

Tracking Tourist Behaviour During Environmental Crises: Analysing Economic Indicators, Social Sentiment, and Tourist Mobility in the Mar Menor Lagoon

Daria Mitroshenko  ¹

José Giner Pérez de Lucia  ²

Fernando Terroso-Sáenz  ³

José M. Cecilia  ⁴

Ginesa Martínez - del Vas  ⁵

Andrés Muñoz  ⁶

1. Universidad Católica de Murcia (UCAM), Murcia, Spain

2. Sensing Tools, S.L., Spain

3. Universidad Politécnica de Cartagena (UPCT), Cartagena, Spain

4. Universitat Politècnica de València (UPV), Valencia, Spain

5. Universidad Católica de Murcia (UCAM), Murcia, Spain

6. Universidad de Cádiz (UCA), Cadiz, Spain

ABSTRACT

The Mar Menor, one of Europe's largest coastal lagoons, has experienced severe ecological crises over the past decade due to ongoing environmental degradation. These events, characterized by algal blooms and mass mortality of marine life have sparked widespread public concern and threaten the region's vital tourism industry. This study quantifies the impact of these environmental catastrophes on tourism across three key dimensions: economic, social, and mobility. To achieve this, we employ a mixed-methods approach using three distinct data sources. First, we analyse official economic statistics to track fluctuations in traveller arrivals, overnight stays, and average stay durations between 2012 and 2022. Second, we utilize social sensing to Twitter data to evaluate public discourse and tourist sentiment regarding the crises. Finally, we analyse nationwide human mobility datasets to detect shifts and structural breaks in tourist flows. Our findings demonstrate a direct correlation between the ecological crises (specifically the 2016, 2019, and 2021 episodes) and significant declines in tourism. This research highlights how severe environmental degradation drastically alters tourist behaviour, emphasizing the need for sustainable coastal management to protect local economies.

KEYWORDS

Ecological Crisis, Tourism Impact, Social Sensing, Tourist Mobility, Economic Analysis.

ARTICLE HISTORY

Received 11 May 2026 Accepted 15 September 2026

1. Introduction

Mar Menor is one of the largest coastal lagoons in Europe and the Mediterranean Sea with a surface area of 135.5 km² and a coastline of 74 km (Belando et al., 2021). The pleasant temperatures, lack of precipitation, and beach make Mar Menor a representative of Costa Cálida's main tourist attraction. However, for decades the Mar Menor has been suffering a progressive degradation from mining activity to the arrival of tourism in the 70s and uncontrolled urbanization (García-Ayllón, 2018). Marine pollution has been shown to generate negative economic impacts on coastal destinations, including a reduction in tourist arrivals, a decrease in housing prices, and an increased risk of business failure in affected area (Fernández Ferrero et al., 2022; Lamas Rodríguez et al., 2023; Aparicio et al., 2024).

These environmental disturbances often manifest as ecological crises that can attract media attention, particularly on social media platforms, where information spreads rapidly (Jurgens & Helsloot, 2017). User-generated content, including comments and opinions shared online, becomes a key factor in shaping the public perception of affected destinations (Correia-Loureiro et al., 2021), with direct implications for tourist demand and even destination image (Becken et al., 2017). In the case of Mar Menor, the widespread awareness of environmental issues changed the willingness of tourists to visit the coastal lagoon, leading many to choose alternative destinations (Fernandez Ferrero et al., 2022).

Given that these perception changes are primarily expressed through the news and user-generated textual content on social media, an analytical method capable of systematically evaluating opinions is required. In this context, sentiment analysis provides a useful methodological approach to assess public attitudes and emotional responses conveyed online. Sentiment analysis (SA) is the process of collecting and analysing people's opinions, ideas, and perceptions about different topics, products, subjects, and services, etc. It identifies and extracts subjective information from the text using natural language processing and text mining (Wankhade et al., 2022). SA provides a technological solution to sensing and understanding consumer experiences in all the areas, especially in tourism (Jain et al., 2021; Manosso & Domareski Ruiz, 2021).

The main objective of this study is to analyse the impact of the various ecological crises of Mar Menor on the three tourism dimensions: economic, social, and mobility. To do so, first, we relied on the publication of news and posts in social media about environmental problems that occurred in Mar Menor from 2014 to 2021 to distinguish the phases of the ecological crisis. For the economic part, we used statistical data from National Institute of Statistics (INE) (<https://ine.es>) that has been reprocessed with the collaboration of the Regional Statistics Centre of the Region of Murcia and the services of the Ministry of Industry, Tourism, Business and Innovation. This data includes the number of travellers and overnight stays in the Mar Menor area, and their average stays.

Moreover, we have used a social sensing tool developed as a part of the SMARTLAGOON project (Prandi et al., 2022) to study the sentiments and to measure the social impact on tourism of Mar Menor lagoon. Finally, we applied the analysis of tourist flows. By means of statistical data extracted from the INE mentioned previously, we could discover the number of travellers and overnight stays from 2012 to 2022 in the Mar Menor area to see the general tendency of arrivals. Next with the dataset of the Spanish Ministry of Transportation (SMT) we were able to evaluate the impact of the last crisis of the Mar Menor in 2021 in terms of tourist mobility.

This study was conducted to address the following research questions (RQs):

RQ1. Is there a relationship between ecological conditions in the Mar Menor lagoon and fluctuations in tourist arrivals over an eleven-year period based on statistical data?

RQ2. Do sentiment analysis patterns correspond with changes in economic indicators and ecological conditions on the Mar Menor lagoon?

RQ3. What patterns can be identified in tourist mobility in the region in relation to ecological changes in the Mar Menor lagoon?

This paper is structured as follows. Section 2 reviews the related literature, while section 3 highlights the background and problems related to the Mar Menor. Section 4 presents the research methodology

and the data used for the study. Section 5 presents the results. Discussion in section 6 debates the main results, while section 7 summarises the key findings and limitations along with future work lines.

2. Literature Review

2.1 Tourist Behaviour under Environmental Crises

Environmental crises pose a severe threat to destination sustainability and local economies. To understand how these crises affect tourism demands, there are some theoretical foundations in the literature that can be used to link environmental degradation with tourists' psychological and behavioral responses. Two main frameworks in this line are the Theory of Planned Behavior (TPB) (Ulker-Demirel & Ciftci, 2020) and Protection Motivation Theory (PMT) (Suess et al., 2024).

Under the TPB, behavioral intentions are shaped by attitudes, subjective norms, and perceived behavioral control. When an environmental crisis damages a destination's image, it acts as a significant "travel constraint," altering the tourist's positive attitude toward the location and reducing their willingness to recommend or revisit it (Awais-E-Yazdan et al., 2025). On the other hand, PMT explains how individuals evaluate risks and make protective travel decisions. PMT operates through a dual-appraisal system: threat appraisal (evaluating the severity and personal vulnerability associated with a crisis) and coping appraisal (assessing self-efficacy and response costs). When perceived ecological risk exceeds their coping capacity, tourists engage in protective behaviors, such as "spatial substitution" (choosing alternative, less contaminated destinations) or canceling planned trips (Smolčić Jurdana & Agbaba, 2025).

Consequently, modern crisis management in environmental tourism must move beyond physical ecosystem remediation; it must address how administrative and safety responses shape risk perceptions to prevent long-term socioeconomic decline.

2.2 Social Sensing and Sentiment Analysis during Environmental Disruptions

To evaluate public perception and the subsequent reputational damage caused by environmental crises, researchers have turned to social sensing (Wang et al., 2015). Social sensing leverages human-centric data streams to capture public opinions, feelings, and behavioral reactions in real time. Microblogging platforms, particularly Twitter (Now 'X', hereafter referred to consistently as Twitter to align with the historical nature of the 2010–2022 dataset and standard terms such as 'tweets'), serve as valuable public forums where tourists and residents openly express satisfaction or distress during ecological anomalies (Paolanti et al., 2021).

Current studies address this topic by utilizing advanced Natural Language Processing (NLP) pipelines. To map shifting public discourse during crises, topic modelling such as Latent Dirichlet Allocation (LDA) are used to automatically group millions of messages into thematic clusters (Correia-Loureiro et al., 2021). These topic modeling structures are combined with deep learning architectures like Bidirectional Encoder Representations from Transformers (BERT) to classify sentiment polarities as positive, neutral, or negative during disruptions like bushfires, earthquakes, and toxic spills (Yan et al., 2020; Willson et al., 2021; Viñán-Ludeña & de Campos, 2022).

These studies demonstrate that public online sentiment behaves as an early indicator of tourism demand. While online perception remains relatively stable during minor environmental events, acute crises (e.g., mass marine mortality) spark rapid, persistent increases in negative sentiment that correlate directly with declines in tourism destinations (Sánchez-Franco & Rey-Moreno, 2021; Wang et al., 2025). Social sensing thus acts as a virtual reflection of real tourism behavioral changes (Kurniawan et al., 2025).

2.3 Human Mobility Tracking

While social sensing captures cognitive perceptions, tracking technologies are required to map the physical spatiotemporal changes in tourist flows during crises. Literature in tourism geography identifies a methodological transition from active tracking to passive digital tracking (Schmücker & Reif, 2022).

Active methodologies, like travel diaries, often face limitations due to recall bias and low spatial resolution (Vu et al., 2020). In contrast, passive tracking utilizes network-level cellular data to capture macro-level human mobility (Möhring et al., 2021; Xu et al., 2021a). Passive mobile positioning data allow researchers to monitor tourist densities, calculate stay durations, and identify spatial clusters across extensive regions without active user intervention (Xu et al., 2021b). Recent studies highlight the value of combining passive mobile data with social media indicators to construct complete profiles of tourist behavior (Kovács et al., 2021).

During destination disruptions, human mobility analyses demonstrate that crises alter physical travel routes, generate structural breaks in traveler volume, and accelerate departure rates (Park et al., 2022). Applying structural break and change-point algorithms to high-frequency mobility datasets allows researchers to identify the exact moments tourist patterns deviate from baseline seasonality during health emergencies or environmental shocks (Czarnecki et al., 2023). However, mapping these physical flow anomalies to ecological changes is still an emerging domain, particularly within highly sensitive coastal ecosystems.

2.4 Identified Gaps

Existing literature has established that environmental degradation impairs destination attractiveness and tourist satisfaction, while social media sentiment tracking and human mobility analysis offer valid real-time tools to assess public perception and spatial behaviors during crises. However, what remains unknown is how these distinct dimensions interact and evolve together across the progressive phases of long-term environmental degradation. Previous research typically evaluates these factors in isolation, leaving a gap in understanding the temporal alignment between arrivals, subjective online discourse, and rapid destination departures. This study addresses this gap by presenting a multidimensional analysis that integrates economic statistics, online social sensing, and physical mobility analysis to provide a holistic assessment of tourist behavior during successive ecological crises in the unique Mar Menor environment.

