

Article

# Geospatial Analysis of the Evolution of European Tourism in Spain Using Mobile Phone Data, the Space–Time Cube, and Emerging Hot Spot Analysis

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## Abstract

In Spain, inbound European tourism exhibits marked territorial imbalances whose evolution is difficult to characterize using aggregate indicators. This study analyzes its spatiotemporal patterns at the municipal level between July 2019 and December 2025 based on experimental statistics from the National Institute of Statistics compiled using mobile phone data. The objective is to identify processes of growth, persistence, and spatial intensification using a geospatial methodology based on the Space–Time Cube (STC) and Emerging Hot Spot Analysis (EHSA). The analysis covers the 1000 municipalities with the highest cumulative volume of European tourists, which account for most of the flows recorded during the period. The results show positive and statistically significant temporal trends in 911 municipalities, although the formation of persistent spatial clusters is considerably less widespread. EHSA identified 48 municipalities classified as hot spots when applying a one-month temporal neighborhood and 77 when using a three-month configuration. The two classifications showed an observed agreement of 96.0% and, for the four shared categories, a Cohen’s kappa coefficient of 0.660. The post-pandemic recovery in tourism did not, therefore, result in a homogeneous territorial consolidation of stable spatial patterns. We identify persistent hubs, areas undergoing intensification, and destinations with episodic behavior, located primarily in metropolitan, coastal, and island areas. The main contribution of the study lies in the development of a reproducible workflow based on the STC–EHSA integration, capable of distinguishing between temporal growth, persistence, intensification, and spatial intermittency, and of evaluating the stability of the results under different temporal neighborhood configurations.

**Keywords:** inbound tourism; spatiotemporal analysis; geoinformation; Space–Time Cube; Emerging Hot Spot Analysis; mobile phone data; Spain



Academic Editors: Wolfgang Kainz and Godwin Yeboah

Received: 20 June 2026

Revised: 20 July 2026

Accepted: 23 July 2026

Published: 24 July 2026

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## 1. Introduction

Arrivals, overnight stays, and length of stay provide a measure of tourism activity, but they only partially explain its spatial organization, which is much more complex [1,2]. This is because tourism exhibits marked spatial selectivity and high temporal heterogeneity, determined by the interaction between accessibility, connectivity, functional specialization, agglomeration advantages, and territorial hierarchies [3–7]. In this sense, differences between destinations are not merely a matter of quantitative comparisons but reflect unequal positions within complex territorial systems. Within these systems, proximity,

agglomeration economies, and functional relationships determine the capacity to attract and sustain tourist flows.

The specialized literature has documented the existence of spatial dependence, spillover effects, and relationships of complementarity or competition among destinations [6–8]. A municipality's attractiveness must therefore be interpreted in relation to the territorial system of which it is a part. Thus, tourist clusters form hierarchical structures with varying degrees of stability and dynamism. While some centers maintain consolidated positions over extended periods, others undergo processes of expansion, intensification, or discontinuity linked to changes in demand, accessibility, or market conditions [8,9]. Analyzing these trajectories requires going beyond static approaches, which are limited to the spatial distribution observed at a specific point in time.

Spain offers a particularly relevant context for examining these processes. Its position among the leading international tourist destinations is underpinned by high air and land connectivity, a diversified range of offerings, and close integration with European source markets [10–12]. In 2025, it received 96,770,515 international tourists, of whom 81,169,010 came from European countries, accounting for 83.88% of the total. The United Kingdom, France, and Germany together accounted for 45.35% of international arrivals, indicating that the source market structure has remained largely unchanged in recent years [13,14]. These figures are not directly comparable with the mobile phone-based estimates used in this study, due to differences in observation units, estimation procedures, and temporal assignment criteria. Despite the differences between these official statistics, geographic proximity, lower travel costs, economic integration, and cultural familiarity underpin the predominance of European markets in the Spanish tourism system [13].

Spain also provides an appropriate case for examining the interaction between spatial polarization and scale effects. The territorial predominance of the archipelagos, Mediterranean regions, and metropolitan areas is well established, but this national structure contains substantial internal heterogeneity. Regional or provincial totals may combine consolidated centers, seasonal destinations, emerging municipal trajectories, and areas with limited participation in spatial clusters. A municipal spatiotemporal analysis is therefore required not merely to increase spatial detail, but to test whether the aggregate geography of concentration is reproduced, fragmented, or qualified at the local scale.

The importance of European demand was also evident during the recovery following the health crisis caused by COVID-19. In this regard, the main source countries played a decisive role in the revival of international tourist flows and reaffirmed the structural importance of traditional markets [13,14]. The recovery, however, showed an uneven geographical distribution. International visitor arrivals continued to be concentrated in the archipelagos, the Mediterranean coast, and the major metropolitan areas, during both the recovery and stabilization phases. Nevertheless, alongside this established pattern, recent trends toward territorial and seasonal diversification have emerged, linked to the expansion of tourism to inland destinations and a broader temporal distribution of tourist flows [10–12,15].

This scenario raises questions about the recent evolution of the Spanish tourism system. Consequently, the analytical focus goes beyond quantifying the volume recovered after the 2020 disruption and aims to determine whether the recovery reinforced preexisting territorial hierarchies, fostered new centers of activity, or generated distinct trajectories among destinations. To determine these hierarchies, the municipal level is particularly appropriate, since contrasts between prominent tourist areas tend to be diluted when more aggregated territorial units are used [8,15].

In particular, the pandemic highlighted the need to study tourism as a process that is shaped simultaneously by spatial and temporal dimensions. In this regard, restrictions on

international mobility affected destinations unevenly, revealing substantial differences in their capacity for adaptation, resilience, and recovery. From the perspectives of tourism resilience and path dependence, recovery does not necessarily entail a structural transformation of the system. Furthermore, disruptions can reinforce preexisting advantages associated with accessibility, connectivity, functional specialization, or integration into source markets [16–25]. For all these reasons, the central question is whether the post-pandemic recovery reproduced the inherited tourism geography or drove processes of territorial reorganization.

Experimental statistics based on mobile phone data expand the possibilities for analyzing these dynamics. These sources allow the observation of tourism mobility with spatial and temporal resolutions difficult to achieve with conventional statistics, in addition to facilitating longitudinal tracking of municipal trajectories [14,26–28]. Furthermore, their integration with spatiotemporal analysis tools, such as Space–Time Cube (STC) and Emerging Hot Spot Analysis (EHSA), makes it possible to detect processes that often appear overlapping in traditional studies, such as temporal growth, spatial persistence, or the recent intensification and intermittency of tourist concentrations [29–31].

Despite advances in tourism geography, geographic information science, and mobility analysis, a methodological gap persists between studies focused on cumulative volumes or static spatial distributions and those that integrate temporal trends, spatial dependence, and the stability of concentrations. Classifications based on tourism metrics or growth rates allow for the identification of prominent destinations and dynamic municipalities, but they do not clarify whether high values form spatially coherent clusters, whether these clusters persist over time, or whether their statistical intensity has recently increased. However, municipal-level applications that combine these dimensions and assess the stability of results under different spatiotemporal configurations remain scarce.

Based on this approach, the study formulates three research questions. To what extent was the recovery of European inbound tourism following the disruption of 2020 geographically widespread? Did this recovery reinforce established centralities or foster the emergence of new spatial configurations? What additional information does the joint analysis of municipal temporal trends and the persistence, intensification, and intermittency of spatial clusters under alternative temporal configurations provide?

To answer these questions, the main objective was to develop and evaluate a reproducible workflow based on the integration of STC and EHSA, capable of distinguishing temporal growth, spatial persistence, recent intensification, and territorial intermittency. In addition, the proposal incorporates explicit handling of censored observations, the calibration of the spatiotemporal neighborhood, and a sensitivity analysis of the obtained classifications. Furthermore, its application to the Spanish case allows us to determine whether cumulative tourism volume, municipal temporal trends, and spatiotemporal clustering patterns generate convergent or divergent territorial interpretations in one of the most mature, concentrated, and market-dependent tourism systems in Europe.

These questions are addressed at the municipal scale but interpreted in relation to the broader regional and national hierarchy. This design makes it possible to examine whether aggregate spatial polarization corresponds to homogeneous local trajectories or results from the combination of municipalities with different temporal and clustering behaviors.

The contribution is therefore both methodological and territorial. Methodologically, the study separates municipal temporal change from the evolution of spatial clustering. Territorially, it examines whether the polarization observed in aggregate Spanish tourism statistics is reproduced at the municipal scale or qualified by heterogeneous trajectories of persistence, intensification, and intermittency.

## 2. Conceptual and Analytical Foundations

Tourism research has progressively moved away from viewing destinations as isolated units toward interpreting them as components of territorial systems linked by spatial, functional, and institutional interrelationships [32–37]. Their attractiveness does not depend exclusively on local resources, but also on accessibility, connectivity, infrastructure, specialization, and their position within tourism networks of varying scales [6,8,9]. From this perspective, tourism clusters reflect hierarchical structures whose centralities can be maintained, intensified, weakened, or manifest themselves discontinuously in space and time [28,33,38].

This approach is particularly well-suited to Spain, where it helps explain why certain areas retain established centralities while others follow a trajectory that is more sensitive to external disturbances, changes in connectivity, or competitive dynamics. In this context, the unequal territorial distribution of tourism reflects differences not only in magnitude but also in stability and functional integration within broader regional systems [8,30]. Consequently, the analysis is no longer limited exclusively to the observed spatial configuration but seeks to investigate the mechanisms that reproduce or transform territorial hierarchies.

Research on tourism in Spain has progressively moved from documenting aggregate concentration toward examining regional heterogeneity, spatial dependence, and differences in destination trajectories. Initial territorial interpretations emphasized the structural concentration of international tourism in the archipelagos, the Mediterranean coast, and major metropolitan areas. Subsequent studies showed that this distribution is not merely uneven but spatially interdependent, since tourism performance in one region may be associated with flows, infrastructure, specialization, and competitive or complementary relationships in neighboring territories [6–8,30]. Dynamic spatial analyses have further demonstrated the persistence of tourism arrivals, stronger spatial dependence in international than in domestic tourism, and heterogeneous regional sensitivity to changes in demand [8].

This research trajectory suggests that tourism polarization should be examined as a multiscalar phenomenon. At the national scale, polarization refers to the concentration of European inbound tourism in a limited number of coastal, island, and metropolitan territories. At the regional and provincial scales, it reflects differences in the cumulative volume, specialization, seasonality, and responsiveness of territorial tourism systems. At the municipal scale, polarization is expressed through the coexistence of dominant tourism centers, intermediate destinations, and municipalities with limited or discontinuous participation in statistically significant clusters.

