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Spatial Interaction Model: a shift towards network-based territorial configurations assessment for data-driven sustainable planning

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Contents

List of figures

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Abstract

Cartographic representation reveals where territorial phenomena occur, but not how they are generated. The location of services, infrastructures, attractors, and socio-economic activities reflects deeper spatial processes structured by proximity, accessibility, complementarity, hierarchy, and interaction. The difficulty of defining these processes lies in the complexity of territorial systems, which are not fixed in space but relational configurations shaped by flows, dependencies, feedback mechanisms, and multi-scalar interactions among places, infrastructures, services, institutions, and communities. The identification of latent relational structures is therefore central to territorial analysis. By modelling territorial components as networks, the research uncovers the spatial organization of the system and the constraints that shape its configuration. Starting from this assumption, the thesis addresses the limits of traditional cartographic modelling and GIS-based overlay approaches. The central research hypothesis is that territorial phenomena are not random spatial arrangements, but emergent configurations generated by underlying interaction processes. The research proposes a spatial interaction model for network-based territorial configuration assessment, aimed at reconstructing emergent territorial structures from fine-grained spatial data. Tourism is chosen as the empirical field through which the analytical framework is developed and tested. As an inherently spatial and relational phenomenon, tourism involves the interaction between attractors, services, accessibility components, and territorial resources. The contribution of the thesis is threefold. Conceptually, it frames territorial systems as complex relational structures and interprets spatial sustainability as a configurational property of territory. Methodologically, it integrates spatial interaction modelling, graph theory, and data-driven spatial analysis into an analytical framework for territorial assessment. In conclusion, it provides a planning-support approach capable of identifying functional geographies, revealing service disparities, supporting sustainable tourism strategies, and assessing how territorial investments may reshape local configurations.

1 Introduction

1.1 Cartographic modelling in the evolution of geospatial reasoning: potentials and limits for territorial analysis

The early development of Geographic Information Systems (GIS) was founded in cartographic modelling, an analytical approach based on the systematic overlay and manipulation of spatial data layers. Cartographic modelling is a systematic series of spatial operations, including overlay, buffering, reclassification and aggregation, which are performed on geographic data sets to respond to a particular spatial query (Tomlin, 1990; Longley et al., 2015; Goodchild, 1992). Theoretically, the method is based on previous manual map-overlay methods of landscape planning, most famously defined by McHarg in Design with Nature (1969). Spatial analysis involves the integration of thematic layers of environmental, infrastructural or socio-economic variables to produce suitability maps or decision-support products. Tomlin (1990) explicitly defines cartographic modelling as a structured sequence of map operations (overlay, local, focal, zonal, and global functions). This is the seminal work introducing map algebra and formalizing cartographic modelling as a sequence of spatial operations applied to raster layers. The method has been found to be especially useful in a broad variety of applications, such as environmental suitability analysis, habitat modelling, infrastructure location, and risk assessment (Malczewski, 2004; Store and Jokimaki, 2003). It was particularly useful in visual terms in planning practice: graphical workflows can be used to describe the modelling process and it can be implemented without high-level programming, so the planner can operate in multi-criteria spatial decision-making processes (Jankowski and Richard, 1994).

Arundel and Li (2021) successfully summarize this wider trend by outlining the development of geospatial reasoning by four significant scientific paradigms, such as empirical description, theoretical generalization, simulation of complex phenomena, and data-driven exploration. Their study is helpful since it enables cartographic modelling to be placed in history as a component of the process of the second and third paradigm transition. It generalizes map-based reasoning to computational settings and implementing spatial analysis, but is still closely connected to a representational logic where space is viewed as a collection of mapped conditions to be combined (Arundel & Li, 2021; Gahegan, 2020; Goodchild, 2010). These attributes are very useful in the context of planning since they can be used to facilitate communicability, procedural justification, and decision-support transparency (Jankowski and Richard, 1994; Malczewski, 2004). Nevertheless, in spite of its historical and methodological significance, cartographic modelling could be considered also as a reductionist conception of spatial phenomena. The methodology is mainly concerned with fixed spatial arrangements, where geographic variables are layers, which are then merged using deterministic rules. Although the paradigm is useful in determining spatial suitability or mapping constraints, it tends to overlook the processes that produce spatial patterns. That is, cartographic modelling is more likely to model the apparent spatial distribution of phenomena, without actually modeling the processes that generate them.

This shortcoming has been much debated in the development of spatial analysis and GIScience. According to Batty (2013), cities and territorial systems cannot be sufficiently perceived as fixed spatial systems, but should be viewed as dynamic systems of interactions, flows, and networks. On the same note, Raimbault (2019) points out that territorial systems are characterized by the properties of complex systems, whereby spatial patterns are formed by multi-scalar interactions of heterogeneous actors, infrastructures, and institutions. In this view, the classical GIS paradigm of layer overlay does not seem to be adequate to reflect the relational and systemic aspects of spatial phenomena.

The second weakness is related to the implicit assumption of independence of spatial variables in most cartographic modelling processes. The analysis with overlay normally considers the spatial layers as independent criteria which can be combined linearly to generate an outpus. Such assumptions are, however, rarely met by spatial data. Spatial dependence, heterogeneity and feedbacks are the features of spatial processes that imply that locations affect each other because of their proximity, connection, or flows (Tobler, 1970; Anselin, 1988). When these relational dynamics are ignored, analytical frameworks that can only describe the patterns but not the processes underlying the territorial organization may be obtained.

Another limitation concerns the way spatial entities are represented within the traditional GIS paradigm. Cartographic modelling typically operates on spatial layers structured as continuous surfaces or aggregated spatial units, such as raster cells or administrative boundaries. While these representations are computationally efficient and have proven extremely useful for many planning applications, they inevitably simplify the internal organization of territorial systems. In many territorial phenomena, such as urban systems, transportation infrastructures, or tourism ecosystems, the spatial configuration of the system cannot be fully understood by considering only the distribution of attributes across space. Instead, these systems are structured through interdependencies among spatial components, where the behaviour of one element is influenced by its connections with others. When analysis is restricted to overlay operations on spatial layers, these interdependencies may remain only partially observable.

For this reason, the main limitation of cartographic modelling does not lie in the maturity of the technology itself, but in the type of analytical questions it is able to address. The overlay-based workflows are efficient in cases when the spatial phenomena can be modeled as independent or weakly dependent criteria that are distributed across a surface. They are far less useful in the case when the phenomenon of territory studied is inherently relational. Tourism system provide a clear example, it cannot be simplified to the overlay of attractors, services, infrastructures and accessibility conditions. Its form arises out of how these elements interact in space, creating clusters, asymmetries, centralities, peripheral formations and differentiated destination areas. A cartographic model can be used to determine appropriate locations or map tourism resources, but it does not include the functional organization of the system. What it describes well are space conditions; what it describes less well are the processes of co-organization of the differetn entities on the territory.

Arundel and Li's (2021) discussion of the fourth paradigm reinforces this critique. They argue that the current phase of GIScience is increasingly concerned with data exploration, machine learning, and GeoAI, but they also warn against purely data-driven opacity and the risk of replacing one black box with another. Their conclusion is not that theory should be abandoned, but that future geospatial knowledge discovery must integrate theory-driven and data-driven reasoning (Arundel & Li, 2021; Gahegan, 2020; Li, 2020). This point is especially relevant here. The challenge is to move from a layer-based conception of space to a relational one, and from static representation to process-oriented explanation, while maintaining analytical transparency. This distinction corresponds closely to the conceptual stance adopted in the present thesis. As stated in the research framework, map representations should not be interpreted as random spatial arrangements, because the question we try ti answer is not only what is visible in the spatial distribution, but what processes generated those data. The research therefore distinguishes between the visible dimension of spatial associations and the less directly observable dimension of spatial processes, arguing that territorial analysis must move beyond descriptive mapping toward the identification of the generative mechanisms shaping spatial patterns. From this perspective, cartographic representations of spatial data capture only the observable outcomes of territorial dynamics, while the processes that produce these configurations remain analytically implicit. For this reason, descriptive cartographic approaches, are insufficient for understanding the organization of complex territorial systems. This shift is particularly relevant in the context of territorial planning and policy design. Traditional suitability analyses provide valuable descriptive insights into the spatial distribution of phenomena, but they often struggle to capture the relational and dynamic nature of territorial systems. Understanding how spatial components interact is crucial for anticipating the potential effects of planning interventions and policy decisions. Consequently, emerging analytical frameworks seek to integrate spatial data, interaction models, and network structures, enabling more robust and evidence-based approaches to territorial analysis and decision-making. Accordingly, this thesis does not dismiss cartographic modelling as irrelevant. On the contrary, it recognizes it as a foundational stage in the evolution of GIS-based reasoning: a necessary analytical discipline that introduced formal workflows, explicit parameterization, and reproducibility. What is argued, however, is that this paradigm becomes insufficient when the objective is to interpret territorial systems as complex spatial formations. In that sense, the transition toward spatial interaction modelling, graph-based representations, and network-informed territorial analysis should be understood not as a mere technical update, but as a development within the broader evolution of geospatial analytical frameworks. It reflects a shift from asking where suitable conditions are located to asking how territorial structures are produced, maintained, and transformed through relations among heterogeneous spatial entities.