3. Background

The Mar Menor is the largest hypersaline coastal lagoon of the Mediterranean basin with a surface area of 135.5 km², a coastline of 74 km (Belando et al., 2021). It is one of the ecosystems with higher ecological and socioeconomic importance of the region. It took part in several protected area networks established by regional, international, and European laws (Martínez Dalmau, 2023).

Figure 1 indicates the municipalities that surround Mar Menor: San Pedro del Pinatar (Lo Pagán and Los Cuarteros), San Javier (Santiago de la Ribera and a large part of La Manga), Los Alcázares and Cartagena (El Carmolí, Los Urrutias, Los Nietos, Islas Menores, Mar de Cristal, Playa Honda, Playa Paraíso and part of La Manga).

Figure 1. Map of the Mar Menor Lagoon and its Surrounding Municipalities

Source: Región de Murcia Digital Integra (n.d.)

Since the early 20th century, the Mar Menor's ecosystem started to change due to mining, agricultural runoffs, urban effluents, and fast-growing tourism in the area (García-Ayllón, 2018). The apparent colour of the lagoon's water changed from blue to greenish in the summer of 2015, when the excess nutrients triggered algal blooms (Lamas Rodríguez et al., 2023). This change was considerably more noticeable at the beginning of 2016 and sparked a widespread complaint from the tourism industry.

A cold drop of isolated high-level depression (DANA) struck Southeast Spain in September 2019, particularly affecting the Region of Murcia. Prolonged and intense precipitation resulted in extensive floods, grave destruction, and an overall impact on the entire populace. Pollutants build up more in these semi-enclosed bays than in open waters. An estimated 500–1.000 tonnes of nitrates, 35 tonnes of ammonium, and more than 100 tonnes of phosphates were released into the lagoon during the DANA episode which caused the huge influx of nutrients that had accumulated in the watershed and led to a significant loss of the biodiversity of the Mar Menor (RTVE., 2021). This episode repeated in summer of 2021 when the beaches of the Mar Menor were full of hundreds of dead fish.

The Mar Menor catastrophe is not just one single episode. The Mar Menor lagoon has been suffering from environmental degradation - due to the excess of nutrients in the waters for a long time (Pérez-Martín, 2023).

4. Methodology

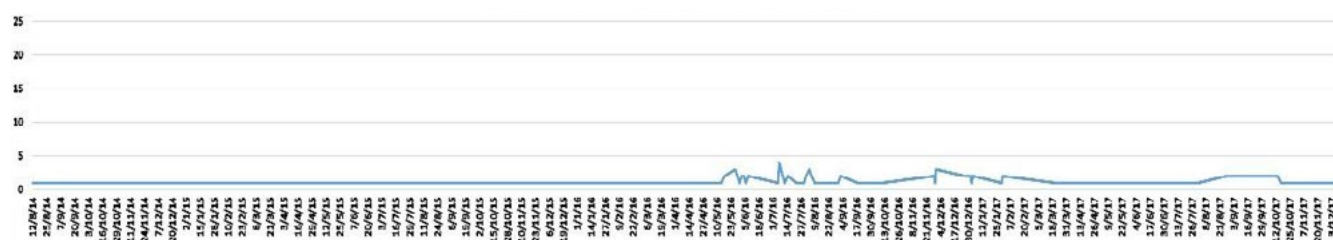
4.1 Relevant Dates of Episodes of Ecological Crisis in Mar Menor

To study the impact of the various ecological crises on the three tourism dimensions under consideration, namely economic, social, and mobility, we first identified the time periods of each crisis to analyse them

separately and then compared the observed effects. We relied on the publication of news about environmental problems occurred in Mar Menor since 2014 to 2021 in 3 regional newspapers (La Opinión de Murcia, La Verdad and Murciaplaza), 6 Spanish national newspapers (including the internationally prestigious “El País”) and 6 international newspapers and news agencies (Environmental Justice Atlas, Euro Weekly News, Express, BBC, The Guardian and National Geographic).

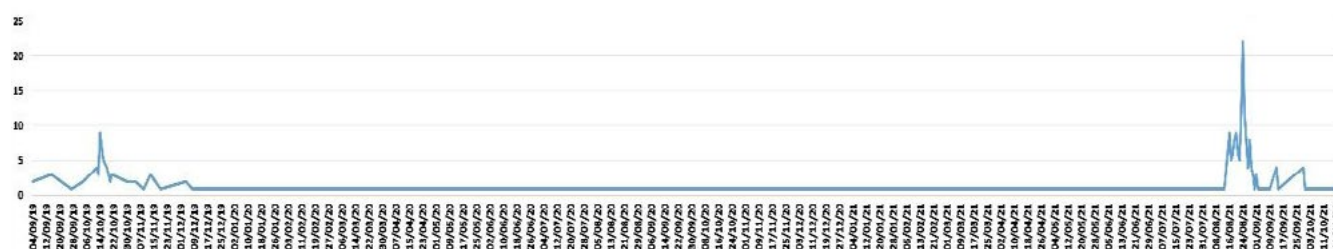
Figure 2 and 3 show the timeline of the total numbers of news found in these sources during those 7 years. As observed, it is possible to identify three intervals with different levels of impact and duration of news coverage related to ecological problems in the Mar Menor. The details of each interval are given next.

Figure 2. Number of News from August 2014 to December 2017



Source: Own Elaboration

Figure 3. Number of News from September 2018 to October 2021



Source: Own Elaboration

Phase 1 (May 2016-November 2017): This phase represents the first appearance of an ecological crisis on the media, although with a very low relevance according to the total number of news. It is observed a continuous series of publications, which involved several warnings about the degradation and extreme turbidity of the Mar Menor at that time. According to the news, it was observed that 85% of the initial extension of marine meadows had been lost. At the beginning of 2017, thousands of dead molluscs and sea cucumbers started to appear in the waters of Mar Menor and on its shores. Moreover, NASA images highlighted on the news a strong colour contrast between the Mar Menor lagoon and the Mediterranean Sea. Thus, this first crisis resulted in water in the Mar Menor turning green, a significant increase in turbidity levels and the death of some types of marine life.

Phase 2 (September 2019-December 2019): A second ecological crisis is detected at the end of 2019, with a moderate relevance on the media. In this crisis, the appearance of thousands of dead fish confirmed a new ecological catastrophe. The event was attributed to a large volume of fresh water, laden with sediments and organic matter, that was displaced by torrential rainfall. This event was commonly referred to as the cold drop of isolated high-level depression (DANA), which left marine life without oxygen. The media's focus on this crisis had a shorter duration than in the first occurrence.

Phase 3 (August 2021-October 2021): The third ecological crisis has showed the highest relevance in the media until now, again during a short period. It was covered not only in local/national newspapers, but also in international ones. In this crisis, hundreds of small fish appeared dead on the shores of the

beaches adjacent to the Mar Menor. The Regional Government of Murcia and researchers from the Polytechnic University of Cartagena initially rejected anoxia as the cause of aquatic fauna mortality, in contrast to the 2019 crisis, while environmental organisations attributed the event to aquifer over-exploitation and intensive agriculture.

Note that, between these intervals, there are silent periods in the news about any environment problems in the Mar Menor: August 2014–May 2016 (before the first crisis), December 2017–August 2019 (time lapse between the first and second crises) and January 2020–July 2021 (between the second and third crises). In this latter silent period, other news related to the Mar Menor highlighted the measures that the authorities and the people from Mar Menor were taking to improve the conditions of the lagoon, for example, achieving that the Mar Menor became a legal entity.

The following subsections delve into the impact of the identified crises in the Mar Menor from an economic, social, and tourist mobility perspective.

4.2 Economic Data

To assess the impact of the Mar Menor crises from an economic perspective, we analysed official statistical data on the number of travellers and overnight stays in the Mar Menor area. These statistical data was provided by the National Institute of Statistics (INE) by means of surveys on hotels' occupancy, in collaboration with the Regional Statistics Centre of the Murcia Region and the services of the Ministry of Tourism, Business and Innovation. The data is available on the Murcian Institute of Tourism's website (<https://www.itrem.es/itrem/estadistica>). According to the INE, the statistical data related to the tourism in the Mar Menor area involve the following towns: El Algar, Torre Pacheco, Los Urrutias, Los Alcázares, San Pedro del Pinatar, San Javier, Los Nietos, Los Belones and Cabo de Palos, which are in the proximate vicinity to the coastal lagoon.

Moreover, we modelled the monthly series of travellers (natural-log scale) within an interrupted time-series (ITS) (Box & Tiao, 1975; Bernal et al., 2017) to isolate the ecological degradation effect from the COVID-19:

$$\ln(Y_t) = \beta_0 + \beta_1 \cdot t + \beta_2 \cdot t^2 + \sum \gamma_m \cdot \text{Month}_m + \theta_1 \cdot \text{Lockdown}_t + \theta_2 \cdot \text{Restrictions}_t + \delta_1 \cdot \text{Phase1}_t + \delta_2 \cdot \text{Phase2}_t + \delta_3 \cdot \text{Phase3}_t + \varepsilon_t$$

where t is a linear trend; Month are eleven calendar-month indicators capturing seasonality; Lockdown and Restrictions capture the COVID-19 disruption (March–June 2020 and July 2020–December 2021); and Phase1–Phase3 are previously described intervals. Standard errors are heteroskedasticity- and autocorrelation-consistent (HAC) following Newey and West (1987), using 12 lags. The post-2021 ecological effect is identified from the post-pandemic period that started in 2022. We complemented this with a pre-pandemic subsample (2012m1–2020m2, $n = 98$) that isolates the 2016 and October-2019 events free of COVID-19; a seasonal ARIMA model with intervention regressors (SARIMAX(1,0,0)(0,1,1)₁₂); and a pre-pandemic counterfactual with a 95% prediction interval. Analyses were run in Stata 16 software.

4.3 Social Sensing Data

Beyond traditional tourism indicators, social sensing based on Twitter data was incorporated to analyse how environmental degradation of the lagoon is reflected in public discourse online.

As part of the SMARTLAGOON project mentioned in the introduction, a tool named SensingTools has been developed to measure the social impact of political, economic and/or environmental actions on the citizens living in the vicinity of the Mar Menor. SensingTools analyses the messages posted by users on Twitter since 2010 about the Mar Menor. These tweets have been collected through the Twitter Academic Research API.