These patterns are affected by the scale of observation. Regional and provincial aggregation may conceal internal contrasts between municipalities with different volumes, temporal trends, and levels of integration into tourism clusters. Conversely, municipal analysis may reveal local discontinuities while underrepresenting functional relationships extending beyond administrative boundaries. Scale is therefore not treated as a neutral cartographic choice but as a component of the analytical design. The municipal scale permits the identification of local trajectories and spatial associations that would be obscured by aggregation, although the resulting patterns remain conditioned by the definition of the analytical subset and the spatial neighborhood [8].

In this study, spatial polarization denotes the unequal territorial concentration of tourism volume and statistically significant high-value clusters. It is examined descriptively through the cumulative distribution of tourists and analytically through the local Getis–Ord  $G_i^*$  statistic. Scale effects refer to changes in the visibility and interpretation of that polarization when data are considered at national, regional, provincial, or municipal levels, or when different spatial and temporal neighborhoods are applied. The study does not

estimate a formal multilevel model; rather, it uses the comparison of territorial summaries and municipal spatiotemporal patterns to show how aggregation may produce different interpretations of the Spanish tourism system.

The tourism area life cycle, path dependence, and resilience provide complementary perspectives for interpreting destination trajectories (Table 1). The tourism area life cycle describes changes in the scale and organization of tourism activity through successive stages of exploration, involvement, development, consolidation, stagnation, and possible decline or rejuvenation [39]. Its analytical value lies in recognizing that destinations evolve and that growth, stability, and decline may represent different moments in that evolution. Nevertheless, the framework does not imply that all destinations follow a single linear sequence. Destinations may experience overlapping, interrupted, or repeated cycles, particularly when they form part of metropolitan, coastal, or island systems with multiple tourism products and market segments [39]. A spatiotemporal perspective therefore makes it possible to interpret simultaneous processes of continuity, intensification, discontinuity, and territorial readjustment rather than assuming a uniform evolutionary path.

**Table 1.** Relationship between theoretical constructs, operational concepts, indicators, and interpretive scope.

| Theoretical Construct         | Expected Empirical Manifestation                                                      | Operational Concept                          | Indicator and Technique                                                                  | Interpretation Permitted                                                                                     | Interpretation Not Permitted                                                                         |
|-------------------------------|---------------------------------------------------------------------------------------|----------------------------------------------|------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| Tourism area life cycle       | Growth, stabilization, intensification, discontinuity, or decline in tourism activity | Local growth; intensification; intermittency | Mann–Kendall trend in municipal values; EHSA classification and trend in $Gi^*$ z-scores | Identification of temporal trajectories compatible with expansion, consolidation, or discontinuity           | Assignment of a municipality to a definitive life-cycle stage                                        |
| Path dependence               | Continuity or reinforcement of established spatial structures                         | Persistence; intensification                 | Frequency of significant hotspot intervals; Mann–Kendall trend in $Gi^*$ z-scores        | Detection of territorial continuity or cumulative reinforcement consistent with inherited centralities       | Demonstration of historical causation or identification of specific lock-in mechanisms               |
| Tourism resilience            | Recovery or reorganization after the 2020 disruption                                  | Local growth; persistence; intensification   | Municipal Mann–Kendall trend; final hotspot status; EHSA trajectory                      | Identification of post-shock recovery and continuity or strengthening of clusters during the observed period | Measurement of resistance, adaptive capacity, transformation, or return to a pre-crisis trajectory   |
| Relational destination system | Concentration of high values in a spatially connected context                         | Spatial clustering                           | Local Getis–Ord $Gi^*$ within the defined spatial and temporal neighborhood              | Detection of statistically significant high-value territorial clusters                                       | Attribution of clustering to connectivity, governance, accommodation supply, or other causal factors |
| Temporal variability          | Discontinuous appearance of significant concentrations                                | Intermittency                                | EHSA sporadic-hotspot category                                                           | Detection of discontinuous clustering                                                                        | Direct identification of seasonality, events, irregular recovery, or market-specific causes          |

Path dependence explains why these trajectories are conditioned by historically accumulated assets and previous decisions. Infrastructure, transport connectivity, accommodation capacity, tourism specialization, institutional arrangements, and destination image may generate self-reinforcing processes that favor the continuity of established tourism centers [16–25]. From this perspective, the persistence of a spatial cluster is compatible with the reproduction of an inherited territorial structure, whereas the intensification of an established cluster may indicate the reinforcement of cumulative advantages. These correspondences are interpretive rather than causal because the present study does not directly measure the historical mechanisms responsible for path dependence.

Tourism resilience concerns the capacity of a destination or territorial system to absorb a disturbance, recover its activity, adapt its functions, or reorganize its development trajectory [16–20,25]. These dimensions should not be treated as equivalent. A return to growth after a shock may indicate recovery, but it does not by itself demonstrate adaptation or structural transformation. The COVID-19 crisis showed that both the impacts and the pace and intensity of recovery varied according to source-market structures, connectivity conditions, and the adaptive capacities of destinations [16–20]. Consequently, the post-pandemic phase must be understood as a territorially unequal process in which dynamics of continuity and change coexist. In the present study, the predominance of positive municipal trends after the disruption of 2020 can be interpreted as evidence of recovery within the observed period. However, the limited pre-pandemic baseline prevents the estimation of resistance to the shock or the demonstration that destinations returned to, departed from, or transformed their previous trajectories.

Furthermore, the temporal dimension of tourism extends beyond seasonality. Tourist flows exhibit persistence, discontinuities, accelerations, and territorial compensation processes whose manifestation varies according to the spatial scale and temporal interval considered [40–42]. Capturing these dynamics requires information sources capable of identifying mobility patterns, same-day visitors, and other forms of tourism that often remain invisible in conventional accommodation statistics [43]. This requirement is particularly relevant in Spain, where metropolitan, coastal, island, and inland destinations display markedly different temporal behaviors.

Recent advances in geographic information science, the growing availability of mobility datasets, and the development of spatiotemporal analytical methods have considerably expanded the ability to study these dynamic processes [44–46]. Among the available approaches, the Space–Time Cube (STC) and Emerging Hot Spot Analysis (EHSA) are especially useful because they allow the reconstruction of territorial trajectories and the identification of persistence, discontinuity, and intensification patterns within a common analytical framework [47–61].

These theoretical perspectives are connected to the empirical analysis through five operational concepts: local growth, spatial clustering, persistence, intensification, and intermittency. These concepts do not constitute direct measurements of life-cycle stages, path dependence, or resilience. Instead, they describe observable spatiotemporal properties that can be interpreted in relation to these frameworks when the limitations of the indicators are explicitly acknowledged.

Local growth refers to a statistically significant positive temporal trend in the monthly number of European tourists recorded for an individual municipality. It is measured through the Mann–Kendall trend test applied within the Space–Time Cube. Local growth is consistent with recovery or expansion during the observed period, but it does not identify a specific stage of the tourism area life cycle and, by itself, does not demonstrate resilience.

Spatial clustering denotes the statistically significant concentration of high tourism values around a municipality within the spatial and temporal neighborhood specified in the Emerging Hot Spot Analysis. It is measured using the local Getis–Ord  $G_i^*$  statistic. Spatial clustering represents a relational property of the territorial system rather than an attribute derived solely from the tourism volume of an individual destination.

Persistence refers to the repeated presence of a statistically significant high-value cluster throughout most of the analyzed intervals, without a significant temporal increase or decrease in clustering intensity. In EHSA, a persistent hotspot is significant in at least 90% of the intervals, including the final interval, while the Mann–Kendall trend applied to the sequence of  $G_i^*$  z-scores is not significant. Persistence is compatible with path-dependent

continuity and with the maintenance of established territorial structures, although it does not identify the mechanisms that produced that continuity.

Intensification refers to a statistically significant strengthening of the clustering of high values over time. An intensifying hotspot satisfies the temporal frequency criterion for hotspot occurrence, is significant in the final interval, and exhibits a significant positive trend in the  $G_i^*$  z-scores. Intensification may be consistent with cumulative reinforcement, renewed expansion, or post-shock consolidation. However, it cannot be interpreted automatically as destination emergence, rejuvenation, or increased resilience because such interpretations require additional historical and explanatory evidence.

Intermittency denotes the discontinuous occurrence of significant high-value clusters. In this study, it is represented by the EHSA sporadic-hotspot category, in which a municipality is a significant hotspot in some, but fewer than 90%, of the analyzed intervals, has no significant cold-spot intervals, and remains a hotspot in the final interval. Intermittency may reflect seasonality, irregular recovery processes, temporary demand peaks, territorial compensation effects, events, or changes in connectivity [40–42]. Nevertheless, EHSA identifies the temporal discontinuity of clustering and does not allow direct discrimination among these mechanisms.

The conceptual model comprises three levels: municipal temporal change, measured through the Mann–Kendall trend in tourism values; relational spatial clustering, measured through local Getis–Ord  $G_i^*$ ; and spatiotemporal cluster trajectories, represented by persistence, intensification, and intermittency. Their joint interpretation identifies patterns compatible with recovery, continuity, or reinforcement without equating statistical categories with theoretical constructs.

The value of the STC–EHSA workflow lies not in the separate application of these two techniques, but in their integration into a coherent analytical sequence. In this regard, it is worth noting that cumulative volumes allow for the identification of the main destinations; municipal trends show the direction of change; and static spatial analyses pinpoint concentrations at specific points in time. It is also important to emphasize that none of these approaches, when considered in isolation, allows us to determine whether local growth forms spatially coherent clusters, whether these clusters are enduring, or whether their intensity has recently increased. The combination of STC and EHSA techniques distinguishes between these dimensions and reduces the risk of interpreting the generalization of positive trends as sufficient evidence of territorial restructuring.

Building on this conceptual foundation, the study proposes an analytical sequence that distinguishes the temporal trajectory of each municipality from the spatiotemporal behavior of the territorial system of which it is a part. Furthermore, its application makes it possible to determine whether the recovery of inbound European tourism in Spain was primarily due to a generalized increase in municipal values, the strengthening of established centralities, or the emergence of new territorial configurations.

### 3. Materials and Methods

The research uses experimental inbound tourism statistics compiled by the National Institute of Statistics (INE) based on mobile phone location data [14]. The analysis covers tourists from Europe recorded at the municipal level through a monthly time series spanning from July 2019 to December 2025. This source was selected for its high spatial resolution and temporal continuity, meeting the necessary requirements for the application of the geostatistical techniques STC and EHSA [26,45,46].

Unlike FRONTUR, which is based on a specific statistical design for measuring tourist movements at the border, experimental statistics based on mobile phone data infer travel patterns and primary destinations using aggregated signals from devices with foreign SIM

cards [14,26]. FRONTUR is used exclusively as a contextual reference. Therefore, mobile phone data constitute the primary analytical source due to their municipal disaggregation and monthly frequency.

However, the data source has several limitations. These include the possibility that a single person may use more than one device, that certain travelers may not be detected, that trips are assigned to the month of departure from Spain, and that confidentiality restrictions result in censored values. These factors are significant at the municipal level, where territorial heterogeneity, differences in signal coverage, and seasonality can affect the data. Therefore, the analytical validity of the data source depends on its suitability for the study's objectives, territorial scale, and temporal resolution.