1.2 Spatial Interaction models and the inference of territorial processes

Building on the transition outlined in the previous section, spatial interaction modelling provides the analytical framework through which territorial systems can be interpreted as processes structured by relations among places (Castells, 1996; Rodrigue, Comtois, & Slack, 2020). The Spatial Interaction models (SI) focus on the mechanisms that connect spatial entities through flows, accessibility, and functional interdependence. The theoretical foundations of SI lie in regional science and human geography, particularly within the gravity model tradition. Inspired by Newtonian physics, early spatial interaction models conceptualized flows between origins and destinations as proportional to the "mass" or attractiveness of locations and inversely proportional to the cost of distance separating them (Haynes & Fotheringham, 1984; Sen & Smith, 1995). In its basic formulation, the interaction between two locations is expressed as a function of the attributes of the origin and destination, combined with a distance-decay function representing spatial impedance. This formulation provided a powerful conceptual framework for analysing commuting flows, migration patterns, trade relations, and transportation systems. More broadly, it introduced a relational understanding of spatial organization in which the significance of a place depends not only on its intrinsic characteristics but also on its position within a system of interactions.

Over time, the spatial interaction paradigm evolved beyond its initial gravity-based formulation. Advances in transport modelling, accessibility analysis, and spatial econometrics introduced increasingly sophisticated ways of representing the determinants of spatial flows, incorporating behavioural assumptions, heterogeneous costs, and probabilistic decision frameworks (Ortúzar & Willumsen, 2011; Wilson, 1971). These developments reinforced the idea that spatial interaction models serve as an interface between spatial theory and empirical observation. They translate assumptions about spatial behaviour into quantifiable relational structures that can be tested and interpreted. In doing so, they enable researchers to move from the mapping of spatial distributions toward the inference of generative mechanisms underlying territorial organization. This relational perspective aligns closely with contemporary interpretations of territorial systems as complex, multi-scalar formations. Cities and regions are increasingly understood not as static spatial structures but as dynamic systems of flows involving people, goods, services, and information (Batty, 2013; Barthélemy, 2019). Spatial structure emerges from the organization of interactions over time, producing accessibility patterns, functional complementarities, and hierarchical relations between places. Spatial interaction models therefore provide a formal framework for analysing how territorial structures emerge from relational processes.

This view is especially applicable to territorial planning, where interaction-based models have become popular in the analysis of accessibility, spatial organization of services, and the effects of planning interventions (Wegener, 2004; Geurs & van Wee, 2004; McCann, 2013).

In the case of tourism, the spatial layout of attractions, accommodations, services and infrastructures constitute a system of complementarities that cannot be simplified to the mere co-location of elements.

Analytically, it is the interaction of these factors in terms of spatial proximity, accessibility, and functional synergies that produces differentiated territorial subsystems and destination areas.

In this study, SI is applied as an intermediate between descriptive spatial analysis and network-based models of territorial systems. The methodology retains the intuition of the classical models of interaction, which is that spatial organization is a result of the relationship among locations, and generalizes it in a number of ways. First, the analytical emphasis is no longer on the aggregated flows between administrative zones but on interactions between fine-grained spatial entities, including Points of Interest (PoI) and service locations. Second, spatial interaction is not merely understood as movement between origins and destinations, but also as a more general manifestation of functional connectivity between territorial elements. Third, the interaction structure is combined with graph-based analysis methods that allow identifying communities, hierarchies, and new territorial structures.

This perspective shifts the focus from spatial distributions to structures emerging from interaction processes. In this sense, spatial interaction models provide a conceptual bridge between descriptive spatial analysis and relational understandings of territorial systems. SI offers the conceptual framework by which GIS-based spatial reasoning can be redirected to relational and network-based understandings of territorial complexity. By so doing, they provide the basis of the methodological framework that will be developed in the subsequent sections of this thesis in which the principles of spatial interaction are implemented using graph representations and community detection methods to examine the structure of tourism ecosystems and their emergent destination regions. Building on this theoretical framework, the thesis is guided by three main research questions:

How can spatial interaction models support the identification of functional territorial configurations beyond administrative boundaries?

To what extent can network-based methods reveal service communities and Destination Areas within tourism-oriented territorial systems?

To address these questions, it becomes important to determine the latent relational structure of territorial systems. By modeling the territorial systems as graphs, in which places, services, and attractions are nodes and their relationships are the edges, it becomes possible to uncover the inherent spatial structure of the system and the constraints that govern it. These limitations are geographical and geometrical, which arise due to the spatial closeness, the availability of conditions, and the pattern of interactions between the territorial elements. The discovery of these structures allows the formalization of the territorial system as a networked representation that embodies the relational architecture in which the spatial processes are carried out.

This description is especially applicable to the emerging GeoAI methods, which are starting to focus more on the significance of integrating spatial structure into machine learning models (Li et al., 2020; Janowicz et al., 2020). Conventional machine learning techniques tend to assume that observations are independent and thus cannot easily capture the spatial relationships and structural arrangements that define geographic phenomena. Graph based representations offer a solution to this shortcoming by explicitly representing spatial relationships and interaction patterns in the data structure itself. This has prompted the increased interest in graph-based learning systems, such as graph neural networks and spatially explicit machine learning models, which allow the incorporation of spatial structure into AI systems. In a broader sense, this view is consistent with recent demands of theory-informed or physics-informed artificial intelligence, in which machine learning models are not constructed by data-driven optimization, but instead by domain knowledge and structural constraints based on the underlying system (Camps-Valls et al., 2021; Reichstein et al., 2019). Within the framework of the territorial analysis, the graph form of the spatial interaction systems offers exactly such a structural antecedent, whereby the spatial relationships, distance decay processes, and network dependencies can be incorporated into the modelling framework.

Therefore, the discovery of the latent network structure of territorial systems is a preliminary step to the creation of spatially explicit GeoAI models because it allows encoding spatial relations and interaction structures that can be subsequently integrated into machine learning systems. Through the combination of spatial interaction modelling and graph-based representations, the analytical framework suggested in this thesis provides an opportunity to connect the analysis of the territorial systems with the state-of-the-art techniques of the Machine Learning that can learn both spatial data and the relational networks that structure them.

2. Spatial interaction and the inference of spatial processes

2.1 From spatial data to spatial processes.

To analyze the systems of territory, it is necessary to go beyond the description of spatial patterns and identify the processes that generate them. Spatial datasets and maps are just the visible expression of the dynamics that are taking place in geographic space. But these trends are rarely accidental. Rather, they refrect the role of geographical determinants that organize the space and place of the occurrence of socio-economic phenomena. This principle is well depicted by some examples depicted in the following figure.

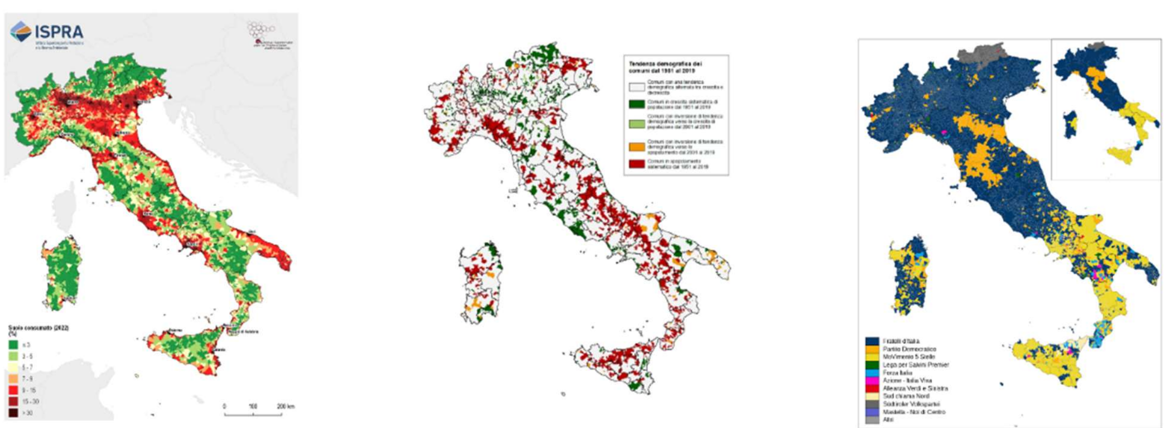

Figure 1 Examples of clustered spatial patterns in Italy. Demographic decline, electoral geography and land consumption show how territorial phenomena tend to organize spatially according to underlying geographical, socio-economic and institutional determinants

The distribution of depopulation in Italy shows a sharp contrast between the densely populated plains and the inner areas, especially in the Apennine ridge where the demographic reduction over a long period has transformed the settlements. Electoral geography also displays high levels of spatial clustering, with neighbouring regions commonly having similar voting patterns as a result of similar socio-economic factors, cultural identities and information environments. Another example is the patterns of land consumption: the soil sealing in highly urbanized areas like Emilia-Romagna is an indicator of interactions between economic development, accessibility of infrastructure and planning policies.

