Patterns of Place in Rural Basilicata: A Point Pattern Approach to Tourism Services and Attractors

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Abstract. This research shows how tourism is inherently a place-oriented activity, where the spatial dimension can play a crucial role in the distribution of added value across the territory. The aim is to explore the potential of tourism supply mapping tools in rural and peripheral settings derived from Point pattern analysis, with a focus on selected case studies in the Basilicata region. Using spatial analysis techniques, we investigated the spatial organization of tourism and cultural services in a relevant case study. By analyzing the interdependence of cultural services and attractors in selected rural areas of the Basilicata region, this approach has proven to be significant in uncovering spatial insights for policy makers. The results confirm that spatial proximity to attractors, especially within 2 km, can be a determinant factor in shaping the geography of tourism supply in inner areas. The potential development of this work can thus be identified in supporting the management of the information complexity of the tourism phenomenon at the micro scale, by identifying the importance of point analysis of the tourism phenomenon to interpret the dynamics at the territorial scale.

Keywords: Tourism supply · Spatial analysis · Inner areas · Territorial cohesion · Point patter analysis

1 Introduction

The spatial organization of tourism services is not only a geographical matter but also an economic one. Tourism can contribute to local economies only where it is embedded in the existing economic fabric, since its impact depends on tourists' consumption of goods and services. However, the management and enhancement of spatial assets [1] for tourism purposes requires extensive mapping of the sectors' value chain. Therefore, understanding the spatial clustering of services near cultural attractors helps identify areas where tourism-related services are more active and spatially interdependent [2].

Tourism is place-oriented activity, and the spatial dimension of these phenomena is the focus of this research. The aim is to explore the potential of tourism supply mapping tools in rural and peripheral settings derived from Point pattern analysis, with a focus on selected case studies in the Basilicata region. This study is part of a broader research

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initiative carried out by the Laboratory of Urban and Territorial Systems Engineering (LISUT) at the University of Basilicata, within the framework of the Tech4You project funded by Italy's National Recovery Fund (PNRR) [3]. Within this context, the tourism sector is analyzed in relation to the territorial dynamics it affects. Although tourism is widely acknowledged as a driver of development in disadvantaged areas [4].Territorial development policies targeting peripheral areas often support the creation of tourism value chains through public investments aimed at enhancing the offer, frequently centered around landmark assets, embedded in their local contexts [5, 6].

This paper contributes to this research topic by employing second-order spatial analysis, particularly Ripley's K-function [7] to understand how tourism-related services and cultural attractors are spatially distributed and how they interact across the "Vulture" and "Alto Bradano" area. The observed clustered patterns help to define spatial lens at which these phenomena intensify, enabling the interpretation of spatial influence zones and interrelations between services and attractors. The discussion of the results offered useful insights into the functional relationships between services and attractors. In the end, this approach supports the mapping of tourism value chain geographies and could provide a valuable framework for assessing spatial dynamics and operational interdependencies across the territory [8].

2 Materials and Method

2.1 Study Area and Dataset

The study area is in southern Italy, mainly in Basilicata region. This area has historically been affected by development lag that stems from a infrastructure deficit, low fertility rate, working-age migration and economic decline [9, 10]. The delineation of the analytical region was not constrained by Italian municipal administrative boundaries. Instead, it was defined to include some key regional asset for the mapping process better defined in the next paragraph. This extent encompasses the "Alto Bradano" and "Vulture" area, covering approximately 3,722 km^2 primarily located in the northern part of the Basilicata, with a small part extending into western part of Apulia. These boundaries have been defined to account for the homogeneous characteristics expressed by the territorial structures. Indeed, the area is characterized by a complex mix of land uses, ranging from untouched high-natural landscapes to agriculturally wine-oriented hills and small villages that shape its environmental and natural identity. Traces of historical influences are evident with signs of the cultural matrix that has shaped over the centuries the current configuration of settlement structures and scattered unique element far beyond the planned urban form. These features are expressions of the area's cultural identity, enhancing its potential as a tourist destination. In detail, the area boasts the Vulture Regional Park, numerous castles from the Federician era, museums of national and regional interest, UNESCO sites and archaeological landmarks. These assets represent significant opportunities for the development of a tourism ecosystem, a potential that unfortunately remains largely untapped and inadequately exploited.