However, the municipal scale offers a balance between territorial resolution and statistical stability, as it allows for the study of the spatial selectivity of inbound tourism without encountering the problems of fragmentation and instability associated with more detailed units. It also facilitates the identification of patterns of persistence, intensification, and intermittency, as well as changes in the centralities of the Spanish tourism system [8,62–64]. The initial data are included as Supplementary Materials in Table S1.

The period analyzed spans 78 months, from July 2019 to December 2025, which are the only months available from the official source. This means that the time series contains only six months prior to the pandemic, a circumstance that limits the characterization of pre-pandemic tourism behavior. Therefore, the trends obtained should be interpreted as trajectories corresponding to the entire observed period, which encompasses the pre-COVID-19 situation, the disruption of 2020, and the subsequent recovery.

The 78-month sequence satisfies a broad five-to-seven-cycle reference in terms of total duration, but not in terms of balanced pre- and post-shock observation. Only six months preceded the pandemic disruption. Consequently, the principal limitation is not the total number of observations but the asymmetric temporal structure of the series and the absence of multiple complete pre-pandemic annual cycles.

Prior to the analysis, we verified the consistency of administrative identifiers, the continuity of the time series, and the presence of non-analytical records. This check is particularly important for sources derived from digital footprints due to the potential presence of noise, discontinuities, and observation biases [28,65]. In this regard, of the 8132 Spanish municipalities considered, 1244 had no observations for the entire period, and 6888 recorded at least one positive value. It is also worth noting that the matrix corresponding to the municipal dataset contained 315,876 monthly cells with missing information. This high number necessitated a thorough cleaning of the entire database. After conducting various tests, it was decided to exclude many municipalities that provided little information and to limit the analysis to the 1000 municipalities with the highest cumulative volume. With this selection, the number of cells without information was reduced to 286. Some of the missing values are related to the application of the confidentiality threshold set at 30 tourists. This subset accounts for 92.48% of the recorded volume and provides a time series with sufficient continuity to apply the techniques necessary to meet the objectives. Its annual coverage exceeds 88% of municipal tourist volume in all years of the analyzed period (Table 2), thereby covering a very large proportion of the European tourists included in the official statistics.

A selection-sensitivity check compared the cumulative Top 1000 used in the STC–EHSA with the annual Top 1000 based on 2025 tourism volume. The comparison identified 73 municipalities included in the 2025 ranking but excluded from the cumulative subset (Table S2). Their individual temporal trajectories were screened using a minimum of 60 directly published monthly observations and Mann–Kendall trends under three censor-

ing scenarios (Table S3). This supplementary analysis was municipal and non-spatial; no STC–EHSA classifications were calculated for these municipalities.

**Table 2.** Annual coverage of the subset of the top 1000 relative to the municipal total.

| Year | Coverage of the Top 1000 (%) |
|------|------------------------------|
| 2019 | 92.79                        |
| 2020 | 88.22                        |
| 2021 | 90.35                        |
| 2022 | 93.51                        |
| 2023 | 93.07                        |
| 2024 | 93.20                        |
| 2025 | 92.50                        |

Source: Tourism measurement via mobile phones: inbound tourism [14].

In the main subset, missing data cells account for 0.37% of the 78,000 potential observations, with only 0.70% of the units having twelve or more consecutive months without observations. This temporal continuity is particularly important for the reliable application of these techniques, whose reliability requires sufficiently complete sequences [47].

Consequently, selecting the 1000 main municipalities substantially reduces the occurrence of missing data and the need for imputation. The source, however, imposes an additional restriction: values below 30 tourists are not published for confidentiality reasons. These observations were treated as censored data within the range of 1–29. Four scenarios were defined: original data without imputation, a lower limit of 1 tourist, a midpoint of 15 tourists, and an upper limit of 29 tourists. The midpoint scenario was adopted as the reference, while the others were used to assess the sensitivity of the results.

Imputation has a minimal effect on the aggregate measures. In the analytical subset, the cumulative volume ranges from 393,840,991 to 393,849,285 tourists, depending on the scenario considered. The maximum difference from the unimputed data is 0.00211% (Table 3). The treatment of censored values therefore improves the integrity and traceability of the procedure without appreciably altering the overall magnitude of the phenomenon.

**Table 3.** Comparison of imputation scenarios for censored cells in the subset of the top 1000.

| Scenario                         | Censoring Treatment                                            | Cumulative Volume, July 2019–December 2025 | Absolute Difference | Relative Difference (%) |
|----------------------------------|----------------------------------------------------------------|--------------------------------------------|---------------------|-------------------------|
| Original data without imputation | Censored cells due to disclosure are treated as missing values | 393,840,991                                |                     |                         |
| Lower bound (1)                  | Replaced with the lower bound (1)                              | 393,841,277                                | 286                 | 0.00007                 |
| Midpoint (15)                    | Replacement with the midpoint (15)                             | 393,845,281                                | 4290                | 0.00109                 |
| Upper limit (29)                 | Replacement with the upper limit (29)                          | 393,849,285                                | 8294                | 0.00211                 |

Once cleaned, the dataset was converted to long format, with one record per municipality and month, and linked to the official municipal map using INE identifiers. The map was projected into the ETRS89/UTM Zone 30N system, and its topological consistency, treatment of island territories, and geometric validity were verified.

Since the spatial units remain fixed throughout the period, the cube was constructed using the “Create Space–Time Cube from Defined Locations” tool, employing 78 consecutive monthly intervals and the 15-tourist scenario as the main variable [50–52]. Cubes corresponding to the 1- and 29-tourist scenarios were also retained to assess the stability of the classifications in the face of extreme values at the censoring interval.

STC organizes municipal observations into a homogeneous spatiotemporal structure and applies the Mann–Kendall test to identify temporal trends at each location [51,52]. EHSA was run on the cube, combining two operations. First, it calculates the local Getis–Ord  $G_i^*$  statistic for each time interval to detect clusters of high or low values relative to their spatiotemporal context [54,55]. Next, it applies the Mann–Kendall test to the time series of z-scores to determine whether the intensity of the local clustering exhibits a statistically significant trend [56,57]. Thus, EHSA classifies the spatiotemporal trajectory of each municipality.

In the analytical model, these outputs perform different conceptual functions. The Mann–Kendall trend calculated from the original municipal values operationalizes local growth, whereas the Getis–Ord  $G_i^*$  statistic operationalizes spatial clustering. The frequency with which a municipality forms part of a significant high-value cluster operationalizes persistence or intermittency, and the Mann–Kendall trend calculated from the sequence of  $G_i^*$  z-scores operationalizes intensification or diminution of clustering. Consequently, the trend in municipal tourism values and the trend in clustering intensity are not interchangeable. The former describes change within a municipality, while the latter describes change in the municipality’s position within a spatiotemporal concentration of high values.

An intensifying hotspot must have been statistically significant in at least 90% of the intervals, including the last one, and must show a significant increase in clustering intensity. A persistent hotspot must meet the same frequency threshold but without showing a significant trend in its intensity. A sporadic hotspot appears intermittently in fewer than 90% of intervals, without any intervals classified as significant cold spots, and maintains its status as a hotspot in the final interval.

However, caution is warranted when interpreting trends. The time series includes the 2020 disruption; although it has only six pre-pandemic monthly observations, it exhibits marked seasonality and may contain serial correlation. Despite this caution, it should be noted that a positive Mann–Kendall trend indicates an upward trajectory between July 2019 and December 2025, a period that includes both the pandemic-related contraction and the subsequent recovery. This result does not demonstrate the existence of structural growth relative to a stable pre-pandemic trend, which cannot be reliably estimated with only six-monthly observations.

Accordingly, the trend is interpreted as an overall trajectory across a sequence dominated by disruption and recovery, not as a direct measure of resilience.

Additionally, the temporal extent of the spatiotemporal neighborhood was established using the “Neighborhood Time Step” parameter, which determines the number of previous monthly intervals included in the calculation of the Getis–Ord  $G_i^*$  statistic. This parameter does not aggregate the observations or transform the monthly series into quarterly data; rather, it modifies the temporal context used to evaluate each location. Two configurations were compared: a one-month neighborhood, referred to as Step 1, and a three-month neighborhood, referred to as Step 3 [59–61].

The spatial neighborhood was defined within the cumulative subset of the 1000 leading municipalities. Preliminary tests considered configurations based on a fixed distance and on the k-nearest neighbors. A structure of eight nearest neighbors was selected to ensure a minimum common number of spatial relationships across all municipalities. Furthermore, proximity is defined within the analyzed tourism subset, not relative to the entire set of Spanish municipalities. In areas where the selected municipalities are sparsely distributed, some neighbors may be located at considerable distances or separated by municipalities excluded from the subset. This dependence on the sample constitutes a methodological

limitation and warrants conducting sensitivity analyses with alternative values for  $k$ , distance bands, and specifications adapted to the configuration of the archipelagos [65,66].

A spatial lag or spatial error model was not used as a direct robustness test for the EHSA classifications because these methods address a different analytical question. EHSA identifies local spatiotemporal concentrations and classifies their temporal trajectories, whereas spatial autoregressive models estimate a global relationship between a continuous dependent variable, its spatial lag or spatially correlated errors, and a theoretically specified set of explanatory variables. In the absence of harmonized municipal covariates for connectivity, accommodation capacity, source-market composition, accessibility, and destination specialization throughout the complete monthly period, a simplified spatial regression would risk attributing explanatory meaning to an underspecified model. Stability was therefore assessed through changes in censoring treatment and temporal neighborhood configuration.

In all tests, the false discovery rate (FDR) correction built into the tool was maintained; its purpose is to control the expected proportion of false positives resulting from the simultaneous performance of multiple tests [67]. Its application is particularly relevant in extensive municipal analyses, where the multiplication of local tests increases the probability of obtaining significant results by chance.

Similarly, the cube maintained its monthly resolution throughout the procedure. The results obtained using time intervals of 1 and 3 months represent alternative ranges of the temporal neighborhood applied to the same cube and do not constitute a comparison between monthly and quarterly aggregated data.

The robustness of the results was examined using two tests. The first assessed the stability of the classifications under various censoring scenarios. The second analyzed their sensitivity to the width of the temporal neighborhood by comparing Step 1 and Step 3. During calibration, alternative spatial neighborhoods were also explored, although no formal analysis of agreement between different spatial weighting matrices was performed. This omission limits the assessment of the results' sensitivity to the specification of the spatial neighborhood.

As an additional analysis, a concordance matrix was constructed between the EHSA classifications obtained with the two temporal configurations (Table S4). Municipalities were matched using the INE code, and concordance was estimated using Cohen's kappa coefficient, which corrects the observed agreement based on what would be expected by chance [68].