These regularities indicate that spatial data are organized in terms of relationships and dependencies. What we see on maps the spatial distribution of population, services or economic activities is the visible result of spatial interactions. The spatial data, then, is to be understood as the quantifiable consequences of the interactions between attributes of the territorial systems. This view has strong quantitative geographical origins. According to Fotheringham and Sachdeva (2022), processes that take place in geographical space generate spatial distributions, and one spatial pattern can represent several processes that are running at various spatial scales. The task of the spatial analyst is then to deduce these processes based on the patterns that they produce.

In the past, the study of geography represent geographic data as descriptive maps. The introduction of statistical methods to formally examine spatial relationships with the quantitative revolution of the 1960s resulted in the creation of spatial dependence and spatial autocorrelation measures (Cliff and Ord, 1981; Anselin, 1988). The first law of geography, which is considered to be one of the most powerful principles of this tradition, is that everything is related to everything and that things that are close are more related than those that are far (Tobler, 1970). Nevertheless, the fact that spatial dependence is identified does not give the reasons why spatial patterns are observed. With the maturity of geographic analysis, scholars began to pay more attention to the processes that brought about patterns rather than the description os spatial distibution of the phenomena. Harvey (1967) pointed out that various processes could have different meaning at various spatial scales and it is important to understand spatial structures as the result of interacting processes.

Most social and territorial processes are not directly observable as opposed to the situation in physical systems where the causal mechanisms can be often inferred based on first principles. Rather, they have to be infer out of the results they give. In spatial analysis, researchers work in a system where processes are not visible, and spatial data are only visible manifestations of these processes (Fotheringham and Sachdeva, 2022).

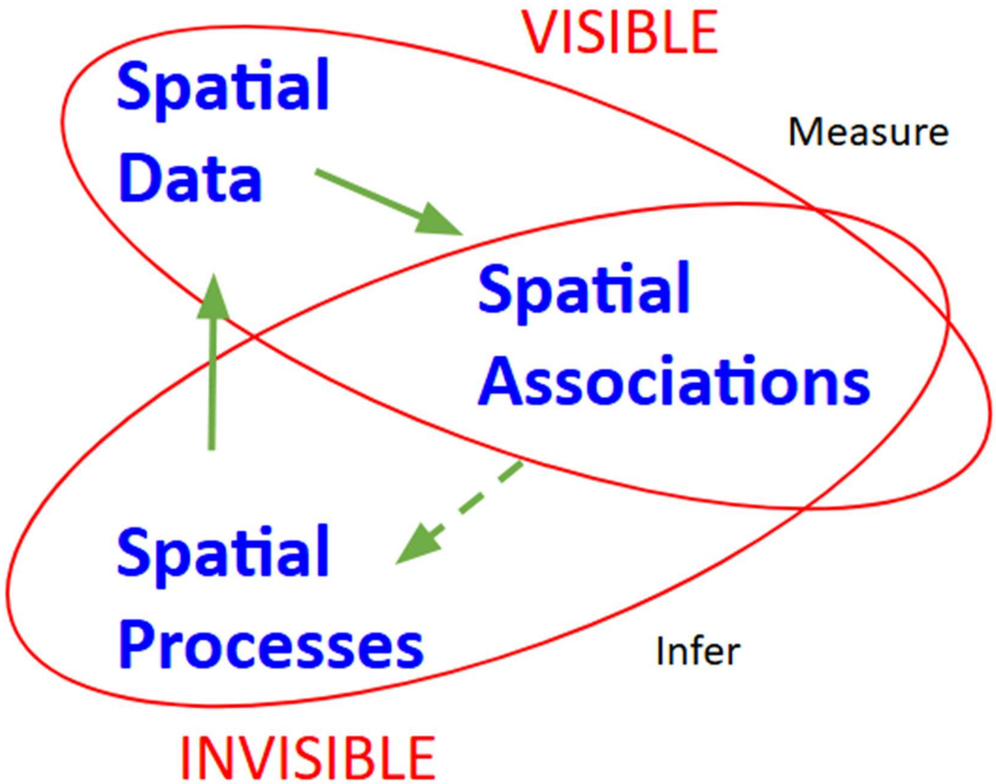

Figure 2 Three-tier analytical framework for interpreting territorial phenomena. The figure represents the relationship between spatial data, spatial associations and spatial processes. It highlights how the analysis of territorial systems requires moving beyond the observation of visible spatial patterns toward the inference of the hidden processes and interactions

This association can be theorized as a three-tier analytical framework:

- Spatial data - observable and measurable phenomena represented in geographic space.
- Spatial associations - statistical patterns and relationships observed among spatial variables.
- Spatial processes - the underlying mechanisms and interactions that generate these patterns and spatial outcomes

Spatial analysis therefore bridges these levels by moving from the observation of spatial patterns toward the inference of the processes that generate them.

2.2 Complex systems and territorial systems

The difficulty of defining spatial processes lies in the complexity of territorial systems. Cities, regions and socio-economic landscapes are not to be represented as definite spatial arrangements but are dynamic systems of interacting elements whose behaviour varies over time. This perspective is theoretically based on the General Systems Theory, which was proposed by Ludwig von Bertalanffy (1968), who proposed that complex phenomena are to be viewed as systems of interdependent components that are interrelated through feedback. Here a system may be described as something more than the sum of its parts because interactions between elements give rise to emergent properties that cannot be explained by studying each component individually. This systemic perspective was further developed by system dynamics, suggested by

Jay Forrester (1969), which stressed the significance of feedback loops and non-linear interactions in the behaviour of complex socio-economic systems. Similatly, Meadows et al. (1972) demonstrated using global modelling methods that large-scale socio-environmental processes are the result of interaction between population increase, economic growth, and resource constraints. These initial modelling attempts showed that the processes of territories cannot be conceptualized without analytical frameworks that can capture interdependent interactions among more than two variables. The theory of complex adaptive systems was later developed, especially by Holland (1995), who further stressed the significance of decentralized interactions, adaptation, and emergent behaviour. The interactions of many heterogeneous agents give rise to large-scale structures in such systems. This is especially true of territorial systems, in which interactions between individuals, institutions, infrastructures and environmental elements produce macro-level spatial patterns including urban hierarchies, regional specialization and spatial clustering.

Previous spatial theories tried to explain the organization of the territory by simplified and equilibrium-based models. As an example, the Central Place Theory of Walter Christaller (1933) explained the spatial distribution of settlements and services in hierarchical and geometrically regular forms. Despite the significance of this framework as a conceptualization of spatial organization, it assumed the conditions of static equilibrium and homogeneous space. Conversely, the above systemic and complexity-based approaches highlight that territorial structures are the result of dynamic interactions between various agents and processes. One of the most important features of territorial complexity is its spatiality. Territorial systems are not merely made of components that interact, but the interactions are enclosed in the geographic space. The spatial arrangement of objects, the distance between actors, and the accessibility of relations between locations influence the manner in which interactions take place and eventually define how territorial forms change over time. Cities and territorial systems may be viewed as complex networks of interacting subsystems where spatial relations are central to the formation of systemic behaviour (Caldarelli et al., 2023). Territories are thus multi-dimensional systems spanning environmental, economic, governance, infrastructural, and social domains.