Establishing a territorial knowledge base is the first step of this research work. The mapping of tourism phenomena and related spatial dynamics at local was conducted through a methodological approach that ensures generalization, making it replicable for

broader analysis. For this purpose, open-source data resources such as OSM and Google applications were used, as they, in our opinion, provide the ideal data detail and update for mapping interaction among hospitality services, accessibility facilities and tourism attractions at local scale [11]. The spatial and non-spatial dynamics that may potentially develop between these elements in the territory and the related operators (tourism sector stakeholders) can be an important parameter for assessing the quality of the tourism offer in a specific area. The dataset consists of tourism-related services categorized as follows: hospitality providers, accessibility facilities, and cultural attractions.

2.2 Point Pattern Analysis

Following the mapping process, this research focuses on analyzing the spatial distribution of point entities on the territory and their spatial interactions. The study of spatial interactions is a valuable exercise in understanding how different spatial entities influence each other and if their distribution is affected by the context in which they are embedded. Moreover, by decoding the connections that bind spatial systems, it is possible to highlight interdependencies (both attraction and competition) as well as potential synergies and/or critical issues emerging from the interaction among these components. This approach is helpful in the definition of spatial functional networks and some territorial hierarchies.

To achieve this, spatial analysis techniques were employed, as they are widely used in territorial planning to investigate relationships among spatial units and to identify areas of particular interest or concern. In this context, the application of spatial statistical techniques in planning provides valuable insights to inform the design of place-based and targeted actions.

Point Pattern Analysis (PPA) is a series of techniques and methods for analyzing the spatial distribution of POIs [12] to understand how they are distributed over the territory and interact with each other. Thus, it studies the spatial distribution in two dimensions [13], uses the density, dispersion and homogeneity of the POI dataset in space to evaluate, quantify, and characterize the spatial distribution of the events.

We believe that this methodological approach is useful to interpret the underlying spatial processes that govern the distribution of tourism-related entities, how they are arranged over space and where to set the limit of their interactions. Spatial objects can be conceptualized in two fundamentally different ways: as points or as events. It is crucial to differentiate between these concepts, as points refer to objects with arbitrary positions, whereas events represent occurrences at specific locations, where position is not entirely arbitrary. When points are considered as events occurring at selected locations, the resulting collection is called a point pattern, so the location of points becomes a key aspect and of interest. In addition, point patterns can be defined as marked (if multiple attributes are associated with each location) or unmarked (if only spatial coordinates are provided). The latter considers only the coordinates, thus the location, while the former is the most complex, although the marks may be limited but include more information characterizing each point. For example, for the tourism sector, with the market point pattern we can discriminate which points are accommodation services and which are attractors in the area and which are transportation facilities. Information crucial for mapping the mutual influence between services and facilities on the territory.

More in detail, PPA is structured around two approaches depending on the spatial properties being analyzed [13]:

1. First-order properties: These focus on the characteristics of individual locations and their variations across space. Density-based methods primarily examine first-order properties by assessing the variation in individual point locations within the study area, characterizing the dataset's spatial distribution in terms of density. Density-based techniques are used to characterize the spatial pattern by analyzing its distribution at both global and local scales. Quadrat Analysis, a simpler approach, and Kernel Density Estimation (KDE), a more sophisticated statistical technique, both enable visualization of density variations across space.
2. Second-order properties: These consider interactions between points and their mutual interaction and influences. Distance-based methods analyze the spatial distribution of points by measuring distances between pairs of points, typically using the Euclidean distance to determine whether a spatial distribution of events exhibit random dispersion or clustering.

These methods provide a statistical founded analysis to density-based approaches, enabling the assessment of spatial distribution. Unlike first-order properties, second-order analysis incorporates a distance variable measuring the correlation between all point pairs separated by a given distance d [14].

Definitively, the most used approach is the Average Nearest Neighbor (ANN) analysis, which calculates the average distance between each POI and its closest neighbor.

But beyond ANN, other second-order statistical functions overcome the limitations of grid-based methods. Among the most widely used are Ripley's K function K(d) [7] and its transformed version L(d), as well as the pair correlation function g(d). Both approaches have advantages and particular weaknesses. First-order is conceptually simple but trivial, quantifying only the relationship between a point while ignoring the rest of the points present in the study area [12]. Therefore, we focus in this paper on the description and application of second-order approaches.