For the four comparable categories "No pattern detected," "Sporadic hotspot," "Intensifying hotspot," and "Persistent hotspot," the observed agreement reached 96.0%, and the Kappa coefficient was 0.660. When the categories were regrouped into a binary classification between municipalities with some hotspot pattern and municipalities with no detected pattern, the kappa coefficient increased to 0.753. These results indicate substantial stability in the classifications obtained using both temporal configurations (Steps 1 and 3).

In summary, the methodology is structured around an explicit sequence of decisions beginning with the delineation of the analytical universe, the handling of censored cells, cartographic integration, the construction of STCs, the parameterization of EHSA, and, finally, the assessment of robustness. Replicability depends not only on the GIS tools used but also on the documentation of the conditions for spatial and temporal comparability, the imputation rules, and the criteria used to define neighborhoods. Therefore, transferring the workflow to other territories requires adapting its parameters to the characteristics of the data source, the data frequency, and the spatial configuration of the study area.

On the one hand, Table 4 summarizes the requirements related to temporal continuity, stability in spatial units, handling of censoring, calibration of neighborhoods, and validation of results.

**Table 4.** Conditions for applying and adapting the STC-EHSA workflow to other contexts.

| Dimension             | General Requirement                             | Conditions in This Study                                                                                                             | Adaptation to Other Contexts                                                |
|-----------------------|-------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| Temporal continuity   | Regular and sufficiently complete series        | 78 consecutive months                                                                                                                | Assess the percentage of blank cells and the length of the series           |
| Spatial unit          | Stable boundaries throughout the entire period  | Municipalities                                                                                                                       | Harmonize administrative changes before creating the cube                   |
| Temporal resolution   | Regular intervals                               | Month                                                                                                                                | Adjust the time interval to account for the seasonality of the phenomenon   |
| Censoring             | Known threshold and explicit treatment          | Values below 30 tourists                                                                                                             | Define scenarios based on each source's publication thresholds              |
| Data integrity        | Low proportion of missing observations          | 0.37% in the subset of the 1000 main municipalities; a minimum of 60 observations published directly for the supplementary selection | Exclude or analyze units separately with excessively incomplete time series |
| Spatial proximity     | Calibration according to territorial morphology | eight nearest neighbors                                                                                                              | Compare different values of k or distance bands                             |
| Temporal Neighborhood | Comparison of plausible windows                 | Step 1 and Step 3                                                                                                                    | Adapt to the frequency and duration of tourism cycles                       |
| Validation            | Sensitivity of the classifications              | Censoring scenarios and temporal Kappa                                                                                               | Incorporate spatial consistency and auxiliary sources                       |
| Interpretive scope    | Distinction between detection and causality     | Descriptive and classificatory analysis                                                                                              | Add explanatory models if the goal is to establish causality                |

Also, Figure 1 summarizes the study's analytical workflow, from data collection and cleaning to the construction of the STC, the application of the EHSA, robustness testing, and the territorial interpretation of the results.

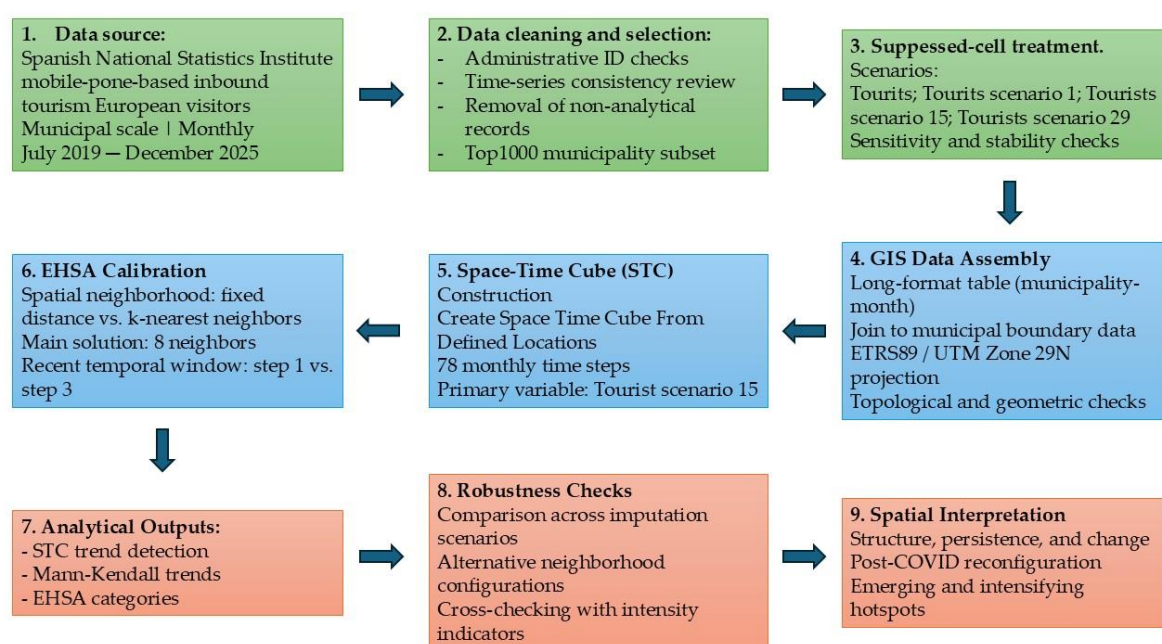


**Figure 1.** Methodological workflow for spatiotemporal analysis.

## 4. Results

### 4.1. Territorial and Temporal Structure of European Inbound Tourism

The evolution of European inbound tourism in Spain between July 2019 and December 2025 shows a clear temporal sequence (Table 5), although, as previously noted, the 2019 data constitute only a partial pre-pandemic reference, as they cover only the months of July through December. The contraction observed in 2020 coincided with restrictions imposed on international travel, which gave way to a recovery that began in 2021, consolidated in 2022, and continued with an expansion in tourism volume during the following years. Consequently, the time series does not allow for a consistent year-over-year comparison between 2019 and subsequent full years. Its interpretation must consider a trajectory comprising a partial pre-pandemic baseline, the disruption of 2020, the subsequent recovery, and a final phase of growth.

**Table 5.** Aggregate annual volumes of European inbound tourism in Spain.

| Year               | Tourists   | Period                              |
|--------------------|------------|-------------------------------------|
| July–December 2019 | 39,933,564 | Partial pre-pandemic reference      |
| 2020               | 27,234,351 | Pandemic-related contraction        |
| 2021               | 35,479,818 | Initial recovery                    |
| 2022               | 66,564,511 | Consolidated recovery               |
| 2023               | 77,932,581 | Post-pandemic expansion             |
| 2024               | 87,250,567 | Continued growth                    |
| 2025               | 91,467,082 | Highest annual figure in the series |

The volume recorded in 2025 far exceeds that of 2020, a year marked by a decline in international travel. This difference alone does not imply a profound territorial redistribution of the tourism system (Figure 2). Likewise, the highest volumes continue to be concentrated in coastal, island, and metropolitan destinations, consistent with the territorial structure of international tourism observed in Spain [8,10–15]. The data therefore show a strong recovery within a destination system that maintains a marked territorial hierarchy.

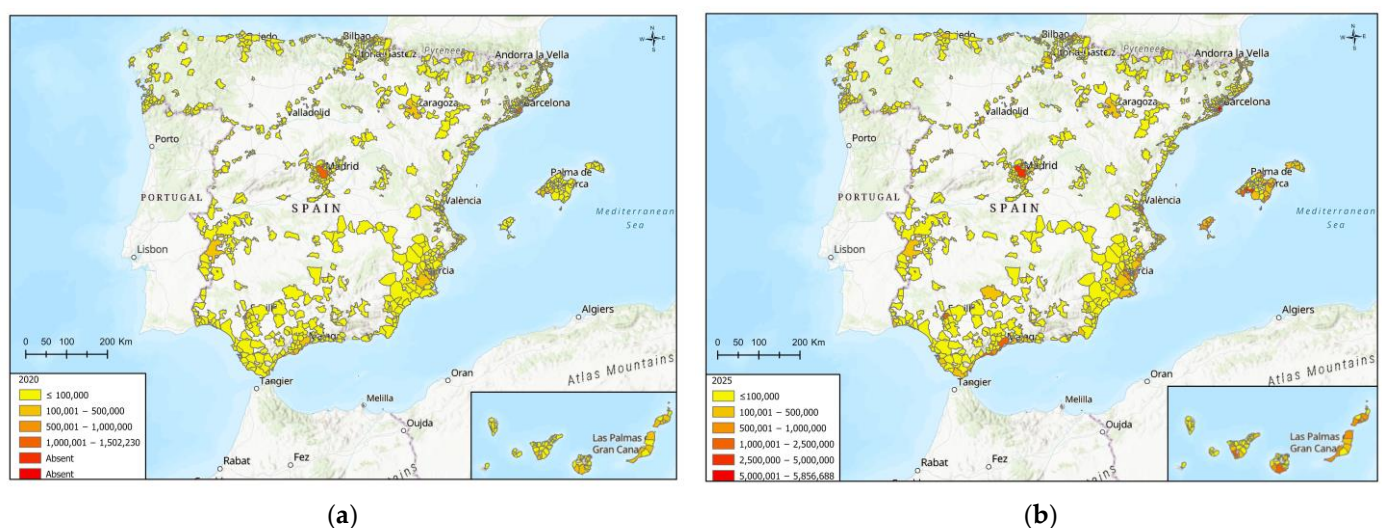


**Figure 2.** Municipal distribution of incoming European tourists within the cumulative analytical subset of the top 1000: (a) 2020; (b) 2025. Both maps use identical class intervals, symbol sizes, and cartographic scales to ensure a direct comparison.

The monthly medians calculated for 2020–2025 show a distinct annual cycle, although their interpretation is influenced by the inclusion of the 2020 disruption and the subsequent recovery (Table 6). The volume increases starting in April, intensifies during May and June,

and reaches its peak in July and August. September and October maintain high levels, while the first quarter, November, and December show lower levels. This distribution reflects the persistence of the summer vacation schedule. The values for September and October also show that a substantial portion of the activity continues beyond the peak reached in July and August [43].

**Table 6.** Monthly median of aggregate tourism volume for the 2020–2025 period.

| Month     | Median 2020–2025 |
|-----------|------------------|
| January   | 3,988,302.5      |
| February  | 3,951,577.0      |
| March     | 4,400,819.5      |
| April     | 6,019,687.5      |
| May       | 6,808,216.5      |
| June      | 6,927,919.5      |
| July      | 8,601,028.0      |
| August    | 9,091,678.5      |
| September | 7,512,473.0      |
| October   | 7,112,635.5      |
| November  | 4,583,515.0      |
| December  | 4,315,891.5      |

The aggregated seasonal distribution should be interpreted with caution, as it may mask significant differences among municipalities, provinces, and autonomous communities. In a territorially polarized system, the national pattern results from the overlap of distinct dynamics. This is evident when coastal destinations with a high concentration of summer visitors, island destinations with a more even annual distribution, large urban areas with relatively continuous visitor flows, and municipalities whose performance depends on specific periods of recovery are all considered together.