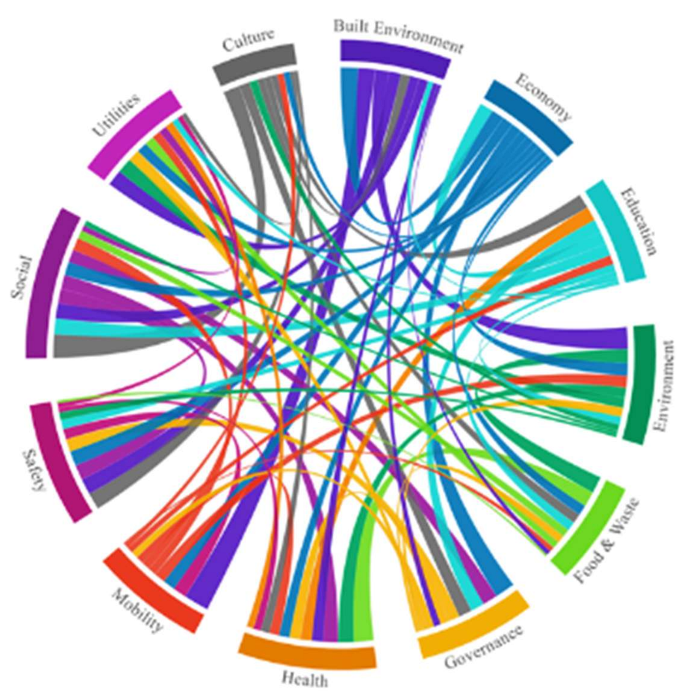

Figure 3 Multi-dimensional structure of territorial complexity. The figure illustrates the territorial system as a complex configuration composed of multiple interconnected domains. The relationships among social, economic, environmental, cultural, infrastructural and institutional components highlight that territorial dynamics emerge from the interaction between different systems rather than from isolated elements.

This complexity is often described through three main dimensions (Laganier et al., 2002). The spatial dimension is the physical characteristics and spatial structure of the land. The organizational aspect is related to the system of social, economic and institutional actors. Lastly, the identity dimension indicates the cultural and symbolic associations between communities and places and how they define their belonging. Collectively, these dimensions emphasize that the territorial systems cannot be perceived only in terms of their physical structure, but they have to be analysed in terms of the organizational networks and socio-cultural relations that define the territorial dynamics. In terms of complexity science, territorial systems may thus be understood as self-organized socio-spatial systems (Pumain, 1997). This explanation aligns with the paradigm of evolutionary urban theory that views urban and regional systems as multi-level systems where the co-evolution of various agents and components defines their long-term dynamics (Pumain, 2018). Local interactions between spatially embedded agents in such systems produce macro-scale patterns including urban hierarchies, spatial clustering and regional inequalities. According to Raimbault (2019), complex systems are archetypal examples of territorial systems, where spatial interactions of heterogeneous agents produce emergent spatial structures that cannot be reduced to the properties of individual components.

Thus, city and regional systems have a number of basic traits of complex systems:

- Non-linearity, where minor changes can produce disproportional effects.
- Reinforcing and dampening feedback processes.
- Multi-scale interactions, where processes are active at multiple spatial scales.
- Emergent behaviour, where macro-scale spatial patterns are a result of local interactions between agents.

These properties emphasize the fact that territorial systems are dynamic systems that are influenced by interactions among spatially embedded actors and structures. This complexity makes territorial phenomena difficult to understand through descriptive analysis alone. Analytical frameworks are therefore needed to capture the interactions between spatial elements. The identification of the spatial complexity of territorial systems thus offers the basis of analytical methods that can model interactions among spatial entities. This makes it possible to explicitly describe the relational processes through which territorial structures are created and developed.

2.3 Spatial interaction: conceptual basis and modelling tradition

Spatial interaction (SI) is an analytic approach of quantitative geography, regional science, and GIScience. In general, SI can be defined as the overall movement of people, goods, capital, or information over space due to a decision process (Farmer and Oshan, 2017; Fotheringham and O'Kelly, 1989). In the view of the territorial systems, these interactions are the visible expression of the spatial processes underlying the relationships between places by flows and functions. Spatial interaction in this sense offers an analytical toll to identify spatial structure (the organization of opportunities in space) and spatial behaviour (the choices that bring flows between them) (Roy and Thill, 2004; Sen and Smith, 1995). The basis of the SI modelling is a simple law of behaviour: the interactions arise when the utility of using a destination is greater than the costs of being separated spatially (Fischer, 2001). Spatial distance can be in various forms such as geographic distance, time taken during travel, economic distance, institutional distance or even cultural distance. The ensuing pattern of interactions is thus determined by the trade-off between destination attractiveness and spatial impedance, which is typically summarized in the principle of distance decay, according to which the intensity of interaction tends to decline with distance (Farmer and Oshan, 2017; Sen and Smith, 1995).

The spatial interaction is normally modeled in the form of origin-destination (*OD*) matrices, where T_{ij} are interactions between the origins *i* and destinations *j*. The matrix therefore describes the set of flows occurring within the system.

$$T_{ij}$$

The total outflow generated by each origin iii corresponds to the sum of all flows directed toward the different destinations *j*:

$$O_i = \sum_j T_{ij}$$

where O_i represents the total interactions originating from location *i*.

Similarly, the total inflow received by each destination *j* is obtained by summing all incoming flows from the different origins *i*:

$$D_j = \sum_i T_{ij}$$

where D_j denotes the total interactions attracted by destination .

Finally, the overall level of interaction within the system corresponds to the total magnitude of all flows in the *OD* matrix:

$$T = \sum_i \sum_j T_{ij}$$

where T represents the total volume of interactions occurring in the spatial system.

Such representation allows the analysis of a different spatial phenomena in a shared analytical context, such as migration, commuting, tourism mobility, commodity exchanges, knowledge flows, and ecological movement patterns (Fotheringham and O'Kelly, 1989; Fischer, 2001).

Due to this generality, SI models have come to be a key tool of analysis in the functional organisation of territorial systems. SI models can be used to quantitatively examine the relationship between spatial structure and interaction patterns by translating heterogeneous spatial attributes (population size, economic opportunities, accessibility, or infrastructural constraints) into predicted flows (Haynes and Fotheringham, 1984). This ability is especially useful to planners and regional analysts since flows are the means by which spatial policies, including infrastructure investments, redistribution of services, or land-use regulation, influence the dynamics of the territory.

2.4 Evolution of spatial interaction modelling

The SI modelling theory can be dated back to the initial studies on the migration flows. Ernst Georg Ravenstein (1885) in his classic work found patterns that indicated that large cities were likely to receive migrants of other large cities and that the intensity of migration was inversely related to the distance. These observations led to the development of gravity models, which take an analogy to the Newtonian physics: the interaction between two locations grows as their mass (e.g., population or economic activity) and declines as the distance between them (Carrothers, 1956; Stewart, 1941).

The use of gravity models in geography, economics, transportation planning, and regional science has been widespread. They offer a flexible model of the representation of the process of spatial interaction in a wide range of contexts, such as migration, trade, and commuting flows. Flows have been modeled as a variable of source mass, destination mass and distance. This form reflects the intuitive idea that bigger or more economically active places have a tendency to produce and draw more amounts of interaction.

The overall shape of the gravity model is that flows between origin *i* and destination *j* are a function of origin size, destination size and a distance-decay term:

$$T_{ij} = k\frac{P_i^{\alpha} P_j^{\gamma}}{d_{ij}^{\beta}}$$

and where P_i and P_j are the sizes of the origin and destination, $d_{ij}$is the distance between them, and the parameters α, γ, β represent the relative effect of the masses and distance (Sen & Smith, 1995). Gradually, the gravity models turned out to be one of the most popular empirical models in geography and regional science, which are employed to examine such phenomena as retail trade areas, commuting patterns, and international trade flows (Haynes and Fotheringham, 1984; Head and Mayer, 2014). Although early gravity models were empirically successful, they were criticized as having a weak theoretical foundation. A number of research streams thus aimed at offering more conceptual underpinnings. Huff (1959; 1963) and other behavioural models like the probabilistic retail model proposed by Huff, brought about probabilistic choice models that explicitly took into account consumer decision-making between competing destinations. In the same vein, the theory of intervening opportunities (Stouffer, 1940; 1960) proposed by Stouffer postulated that the distance is not the only factor that affects the migration patterns but also the number of opportunities that one encounters between the two locations. These contributions changed the emphasis of SI modelling away to behavioural explanations of the spatial choice process. Another significant theoretical advance came with the work of Wilson (1967, 1970), who obtained a family of spatial interaction models based on the principles of statistical mechanics and information theory. In the entropy-maximization model, the observed *OD* matrix, is interpreted as the most likely macro-state that can be produced out of the highest number of individual movement configurations (micro-states), under known constraints on the system.

Various constrained formulations can be obtained depending on the information available, such as:

- Unconstrained models, in which neither origin nor destination totals are given;
- Origin-constrained models, which maintain total outflows of each origin;
- Destination-constrained models, where inflows to any destination are maintained;
- Doubly constrained models, which maintain both source and destination totals.

These formulations provide a statistical explanation of gravity-type models and spatial interaction modelling was formalized as a part of urban and regional modelling (Fotheringham and O'Kelly, 1989).

Within the competing destinations framework, individuals evaluate a destination not in isolation but relative to other available alternatives. Consequently, the attractiveness of a given destination is determined not only by its intrinsic characteristics but also by the spatial distribution and accessibility of competing destinations. The Competing Destinations Model, originally proposed by A. Stewart Fotheringham (1983), explicitly incorporates the influence of alternative destinations into the gravity modelling framework. By integrating measures of accessibility to competing locations, the model accounts for the spatial configuration of destinations within the system and their mutual interactions.