We implemented a filtering procedure to identify tweets relevant to the Mar Menor ecological crisis. Tweets were classified according to three contextual groups based on the presence of specific location-related keywords. The first context (C_1) includes tweets explicitly mentioning “Mar Menor” or “#MarMenor”.

The second context (C_2) comprises tweets referring to lagoon-side towns within the Mar Menor basin that are closely associated with the environmental crisis. More specifically, the keywords added to C_2 are: “San Javier”, “Los Alcázares”, “La Manga”, “Lo Pagan”, “Los Narejos”, “Santiago de la Ribera”, “Los Cuarteros”, “Las Lomas del Rame”, “El Carmolí”, “Bahía Bella”, “Los Urrutias”, “Los Nietos”, “Islas Menores”, “Mar de Cristal” and “Playa de la Llana”. The third context (C_3) includes tweets mentioning the main nearby urban centres, Murcia and Cartagena. After applying these contextual filters, the proportion of false positives within each group was evaluated to estimate the number of relevant messages for each context.

The proportion of false positives was assessed through a manual labelling process carried out using the SensingTools application. A random sample of 500 tweets was extracted from each contextual group and manually reviewed by several experts and local citizens familiar with the Mar Menor area. Tweets were considered false positives when they did not express concern about the Mar Menor ecological crisis, did not refer to the environmental degradation of the lagoon, or were unlikely to affect other users’ perception of the crisis. This manual validation was necessary because the interpretation of local toponyms is highly context-dependent and may vary depending on the geographical and social knowledge of the annotators.

After selecting the most suitable context for the analysis, the tweet corpus was preprocessed to reduce noise. First, highly repetitive messages and near-duplicate tweets posted by the same users were removed using a text-similarity threshold of 0.8, corresponding to more than 80% similarity. Second, messages not written in Castilian Spanish were excluded because the topic modelling pipeline is sensitive to linguistic heterogeneity and the subsequent sentiment analysis was designed for Spanish-language content. Finally, tweets were normalised by converting text to lowercase and removing URLs, punctuation marks, emojis and digits.

Topic discovery was then performed on the preprocessed tweet corpus using BERTopic (Grootendorst, 2022), with the aim of identifying the main themes discussed in relation to the Mar Menor and, subsequently, isolating those topics related to tourism. BERTopic is a topic modelling framework that generates coherent topics from textual data through a multi-step pipeline. First, document embeddings are generated from the tweets using a pre-trained transformer-based model from the Sentence-BERT framework (Reimers & Gurevych, 2019). These embeddings represent tweets as dense vectors, allowing messages with similar semantic content to be located close to each other in the embedding space. The dimensionality of these embeddings is then reduced using UMAP (McInnes et al., 2018), which preserves relevant structures from the original high-dimensional representation. Next, HDBSCAN (Malzer & Baum, 2020) is applied to cluster semantically similar tweets and identify groups of messages corresponding to different topics, while also allowing outliers to be modelled. Finally, topic representations are generated using a class-based TF-IDF matrix (Sammur & Webb, 2010), which identifies the most representative terms for each topic. In this study, BERTopic was used exclusively for topic discovery and for identifying tourism-related tweets; sentiment polarity was assigned afterwards as a separate classification task.

Sentiment polarity was then used to characterise the tone of tourism-related messages. Polarity assignment was performed within the SensingTools pipeline using the multilingual Twitter-XLM-RoBERTa-base sentiment model developed by CardiffNLP (Barbieri et al., 2022), a transformer-based model adapted to social media text. According to the original model evaluation, this architecture achieves an F1-score of 68.5 when trained and evaluated on Spanish tweets. Each tourism-related tweet was classified into one of three categories: positive, neutral, or negative. Positive tweets were defined as those expressing favourable perceptions of the Mar Menor as a tourist destination, including enjoyment, satisfaction, recommendation, promotion of tourism activities, or positive references to local attractions. Negative tweets were defined as those expressing criticism, concern, dissatisfaction, or adverse perceptions associated with the ecological crisis, environmental degradation, water quality, loss of attractiveness, or the negative impact of the crisis on tourism. Neutral tweets corresponded to descriptive, informative, promotional, or ambiguous messages without a clearly identifiable positive or negative stance.

4.4 Mobility Data

Another important factor to measure the impact of crises in the Mar Menor is the analysis of its tourist mobility. Regarding the data related to this factor, the Spanish Ministry of Transportation (SMT) provides a

nation-wide human mobility dataset reporting displacements in Spain since February 2020 (<https://www.mitma.es/ministerio/covid-19/evolucion-movilidad-big-data/opendata-movilidad>). Given the time period covered by our study, this official dataset allows us to evaluate the impact of the Phase-3 crisis of the Mar Menor in terms of tourist mobility. Note that the SMT is the only public institution providing an open dataset on human mobility covering the Spanish territory. As it only covers the period from February 2020 onwards, it is not feasible to perform a similar study for the previous crisis in 2017 and 2019.

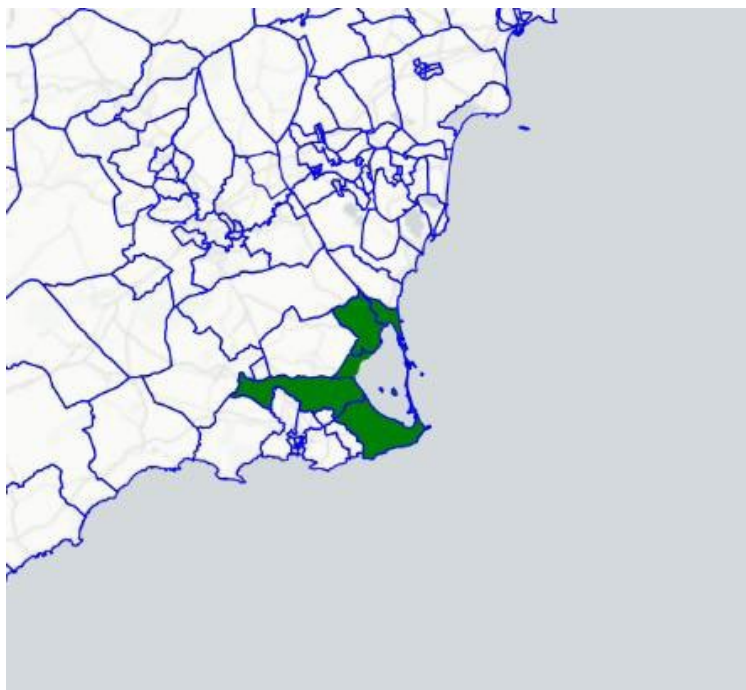
In terms of data format, the mobility dataset provides information on the number of trips among 3216 ad-hoc administrative areas (hereby Mobility Areas, MA) per hour in Spain, including both its peninsular and insular extension. A single trip represents the spatial displacement of an individual covering a distance greater than 500 meters. Consequently, this dataset could be regarded as a set of tuples, each following the format

$$\langle date, hour, m_{(origin)}, m_{(dest)}, a_{(origin)}, a_{(dest)}, n_{(trp)}, dist \rangle$$

reporting that there were $n_{(trp)}$ human trips from the MA $m_{(origin)}$ with $a_{(origin)}$ as primary activity to the MA $m_{(dest)}$ with $a_{(dest)}$ as primary activity and whose distance were $dist$ km during the indicated date and hour. Regarding the primary activities, the study only indicates home, work and other as possible values. As a result, the study distinguishes flows related to frequent movements (e.g. home-to-work trips) or infrequent ones (e.g. work-to-other trips).

In this work, we focus our analysis on the 5 MAs that are next to the Mar Menor sea. Figure 4 shows these MAs in green along with the spatial boundaries of their surrounding MAs as blue lines.

Figure 4. Map Showing the Target MAs of the Mobility Study in Green. The Boundaries of the Surrounding MAs are Shown as Blue Lines



Source: Own Elaboration

The following section presents the main results of the analyses described above, which contribute to addressing the research questions of this study.

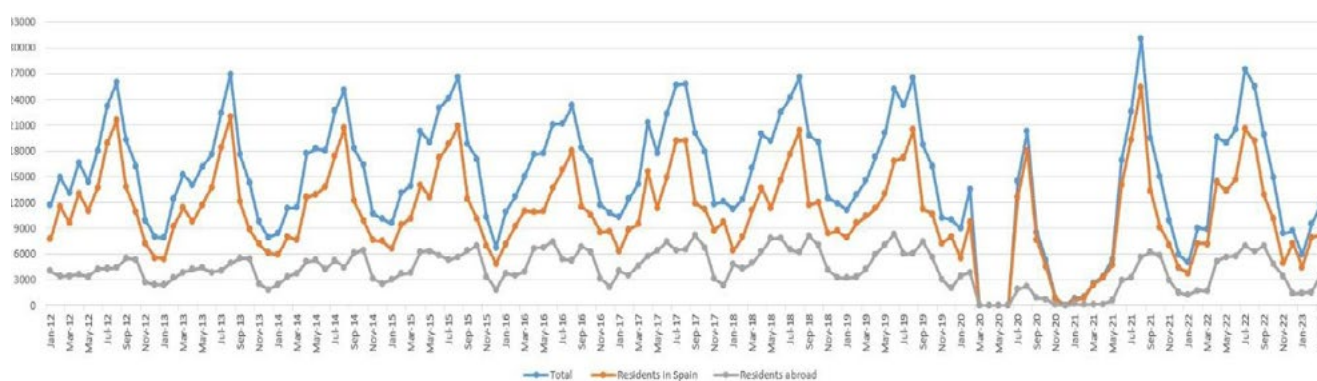
5. Findings

5.1 Economic Outcomes

This section presents the results of the tourism data analysis, highlighting the evolution of travellers and overnight stays in the Mar Menor area over the eleven-year period, with the aim of addressing Research Question 1.

Figure 5 and Figure 6 show the timeseries with the number of travellers and overnight stays from 2012 to 2022 in the Mar Menor area, grouped by their country of residence. As defined by the INE, travellers refer to “individuals who have made one or more consecutive overnight stays in the same accommodation”, while overnight stays are each night that a traveller stays at the establishment. Seasonality strongly shapes tourist arrivals, with peak flows in August for Spanish residents, while foreign visitors peak mainly in September–October, with some other relevant peaks in June 2016 and June 2019.