The distribution by autonomous community confirms the territorial concentration of tourist flows (Table 7). Catalonia, the Canary Islands, the Balearic Islands, Andalusia, and the Valencian Community account for much of the cumulative tourist volume. The autonomous community level, however, oversimplifies the internal diversity of the host system. A community may occupy a prominent position in the national hierarchy while encompassing municipalities with very different profiles in terms of specialization, seasonal intensity, and stability of tourist flows.

**Table 7.** Autonomous communities with the highest cumulative volumes of European tourists, 2019–2025.

| Autonomous Community | Cumulative Total | Percentage of Spain (%) |
|----------------------|------------------|-------------------------|
| Catalonia            | 85,983,345       | 20.19                   |
| Canary Islands       | 67,845,970       | 15.93                   |
| Balearic Islands     | 67,273,923       | 15.80                   |
| Andalusia            | 59,408,163       | 13.95                   |
| Valencian Community  | 47,146,974       | 11.07                   |
| Community of Madrid  | 26,365,552       | 6.19                    |
| Basque Country       | 15,177,192       | 3.56                    |
| Castile and León     | 12,243,502       | 2.87                    |

Even at the provincial level, this territorial polarization persists (Table 8). The Balearic Islands rank first, followed by Barcelona, Las Palmas, Alicante, Málaga, Santa Cruz de Tenerife, Madrid, and Girona. Spain's tourism hub, therefore, does not follow a single

spatial pattern but rather the coexistence of specialized archipelagos, provinces along the Mediterranean coast, and large metropolitan areas with high international connectivity.

**Table 8.** Provinces with the highest cumulative volume of European tourists, 2019–2025.

| Province               | Cumulative | Percentage of Spain's Total (%) |
|------------------------|------------|---------------------------------|
| Balearic Islands       | 67,273,923 | 15.80                           |
| Barcelona              | 46,626,912 | 10.95                           |
| Las Palmas             | 39,801,325 | 9.35                            |
| Alicante               | 30,729,604 | 7.22                            |
| Málaga                 | 30,062,608 | 7.06                            |
| Santa Cruz de Tenerife | 28,044,645 | 6.59                            |
| Madrid                 | 26,365,552 | 6.19                            |
| Girona                 | 25,973,454 | 6.10                            |
| Valencia               | 12,892,079 | 3.03                            |
| Tarragona              | 9,593,738  | 2.25                            |

The Balearic Islands' ranking confirms the structural importance of island tourism in attracting European visitors. Barcelona and Madrid represent metropolitan areas with more diversified tourism markets, while Las Palmas, Santa Cruz de Tenerife, Alicante, Málaga, and Girona reflect the significance of coastal and island destinations in the territorial organization of inbound tourism [8,62].

More specifically, the ten destinations included attracted a total of 109,029,203 tourists between July 2019 and December 2025, equivalent to 27.67% of the volume recorded in the subset of the 1000 leading municipalities. This proportion confirms the marked hierarchy of the Spanish tourism system, although it also reveals a diverse internal distribution, underpinned by metropolitan, island, and coastal centers (Table 9).

**Table 9.** Municipalities with the highest cumulative volume of European tourists among the top 1000.

| Municipality              | Province               | Cumulative | Percentage of the Top 1000 Municipalities (%) |
|---------------------------|------------------------|------------|-----------------------------------------------|
| Barcelona                 | Barcelona              | 27,185,754 | 6.90                                          |
| Madrid                    | Madrid                 | 18,486,317 | 4.69                                          |
| Palma                     | Balearic Islands       | 12,738,096 | 3.23                                          |
| Adeje                     | Santa Cruz de Tenerife | 8,559,476  | 2.17                                          |
| Calvià                    | Balearic Islands       | 8,258,168  | 2.10                                          |
| San Bartolomé de Tirajana | Las Palmas             | 8,000,687  | 2.03                                          |
| Arona                     | Santa Cruz de Tenerife | 7,543,440  | 1.92                                          |
| Valencia                  | Valencia               | 6,737,922  | 1.71                                          |
| Benidorm                  | Alicante               | 6,002,444  | 1.52                                          |
| Málaga                    | Málaga                 | 5,516,899  | 1.40                                          |

Barcelona ranks first, with 27,185,754 tourists and 6.90% of the total for the subset analyzed. Madrid recorded 18,486,317 tourists, equivalent to 4.69%. Together, these two cities account for 45,672,071 tourists, representing 11.59% of the total volume of the top 1000 municipalities. The difference of 8,699,437 tourists between Barcelona and Madrid highlights Barcelona's dominance during the period studied. Its position should be interpreted because there are municipalities located within metropolitan areas with high international connectivity, a diversified tourism offering, and urban functions that extend beyond vacation tourism. However, the table reflects only the cumulative volume and does not allow for attributing a causal influence to these factors.

The second tier of the hierarchy consists of island destinations. Palma ranks third, with 12,738,096 tourists and a 3.23% share. It is followed by Adeje, Calvià, San Bar-

tolomé de Tirajana, and Arona, whose figures range from 7.54 to 8.56 million tourists. Together, these five island municipalities account for 45,099,867 tourists, equivalent to 11.45% of the analytical subset. Their volume is virtually identical to that recorded jointly by Barcelona and Madrid, highlighting the structural importance of the archipelagos in hosting European tourism.

The distribution of these municipalities also reveals the presence of several island hubs. The Balearic Islands are represented by Palma and Calvià, while the Canary Islands include two hubs in Tenerife—Adeje and Arona—and one in Gran Canaria—San Bartolomé de Tirajana. This configuration shows that the concentration of tourism on the islands is not limited to capital cities but also extends to specialized municipalities that, despite their smaller population and functional scale, achieve volumes comparable to those of some of Spain's major cities.

Valencia ranks eighth, with 6,737,922 tourists and 1.71% of the total. Its presence introduces an urban and coastal profile that combines metropolitan functions with a Mediterranean location. Benidorm, with 6,002,444 tourists and 1.52%, represents a highly specialized coastal hub, while Málaga brings up the rear with 5,516,899 tourists and 1.40%. These three municipalities account for a total of 18,257,265 tourists, corresponding to 4.63% of the subset analyzed.

The gap between the extremes of the ranking also reflects the internal inequality of the hierarchy. Barcelona's cumulative volume is 4.93 times that of Málaga, even though both municipalities are among the top ten destinations. Concentration, therefore, occurs not only between the selected municipalities and the rest of the territory but also within the top tier of the tourism system.

The composition of Table 9 allows us to distinguish three territorial profiles. The first corresponds to major metropolitan centers, represented by Barcelona and Madrid. The second comprises island destinations, including Palma, Adeje, Calvià, San Bartolomé de Tirajana, and Arona. The third group includes cities and municipalities along the peninsular Mediterranean coast, such as Valencia, Benidorm, and Málaga. The presence of these profiles shows that European inbound tourism is not organized according to a single territorial model, but rather through the coexistence of diversified metropolitan areas and specialized vacation destinations.

The results indicate that the post-2020 recovery occurred within a highly concentrated tourism system. The descriptive patterns align with the known geography of international tourism in Spain and provide the frame of reference for the subsequent spatiotemporal analysis. Their purpose is to determine whether the cumulative volume, municipal trends, and clusters identified using STC-EHSA lead to convergent or divergent territorial interpretations.

#### 4.2. Coverage and Quality of the Subset of the Top 1000 Municipalities

The selection of the 1000 municipalities that cumulatively record the most foreign tourists represents 12.30% of the 8132 that make up the original set. Nevertheless, during the period analyzed and according to the source used, they account for 393,840,991 tourists, equivalent to 92.48%. Meanwhile, the 7132 excluded municipalities account for 32,021,483 tourists during the same period, representing the remaining 7.52%. This distribution highlights a high territorial concentration of inbound European tourism.

Table 10 shows a marked concentration within the tourism system itself (Figure 3). Across all municipalities, the top ten destinations account for 25.60% of the cumulative volume; the top fifty, 52.36%; and the top one hundred, 64.35%. In the subset of 1000 municipalities, these proportions rise to 27.68%, 56.61%, and 69.58%, respectively.

The difference is partly due to the change in the denominator, since in the second column, the shares are calculated based on a total that is smaller than that of the entire municipal universe. It does not, in and of itself, represent an increase in concentration, but rather the same hierarchy expressed in terms of the volume retained by the sample.

**Table 10.** Synthetic indicators of structure and quality for all municipalities and the selection of the top 1000.

| Structural Indicator                                     | All Municipalities | Top 1000 Municipalities |
|----------------------------------------------------------|--------------------|-------------------------|
| Municipalities                                           | 8132               | 1000                    |
| Cumulative total                                         | 425,862,474        | 393,840,991             |
| Monthly cells with no data                               | 315,876            | 286                     |
| Median number of months without data per unit            | 41                 | 0                       |
| 90th percentile of months with missing data              | 78                 | 0                       |
| Municipalities with $\geq 12$ months of missing data (%) | 65.46              | 0.70                    |
| Percentage of the top 10 municipalities (%)              | 25.60              | 27.68                   |
| Percentage of the top 50 municipalities (%)              | 52.36              | 56.61                   |
| Percentage of the top 100 municipalities (%)             | 64.35              | 69.58                   |
| Cumulative coverage of the top 1000 (%)                  | 100.00             | 92.48                   |



**Figure 3.** Municipal distribution of the cumulative number of European tourists visiting the country, July 2019–December 2025.

The data show that concentration is not limited to the difference between the 1000 selected municipalities and the remaining 7132. There is also a marked hierarchy within the main subset. Just ten municipalities account for more than a quarter of the

total tourist volume, while the top 100 account for nearly seven out of every ten tourists recorded in the sample. The remaining 900 municipalities account for 30.42%. The territorial structure thus combines a relatively broad base of destinations with a highly concentrated top tier.

#### 4.3. Trend Analysis Using STC and EHSA

The STC–EHSA was applied to the 1000 municipalities with the highest cumulative volume of European tourists. The procedure generates three main results: municipal temporal trends derived from STC and EHSA classifications obtained using the eight nearest neighbors and two time periods, 1 and 3 months. This sequence allows us to distinguish the individual trajectory of each municipality from the formation and evolution of statistically significant spatiotemporal clusters.

The trends identified using the STC exhibit marked asymmetry (Table 11). Of the 1000 municipalities analyzed, 911 show a statistically significant positive trend, 61 show no significant trend, and 28 show a statistically significant negative trend. The predominance of upward trajectories indicates that most municipalities experienced an increase in values over a time series that includes the contraction of 2020 and the subsequent recovery. Due to this temporal structure, the result does not demonstrate structural growth relative to a stable pre-pandemic trajectory.