2.5 The interpretation of distance decay and spatial structure

Spatial structure, in the context of SI, refers to the pattern of spatial organization of origins and destinations, their relative locations, clustering, and accessibility relations. Such spatial arrangements determine the probability with which interactions take place between specific locations. Spatial interaction and spatial structure became a major subject in quantitative geography in the 1970s. Curry (1972) was one of the first to conduct a systematic study, and he studied the effect that the spatial layout of locations could have on the statistical behaviour of gravity models. According to Oshan (2020), the work by Curry provide a wider debate about the fact that the estimated parameters in spatial interaction models might be affected by spatial structure, and not by behavioural mechanisms alone. Over the following decade, an important controversy emerged regarding the interpretation of spatial interaction parameters and the extent to which they reflect behavioural processes. Rather than using purely classical formulations of gravity, scholars started to consider other methods that could bring out the spatial structure in a more explicit manner in modelling models. Empirical studies soon showed that a single set of parameters could not fully explain the behaviour of interactions across an entire region. In particular, studies revealed considerable spatial heterogeneity in estimated parameters, especially the distance-decay coefficient. Results obtained using origin-specific calibrations often showed that highly accessible locations exhibited weaker distance-decay effects compared to peripheral areas, and in some cases even positive distance-decay parameters (Fotheringham, 1981).

Distance decay describes the tendency for the intensity of interaction to decrease with increasing distance between locations. It reflects the growing costs or frictions associated with spatial separation. The distance-decay parameter is therefore typically interpreted as the sensitivity of spatial interaction to distance. However, there has been a long-standing debate regarding the interpretation of this parameter. Various functional forms have been proposed to model distance decay, including exponential and power-law functions, which reflect different behavioural assumptions about the role of spatial separation in interaction patterns. These findings contributed to the so-called spatial structure debate, which argued that differences in distance-decay parameters may not reflect real behavioural differences but may instead be artefacts of the spatial structure of opportunities (Roy, 2004). Later studies demonstrated that distance decay is strongly influenced by the spatial proximity of destinations and the level of competition among destinations (Griffith and Jones, 1980; Fotheringham and Webber, 1980).

In response to these issues, Fotheringham (1983) developed the Competing Destinations model, which extends the traditional gravity formulation by incorporating accessibility measures that account for the availability of alternative nearby destinations. In this framework, individuals first select a broader destination environment and subsequently choose among competing alternatives within that environment, reflecting a hierarchical decision process. The explicit modelling of destination competition significantly improved the interpretability of spatial interaction parameters and highlighted the importance of spatial structure as an intrinsic component of interaction processes. Further methodological developments introduced additional techniques for representing spatial structure. Some approaches incorporate spatial autocorrelation terms to model dependencies between flows, while others employ spatial filtering techniques to capture unobserved spatial processes influencing interactions (LeSage and Pace, 2008; Fischer and Griffith, 2008). These developments underline that spatial interaction systems exist within structured spatial environments in which flows are not independent but interdependent observations. The debate on spatial structure has left permanent effects on the development of spatial interaction modelling. It has emphasised the necessity of separating behavioural processes from structural features of spatial systems. Modern studies increasingly recognise that spatial interaction models should not only consider the effects of distance and mass, but also accessibility, spatial dependence, and network relationships. Recent research has therefore focused on generalizing spatial interaction models to include additional spatial mechanisms. In this regard, spatial interaction modelling has evolved into a more comprehensive analytical framework capable of reflecting the complexity of spatial flows in territorial systems.

Practically, the estimation or calibration of SI models consists of finding the values of the parameters that most effectively reproduce the observed patterns of interaction (Farmer & Oshan, 2017). Traditionally, gravity models have been estimated using log-linear regression derived by applying logarithmic transformations to the multiplicative gravity equation (Fotheringham and O Kelly, 1989). However, despite its convenience, this method presents several statistical issues, such as transformation bias, heteroskedasticity, and the problem of zero flows. To overcome these issues, Flowerdew and Aitkin (1982) suggested estimating spatial interaction models using a Poisson regression model, where flows are considered non-negative counts produced by a stochastic process. Since Poisson models belong to the class of generalised linear models (GLM), they offer several advantages, including the possibility of incorporating additional explanatory variables, performing standard diagnostic tests, and estimating constrained SI models with origin and destination fixed effects (Griffith and Fischer, 2013). These advances have made SI model estimation significantly more robust and flexible.

Recent developments in data availability and computational modelling have further broadened the methodological frontiers of spatial interaction modelling. Neural spatial interaction models are non-parametric approaches based on artificial neural networks that approximate complex and nonlinear interaction processes without predetermined functional forms (Fischer, 2002; Openshaw, 1993). These models can achieve high predictive accuracy when large datasets are available, although they often sacrifice interpretability. Oshan (2020) emphasizes that researchers have long been uncertain whether the variation observed in estimated parameters reflects actual differences in behaviour or whether it is instead driven by the spatial structure of origins and destinations. Another research direction concerns the development of universal mobility models, including the radiation model proposed by Simini et al. (2012). Unlike gravity models, the radiation model predicts flows based on the distribution of opportunities between origins and destinations rather than relying on explicit distance-decay parameters. Although appealing due to its parameter-free formulation, empirical comparisons suggest that gravity models often outperform radiation models because they are more flexible in capturing context-specific interaction dynamics (Lenormand et al., 2016).

Together, these developments reflect the diversification of spatial interaction modelling. Contemporary research increasingly integrates traditional parametric frameworks with data-driven methods and network-based representations, enabling the analysis of spatial interactions within complex territorial systems characterized by heterogeneity, multi-scale dynamics, and evolving spatial structures.

2.6 Implications for spatial planning and future research

The above discussion has followed the development of spatial interaction (SI) modelling. One of the conclusions that can be made after this review is that SI models cannot be seen as technical means of fitting the origin-destination matrices. Instead, they are analytical constructs by which spatial structure, behavioural hypotheses and policy interventions can be converted into measurable spatial results (Sen & Smith, 1995; Ortuzar and Willumsen, 2011). In this regard, spatial interaction models offer a valuable interface between theory and decision-making. They reduce the complexity of the territorial systems to analytically situations that enable researchers and planners to understand how the alteration of infrastructure, accessibility, or distribution of services can impact spatial flows (Wegener, 2004; Raimbault, 2019). This position is especially applicable in the area of spatial planning (McCann, 2013). Planning issues are often linked to the future development of an area and are not necessarily descriptive (Healey, 2006). The decision makers should be able to predict how new infrastructure investments, redistribution of services, zoning rules, or demographic changes can affect the accessibility patterns, mobility behaviour, and the spatial distribution of opportunities (Geurs & van Wee, 2004; OECD, 2018).

Spatial interaction models give a systematic way of exploring such counterfactual situations. Through the simulation of flows in other spatial setups, planners are able to assess the possible outcomes of policy interventions prior to their implementation (Ortuzar and Willumsen, 2011). The anticipatory nature of the present-day spatial planning practice is thus compatible with the scenario-based nature of interaction modelling (Wegener, 2004). Among the most direct contributions of SI models to planning, one can distinguish the possibility of quantifying accessibility (Geurs & van Wee, 2004). Spatial interaction formulations can explicitly answer questions like how many people can access a specific service, at what cost and how often by connecting the population demand with the service supply and the travel impedance in the same analytical model (Sen and Smith, 1995). Consequently, they tend to indicate patterns which are considerably different than those obtained with the help of purely geometric measures. As an illustration, two neighbourhoods at the same physical distance of a hospital can have vastly different degrees of effective accessibility when one of them competes against a much larger demand population (Sen & Smith, 1995). Recent developments in accessibility modelling further emphasize this interaction-based perspective. For example, the Rational Agent Accessibility Model (RAAM) conceptualizes accessibility as the outcome of competition between agents for limited opportunities, simultaneously accounting for travel costs and congestion effects. By modelling accessibility as a dynamic interaction between demand and supply, RAAM provides a more behaviourally consistent representation of accessibility patterns compared to traditional proximity-based measures (Saxon, Snow, & Holloway, 2020).

Moreover, SI models can help make more informed decisions about service allocation and infrastructure planning by explicitly modeling the relationship between spatial structure, accessibility, and demand (Geurs & van Wee, 2004; Páez, Scott, & Morency, 2012). Another important issue of spatial planning is the feedback between land-use patterns and mobility systems (Wegener, 2004). The spatial distribution of the employment and residential places leads to mobility flows, and mobility flows, in their turn, impact the level of congestion, the conditions of accessibility, and the further location choices (Fujita, Krugman and Venables, 1999). The analytical basis of capturing these circular dynamics is spatial interaction models. This is why they are the main element of numerous land-use-transport interaction (LUTI) models applied in urban and regional planning (Wegener, 2004; Batty, 2013).