2.2.1 Second-Order Properties - Ripley's K Function

Ripley's K function is a statistical approach calculated on a set of points distributed in space, estimating the second-order property exhibited by the data. It examines the distance between a point and "all distances" from other points and automatically compares it with a Poisson-distributed point pattern. It accounts for the number and distance between point events and quantifies how much the observed pattern deviates from spatial randomness. The theoretical K function, given a set of point events S, is computed by dividing E, the expected number of events falling within distance d, by the intensity λ of S:

$$K(d) = E(d)/\lambda$$

Ripley's K function represents the cumulative distribution of observed point events S as distance increases. It is expected that $K(d) = \pi r^2$ if the point distribution follows

Complete Spatial Randomness (CSR), $K(d) > \pi r^2$ if points cluster within a distance d, and $K(d) < \pi r^2$ if the data exhibit a regular pattern. The K function is a second-order analysis of point pattern models, usually in a two-dimensional space (Dixon, 2013; Haase et al., 1996). Second-order effects arise from the spatial dependence of the process. Essentially, Ripley's K function approach uses a circular search window (h) around each event (i) and counts how many other events fall within that window. The window moves to the next event until all n points in the study area have been analyzed.

The process iterates through the following steps:

- For a POI, count the POIs within a circle of a given radius.
- Repeat this operation for each POI in the dataset.
- Calculate the number of POIs in each circle and divide them by the overall POI density.
- Repeat this operation using POIs sampled from a Poisson random model for the same set of circles.
- Compare this distribution with the Poisson distribution.

Thus mathematically, Ripley's K function is defined as:

$$K(h) = \left(\frac{A}{n^2}\right) * \sum_{i}^{n} \sum_{j}^{n} (I_h \left(\frac{d_{ij}}{w_{ij}}\right)$$

This equation evaluates the structural characteristics of a given set of events, where d_{ij} is the distance between events i and j, and A is the size of the study region. The term w_{ij} is a correction factor for edge effects.

Ripley's K function can be biased due to edge effects occurring when circles intersect the boundary of the study region. The K function increases as distance h grows. To statistically assess whether the observed point pattern follows a regular, clustered, or random distribution, the K function is evaluated using a large number (M) of Monte Carlo simulations. For each simulation, a number (n) of events (e.g., randomly distributed) are generated within the study area. The theoretical curve of a Completely Random Process (CSR) k_{pois} serves as baseline and represents randomly distributed events within a study area. This is the null hypothesis is often used in spatial point pattern analysis. The others empirical curves, such as k_{iso}, k_{trans}, and k_{bord}, are compared to this CSR curve to estimate spatial clustering or dispersion. In particular, if the empirical curves lie above the CSR curve, it indicates aggregation or clustering of points, otherwise if they lie below k_{pois} suggests repulsion, where the points are more dispersed, see Fig. 1.

As said before, Ripley's K function can be biased due to edge effects occurring when circles intersect the boundary of the study region. The K function increases as distance h grows. Correcting the edge effect of the method is essential, particularly when the interpoint distance for points near the boundary exceeds the distance to the nearest plot boundary [15]. Methods to account for edge effects include the use of a buffer zone, where a zone around the boundary is added to the study area, or treating the study area as a torus (Gignoux et al., 1999). These methods help ensure that the spatial neighbourhood of each point is evaluated without introducing bias from boundary limitations. For points located near the boundary, the actual number of neighbors may be underestimated, as some neighbors may be outside the study area, leading to potential underrepresentation