**Table 11.** Summary of trends detected by the Space–Time Cube.

| STC Result                 | <i>n</i> | %    |
|----------------------------|----------|------|
| Significant positive trend | 911      | 91.1 |
| No significant trend       | 61       | 6.1  |
| Significant downward trend | 28       | 2.8  |

A positive temporal trend also does not imply the consolidation of a hotspot. STC identifies the direction of each municipality’s time series, whereas EHSA requires the existence of a statistically significant spatial cluster and examines its behavior during the analyzed period (Figure 4). Local growth and the formation of spatiotemporal centralities are related but represent different analytical dimensions.

Interpreting these trends requires distinguishing between growth and territorial redistribution. In this regard, the highest cumulative numbers of European tourists remain concentrated in destinations such as Barcelona, Madrid, Palma, Adeje, Calvià, San Bartolomé de Tirajana, and Arona. The positive trends, however, are not limited to these dominant hubs but are also evident in intermediate municipalities. The coexistence of a consolidated volume hierarchy and upward trajectories that are geographically widespread is consistent with the heterogeneity of tourism in Spain highlighted in the literature [8,62].

On the other hand, EHSA introduces a more restrictive criterion. Growth in a municipal series is not sufficient to generate a “hotspot” classification: high values must be part of a statistically significant spatiotemporal cluster and exhibit a classifiable trend (Table 12; Figure 5). The predominance of the “No pattern detected” category in both configurations does not indicate an absence of tourism growth, but rather a lack of clusters that satisfy the defined statistical and spatiotemporal criteria.

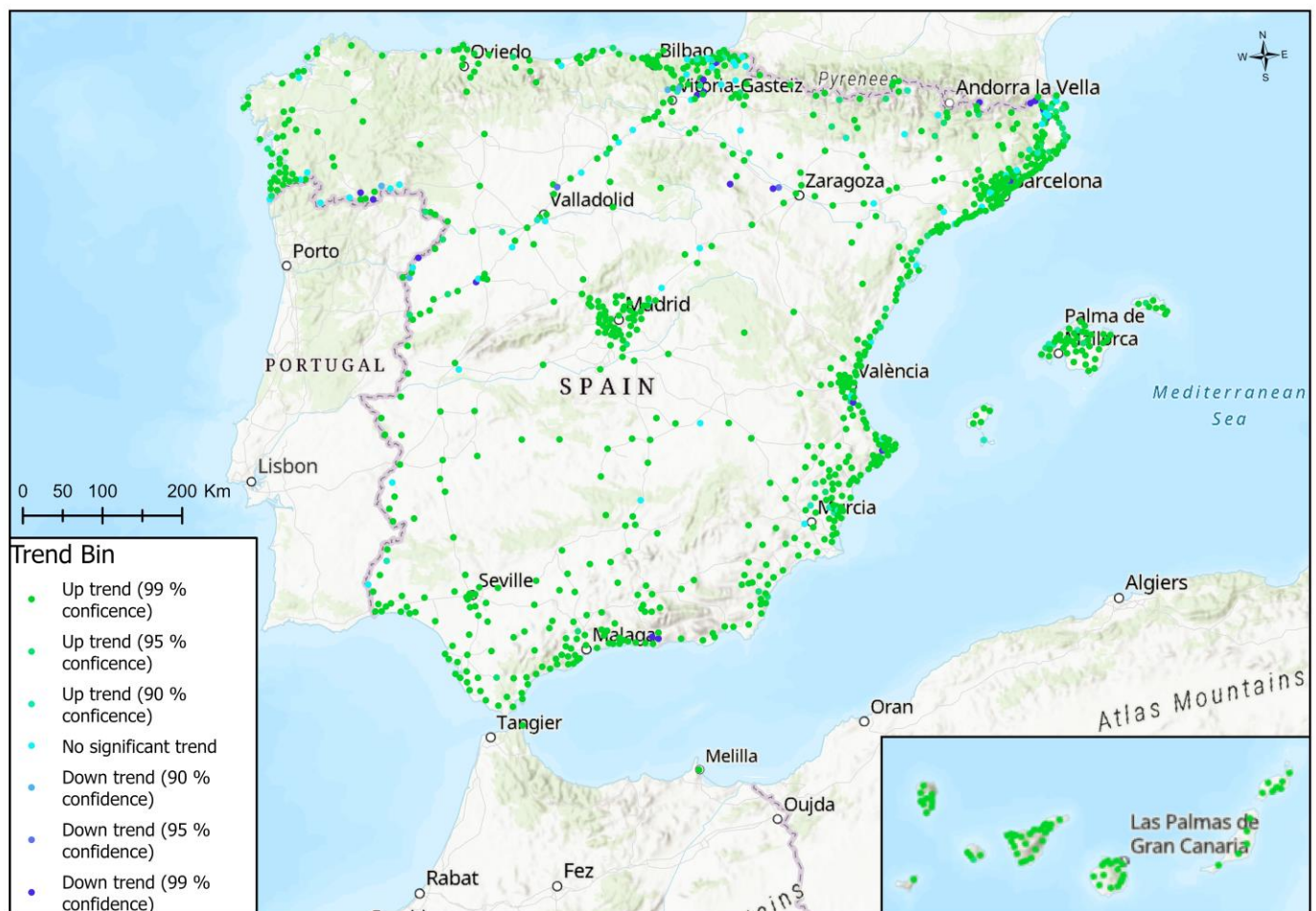


**Figure 4.** Municipal trends in European inbound tourism based on the Mann–Kendall test applied to the monthly Space–Time Cube, July 2019–December 2025. The analysis uses the midpoint imputation scenario (15 tourists) and the cumulative subset of the top 1000 municipalities.

**Table 12.** EHSA categories based on the extent of the temporal neighborhood.

| EHSA Pattern         | Step 1 (n) | Step 1 (%) | Step 3 (n) | Step 3 (%) |
|----------------------|------------|------------|------------|------------|
| No pattern detected  | 952        | 95.2       | 923        | 92.3       |
| Sporadic hotspot     | 35         | 3.5        | 51         | 5.1        |
| Intensifying hotspot | 6          | 0.6        | 18         | 1.8        |
| Persistent hotspot   | 6          | 0.6        | 8          | 0.8        |
| Decreasing hotspot   | 1          | 0.1        | 0          | 0.0        |

The difference compared to the STC results is considerable. Although 911 municipalities show significant positive temporal trends, only 48 are classified into any EHSA hotspot category when using a one-month temporal neighborhood. This figure increases to 77 when using a three-month temporal neighborhood. The widespread municipal growth did not, therefore, translate into an equivalent formation of persistent, sporadic, or intensifying spatial clusters. This divergence constitutes one of the main findings of the integrated analysis.

It follows that the one-month configuration identifies persistent clusters in Madrid and intensifying clusters in Barcelona. Their correspondence with metropolitan areas suggests a possible relationship with connectivity and functional integration, which is not tested in this analysis. Nevertheless, the difference between the two cities is substantial; while Madrid exhibits sustained metropolitan agglomeration, Barcelona shows a statistically significant

strengthening of its high-value agglomeration toward the end of the time series. This does not mean that Barcelona is a recently emerged destination; the intensification refers to the trajectory of spatial agglomeration, not to the recent emergence of the destination itself.

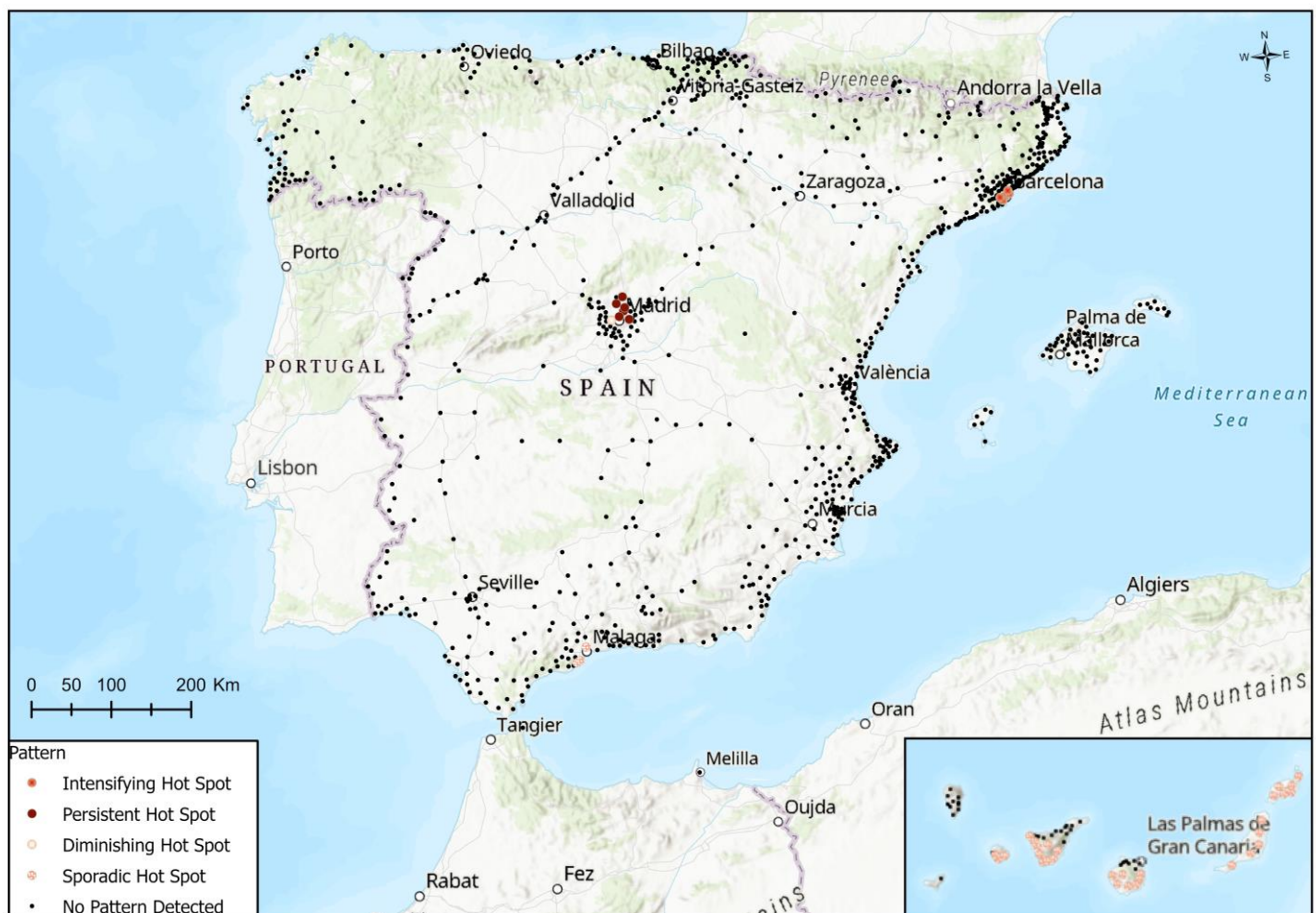


**Figure 5.** Emerging Hot Spot Analysis of European inbound tourism using the eight nearest neighbors and a one-month temporal neighborhood (Step 1), applied to the monthly Space–Time cube corresponding to July 2019–December 2025. False discovery rate correction was applied.