Interaction models in LUTI systems assign trips or migration flows within current spatial conditions, and other model components update land-use allocations or infrastructure systems. The system then repeats the cycles, producing new spatial equilibria and enabling the researchers to study the long-term urban dynamics (Wegener, 2004). Such dynamic view is especially significant in policy analysis since the long-term impacts of interventions like transit corridors, development zones, or new service hubs are usually underestimated in the case of the static forecasts (Ortuzar and Willumsen, 2011). Planners can investigate path-dependent trajectories, cumulative effects and unintended consequences of planning decisions by integrating SI models into iterative or simulation-based systems (Birkin and Heppenstall, 2011).

These abilities reinforce the strategic aspect of the planning practice and contribute to more responsive governance systems that can deal with uncertainty and long-term change (Healey, 2006).

The diversification of SI modelling which has been witnessed over the past decades suggests that planners currently have a set of alternative modelling tools, each with its own advantages and disadvantages. The classical gravity models are appealing due to their conceptual clarity and their simplicity of conveying the information to policymakers and stakeholders (Sen & Smith, 1995). Accessibility or competing destinations extensions enhance realism in behaviour, and are interpretable (Fotheringham, 1983). Spatial econometric and filtering methods have greater statistical power in the presence of latent spatial processes, but their substantive interpretation is less intuitive (LeSage and Pace, 2008; Griffith, 2003). In the meantime, complex structural and behavioural interactions can be represented by network-based and agent-based models, but at the expense of increased data requirements and computational complexity (Birkin and Heppenstall, 2011).

It it is more useful to think these modelling approaches as complementary tools in a larger modelling portfolio (McCann, 2013). Additional diagnostic tools that may be used to detect residual spatial dependence and enhance model specification include spatial econometric techniques or spatial filtering methods (Anselin, 1988; Griffith, 2003). This stratified modelling approach resembles engineering practice, where simplified representations are progressively refined through more detailed modelling stages, balancing analytical rigour with practical feasibility. As Box (1976) famously noted, “all models are wrong, but some are useful.”

Moreover, the rapid expansion of digital sensing technologies has generated what is often described as a data deluge, characterized by the massive and continuous production of spatial and mobility data (Hey, Tansley, & Tolle, 2009; Mayer-Schönberger & Cukier, 2013). This phenomenon is commonly framed within the concept of Big Data, often summarized by the five dimensions of volume, velocity, variety, veracity, and value, which capture the scale, speed, diversity, reliability, and analytical potential of contemporary data environments (Laney, 2001; Chen, Mao, & Liu, 2014; Gandomi & Haider, 2015). In the context of spatial analysis, the proliferation of digital technologies has produced vast streams of mobility-related data, including smart-card transactions in public transport systems, mobile phone records, GPS traces, and platform-based service data (Arribas-Bel, 2014; Kitchin, 2014). Such datasets significantly expand the possibilities for spatial interaction modelling, as they enable the direct observation of spatial flows in near real time, rather than relying solely on indirect estimates derived from traditional sources such as surveys or census data (Calabrese et al., 2013; Toole et al., 2015). For planners, these data sources make it possible to monitor system performance almost in real time and to rapidly assess the impacts of policy interventions. The calibration of interaction models using such datasets can therefore support decision-making processes, including service frequency adjustments, congestion management, or emergency response (Rodrigue, 2020). Nevertheless, the increasing availability of mobility data also introduces new challenges. Issues related to privacy protection, data representativeness, and algorithmic transparency have become central concerns in data-driven spatial analysis (Kitchin, 2014). Machine learning models trained on large datasets can achieve high predictive performance, but their internal reasoning is often opaque and therefore difficult to interpret or justify in policy contexts (Rudin, 2019; Molnar, 2022). For this reason, theory-based spatial interaction models remain critically important even in highly data-rich environments. They provide an explanatory framework that helps ensure that predictive systems are not solely optimised for statistical performance but are also aligned with planning objectives (Healey, 2006). In this sense, theoretical modelling and data-driven approaches should be regarded as complementary rather than competing paradigms.

A number of research directions seem to be especially promising in the development of the role of the spatial interaction modelling in the spatial planning. To begin with, closer collaboration between behavioural theory and data-driven approaches can result in hybrid models that will be interpretable and predictive at the same time (Athey, 2018; Varian, 2014). Second, the nested structure of the territorial systems can be better reflected by multiscale modelling methods that can interconnect neighbourhood-level interactions with metropolitan and regional dynamics. Third, systematic simulation experiments may assist the researchers to learn the reaction of various model specifications to misspecification, uncertainty, and policy shocks, which would enhance methodological robustness. Lastly, the creation of open and reproducible modelling frameworks will be needed to facilitate the practical applicability of spatial interaction models. Open-source software, common datasets, and transparent modelling processes enable knowledge to be accumulated across studies and planning agencies to adopt sophisticated methods of analysis without prohibitive barriers (Arribas-Bel, 2014). In this regard, methodological transparency and reproducibility gain as much importance as statistical sophistication (Molnar, 2022).

A promising direction lies in the explicit representation of the relational structure underlying territorial systems. By modelling territorial systems as networks, where places, services, and infrastructures are represented as nodes and their interactions as edges, it becomes possible to uncover the latent spatial organization that governs interaction patterns. Such graph-based representations allow spatial relationships, accessibility structures, and interaction dependencies to be formally encoded within analytical models. This perspective aligns with recent developments in GeoAI, which emphasize the integration of spatial structure into machine learning frameworks in order to overcome the traditional assumption of independent observations (Li et al., 2020; Janowicz et al., 2020). In particular, advances in graph-based machine learning, including graph neural networks and attention-based mechanisms, provide powerful tools for modelling complex relational systems and learning from structured spatial data (Kipf & Welling, 2017; Veličković et al., 2018; Liò et al., 2022). These approaches enable models to capture higher-order dependencies and interaction patterns embedded within spatial networks, offering new possibilities for representing territorial systems as interconnected structures rather than collections of independent observations. Therefore, identifying the latent relational structure of territorial systems represents a crucial step toward the development of spatially explicit data-driven models capable of learning not only from spatial attributes but also from the interaction networks that organize territorial systems (Liang et al., 2025).

To conclude, SI modelling has developed in the past sixty years. Although this methodological development has changed, the basic goal has not been changed: to comprehend and predict the influence of spatial structure on the mobility of people, goods and information. To spatial planners, this is a goal that is necessary to make the development of territorial systems efficient, equitable, and sustainable (Las Casas, 2016).

2.7 Spatial data, network representations and relational analytical frameworks

Territorial systems cannot be adequately understood through static areal representations alone, as their organisation emerges from relations, flows, and interdependencies. Conventional cartographic approaches, including aggregated indicators and overlay mapping techniques (McHarg, 1969), remain fundamental for exploratory analysis and for the identification of spatial patterns. However, they struggle to capture the relational, functional and process-based dimensions that underpin the dynamic behaviour of territorial systems (Batty, 2003). In particular, these approaches tend to privilege spatial contiguity and aggregation while hiding the networked interactions that operate both locally and across distance, thus limiting the ability to interpret how territorial systems actually function.

This limitation has led to a progressive reconsideration of the foundations of spatial analysis, shifting attention from the representation of spatial units to the analysis of the relations that connect them. Traditional GIS frameworks have historically been grounded in a representational paradigm centred on discrete spatial entities, points, lines and polygons, whose attributes are stored, visualised and analysed within a largely static and geometrically defined space. However, such an approach implicitly reflects a “geography of locations not relations”, in which spatial objects are treated as isolated units and the relational structures that connect them remain underrepresented (Batty et al., 1999; Miller and Shaw, 2001). This results in a descriptive representation of territory that captures where things are, but not how they interact.

Within this perspective, the concept of “system” in GIS has often referred more to the organisation of information than to the nature of geographical systems themselves, lacking the stronger connotation associated with general system theory, where systems are understood as ensembles of interacting components whose collective behaviour cannot be reduced to the sum of their parts (Bertalanffy, 1968; Iberall and Soodak, 1987). In this sense, spatial data are a partial and incomplete expression of underlying generative processes. The observed spatial configurations, such as the distribution of services, the concentration of activities, or the gradients of accessibility, are the visible outcomes of deeper mechanisms governed by flows, spatial constraints and systemic interdependencies (Goodchild, 2007; Kitchin, 2014; O’Sullivan & Perry, 2013). The shift towards a relational understanding of geography is closely linked to the broader development of complexity science and network theory, which have increasingly influenced spatial analysis across disciplines. In such frameworks, large systems are not governed by top-down control but are instead shaped by bottom-up processes, where order emerges through local interactions rather than external design (Bak, 1996; Wolfram, 2002).