Figure 5. Timeseries with the Number of Travellers in the Area of Mar Menor

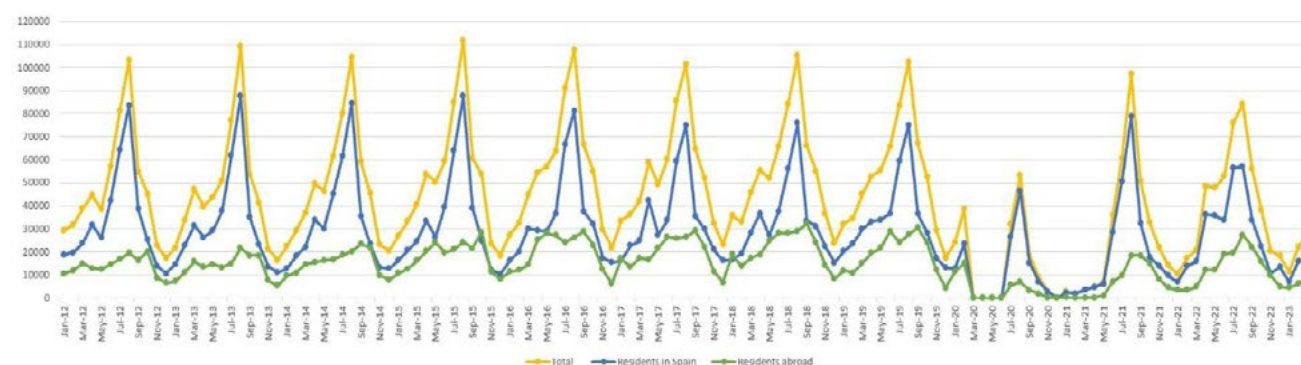


Source: Own Elaboration

Regarding the periods of crises in the Mar Menor, a first significant decline occurred in August 2016, where both the total number of travellers and Spanish residents experienced a 13% decrease (from 26,614 total travellers in 2015 to 23,284 in 2016). According to Figure 2, the highest concentration of news related to the onset of the first crisis took place in July and August 2016.

The next decrease of 6% was observed in September 2019, which continued in the following month, with a 14.5% decrease in the total number of tourists and with a decline of 8.6% in overnight stays compared to October 2018. Those negative trends coincided with the Phase-2 crisis of the Mar Menor, when the marine life of the coastal lagoon was left with no oxygen and started to die out (Figure 3).

Figure 6. Timeseries with the Number of Overnight Stays in the Mar Menor Area

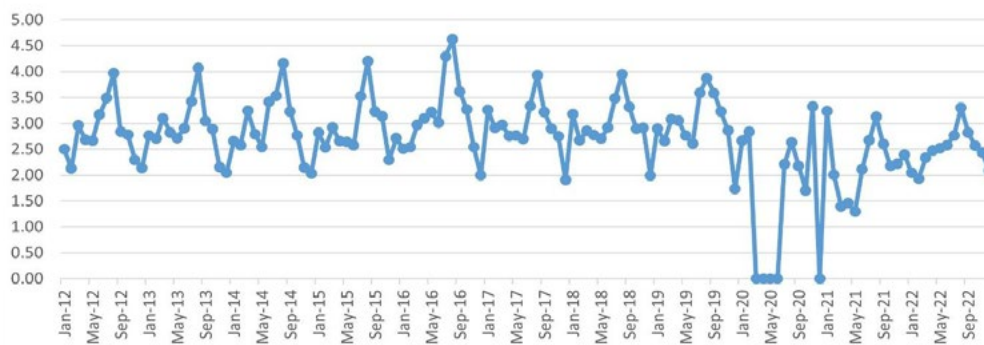


Source: Own Elaboration

In 2020, a significant decrease in the number of travellers occurred due to the impact of the Covid-19 pandemic. Therefore, it is more appropriate to compare the data from 2021 with that of 2019. In August 2021, there was a noticeable increase in the number of travellers. However, in October of the same year, there was a decline of 7.7% in the total number of tourists and a decrease of 37.7% in overnight stays in the Mar Menor area. The reduction in the number of travellers could have been impacted by the Phase-3 crisis, which consequences were discussed until the end of October in both national and international news (Figure 3). In August 2022, both the total number of tourists, the number of Spanish residents and total number of overnight stays experienced a decline of 18%, 24.5% and 13%, respectively, when compared to August 2021.

Finally, Figure 7 shows the duration of the average stay in the hotels of Mar Menor. It is calculated as the ratio of overnight stays to the number of travellers. From 2012 to 2015, the average stay rates ranged from 4 to 4.2 days. However, in the summer of 2016, there was a noticeable increase, with Figures rising by 15% compared to the previous years. Nevertheless, from 2017 to 2019, the average stay number declined and fell below 4 days. Lastly, compared to August 2019, summer indicators in 2021 and 2022 remained lower, with average stays decreasing by 19% and 14.5%, respectively.

Figure 7. Timeseries with the Number of Average Stay of Travellers in the Mar Menor Area



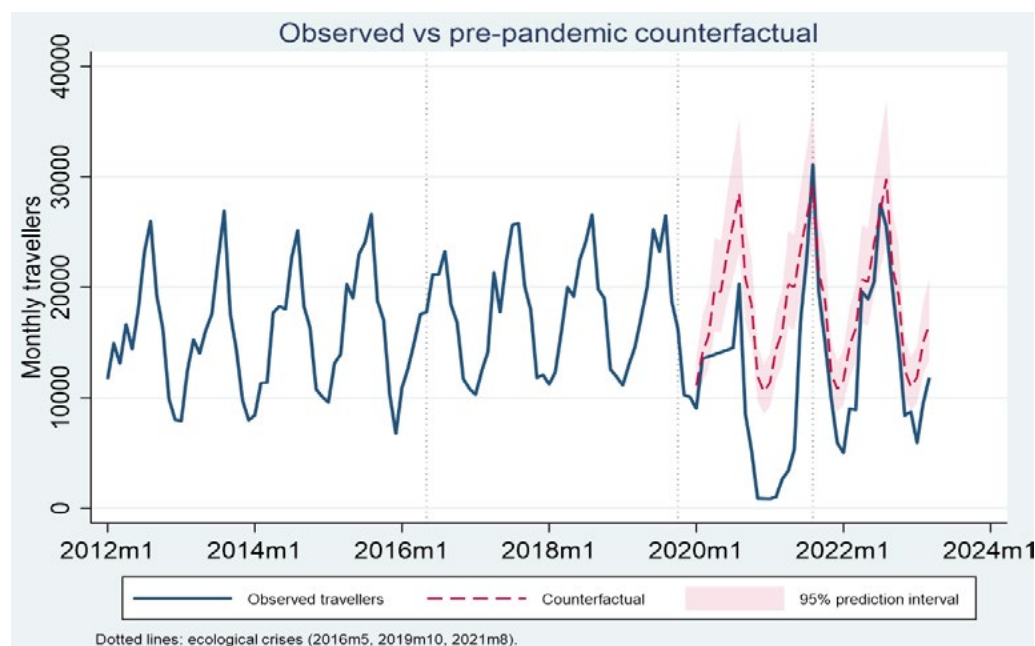
Source: Own Elaboration

After visual timeline comparison, to better quantify the relationship between ecological crises and declines in tourism indicators we applied time series techniques, which estimated effects are summarised in Table 1. Phase 1 showed no significant effect on travellers (+2.4%, $p = 0.57$). Nevertheless, October 2019 (Phase 2) is associated with a significant reduction of 12% (−12.4%, $p < 0.001$), estimated on pre-pandemic interval. The August 2021 event (Phase 3) could not be separated from the pandemic: its coefficient is non-significant once COVID-19 controls are included ($p > 0.10$). The pre-pandemic counterfactual (Figure 8) observed travellers 40% below trend in 2021 and 18% below in 2022, so the 2021–2022 decline cannot be attributed specifically to the ecological crisis with single-destination data.

Table 1. Estimated Effects on Monthly Travellers

Event / shock	Window	Model	Effect	p -value
Phase 1 — 2016 eutrophication	Pre-COVID	ITS (quadratic trend)	+2.4%	0.57 (n.s.)
Phase 2 — Oct 2019 mortality	Pre-COVID	ITS (quadratic trend)	−12.4%	< 0.001
Phase 3 — Aug 2021 mortality	Full sample	ARIMA intervention	+33.0%	0.60 (n.s.)
COVID-19 restrictions	Full sample	ARIMA intervention	−34.6%	0.011
2021 vs counterfactual	2021	Pre-pandemic projection	−40.1%	outside 95% PI
2022 vs counterfactual	2022	Pre-pandemic projection	−18.4%	within 95% PI

Source: Own Elaboration. n.s. = not significant; PI = prediction interval. Effects are multiplicative (percentage) changes derived from log-linear coefficients

Figure 8. Monthly Travellers Versus the Pre-Pandemic Counterfactual

Source: Own Elaboration. 95% prediction interval. Vertical dotted lines mark the three ecological crises; the model controls for COVID-19

Moreover, we applied the same models to the other two indicators – overnight stays and average stay (Table 2). In the pre-pandemic interval, the October 2019 event significantly reduced both travellers (–12.4%) and overnight stays (–7.8%, $p = 0.02$), while average stay was not affected. Phase 1 again showed no adverse effect, and the COVID-19 period depressed all three indicators (overnight stays –55%, $p = 0.006$; average stay –15%, $p = 0.04$).

Table 2. Ecological-crisis Effects Across the Three Outcomes (Clean Pre-Covid Estimates)

Outcome	Phase 1 — 2016	Phase 2 — Oct 2019
Travellers	+2.4% (n.s.)	–12.4% ($p < 0.001$)
Overnight stays	+8.9% ($p = 0.001$)	–7.8% ($p = 0.02$)
Average stay	+6.4% (n.s.)	+5.2% (n.s.)

Source: Own Elaboration

5.2 Social Sensing Outcomes

With the three contexts defined, the number of tweets retrieved for each context was compiled together with the corresponding percentage of false positives. Table 3 shows that the percentage of false positives increased as the context expanded, indicating that broader geographical filters retrieved a higher proportion of messages unrelated to the Mar Menor ecological crisis. The baseline context, C_1 , which only considered tweets explicitly mentioning “Mar Menor” or “#MarMenor”, retrieved 30,235 tweets and showed a false-positive rate of 32.2%. Context C_2 , which also included lagoon-side towns, retrieved 65,999 tweets and showed a false-positive rate of 43.0%. Finally, context C_3 , which additionally included Murcia and Cartagena, retrieved 835,614 tweets but reached a substantially higher false-positive rate of 82.6%.