Outside the metropolitan centers, the analysis—using a one-month temporal neighborhood as the reference—reveals a constellation of sporadic hotspots dominated by island and coastal destinations with a marked international orientation. Adeje, Arona, San Bartolomé de Tirajana, Tías, Mogán, Pájara, Yaiza, La Oliva, Benalmádena, and Torremolinos are among the most notable examples. The key lies not in the fact that these are weak destinations—since many of them record very high volumes—but rather in the discontinuous nature of their clustering, which may be associated with seasonality, irregular recovery, temporary demand peaks, or other mechanisms not distinguished by EHSA [46–62].

A comparison with a three-month temporal neighborhood allows us to examine the effect of a broader temporal neighborhood. By increasing the number of months included in the calculation from one to three, the analysis uses a more extensive recent temporal context to evaluate local clustering. This configuration can reduce the influence of isolated monthly fluctuations, although the cube retains its monthly resolution in both cases. The observed differences show that the classification of clusters depends on the width of the temporal neighborhood used [47,53].

The main reclassifications affect destinations with high volumes (Table 13; Figure 6). Palma and Calvià change from “No pattern detected” to “Sporadic hotspot.” Adeje, Arona,

Pájara, Benalmádena, and Torremolinos change from “Sporadic hotspot” to “Intensifying hotspot.” Marbella; meanwhile, changes from “No pattern detected” to “Persistent hotspot.” These transitions indicate that certain clusters only meet the criteria for persistence or intensification when a three-month time frame is incorporated.

**Table 13.** Major changes in classification between the one-month and three-month time frames.

| Municipality            | Tourists, 2019–2025 | Step 1 Pattern      | Step 3 Pattern       |
|-------------------------|---------------------|---------------------|----------------------|
| Palma                   | 12,738,096          | No pattern detected | Sporadic hotspot     |
| Adeje                   | 8,559,476           | Sporadic hotspot    | Intensifying hotspot |
| Calvià                  | 8,258,168           | No pattern detected | Sporadic hotspot     |
| Arona                   | 7,543,440           | Sporadic hotspot    | Intensifying hotspot |
| Marbella                | 5,330,681           | No pattern detected | Persistent hotspot   |
| Pájara                  | 4,528,722           | Sporadic hotspot    | Intensifying hotspot |
| Sant Josep de sa Talaia | 3,936,518           | No pattern detected | Sporadic hotspot     |
| Mijas                   | 3,052,769           | No pattern detected | Sporadic hotspot     |
| Benalmádena             | 2,848,955           | Sporadic hotspot    | Intensifying hotspot |
| Torremolinos            | 2,622,968           | Sporadic hotspot    | Intensifying hotspot |



**Figure 6.** Emerging hot spot analysis of European inbound tourism using the eight nearest neighbors and a three-month temporal neighborhood (Step 3), applied to the monthly Space–Time Cube for the period July 2019–December 2025. False discovery rate correction was applied.

The combined interpretation of STC and the two EHSA configurations allows us to distinguish three trajectories of spatiotemporal centrality, although it should be noted that these do not represent three hierarchical levels. The first corresponds to persistent

clusters, in which high values maintain spatial and temporal continuity, as is the case in the Madrid metropolitan area. The second comprises intensifying clusters, whose statistical intensity increases toward the end of the time series, as seen in Barcelona and, with the three-month temporal neighborhood, in several island and coastal municipalities. The third category includes sporadic clusters, characterized by discontinuous occurrences of significant concentrations. These categories describe the trajectories of the clusters and do not constitute a direct classification of the importance of the tourist destinations.

## 5. Discussion

The main contribution of this study lies not in identifying Spain's most significant tourist destinations—whose status has been widely documented—but in demonstrating that cumulative volume, municipal growth, and spatiotemporal clustering offer different territorial interpretations. On the one hand, the Space–Time Cube detected statistically significant positive trends in 911 of the 1000 municipalities analyzed. On the other hand, the Emerging Hot Spot Analysis identified hot-spot trajectories in 48 municipalities when using a one-month temporal neighborhood interval (Step 1) and in 77 when that interval was extended to three months (Step 3). In this regard, the growth recorded between July 2019 and December 2025 was widespread geographically, whereas the formation of significant spatiotemporal clusters was much more selective and varied depending on the length of the time interval considered. It should also be noted that a municipality may exhibit an upward trend without being part of a significant cluster, just as a location with a high volume may fall outside the EHSA categories when its spatial context or temporal sequence does not meet the established statistical criteria [29–31,47–61]. A comparison between using one- and three-month temporal neighborhoods revealed 96.0% agreement and a Cohen's Kappa of 0.660 across the four comparable categories, indicating substantial stability, although the reclassification of several destinations confirms the influence of the time horizon [68].

The divergence between widespread municipal growth and selective hotspot formation clarifies the relationship between spatial polarization and scale. At national, regional, and provincial levels, concentration is visible in the dominant shares of island, Mediterranean, and metropolitan territories. At the municipal level, this structure decomposes into persistent, intensifying, intermittent, and non-significant clustering trajectories. Regional totals therefore combine municipalities with different volumes, seasonal profiles, and positions within spatial clusters. Aggregate polarization does not imply homogeneous local evolution, and municipal analysis identifies the internal trajectories from which broader territorial patterns are constructed.

The results indicate a selective reinforcement of the existing territorial structure, rather than a profound reorganization. This is evident in the continued dominance of major metropolitan, coastal, and island destinations after 2020, in line with the regional concentration and heterogeneity described for Spain [8,10–15,62–64]. However, nuances can be observed, such as metropolitan persistence, the recent intensification of consolidated clusters, and intermittent or seasonal clustering in leisure destinations. Likewise, centrality was reproduced through different spatiotemporal mechanisms.

The territorial pattern of recovery is consistent with the continuity of preexisting competitive advantages documented in previous research, although their effects were not estimated directly.

These results can now be interpreted in relation to the three theoretical perspectives, while maintaining the distinction between empirical correspondence and direct measurement. First, the widespread positive municipal trends indicate recovery and expansion during the observed period, but they do not assign destinations to specific stages of the tourism area life cycle. Second, the persistence of clusters in established metropolitan

areas and the intensification of other consolidated coastal and island clusters are consistent with path-dependent continuity and cumulative reinforcement. However, the analysis does not identify the investments, institutions, infrastructure, or market relations that generated those trajectories. Third, the coexistence of widespread recovery with selective persistence and intensification shows that post-shock growth was territorially uneven. This finding is relevant to tourism resilience, although the indicators capture recovery and spatial reconfiguration rather than the complete set of resistance, adaptation, and transformation capacities.

When applying a territorial interpretation to the main trajectories of the hotspots, distinct results emerge, with large cities and island areas standing out. In this regard, Madrid emerges as a persistent hotspot due to the continuity of a metropolitan cluster, not merely because of the size of the central municipality. In this city, international accessibility, functional diversity, the availability of housing, and the integration of neighboring municipalities offer a plausible territorial explanation for this stability, consistent with the literature on relational destinations, spatial dependence, and functional integration [4–9,32–37]. However, it should be noted that the analysis does not estimate independent causal effects.

In contrast, Barcelona follows a different trajectory. Its classification as an intensifying hotspot does not imply recent significance—since it held the top cumulative position—but rather the strengthening of the cluster of high values toward the end of the time series. The recovery of international demand and connectivity may have reinforced metropolitan spatial coherence, although these mechanisms were not directly estimated.

Meanwhile, in the Canary Islands, Adeje, Arona, and Pájara transition from sporadic hotspots to intensifying areas as the time span is extended. Accommodation specialization, their dependence on European air travel markets, and the concentration of development and extended tourist season favor a more continuous signal when monthly fluctuations are smoothed out [12,15,43,62–64]. Statistical intermittency does not, therefore, equate to low volume.

These island-level classifications also depend on the specification of the eight nearest neighbors, which ensures comparability but imposes spatial relationships in fragmented territories. Without a formal comparison between alternative matrices, the results must be considered conditioned by the selected neighborhood. Therefore, it is necessary to compare specific values of  $k$ , distance bands, and contiguity structures for each island [65,66].

Overall, urban destinations tend to form metropolitan clusters associated with diversified and continuous demand; coastal areas, corridors conditioned by seasonality; and island destinations, patterns linked to specialization and air connectivity. The Canary Islands exhibit a broader annual cycle, while the Balearic Islands show greater summer concentration [12,43]. It should also be noted that the absence of categories in the EHSA does not indicate a lack of tourism relevance but rather the absence of a sufficiently consistent, high-value cluster under the adopted parameters. In this regard, STC and EHSA detect trends and local spatial associations, but they do not estimate the effects of connectivity, accommodation, source-market composition, climate, expenditure, or governance. The proposed explanations are based on the observed geography and on the literature on networks, resilience, and destination evolution [16–25,32–37,69–79].

Testing these explanations requires a subsequent explanatory stage based on spatial panel, spatial lag, spatial error, or Spatial Durbin specifications with harmonized municipal covariates. Model selection should be guided by residual spatial autocorrelation and Lagrange Multiplier diagnostics rather than by assuming a particular specification in advance.

Mobile phone data provide municipal and monthly detail but remain subject to source-specific detection, device-use, disclosure, and temporal-allocation effects [26–28,35–37,40]. They measure estimated tourist presence rather than motivations, expenditure, or experience. The absence of external seasonal validation means that low off-season values cannot be attributed exclusively to reduced tourism, since network activity and detection effects may also contribute. Comparison with hotel occupancy, airport traffic, and other monthly indicators is therefore required.

These limitations require prior data cleansing, as using the entire sample leads to errors. Therefore, we have chosen to use municipalities that ensure greater representativeness and have fewer gaps caused by statistical censoring. The subset of the 1000 main municipalities retains 92.48% of the observed municipal volume and reduces missing monthly data points to 0.37%, thereby ensuring continuity in the STC–EHSA classifications. Extending the analysis to all municipalities would increase the irregularity and relative weight of the censored values. Although it substantially improves temporal completeness and reduces the influence of censoring, the selection limits spatial contiguity, as the excluded municipalities do not contribute to the local context, with a particular impact on inland areas and archipelagos.