An implication of this transition is the need to rethink space not as a homogeneous Euclidean surface but as a structured field of connections, where topology, accessibility and network position play a fundamental role. In many territorial contexts, distance alone is insufficient to explain interaction patterns, as relationships are mediated by infrastructures, hierarchies and functional complementarities that reshape the effective geometry of space (Jong and Ritsema van Eck, 1996; Jiang et al., 1999). This is particularly evident in transportation systems, where GIS has often been used primarily for data management and visualisation, while the underlying network dynamics, flows, route choices and connectivity patterns, have been treated as external analytical components rather than intrinsic elements of spatial representation (Miller and Shaw, 2001). This has motivated the development of approaches that explicitly model spatial systems as networks and allow analysis directly on network structures rather than planar representations (Okabe, 2003). In this analytical shift, the increasing availability of high-resolution spatial data—including volunteered geographic information and digital platform records—has significantly enhanced the capacity to observe territorial systems with high spatial and functional granularity (Haklay, 2010; Sui et al., 2013; Arribas-Bel, 2014). These data environments enable the disaggregation of territory into its constituent elements while preserving relational information that is typically lost in aggregated areal representations (Longley et al., 2018; Kitchin, 2014). Among these elements, Points of Interest (PoIs) assume a particularly relevant methodological role. PoIs encode information on services, activities and attractors that structure everyday territorial practices, providing a fine-grained and functionally explicit description of space (Yuan et al., 2012; Gao et al., 2013).

Unlike areal indicators, which aggregate information within administrative boundaries and often obscure internal heterogeneity, PoIs allow the representation of territory as a constellation of discrete yet interconnected functional units. This enables the analysis of spatial proximity, complementarities between services, and patterns of functional specialisation, offering a more nuanced understanding of territorial organisation (Boeing, 2017; Longley et al., 2018). In this perspective, land is no longer interpreted as a continuous surface divided into zones, but as a structured system of functional elements whose relational configuration becomes analytically accessible (Porta et al., 2006).

The methodological challenge, however, lies in the coherent representations of territorial systems. The key issue is how to translate granular spatial information into relational structures that preserve both spatial embedding and functional meaning. This study addresses this challenge by adopting a network-based analytical framework grounded in graph theory (Newman, 2010). Within this framework, territorial components are represented as nodes, while spatial or functional relations between them are encoded as edges, enabling territorial systems to be analysed as relational structures rather than spatial mosaics. This abstraction establishes a structural isomorphism between complex systems and networks, where systemic properties emerge not from individual elements but from the configuration of their connections (Helbing, 2013).

Network-based representations provide a powerful analytical framework, shifting the focus from location to connectivity, from geometry to topology, and from static form to dynamic interaction. The structure of the network, its density, clustering, path lengths and degree distribution, becomes a key determinant of system behaviour, revealing patterns that remain hidden in traditional cartographic representations (Albert and Barabasi, 2002; Barabasi, 2002). Importantly, these structures evolve over time as connections are formed and reorganised, reflecting the adaptive and non-linear nature of territorial systems.

Closely related to these dynamics is the concept of scaling, which characterises many complex spatial networks through highly skewed distributions of connectivity. In such systems, a limited number of nodes concentrate a large number of links, while the majority remain weakly connected (Simon, 1955; Zipf, 1949;

Mitzenmacher, 2003). These patterns reflect processes of preferential attachment and cumulative advantage, through which certain locations or functions become increasingly central over time (Barabasi, 2001; Barabasi, 2002). The resulting hierarchical organisation is a defining feature of territorial systems, where centrality and marginality emerge from the interplay between local interactions and global constraints. Another relevant property is the small-world effect, which describes networks characterised by strong local clustering combined with short global path lengths (Milgram, 1967; Watts and Strogatz, 1998; Watts, 2003). This structure enables the coexistence of local cohesion and global accessibility, suggesting that territorial systems can maintain internally cohesive clusters while remaining efficiently connected at larger scales. In urban contexts, this is particularly evident in multi-layered transport systems, where different infrastructures interact to reshape the effective topology of space (Cox, 2002; Desyllas, 1999).

Within this framework, the definition of edges becomes the analytical base of network-based territorial modelling. The construction of relational links must account for fundamental spatial principles such as spatial dependence and distance decay (Tobler, 1970; Fotheringham & O'Kelly, 1989; Wilson, 1971). Spatial dependence justifies the creation of connections based on proximity and contiguity, reflecting the tendency of nearby elements to exhibit stronger relationships (Anselin, 1988). Distance decay introduces a functional dimension by modelling the decreasing intensity of interaction with increasing distance, transforming binary relations into weighted networks that more accurately represent real-world interaction processes. Building on these principles, a dual modelling strategy can be adopted. The first approach is proximity-based, where edges are defined through spatial closeness and weighted by distance decay, enabling the identification of local clusters, cores and peripheral structures. The second approach is function-based, where edges reflect complementarities, hierarchies and specialisation patterns, allowing the representation of interactions that occur despite spatial separation. While proximity-based models capture the structural possibility of interaction, functional models capture the actual logic of interaction, particularly in complex territorial systems where relationships are not strictly constrained by distance (Miller, 2004).

The integration of these approaches enables a multidimensional representation of territorial systems in which spatial embedding and functional organisation are jointly considered. Edges thus become the point of convergence between spatial structure, interaction dynamics and functional relationships, allowing network-based spatial analysis to move beyond areal or proximity-based representations. In this perspective, territory could be represented as a network of interactions whose structure and behaviour emerge from the interplay between space, connectivity and function.

2.8 From spatial interaction to network-based configurational modelling

The previous sections have rebuilt the theoretical and methodological development of spatial interaction (SI) modelling, tracing a path from classical gravity models to more advanced econometric, behavioural and network approaches. This evolution highlights two complementary developments. On the one hand, spatial interaction models have progressively incorporated more complex behavioural assumptions, statistical refinements and structural corrections (Wilson, 1970; Fotheringham and O'Kelly, 1989; LeSage and Pace, 2008). On the other hand, territorial systems have increasingly been conceptualised as complex adaptive systems characterised by non-linearity, emergence, path-dependence and multi-scalar feedbacks (Batty, 2013; Holland, 1995; Pumain, 2006).

These developments lead to a critical methodological question:

Are territorial systems relational, adaptive and configurational, and should interaction still be modelled as flows between predefined spatial units?

Classical spatial interaction models assume the existence of ex ante delimited zones. Flows are distributed between zones, parameters are estimated, and behavioural or structural implications are derived. Even in more advanced formulations, such as competing destinations models or discrete choice approaches, space is first partitioned and then interaction is described (Fotheringham, 1983; Anselin, 1988; Train, 2009).

However, if territorial structures are the result of relations rather than administrative divisions, spatial units should not be treated as given containers of interaction. Instead, they can be interpreted as the outcome of interaction processes (Batty, 2005; Portugali, 2011; Raimbault, 2019). This implies an ontological reformulation: territory is no longer a mosaic of bounded units across which flows occur, but a networked structure of nodes and relations whose configuration produces emergent spatial formations (Newman, 2010; Barabasi, 2016). The focus therefore shifts from estimating flows between areas to identifying the relational architecture that shapes territorial form.

In this perspective, the analytical focus moves toward configurational properties of the system, including:

- centrality and hierarchy,
- cohesion and fragmentation,
- redundancy and vulnerability,
- polycentricity and peripherality.

These properties emerge from the structure of relations rather than from the attributes of individual units.

The limits of spatial aggregation have long been recognised, particularly through the Modifiable Areal Unit Problem (Openshaw, 1984). When territorial systems are interpreted as complex adaptive systems, the predefinition of zones risks obscuring the processes that generate spatial structure. In administrative-unit-based interaction models, spatial structure often enters the model as a parameter rather than as an outcome (Fotheringham, 1983; Oshan, 2021). At the same time, planning practice increasingly operates within functional geographies that do not coincide with administrative boundaries (Rodriguez-Posse, 2013). Accessibility systems, service networks, tourism corridors and environmental systems rarely align with political borders. When spatial sustainability is understood in terms of structural properties such as polycentric balance, relational equity and network cohesion, analytical frameworks must be able to reconstruct these configurations independently of predefined partitions.

This shift has important methodological implications. Instead of approximating flows between given spatial units, the analytical objective becomes the identification of emergent configurations. These may take the form of cohesive communities of services, hierarchical structures of attractors, or integrated destination areas emerging from patterns of interaction. The analysis of such structures relies on network-based methods, including community detection algorithms (Blondel et al., 2008; Fortunato, 2010), centrality measures (Freeman, 1979), and information-theoretic approaches (Rosvall and Bergström, 2008). In this framework, geography is not imposed but inferred.