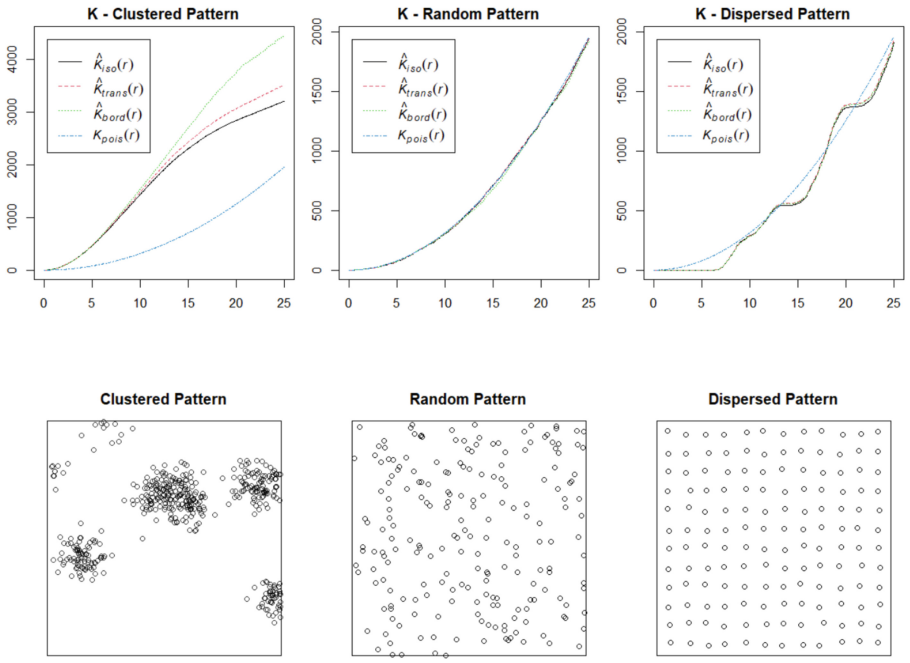

Fig. 1. K-function curves for clustered, random, and dispersed patterns compared to theoretical expectations. And the corresponding spatial distributions illustrating clustered, random, and dispersed pattern.

of spatial relationships [15]. Therefore, edge effect corrections, such as those provided by Ripley's local correcting factor, are highly recommended when comparing point patterns or interpreting ecological phenomena such as neighborhood effects or competition [16].

Finally, we just compute multitype point pattern analysis, implementing K-cross algorithm, in order to estimate if there are significant relationships and influence between the distribution of the different category of points. This module analyzes whether the expected distribution of one category of points within a specific distance is positively affected by a second distribution of points of another category. Indeed, useful model for interpreting interactions between different types of points.

3 Results and Discussion

This paragraph presents the main outcomes of the study, starting from the results of the extensive mapping process involved in the study area. Multi-source datasets were collected and employed to build a rich territorial knowledge base, which represents the foundation of this research work. The mapping of tourism-related phenomena and spatial dynamics at the local scale was conducted through a methodological approach designed to ensure generalizability, making it applicable to broader analyses. For this purpose, OSM and Google applications were utilized. The result is a comprehensive

geodatabase that includes spatial information on both tourism services and cultural attractors categorized as follows:

- Hospitality providers, including Restaurants and Accommodations (e.g., B&Bs), with 417 and 442 respectively, for a total of 859 services (0.231 services/km2).
- Accessibility facilities, comprises Transit Stations (the hubs of intermunicipal mobility) and Parking areas, with 147 and 168 respectively, for a total of 315 facilities (0.084 facilities/km2).
- Cultural attractions categorized based on different certified sources: 1 UNESCO site, 21 MiBACT Museums, 3 "Most Beautiful Villages in Italy," and 147 heritage sites protected under Legislative Decree 42/04, for a total of 172 cultural attractions in the study area (0.0046 attractions/km2).

The data are presented and synthetized in the following Table 1 *and presented in the map below,* see Figs. 2 and 3.

Table 1. Summary of the categorized Point of Interest (PoI) geodatabase used in the analysis.

Main category	Sub-category	Number of POIs	Density [PoI/km2]
Hospitality providers	Restaurants	417	0.112
	Accommodations	442	0.118
		859	0.231
Accessibility facilities	Transit stations	147	0.039
	Parking areas	168	0.045
		315	0.084
Cultural attractions	Unesco site	1	0.0002
	MiBACT – National/Regional Museum	21	0.005
	The Most beautiful Village of Italy	3	0.0008
	Heritage sites	147	0.039
		172	0.046

The pictures above present the PoI mapping for our study area, which spans approximately three thousand square kilometers. The first picture, Fig. 2, represents cultural attractions, where we identify one hundred seventy-two sites. These attractions represent castles, heritage sites, museums and so on are scattered across the territory, reflecting the widespread presence of landmarks, and cultural assets beyond urban centers.

The second map, Fig. 3, depict services, over 1,174 PoI was mapped. As expected, services tend to be highly concentrated in urban areas, following population density and tourism demand. This comparison highlights the spatial mismatch between where attractions are located and where tourism-related services cluster. Understanding these