Likewise, a comparison with the 2025 annual subset of the top 1000 municipalities identified 73 municipalities missing from the cumulative selection. These accounted for 591,644 tourists, or 0.65% of the total number of tourists received by European municipalities in 2025 and therefore do not alter the main hierarchy. However, 72 met the continuity criterion, and 68 exhibited significant Mann–Kendall trends and positive, stable Sen slopes under all three censoring scenarios. The sample represents the territorial segment that accounts for most of the observed European volume, not an exhaustive inventory of low-volume emerging destinations. Nor does the individual growth of the excluded municipalities prove new centralities, as EHSA requires local spatial association and a recognizable trajectory of clustering.

The partial coverage of 2019 adds another constraint, as the time series begins in July and provides only one pre-pandemic half-year. Its totals are not comparable with the full years of 2020–2025. The predominance of positive trends may reflect the asymmetric sequence formed by the 2020 collapse and the subsequent recovery. The analysis identifies a monotonically increasing trend in the available series, but not a stable pre-pandemic trend or a causal effect of the pandemic; seasonality and serial dependence may also play a role.

Furthermore, false discovery rate (FDR) correction is applied, which limits spurious significance in multiple local tests [67], and the comparison between one- and three-month temporal neighborhoods indicates substantial stability across the tested temporal configurations. However, the lack of formal agreement among alternative spatial matrices limits claims regarding the stability of each classification, particularly in archipelagic, metropolitan, and sparsely populated areas. Reproducibility therefore stems from the explicit articulation of decisions, not from the universal validity of a single parameterization.

The results facilitate decision-making and have implications for territorial planning and management. Persistent, intensifying, and sporadic trajectories require different monitoring timeframes. The first justifies structural measures regarding mobility, housing, public space, services, and supramunicipal coordination; the second, early warning of emerging pressures; and the third, flexible responses to seasonal peaks or events. A positive STC trend without an EHSA pattern calls for observation, not automatic intensive measures.

Table 14 lists the appropriate scale, frequency, and response for monitoring for each trajectory.

**Table 14.** Guidelines for territorial monitoring based on STC–EHSA patterns.

| STC–EHSA Trajectory                           | Territorial Interpretation                                 | Areas of Interest                                       | Monitoring Areas                                              | Territorial Scale                                       | Approximate Frequency          |
|-----------------------------------------------|------------------------------------------------------------|---------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------|--------------------------------|
| Persistent clustering                         | Stable and recurring concentration of high values          | Possible structural pressures                           | Mobility, lodging, housing, public space, and services        | Municipal, metropolitan, island-wide, or supramunicipal | Monthly, with annual review    |
| Clustering through intensification            | Significant increase in the intensity of clustering        | Recent consolidation and potential emerging pressures   | Infrastructure, mobility, housing, and services               | Municipal, metropolitan, island, or coastal corridor    | Monthly or quarterly           |
| Sporadic clustering                           | Significant but discontinuous concentration                | Seasonal peaks, events, or temporary congestion         | Transportation, services, waste, and distribution of visitors | Municipal or intermunicipal                             | During periods of peak traffic |
| Positive trend in STC without an EHSA pattern | Municipal growth without a consistent spatial pattern      | Local growth not yet spatially consolidated             | Continued growth and possible formation of clusters           | Municipal and supramunicipal                            | Quarterly or annual            |
| No significant trend or EHSA pattern          | Absence of consistent signals under the applied parameters | Possible stability, discontinuity, or insufficient data | Data quality and normal fluctuations in flows                 | Municipal                                               | Annual or biennial             |

Table 14 serves as a supporting framework, not an automatic prescription. In this regard, EHSA describes the temporal behavior of a significant cluster but does not demonstrate overtourism, exceeding capacity, residential pressure, environmental degradation, or social conflict. These conditions depend on the relationship between visitors and residents, lodging, transportation, housing, environmental sensitivity, services, and governance, and require complementary indicators [80–82]. Therefore, it follows that EHSA functions as a diagnostic or early-warning signal.

Furthermore, its application must be adapted to the specific territory. Metropolitan areas require coordination beyond the central municipality; coastal corridors require intermunicipal management of seasonal services, congestion, and environmental pressure; and islands require joint consideration of air connectivity, accommodation concentration, environmental limits, and infrastructure. The categories are more useful for defining scale, timeline, and monitoring information than as fixed labels for the destination.

Transferring the STC–EHSA workflow requires adapting its parameters. Minimum conditions include temporal continuity, stability of spatial units, transparent handling of censoring, and explicit definition of neighborhoods. The number of neighbors, distance, and time window must be adjusted to each metropolitan system, archipelago, rural region, or municipal structure; the Spanish application does not establish universal parameters.

Future research should extend the time series and evaluate whether intensifying hotspots represent persistent change or a transitional recovery phase. Seasonally adjusted series, the seasonal Mann–Kendall test, and alternative periods excluding the 2020 disruption would help determine the influence of seasonality and temporal asymmetry [83–85]. Formal comparison of alternative spatial weighting matrices would also establish the sensitivity of EHSA classifications to the number of neighbors, distance, and contiguity specification [86,87].

A subsequent explanatory stage should incorporate harmonized indicators of accessibility, air connectivity, accommodation capacity and occupancy, source-market composition, expenditure, and residential or environmental pressures. Spatial panel or related models could then estimate the factors associated with persistence, intensification, and intermittency without attributing causality to descriptive spatial correspondence [88–92].

## 6. Conclusions

The main contribution of the study lies in the integration of the Space–Time Cube (STC) and the Emerging Hot Spot Analysis (EHSA) into a reproducible workflow based on monthly mobile phone data. This approach allows for the differentiation of three dimensions that do not yield equivalent results: cumulative tourist volume, the temporal trend of each municipality, and the persistence, intensification, or intermittency of spatial clusters. The comparison of alternative temporal configurations also incorporates an explicit assessment of the sensitivity of the classifications obtained.

The main finding is the divergence between municipal growth and spatial consolidation. The STC identified statistically significant positive trends in 911 of the 1000 municipalities analyzed, while the EHSA detected hotspot patterns in 48 municipalities with a one-month temporal window and in 77 with a three-month window. The recovery recorded between July 2019 and December 2025 was geographically widespread, but only a small proportion of municipalities formed significant and temporally recognizable spatial clusters. Local growth does not, therefore, constitute sufficient evidence of a new tourism centrality.

In territorial terms, the results show a selective reinforcement of Spain's tourism structure, with no statistically detectable evidence of widespread municipal reorganization under the selected analytical universe, spatial weights matrix, temporal neighborhoods, and observation period. Metropolitan areas, coastal regions, and archipelagos maintained their dominant position, although they followed distinct trajectories. Madrid formed a persistent metropolitan cluster; Barcelona exhibited a pattern of intensification; and several coastal and island municipalities gained greater continuity as their temporal neighborhood expanded. A comparison with the 1000 most-visited municipalities in 2025 also identified low-volume destinations with robust upward trends, although their limited aggregate weight and the absence of a specific EHSA prevent them from being interpreted as new spatiotemporal centers.

The scope of the results is limited by partial coverage in 2019, the disruption in 2020, seasonality, possible serial dependence, the observational characteristics of mobile data, and the selection of the 1000 municipalities with the highest cumulative volume. The sensitivity of the EHSA to spatial and temporal neighborhood specifications must also be considered. The categories obtained represent diagnostic signals, not causal explanations or direct measures of tourism pressure, carrying capacity, or sustainability. Despite these limitations, the STC–EHSA workflow provides a useful tool for territorial monitoring, the identification of areas with distinct trajectories, and the selection of cases requiring further analysis using socioeconomic and environmental indicators and explanatory spatial models.

As a practical reference for future applications, a series covering at least five to seven complete annual cycles would provide a more defensible basis for distinguishing recurring seasonality, temporary disruption, recovery, and subsequent stabilization. When the objective is to assess resilience to a specific shock, the sequence should preferably include at least two complete pre-shock annual cycles, the disruption period, and several post-shock cycles. This range is proposed as an empirical design reference rather than a universal statistical threshold. The required duration must be adjusted to data frequency, seasonal structure, serial dependence, the magnitude and timing of the shock, and the stability of the spatial units.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi15080338/s1>. Table S1: Complementary data. Workflow parameters and reproducibility. This note details the preprocessing rules applied to censored cells, the criteria used to define the subset of the top 1000, the spatial projection and municipal linkage

procedures, the STC construction parameters, and the EHSA configurations tested in the robustness analysis. Table S2: Sensitivity of the cumulative top-1000 selection to municipalities entering the annual top 1000 in 2025. This file identifies the 73 municipalities included in the 2025 annual ranking but absent from the cumulative analytical subset and reports their annual and cumulative volumes, ranks, temporal coverage, and aggregate contribution. Table S3: Temporal trend and censoring-sensitivity analysis of municipalities excluded from the cumulative top 1000 but included in the 2025 annual top 1000. This file reports temporal completeness, Mann–Kendall statistics, and Sen’s slopes for the 73 municipalities identified in Table S2 under lower-bound, midpoint, and upper-bound censoring scenarios. The analysis is municipal and non-spatial and does not constitute an EHSA classification. Table S4: Sensitivity check Kappa. Sensitivity analysis of EHSA classifications under alternative temporal neighborhood configurations. This note describes the evaluation of agreement between EHSA classifications obtained using one-month and three-month temporal neighborhoods applied to the same monthly “Space–Time Cube.” It presents the complete four-class agreement matrices, exact agreement, expected random agreement, and Cohen’s Kappa, along with a complementary binary comparison between municipalities with some hotspot pattern and those in which no pattern was detected. It also identifies the municipalities whose classification changed between the two temporal configurations.

**Author Contributions:** Conceptualization, José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; methodology, José Manuel Sánchez-Martín; software, José Manuel Sánchez-Martín; validation: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; formal analysis: José Manuel Sánchez-Martín; investigation: José Manuel Sánchez-Martín and Ana Beatriz Mateos-Rodriguez; resources: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; data management: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; writing—preparation of the original draft: José Manuel Sánchez-Martín; writing—revision and editing: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; visualization: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; supervision: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; project administration: José Manuel Sánchez-Martín, Felipe Leco-Berrocal, and Ana Beatriz Mateos-Rodriguez; funding acquisition: Felipe Leco Berrocal. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was co-funded by the European Union, the European Regional Development Fund (85%), and the Regional Government of Extremadura. Managing authority: Ministry of Finance (Spain), grant GR24076.

**Data Availability Statement:** The data used in this study are derived from the experimental statistics of the National Institute of Statistics (INE), which are publicly available on its website. The derived files used in the analytical workflow, as well as the supplementary tables mentioned in the manuscript, are included as Supplementary Materials for the article.

**Conflicts of Interest:** The authors declare no conflicts of interest. The funders did not intervene in the study design; in the collection, analysis, or interpretation of the data; in the drafting of the manuscript; or in the decision to publish the results.

## Abbreviations

The following abbreviations are used in this manuscript:

|      |                            |
|------|----------------------------|
| STC  | Space–Time Cube            |
| EHSA | Emerging Hot-Spot Analysis |

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