It is also important to note that the number of retrieved tweets increased substantially as more location-related terms were included. Context C_2 more than doubled the number of tweets retrieved by C_1 , while C_3 retrieved more than 27 times the number of tweets obtained with C_1 . However, this increase in volume came at the cost of a much higher proportion of false positives. Based on these results, C_2 was selected as the final context for the analysis. This context increased the number of potentially relevant tweets compared with C_1 while maintaining a considerably lower level of noise than C_3 . Moreover, C_2 in-

cludes the neighbouring towns most directly affected by the ecological crisis, particularly in relation to its potential effects on tourism activities. In contrast, C_3 introduced substantial noise because many tweets mentioning Murcia or Cartagena were unrelated to the lagoon or to the environmental crisis.

Table 3. Ecological Evaluation Results for the Different Contexts Analysed

Context	Total messages	% False positives
C_1	30,235	32.2
C_2	65,999	43.0
C_3	835,614	82.6

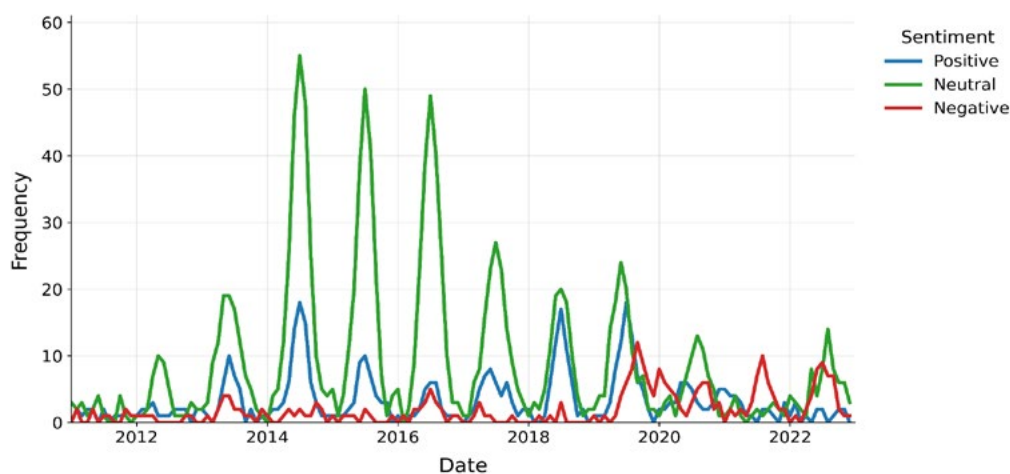
Source: Own Elaboration

After selecting C_2 , the corpus was preprocessed following the procedure described in Section 4.3. Highly repetitive messages and near-duplicate tweets from the same users were removed, resulting in the exclusion of 9.3% of the original tweets. In addition, more than 8,000 messages not written in Castilian Spanish were excluded to ensure linguistic consistency in the topic modelling and sentiment analysis pipeline. After all preprocessing steps, the final corpus contained 51,622 tweets.

BERTopic was then applied to the preprocessed C_2 corpus to identify the main topics discussed in relation to the Mar Menor. The model initially returned more than 500 topics, although only a limited number of them were directly related to tourism. Overall, 2,096 messages out of 51,622, corresponding to 4.1% of the final corpus, were assigned to tourism-related topics. These topics included terms associated with tourism activities and accommodation, such as “hotel”, “camping”, “resort”, and related expressions.

After identifying the tourism-related topics, sentiment polarity was assigned within the SensingTools pipeline following the criteria described in Section 4.3. Figure 9 shows the temporal distribution of tourism-related tweets according to their polarity classification. Since 2014, tourism-related tweet activity showed a seasonal pattern, with higher activity during the summer months and lower activity during the winter. A decrease in tourism-related tweets was observed in 2017 and again in 2021. Regarding sentiment polarity, most summer peaks between 2014 and 2017 were dominated by neutral tweets. However, from late 2019 onwards, negative mentions related to tourism in the Mar Menor became more visible, coinciding with the second major ecological crisis affecting the lagoon.

Figure 9. Sentiment Analysis of Tourism-Related Tweets



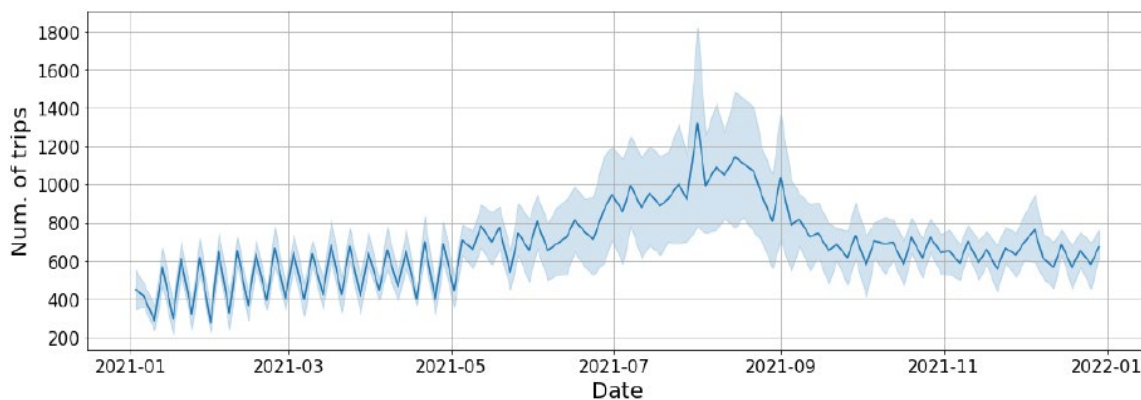
Source: Own Elaboration

5.3 Mobility Outcomes

To answer RQ3 and to measure the impact of crises in Mar Menor, we performed the analysis of tourist mobility, using a nation-wide human mobility dataset provided by the Spanish Ministry of Transportation (SMT).

The first step in the analysis was to extract the flows that corresponded to tourist trips (mobility movements exceeding 100 km in which the destination is neither the user's home nor workplace) towards such MAs from the dataset. To do so, we retained the mobility records that met the following two conditions: (1) $a_{dest} = \text{other}$ and (2) $\text{dist} \geq 100$. Thus, we only considered long displacements (distance higher than 100 km) whose destination was not a frequent spot for the travellers (destination activity neither home nor work). This filter removed 94.2% of the original mobility records in the dataset. As a result, Figure 10 shows the timeseries with the total number of daily incoming trips to each of the 5 MAs in the Mar Menor region. Let us call this timeseries dataset T_{2021} . Observe that the largest number of trips occurred during July and August. This is consistent with the tourist seasonality of the 5 target cities (Arroyo-Mompeán & Vegas-Juez, 2019).

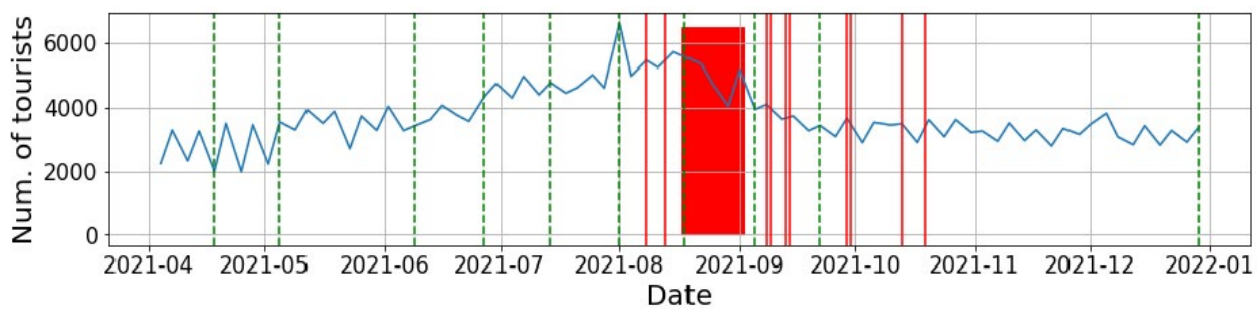
Figure 10. Timeseries with the Total Number of Incoming Trips to the Mar Menor Municipalities



Source: Own Elaboration. The dark blue line indicates the average value of all the MA whereas the bluish area around the line indicates the 95% confidence interval

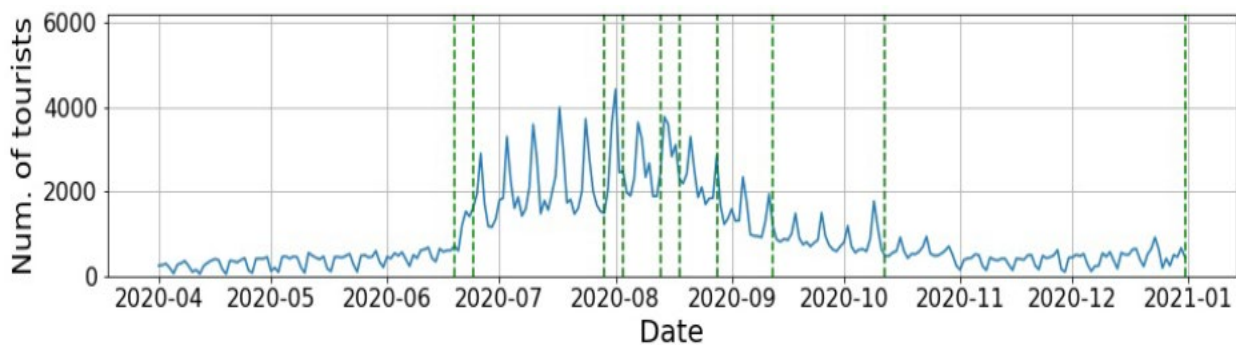
Next, we computed the change points of T_{2021} , i.e., the points where the timeseries meaningfully changed. These points were calculated following a bottom-up strategy (Fryzlewicz, 2007). More in detail, this algorithm starts with a maximum number of change points and gradually deletes the less significant ones. In this manner, the timeseries is divided into many sub-signals along a regular grid. Subsequently, contiguous segments are merged one by one, considering a measure of their similarity. By means of these breakpoints, we were able to detect the moments throughout the year where the arrival of tourists experienced a meaningful change.

Figure 11(a) shows the break points detected in T_{2021} as dashed green lines. The vertical red lines in 11(a) indicate the dates when a piece of news about the Mar Menor was published. The vertical dashed green lines indicate the breakpoints of each timeseries. Bearing in mind the crisis in Phase 3 (August 2021-October 2021), the algorithm detected 3 different points on 2021-08-18, 2021-09-05 and 2021-09-22. This reveals that during the second half of August and September, the arrival of tourist to the Mar Menor region had some relevant shifts.