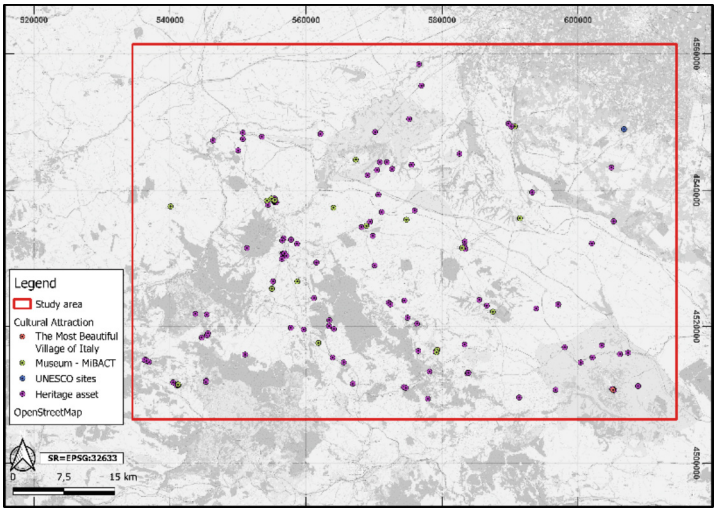

Fig. 2. Map of the study area highlighting the spatial distribution of cultural attractors. The attractors are categorized by type (e.g., UNESCO sites, national/regional museums, and heritage sites).

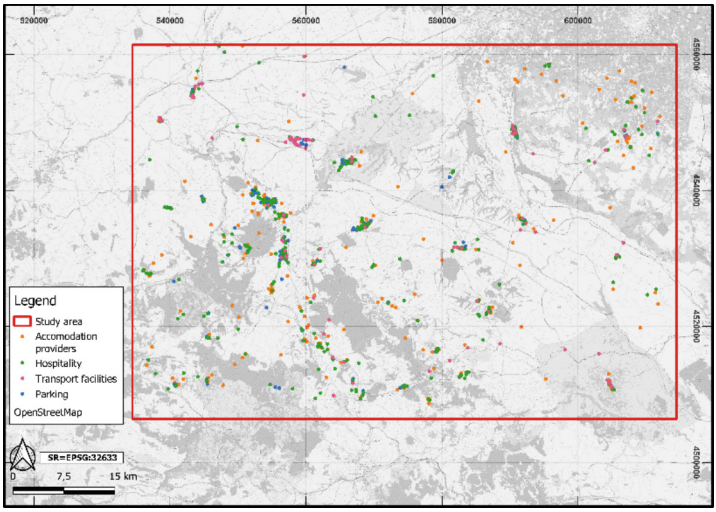

Fig. 3. Spatial distribution of tourism services within the study area, encompassing hospitality providers (restaurants and accommodations) and accessibility facilities (transit stations and parking areas).

patterns is key for planning sustainable tourism strategies and enhancing accessibility to key assets in the region.

Based on this geospatial dataset, we applied Ripley's K function, to evaluate whether the spatial distribution of points exhibits randomness or clustering. The outcomes of this PPT are shown in the two graphs below, see Fig. 4.

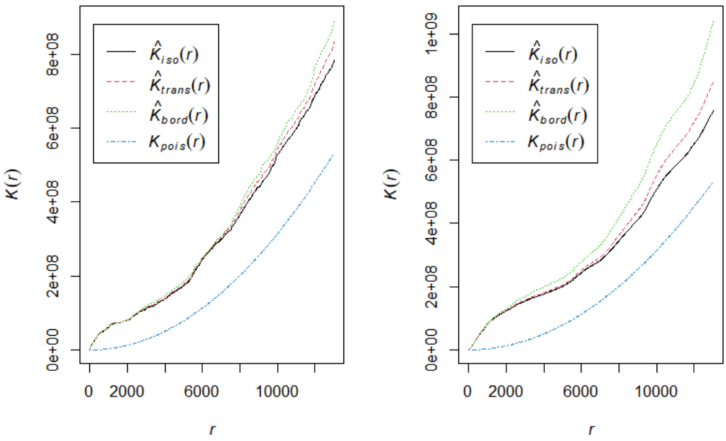

Fig. 4. Ripley's K-function analysis for spatial distribution patterns. The left panel shows the results for cultural attractors, while the right panel refers to tourism services. In both cases, the K-function is compared against the expected values under Complete Spatial Randomness (CSR).

As clearly visible from the graphs, both services and cultural attractors exhibit a strong clustering tendency, particularly within 2 km (r = 2,000 m), see Fig. 5. This is indicated by a quick increase in the K function curve, significantly above the expected values under the CSR assumption. To further explore and investigate if there are some spatial relationships between these two categories of points, we employed the K-cross function.

