making guided by the pursuit of long--term social well-being.

7. Limitations

One might expect the limitation to be noted that this research is confined to the analysis of a single tourist destination; however, this restriction is not acknowledged as a limitation of the study. Overtourism must be evaluated and, where appropriate, diagnosed across the various spaces and moments of each destination. Indeed, the outcome of this work is a tool designed to predict potential overloads in the different spatio-temporal combinations of this specific destination, based on its own historical visitor data. Alternative methodologies could have been considered, as we have recognized.

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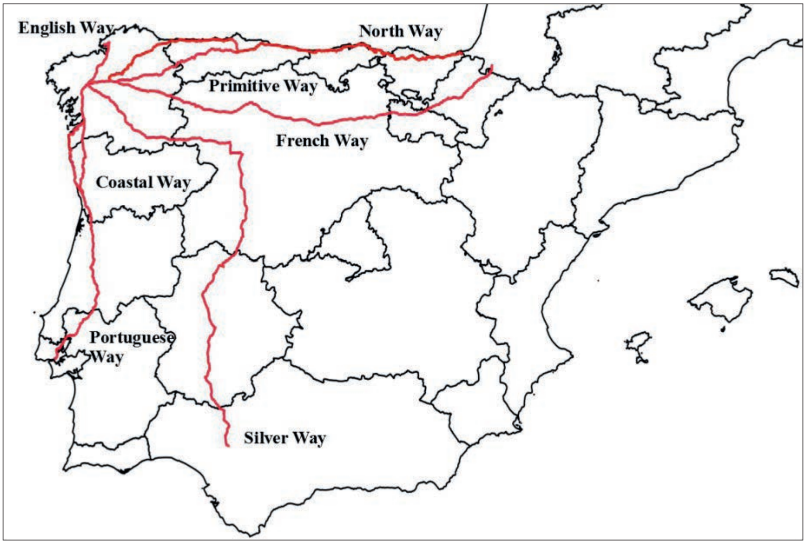
Appendix I. Brief description of the routes of the Saint James Way (sorted by number of visitors)

1) French: It is the most popular route, crossing vast forests and plains, passing through many historically significant cities through inner Spain, and it is one of the two that obtained the World Heritage credential.
2) Portuguese coastal: It is a route that largely runs along the North Portuguese and Galician coast, passing through significant cities and completing an itinerary of low technical difficulty.
3) English: It is a lesser-known route that begins its itinerary through urban and coastal areas and finish crossing forests.
4) North: It is a route that stretches along the northern coast of Spain, being a path of high technical difficulty and oceanic climate; it is the second route to have obtained the World Heritage credential.
5) Silver: It is a route that crosses Spain from south to north, traversing areas with high technical difficulty, sweltering summer climate, and cities with historical value.
6) Portuguese: It is a highly popular route that runs through the interior of Portugal and Galicia, following paths of low technical difficulty and historical cities.
7) Primitive: It is a less popular route that runs through the interior of Galicia and Asturias, through mountainous areas with technical terrain and low levels of urbanization.

The layout of the routes is shown in the figure A.1

FIGURE A.1. Layout of the routes



Notas

[1] The search on the Web of Science (WoS) - carried out on January 4, 2024 - using "overtourism" and "rural" as search terms- yields 24 publications.

[2] According to data from the Pilgrim's Office (Información Estadística Oficina Peregrino, 2024), in 1992, 9,764 pilgrims made the Way of Saint James, in 2023 there were 443,036.

[3] The city of Santiago de Compostela and its Cathedral have received the attention of tourism researchers. The presence/absence of overtourism has been evaluated (Almeida, 2006; García Hernández & De la Calle Vaquero, 2012; Gigirey, 2023; Lopez et al., 2019)

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