Figure 11(a). Tourist Mobility in the Mar Menor in 2021

Source: Own Elaboration

Furthermore, we compared these breakpoints with those related to the tourist flow in 2020, T_{2020} (see Figure 11(b)). This timeseries was extracted from the human mobility dataset released by the Spanish Institute of Statistics (INE), which covered the year 2020. The dataset utilized the same Mobility Areas (MA) tessellation as defined in the SMT (https://www.ine.es/experimental/movilidad/experimental_em4.htm). Since the INE dataset did not include the origin and destination activities of the trips, we applied the same 100-km filtering criteria than for T_{2021} to compose the final timeseries. We obtained some interesting findings from this comparison. First, the number of breakpoints in August and September of 2020 was slightly higher than in 2021: there were 5 breakpoints (2020-08-03, 2020-08-13, 2020-08-18, 2020-08-28, 2020-09-12, 2020-10-12). This reflects a different pattern in the arrival of tourists during these months, particularly in the latter half of August. Indeed, T_{2021} only involved 1 breakpoint (2021-08-18), whereas there were 3 in T_{2020} (2020-08-13, 2020-08-18, 2020-08-28).

Figure 11(b). Tourist Mobility in the Mar Menor in 2020

Source: Own Elaboration

To delve deeper into this finding, Table 4 shows the slope of T_{2021} between consecutive breakpoints. For example, the slope of the linear curve fitting the slice of T_{2021} between 2021-08-18 and 2021-09-05 was -0.111. This table provides valuable insights into the rate of increase or decrease in tourist arrivals during specific time intervals. Additionally, we have included the corresponding slopes of T_{2020} for comparison. It is important to note that the slopes in the table have been calculated based on the normalized version of the timeseries. Thus, the negative values of all the slopes presented in Table 4 are consistent with the visual pattern depicted in Figure 10(a) and 10(b), indicating a steady decline in tourist arrivals from August 18th to October 19th in both years.

Table 4. Slopes of the Tourists' Timeseries for the Time Periods between Break Points

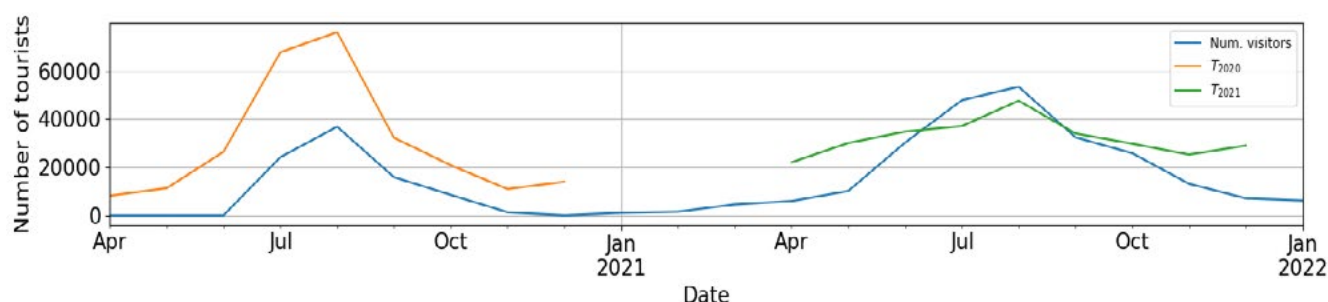
Period (month-day)	T ₂₀₂₁ slope	T ₂₀₂₀ slope
08-18→09-05	-0.111	-0.099
09-05→09-22	-0.135	-0.080
09-22→10-19	-0.022	-0.033
08-08→10-19	-0.041	-0.038

Source: Own Elaboration

As shown in Table 4, the slopes in the first two slides (08-18→09-05 and 09-05→09-22) were more negative in 2021 than in 2020. This indicates that tourists left the Mar Menor region in 2021 at a faster pace during the last two weeks of August and the first of September than in the previous year. It is worth mentioning that these 3 weeks coincided with the central period of the Phase 3 crisis of the Mar Menor, during which a significant number of articles were published in the media. Finally, the last row of Table 4 shows the slope of both timeseries covering the whole time period of the Phase 3 crisis. In this case, the slope of T₂₀₂₁ (-0.041) was slightly more negative than the one in the same period of 2020 (-0.038). This confirms that, in global terms, the decrement of tourist arrivals during the Phase-3 crisis was slightly faster than in the previous year.

Finally, to validate the reliability of the human mobility flows used in this study, they were compared with the official number of visitors to the municipalities of the Mar Menor reported by the Tourism Office of the Region of Murcia (https://www.turismoregiondemurcia.es/es/estadisticas_de_turismo?pagina=viajeros-y-pernoctaciones-segun-destinos). In this regard, Figure 12 shows this visitor flow alongside the mobility flows previously analysed. The Pearson correlation between this visitor flow and the human mobility series T2020 and T2021 was 0.949 and 0.900, respectively. This indicates that both mobility flows reliably capture touristic-related movement within the target geographical area.

It is important to note that the aforementioned official tourist flow presents significant limitations that prevent its use as the primary data source for this study. First, it has a monthly granularity, which precludes a weekly analysis such as that conducted using the mobility flows. Second, the dataset does not include data from March to June 2020, a period that is particularly relevant for the intended analysis.

Figure 12. Tourist Mobility in the Mar Menor in 2020 and 2021 along with the Official Number of Visitors

Source: Own Elaboration

6. Discussion

In this section we are going to answer the established Research Questions (RQs) and relate the results obtained with those of studies related to use of social media for measuring the effect of certain events and actions on the population and surroundings.

6.1 RQ.1: Is there a relationship between ecological conditions in the Mar Menor lagoon and fluctuations in tourist arrivals over an eleven-year period based on statistical data?

The analysis confirms a relationship between the ecological condition of the Mar Menor and tourism performance, measured through travellers, overnight stays, and average stay. Periods without major environmental disturbances show relatively stable tourism indicators, whereas ecological crisis phases coincide with declines across variables, in line with recent evidence linking eco-degradation to changes in tourist behaviour in the Mar Menor (Sarabia-Sánchez et al., 2025).

From 2016 onward, the number of travellers and overnight stays declined steadily after peaking in 2015, with the largest reductions among Spanish residents in 2017, corresponding to Phase 1 of the ecological crisis. However, when time-series models were applied, the observed variation in 2016 was not statistically significant. A further downturn was observed in late 2019, particularly in October, aligning with the Phase 2 environmental degradation of the coastal lagoon, when the number of travellers (-12,4%) and overnight stays (-7,8%) declined significantly, while the average stay remained stable. These patterns are consistent with previous findings showing that marine pollution in the Mar Menor reduces accommodation attractiveness and tourism intensity (Fernandez Ferrero et al., 2022).

After excluding 2020 due to the Covid-19 pandemic, tourism indicators did not recover to pre-crisis levels. Despite an increase in August 2021, which could not be separated from Covid-19 pandemic shock, subsequent months and the year 2022 exhibited renewed declines in travellers and overnight stays, particularly following the Phase 3 crisis. The persistence of these effects supports evidence that once environmental degradation becomes widely perceived, its economic consequences are long-lasting (Lamas Rodríguez et al., 2023).

6.2 RQ.2: Do sentiment analysis patterns correspond with changes in economic indicators and ecological conditions on the Mar Menor lagoon?

It is common among researchers to use social media data to study the sentiments and spatiotemporal behaviour of individuals. Twitter can be used to measure the impact of tweets on tourism (Ramanathan & Meyyappan, 2019; Paolanti et al., 2021; Ramya et al., 2021). Moreover, it allows researchers to trace visitors' satisfaction in natural areas (Becken et al., 2017; Hale, 2018), and shows the correlation between tourism and environment. It even helps to see the sentiments of people during critical events (Ruz et al., 2020). In our study we analysed the messages posted by users on Twitter since 2010 about the Mar Menor.

Since 2014, tweet activity related to the Mar Menor has followed a stable and clearly seasonal pattern, with higher volumes during the summer months and lower activity in winter. This behaviour reflects the strong seasonality of tourism demand in the area and suggests that social media discourse evolves in parallel with tourism dynamics. Notably, a reduction in tourism-related tweets was observed in 2017 and later in 2021, which corresponds with the declines identified in economic tourism indicators, including the number of travellers, overnight stays, and average length of stay during the same periods.

As we mentioned before, social media platforms such as Twitter have been widely recognised as valuable sources for capturing tourists' expressed sentiments, satisfaction levels, and overall perceptions of destinations through user-generated content (Paolanti et al., 2021; Kurniawan, et al., 2025).

In this regard, messages posted during the summer peaks between 2014 and 2017 were predominantly neutral, indicating a relatively stable perception of the destination despite the onset of environmental degradation. However, from late 2019 onwards, a gradual increase in negative tourism-related mentions was detected.

This shift coincides with the second ecological crisis and aligns with the deterioration observed in tourism demand indicators, reinforcing previous evidence that changes in online sentiment reflect broader perception shifts and behavioural responses in coastal tourism contexts (Wang et al., 2025).

Nevertheless, some methodological limitations of the social sensing analysis should be acknowledged. First, messages not written in Castilian Spanish were excluded to ensure linguistic consistency in the topic modelling and sentiment analysis pipeline. Although this decision improves the comparability of the analysed tweets, it may underrepresent the perceptions of international tourists, foreign residents, or users who discussed the Mar Menor in other languages. Therefore, the results should be interpreted

primarily as reflecting Spanish-language public discourse. Second, although the XLM-RoBERTa-based sentiment model used in the SensingTools pipeline reports an F1-score of 68.5 when trained and evaluated on Spanish tweets, no additional supervised training or corpus-specific validation was developed in this study. Creating such a benchmark would require the manual annotation of a sufficiently large sample of tweets, which is a subjective and non-trivial task due to the short length of tweets, the presence of irony or ambiguity, and the need for local knowledge to correctly interpret references to the Mar Menor ecological crisis. Consequently, polarity labels should be interpreted as indicators of the dominant tone of tourism-related discourse rather than as definitive individual-level sentiment annotations.

6.3 RQ.3: What patterns can be identified in tourist mobility in the region in relation to ecological changes in the Mar Menor lagoon?