The analysis confirms the previous findings, the K(r) values between cultural attractors and tourism-related services exceed the Monte Carlo simulation envelope, depicted in grey in the picture, especially within 2 km. This result is interesting from a spatial point of view because it indicates a statistically significant tendency for tourism-related services to be in proximity to cultural attractors than would be expected under complete random spatial distribution. Moreover, this finding is in line with existing literature, which points out how the density of commercial activities, specifically accommodation services, is strongly influenced by the presence of cultural heritages, confirming their role as key drivers in the spatial organization of tourism ecosystems [17].

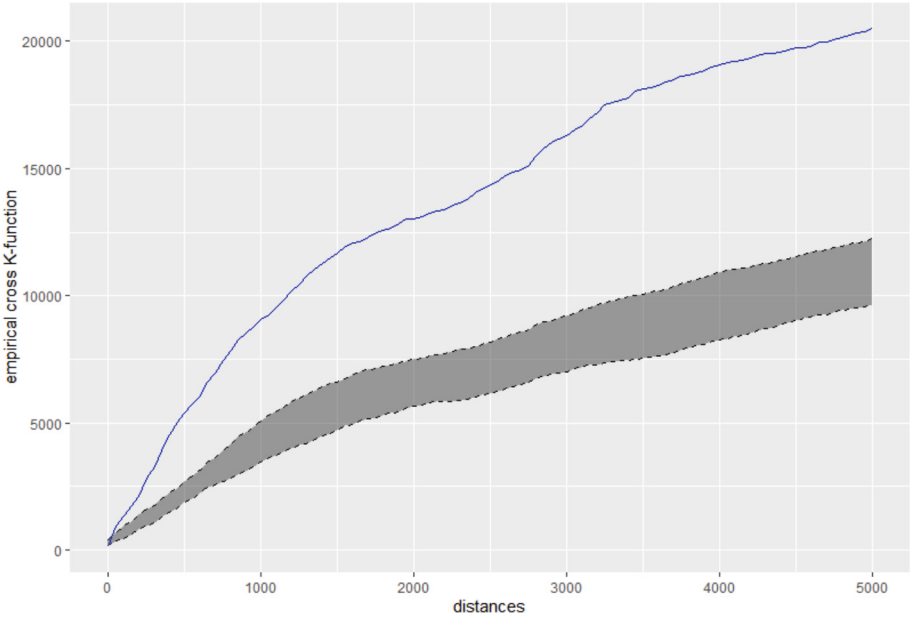

Fig. 5. Cross K-function showing spatial dependence between tourism services and cultural attractors. Values above the Monte Carlo simulation envelope indicate significant spatial clustering.

4 Conclusion

This research shows how tourism is inherently a place-oriented activity, where the spatial dimension can play a crucial role in the distribution of added value across the territory. Using spatial analysis techniques, we investigated the spatial organization of tourism and cultural services in a relevant case study within the framework of the Tech4You project funded by Italy's National Recovery Fund. By analyzing the interdependence of cultural services and attractors in selected rural areas of the Basilicata region, this approach has proven to be significant in uncovering spatial insights for policy makers [18, 19]. The potential development of this work can thus be identified in supporting the management of the information complexity of the tourism phenomenon at the micro scale, by identifying the importance of point analysis of the tourism phenomenon to interpret the dynamics at the territorial scale. Therefore, the analysis shifts from a broad, aggregated municipal-level view of the tourism phenomenon to a low-dimensional vector representation of the points of interest of the entities in the system, namely the POIs. We recorded over 1,174 hospitality providers and accessibility facilities and 172 cultural attractors, ranging from UNESCO sites to local heritage sites in the study area. After the mapping process, this research focused on analyzing the spatial distribution of point entities across the territory and their spatial interactions. Understanding these dynamics is essential not only for mapping the tourism value chain across the territory, but also for informing the design of targeted, place-based policies that support tourism development in rural and peripheral areas.

In this perspective, point pattern analysis emerged as a valuable tool in revealing how tourism-related services tend to cluster in proximity to cultural attractors, pinpointing areas of functional interdependence. Understanding these patterns is key for planning sustainable tourism strategies and enhancing accessibility to key assets in the region [20]. In addition, the identification of this functional influence may be useful to define certain spatial hierarchies that are instrumental in achieving the broader objectives of territorial cohesion. To this end, results confirm that spatial proximity to attractors, especially within 2 km, can be a determinant factor in shaping the geography of tourism supply in this area, confirming how a structured and well-organized proximity service base, which is almost always absent in marginal and peripheral contexts, can offer better fruition of the area from the tourist's point of view and can translate into added value for economic development.

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