To answer RQ3 and identify the mobility patterns in Mar Menor area, we performed the analysis of tourist mobility. While some researchers obtained GPS-based location data from mobile apps (Möhring et al., 2021) or car navigation systems, or data from cell phone towers (Schmücker & Reif, 2022), we used a nation-wide human mobility dataset provided by the Spanish Ministry of Transportation (SMT) since February 2020.

Moreover, tourism mobility analysis has contributed to tracking of the behaviour of tourists and its changes before, during and after crisis and disaster events, whether it's a health or economic crisis or an environmental issue. Park et al. (2022) and Czarnecki et al. (2023) ascertained behavioural changes in travel mobility of tourists in periods before and during such a massive issue as the COVID-19 pandemic. Our study aimed to see the relation between the Mar Menor crisis, and the movements of tourist flows in the area – tourists' altered behaviour. According to our findings travellers left the Mar Menor region in 2021 faster than in the previous year. The time of their leaving coincided with the central time period of the Phase 3 crisis of the Mar Menor. Our results also confirmed that, during the third phase of the crisis, the decline in visitor arrivals was quicker than it was the year before, which shows a clear mobility pattern related to the ecological changes of Mar Menor.

7. Conclusion

This study successfully demonstrates how tourism declines resulting from environmental degradation can be systematically measured and tracked across economic, social, and mobility dimensions. Focused on the Mar Menor crisis, our proposal shows that the ecological crisis phases of 2016, 2019, and 2021 coincided with declines in traveler arrivals and overnight stays. Social sensing demonstrated a sharp drop in tourism-related discourse and a rise in negative sentiment during these events. Finally, the mobility analysis corroborated these findings, indicating that the departure of tourists from the region was significantly accelerated during the 2021 crisis compared to the baseline trends of the previous year.

7.1 Theoretical and Practical Implications

The theoretical implications of this study lie in extending behavioral decision-making models to environmental crises by showing how risk assessments and threat evaluations translate into both cognitive online sentiment and physical mobility changes. Methodologically, this study demonstrates the value of integrating economic, mobility and social sensing data, offering a more complete framework than studies relying on single data sources. Practically, our framework provides the basis for an actionable tool for different actors to manage environmental crises. Thus, for stakeholders, the integration of public data streams serves as a proactive decision-making system to monitor tourism health alongside environmental indicators. Destination management organizations can utilize the social sensing and mobility-tracking dimensions of our proposal to monitor shifts in reputation and tourist flows in real time. Finally, the framework can be adapted to provide tourists with access to transparent information dashboards, empowering travelers to make well-informed destination choices.

7.2 Limitations

Several limitations must be acknowledged in this work. First, the human mobility dataset from the Spanish Ministry of Transportation was only available from February 2020 onward, preventing a comparative long-term mobility analysis for the earlier 2016 and 2019 crisis phases. Second, the social sensing analysis was restricted to Twitter, which might reflect a demographic bias and does not capture the opinions of travelers who do not use microblogging platforms or who utilize specialized travel review sites. Third, while the official economic statistics provide a reliable baseline of traveler behavior, they primarily represent formal hotel and registered apartment accommodation, potentially omitting informal stays or secondary residences. Lastly, the August 2021 event coincides with pandemic restrictions and an uneven recovery, and with single-destination data the two events cannot be fully separated.

7.3 Future Line of Research

Some lines of future work can follow this work. First, the mobility analysis could be expanded by integrating alternative historical datasets—such as localized mobile network data or app-based GPS traces—to evaluate tourist movement patterns during the earlier 2016 and 2019 crises. Second, the social sensing methodology could be broadened to include specialized tourism and hospitality platforms, such as TripAdvisor or Booking.com, to directly correlate environmental sentiment with verified accommodation reviews and local business performance. Finally, future studies should aim to develop predictive machine learning models that integrate real-time water quality indicators with social and mobility data, providing local authorities with proactive early-warning systems to forecast and mitigate the socio-economic impacts of future ecological anomalies.

ACKNOWLEDGEMENTS

Support for this research has been provided by the Instituto de Turismo de la Región de Murcia through project CAT/TU/47-22 “C´atedra Internacional de Inteligencia Turística Región de Murcia UCAM-ITREM”. This work is also part of the project “Diseño de un Espacio de Datos de Movilidad Sostenible para la Albufera de Valencia (AM-DS)” (INREED/2024/1-3), funded by the European Union - NextGenerationEU. Recovery, Transformation and Resilience Plan. GVANEXT. Generalitat Valenciana.

REFERENCES

- Aparicio, G., Camacho, M., & Maté-Sánchez-Val, M. (2024). Quantifying the impact: Are coastal areas impoverished by marine pollution? *Ecological Economics*, 221, Article 108213. <https://doi.org/10.1016/j.ecolecon.2024.108213>
- Arroyo-Mompeán, P., & Vegas-Juez, A. (2019). Turismo en la Región de Murcia 2019 (Technical report). Instituto de Turismo de la Región de Murcia. <https://www.carm.es/web/pagina?IDCONTENIDO=20657&IDTIPO=246>
- Awais-E-Yazdan, M., Popescu, V., Birau, R., & Bărbăcioru, I. C. (2025). Enhancing tourist's perceived safety and their behavioral intention in Thailand: A pathway to sustainable tourism and sustainable economic growth. *Sustainability*, 17(10), 4297. <https://doi.org/10.3390/su17104297>
- Barbieri, F., Espinosa Anke, L., & Camacho-Collados, J. (2022). XLM-T: Multilingual Language Models in Twitter for Sentiment Analysis and Beyond. In *Proceedings of the Thirteenth International Conference on Language Resources and Evaluation (LREC 2022)* (pp. 258–266). European Language Resources Association (ELRA). <https://doi.org/10.63317/4fhqtpvii3vg>
- Becken, S., Stantic, B., Chen, J., Alaei, A. R., & Connolly, R. M. (2017). Monitoring the environment and human sentiment on the Great Barrier Reef: Assessing the potential of collective sensing. *Journal of Environmental Management*, 203, 87–97. <https://doi.org/10.1016/j.jenvman.2017.07.007>
- Belando, M. D., Bernardeau-Esteller, J., Paradinas, I., Ramos-Segura, A., García-Muñoz, R., García-Moreno, P., Marín-Guirao, L., & Ruiz, J. M. (2021). Long-term coexistence between the macroalga *Caulerpa prolifera* and the seagrass *Cymodocea nodosa* in a Mediterranean lagoon. *Aquatic Botany*, 173, Article 103415. <https://doi.org/10.1016/j.aquabot.2021.103415>
- Bernal, J. L., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions. *International Journal of Epidemiology*, 46(1), 348–355. <https://doi.org/10.1093/ije/dyw098>
- Box, G. E. P., & Tiao, G. C. (1975). Intervention analysis with applications to economic and environmental problems. *JASA*, 70(349), 70–79. <https://doi.org/10.2307/2285379>
- Correia-Loureiro, S. M., Guerreiro, J., & Han, H. (2021). Past, present, and future of pro-environmental behavior in tourism and hospitality: A text-mining approach. *Journal of Sustainable Tourism*, 258–278. <https://doi.org/10.1080/09669582.2021.1875477>

- Czarnecki, A., Dacko, A., & Dacko, M. (2023). Changes in mobility patterns and the switching roles of second homes as a result of the first wave of COVID-19. *Journal of Sustainable Tourism*, 30(1), 149–167. <https://doi.org/10.1080/09669582.2021.2006201>
- Fernández Ferrero, M., Teruel Gutiérrez, R., & Sánchez-Val, M. (2022). The environmental degradation impact in Mar Menor on Airbnb prices. *Revista de Métodos Cuantitativos para la Economía y la Empresa*, 34, 446–465. <https://doi.org/10.46661/revmetodoscuanteconempresa.6202>
- Fryzlewicz, P. (2007). Unbalanced Haar technique for nonparametric function estimation. *Journal of the American Statistical Association*, 102(480), 1318–1327. <https://doi.org/10.1198/016214507000000860>
- García-Ayllón, S. (2018). Retro-diagnosis methodology for land consumption analysis towards sustainable future scenarios: Application to a Mediterranean coastal area. *Journal of Cleaner Production*, 195, 1408–1421. <https://doi.org/10.1016/j.jclepro.2018.02.160>
- Grootendorst, M. (2022). BERTopic: *Neural Topic Modeling with a Class-based TF-IDF Procedure*. arXiv. <https://arxiv.org/abs/2203.05794>
- Hale, B. W. (2018). Mapping potential environmental impacts from tourists using data from social media: A case study in the Westfjords of Iceland. *Environmental Management*, 62, 446–457. <https://doi.org/10.1007/s00267-018-1056-z>
- Jain, P. K., Pamula, R., & Srivastava, G. (2021). A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews. *Computer Science Review*, 41, Article 100413. <https://doi.org/10.1016/j.cosrev.2021.100413>
- Jurgens, M., & Helsloot, I. (2018). The effect of social media on the dynamics of (self) resilience during disasters: A literature review. *Journal of Contingencies and Crisis Management*, 26(1), 79–88. <https://doi.org/10.1111/1468-5973.12212>
- Kovács, Z., Vida, G., Elekes, A., & Kovalcsik, T. (2021). Combining social media and mobile positioning data in the analysis of tourist flows: A case study from Szeged, Hungary. *Sustainability*, 13, Article 2926. <https://doi.org/10.3390/su13052926>
- Kurniawan, S., Pramayoga, A. S., & Ashari, Y. F. (2025). Sentiment analysis in coastal tourism: A systematic literature review. *Engineering, Technology & Applied Science Research*, 15(6), 30226–30233. <https://doi.org/10.48084/etasr.14644>
- Lamas Rodríguez, M., García Lorenzo, M. L., Medina Magro, M., & Pérez Quirós, G. (2023). Impact of climate risk materialization and ecological deterioration on house prices in Mar Menor, Spain. *Scientific Reports*, 13, Article 11772. <https://doi.org/10.1038/s41598-023-39022-8>
- Malzer, C., & Baum, M. (2020). A hybrid approach to hierarchical density-based cluster selection. In *2020 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*. IEEE. <https://doi.org/10.1109/MFI49285.2020.9235263>
- Manosso, F. C., & Domareski Ruiz, T. C. (2021). Using sentiment analysis in tourism research: A systematic, bibliometric, and integrative review. *Journal of Tourism, Heritage & Services Marketing*, 7(2), 16–27. <https://doi.org/10.5281/zenodo.5548426>
- Martínez Dalmau, R. (2023). Una laguna con derecho a existir: La naturaleza como sujeto de derechos y el reconocimiento de la personalidad jurídica del Mar Menor. *Teoría y Realidad Constitucional*, 52, 357–375. <https://doi.org/10.5944/trc.52.2023.39021>
- McInnes, L., Healy, J., & Melville, J. (2018). UMAP: *Uniform Manifold Approximation and Projection for Dimension Reduction*. arXiv. <https://doi.org/10.48550/arXiv.1802.03426>
- Möhring, M., Keller, B., Schmidt, R., & Dacko, S. (2021). Google Popular Times: Towards a better understanding of tourist customer patronage behavior. *Tourism Review*, 76(3), 533–569. <https://doi.org/10.1108/TR-10-2018-0152>
- Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), 703–708. <https://doi.org/10.2307/1913610>
- Paolanti, M., Mancini, A., Frontoni, E., Felicetti, A., Marinelli, L., Ernesto, M., & Pierdicca, R. (2021). Tourism destination management using sentiment analysis and geo-location information: A deep learning approach. *Information Technology & Tourism*, 23, 241–264. <https://doi.org/10.1007/s40558-021-00196-4>
- Park, S., Kim, Y. R., & Ho, C. S. T. (2022). Analysis of travel mobility under COVID-19: Application of network science. *Journal of Travel & Tourism Marketing*, 39(3), 335–352. <https://doi.org/10.1080/10548408.2022.2089954>
- Pérez-Martín, M. Á. (2023). Understanding nutrient loads from catchment and eutrophication in a salt lagoon: The Mar Menor case. *Water*, 15(20), Article 3569. <https://doi.org/10.3390/w15203569>
- Prandi, C., Cecilia, J. M., Manzoni, P., Peña-Haro, S., Pierson, D., Colom, W., Blanco, P., Amurrio García, C., Jiménez Navarro, I., & Senent, J. (2022). On integrating intelligent infrastructure and participatory monitoring for environmental modelling: The SMARTLAGOON approach. In *Proceedings of the 2022 ACM Conference on Information Technology for Social Good* (pp. 236–243). Association for Computing Machinery. <https://doi.org/10.1145/3524458.3547228>
- Ramanathan, V., & Meyyappan, T. (2019). Twitter text mining for sentiment analysis on people's feedback about Oman tourism. In *2019 4th MEC International Conference on Big Data and Smart City (ICBDSC)* (pp. 1–5). <https://doi.org/10.1109/ICBDSC.2019.8645596>

- Ramya, V., Sheema, S., Lavanya, V., Heena, S., & Seshiah, T. (2021). Geolocation data and sentiment analysis combined with deep learning for tourism destination management. *Mathematical Statistician and Engineering Applications*, 70(2), 585–602. <https://doi.org/10.17762/msea.v70i2.1834>
- Región de Murcia Digital Integra (n.d.). Naturaleza, Mar Menor. Mar Menor- Turismo - Región de Murcia Digital (regmurcia.com)
- Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing* (pp. 3982–3992). Association for Computational Linguistics. <https://doi.org/10.18653/v1/D19-1410>
- RTVE. (2021). Cientos de peces muertos vuelven a cubrir el Mar Menor. RTVE Noticias. <https://www.rtve.es/noticias/20210816/cientos-peces-muertos-banan-mar-menor/2159500.shtml>
- Ruz, G. A., Henríquez, P. A., & Mascareño, A. (2020). Sentiment analysis of Twitter data during critical events through Bayesian networks classifiers. *Future Generation Computer Systems*, 106, 92–104. <https://doi.org/10.1016/j.future.2020.01.005>
- Sammut, C., & Webb, G. I. (Eds.). (2010). TF-IDF. In *Encyclopedia of Machine Learning* (pp. 986–987). Springer. https://doi.org/10.1007/978-0-387-30164-8_832
- Sánchez-Franco, M. J., & Rey-Moreno, M. (2022). Do travelers' reviews depend on the destination? An analysis in coastal and urban peer-to-peer lodgings. *Psychology & Marketing*, 39, 441–459. <https://doi.org/10.1002/mar.21608>
- Sarabia-Sánchez, F. J., Bruno, J. M., Sarabia-Andreu, F., & Moreno-Micol, M. A. (2025). The impact of eco-degradation on residential tourism: The case of the Mar Menor, Spain. *Tourism and Hospitality*, 6(1), Article 19. <https://doi.org/10.3390/tourhosp6010019>
- Schmücker, D., & Reif, J. (2022). Measuring tourism with big data? Empirical insights from comparing passive GPS data and passive mobile data. *Annals of Tourism Research Empirical Insights*, 3, Article 100061. <https://doi.org/10.1016/j.annale.2022.100061>
- Smolčić Jurdana, D., & Agbaba, R. (2025). Management of crisis situations towards tourism destination sustainability: Key factors and measures. *Sustainability*, 17(23), Article 10871. <https://doi.org/10.3390/su172310871>
- Suess, C., Maddock, J. E., Palma, M., Youssef, O., & Kyle, G. (2024). An application of protection motivation theory to understand the influence of fear-appeal media on stated donations for coral reef restoration. *Tourism Management*, 100, Article 104797. <https://doi.org/10.1016/j.tourman.2023.104797>
- Ulker-Demirel, E., & Ciftci, G. (2020). A systematic literature review of the theory of planned behavior in tourism, leisure and hospitality management research. *Journal of Hospitality and Tourism Management*, 43, 209–219. <https://doi.org/10.1016/j.jhtm.2020.04.003>
- Viñán-Ludeña, M. S., & de Campos, L. M. (2022). Discovering a tourism destination with social media data: BERT-based sentiment analysis. *Journal of Hospitality and Tourism Technology*, 13(5), 907–921. <https://doi.org/10.1108/JHTT-09-2021-0259>
- Vu, H. Q., Li, G., & Law, R. (2020). Discovering highly profitable travel patterns by high-utility pattern mining. *Tourism Management*, 77, Article 104008. <https://doi.org/10.1016/j.tourman.2019.104008>
- Wang, D., Abdelzaher, T., & Kaplan, L. (2015). *A New Information Age. Social Sensing: Building Reliable Systems on Unreliable Data* (pp. 1–8). Elsevier. <https://doi.org/10.1016/C2013-0-18808-3>
- Wang, Y., Zhang, Z., & Zhang, Z. (2025). Exploring coastal tourism experience through social media text mining: Sentiment and thematic patterns. *Applied Sciences*, 15(21), Article 11721. <https://doi.org/10.3390/app152111721>
- Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review*, 55, 5731–5780. <https://doi.org/10.1007/s10462-022-10144-1>
- Willson, G., Wilk, V., Sibson, R., & Morgan, A. (2021). Twitter content analysis of the Australian bushfires disaster 2019–2020: Futures implications. *Journal of Tourism Futures*, 7, 350–355. <https://doi.org/10.1108/JTF-10-2020-0183>
- Xu, Y., Li, J., Belyi, A., & Park, S. (2021a). Characterizing destination networks through mobility traces of international tourists: A case study using a nationwide mobile positioning dataset. *Tourism Management*, 82, Article 104195. <https://doi.org/10.1016/j.tourman.2020.104195>
- Xu, Y., Xue, J., Park, S., & Yue, Y. (2021b). Towards a multidimensional view of tourist mobility patterns in cities: A mobile phone data perspective. *Computers, Environment and Urban Systems*, 86, Article 101593. <https://doi.org/10.1016/j.compenvurbsys.2020.101593>
- Yan, Y., Chen, J., & Wang, Z. (2020). Mining public sentiments and perspectives from geotagged social media data for appraising the post-earthquake recovery of tourism destinations. *Applied Geography*, 123, Article 102306. <https://doi.org/10.1016/j.apgeog.2020.102306>

ORCID

Daria Mitroshenko  <https://orcid.org/0009-0005-1702-9429>

José Giner Pérez de Lucia  <https://orcid.org/0009-0008-5449-4233>

Fernando Terroso-Sáenz  <https://orcid.org/0000-0002-1921-1137>

José M. Cecilia  <https://orcid.org/0000-0001-5648-214X>

Ginesa Martínez - del Vas  <https://orcid.org/0000-0002-2713-0636>

Andrés Muñoz  <https://orcid.org/0000-0002-8491-4592>

Notes on contributors

Daria Mitroshenko is a PhD student at the Faculty of Computer Technologies and Environmental Engineering at the Universidad Católica de Murcia (UCAM). Received her Master's degree in Hotel and Restaurant Business Management in 2018. Her research focuses on sustainability, tourism, and the intersection between environmental management and the hospitality sector.

José Giner Pérez de Lucia is an industrial PhD candidate at the Universitat Politècnica de València, Spain, in collaboration with Sensing Tools, a UPV spin-off company focused on social sensing technologies. He received his BSc degree in Data Science in 2022 and his MSc degree in Artificial Intelligence in 2023, both from UPV. His research focuses on natural language processing and large language models, with particular interest in the analysis of digital content from social media. He is currently developing several applied software solutions and intelligent applications aimed at extracting actionable insights from social data.

Fernando Terroso-Sáenz obtained his B.S. and PhD in Computer Science from the University of Murcia in 2009 and 2013. Since 2023 he is associate professor at Technical University of Cartagena (UPCT). He has published more than 50 articles in international journals and congresses. His research areas include smart mobility, human-generated data analysis and mobile sensing.

José M. Cecilia is full professor at the Computer Engineering Department, Universitat Politècnica de València (Spain). His research interest is in developing applications within the convergence between emergent HPC and Artificial Intelligence, following an application-driven approach where hardware and algorithmic are always considered to offer novel solutions to real problems.

Ginesa Martínez-del Vas is an Associate Professor at the Universidad Católica de Murcia (UCAM). She earned her PhD in Regional Geographical Analysis from the Universidad de Alicante in 2014, with research focused on strategic planning as a tool for tourism policy. Since 2022, she has served as the Director of the International Chair of Tourism Intelligence of the Region of Murcia.

Andrés Muñoz is an Associate Professor at the Universidad de Cádiz. He earned a PhD in Computer Engineering from the Universidad de Murcia in 2011, with research on argumentation in multi-agent systems and Semantic Web environments for resolving knowledge conflicts. His work focuses on artificial intelligence, especially knowledge-based models for context-aware applications, multi-agent systems, Semantic Web technologies, argumentation, and intelligent environments. He is Associate Editor of the Journal of Ambient Intelligence and Smart Environments and has organized several international scientific workshops, such as ISAPEP (Workshop on Intelligent Systems for Agriculture Production and Environment Protection) and ALLEGET (International Workshop on Artificial Intelligence and Machine Learning for Emerging Topics).