Spatial interaction modelling can therefore be reinterpreted as configurational modelling. Its aim is to understand how territorial elements combine into functional subsystems, how interaction structures generate hierarchies, and how network architecture shapes the propagation of local changes. In this sense, spatial sustainability can be analysed as a property of configuration rather than as the sum of sectoral performances.

This paradigm is particularly relevant in contexts where territorial performance depends on complementarities between elements. Tourism represents one such domain, as it is inherently relational and organised through interactions between attractions, services, infrastructures and users (Hall and Page, 2014; Baggio and Cooper, 2010). However, the conceptual framework is not limited to tourism and can be extended to other territorial systems, including innovation networks, healthcare systems and educational infrastructures.

The transition from theory to methodology follows from this perspective. Territorial systems are interpreted as adaptive and relational configurations, and spatial sustainability is framed in terms of their structural organisation. While classical spatial interaction models remain analytically robust, they operate within predefined spatial partitions. By contrast, node-based representations allow the reconstruction of emergent territorial structures, and network-based modelling provides the tools to analyse them.

This shift marks the transition:

- from static distributions to relational architectures,
- from administrative aggregates to functional geographies,
- from flow allocation to configurational evaluation.

Within this framework, the methodological approach developed in the following chapter map territorial systems as networks derived from spatial interactions, enabling the explicit analysis of their relational structure.

2.9 Domain ontology: taxonomy of the specialized tourism ecosystem

The research group develops a domain taxonomy that functions as a conceptual framework to organise knowledge and structure information flows across the analytical stages of territorial classification and strategic decision-making. Within the present research, this taxonomy serves as an ontological structure of the tourism domain.

Tourism research frequently presents ontological gaps that lead to disjointed understandings of destinations and uneven representations of territorial systems. Destinations are often described through descriptive inventories aggregated statistical units. The proposed taxonomy overcoming this limitation by structuring the tourism ecosystem into ontological class. Therefore, the tourism ecosystem is considered as a nested relational structure across three hierarchical levels associated with territorial scale and system complexity: Specialized Destination Area (DA), Specialized Tourism System (TS), and Specialized Tourism Ecosystem (ES). These levels are not alternative interpretations of tourism space but complementary layers within a single relational architecture.

The Specialized Destination Area constitutes the primary spatial configuration relevant for the modelling framework. A Destination Area is defined as a spatially coherent community of elements identified through the interaction of specialized attractions, services, and reachability components. It represents an emergent geographical configuration rather than an administratively bounded unit. The DA captures the spatial organisation of supply-side components within a specific tourism specialisation nd reflects the local configuration in which visitors stay and consume services.

Formally, a Destination Area can be expressed as:

$$DA_j = f(a_j, st, r)$$

where the subscript jjj denotes the specific tourism specialisation associated with a given value chain. The specialisation attribute describes the tourism category—such as cultural, gastronomic, or nature-based tourism—linked to the dominant functional identity of the configuration. Each DA is therefore “specialized” according to the typology that structures its value chain and contributes to its competitive positioning within broader tourism markets.

The function f represents the spatial model constructed to describe tourism specialisation through configurational relationships among evaluated elements (Corrado, Romaniello, et al., 2024). It encapsulates relational dependencies, spatial proximity, accessibility conditions, and systemic complementarities among attractions, services, and reachability components. The Destination Area is not the sum of its elements; it is the outcome of their structured interaction within space. At the second hierarchical level, the Specialized Tourism System corresponds to the spatial identification of one or more specialised Destination Areas within which the interaction between tourism demand and supply can be recognised along a specific tourism value chain. The TS represents a structured subsystem in which functional relations between attractions, services, and visitors produce recognisable patterns of territorial specialisation. It captures the operational dimension of tourism organisation at an intermediate scale.

At the broader level, the Specialized Tourism Ecosystem is defined as a network of interconnected and interdependent nodes characterising one or more Destination Areas and generating collective benefits within a territorial development scenario (Corrado et al., 2024; Scorza & Gatto, 2023). The ecosystem dimension integrates stakeholder communities—public authorities, private operators, and local associations—within a spatially traceable structure. Although governance and stakeholder dynamics are not explicitly modelled in the present network-based interaction framework, the ES level situates Destination Areas within wider territorial development processes. Within this research, the taxonomy operates as an ontological scaffold for the methodological architecture developed in Chapter 4. By defining the Destination Area as a spatially coherent community emerging from the interaction of attractions, services, and reachability components, the taxonomy establishes the conceptual target of the network-based spatial interaction model. The structural modelling of service communities and the functional coupling between attractors and service clusters are directed toward identifying emergent DAs corresponding to specific tourism specialisations.

The supply-side components described in the taxonomy are spatially explicit and compatible with the node–edge representation adopted in the modelling framework. By focusing on the local representation of DA elements within a network structure, the methodology reconstructs tourism geographies from the bottom up. Rather than aggregating tourism indicators within Statistical Territorial Units, the approach derives Destination Areas from relational structures among spatial elements. This ontological alignment ensures that the output of the modelling process, the emergent Destination Areas identified through community detection and interaction analysis, corresponds directly to the DA concept defined within the taxonomy. The taxonomy therefore provides the domain-specific foundation that enables the transition from general network-based territorial modelling to its empirical application within the tourism ecosystem.

3 Methodological approach

The methodological framework developed in this study aims to formalise territorial configurations through a network-based modelling architecture. The approach reconstructs territorial organisation as the result of relationships among spatially embedded entities, focusing on how interaction patterns generate higher-order spatial structures. In this sense, the framework converts fine-grained spatial data into analytically meaningful territorial configurations. Territorial systems are represented as networks, where spatial entities are modelled as nodes, relationships as edges, and configurations as network partitions. The modelling process starts from highly disaggregated spatial elements and progressively builds relational structures, preserving the link between micro-scale components and macro-scale spatial organisation.

The first step concerns spatial granularity. All territorial components are represented as Points of Interest (PoIs), including attractors, service providers, and accessibility infrastructures. This allows maintaining a high spatial resolution in the initial stages and avoids premature aggregation. The dataset is constructed by integrating multiple sources: official institutional data for attractors, digital platforms and open geographic databases for service nodes, and additional information to capture accessibility-related components. Each node is therefore associated with attributes relevant for modelling interactions, such as typology, location, and structural characteristics.

Once the node dataset is defined, the framework introduces the first relational layer by constructing a spatial network of proximity. A Delaunay triangulation is used to define adjacency relations among service nodes without imposing arbitrary distance thresholds. The resulting graph is then weighted using shortest-path distances calculated on the road network, so that edge weights reflect effective accessibility rather than simple geometric proximity. This weighted proximity graph represents the structural layer of the territorial system, capturing local continuity and accessibility gradients.

The graph is then analysed through community detection using the Louvain algorithm, which identifies groups of nodes characterised by strong internal connectivity. These service communities represent cohesive subsystems emerging from spatial proximity and accessibility conditions. For each community, spatial dispersion is summarised through a Standard Deviational Ellipse. The centroid of the ellipse is used as a representative location in subsequent steps, while internal dispersion is retained as an indicator of structural organisation. This transformation reduces node complexity while preserving key configurational properties. The framework then introduces a second relational layer, focusing on functional interactions. A weighted bipartite graph is constructed between attractors and service communities, representing relationships between demand-generating elements and clusters of supply. Edge weights are defined through an interaction function that integrates spatial impedance, attractor attractiveness, rarity indices, and the structural properties of service communities. The resulting network represents the potential intensity of interactions between heterogeneous components of the territorial system.

At this stage, the territorial system is represented as a weighted interaction network linking attractors and service communities. To identify higher-order structures, the network is partitioned using the Infomap algorithm, which detects modules based on the organisation of flows within the network. The resulting modules are interpreted as Emergent Destination Areas, defined as spatially coherent and functionally integrated subsystems. These areas are not imposed by administrative boundaries but emerge from the configuration of interactions.

The overall modelling process can be summarised as a sequence of transformations:

- Spatial objects are represented as nodes
- Nodes are connected through proximity-based weighted edges
- Structural communities are identified
- Communities are aggregated into higher-order nodes
- Attractors are connected to service communities through a weighted interaction function
- The interaction network is partitioned into emergent Destination Areas

Micro-scale spatial organisation influences structural clustering; structural clustering shapes functional interactions; and functional interactions lead to the emergence of higher-level territorial configurations. The framework produces multiple outputs, including service communities, structural indicators at the community level, weighted interaction networks, and emergent Destination Areas. While the application focuses on tourism as a territorially embedded system, the methodological architecture is generalisable to other territorial contexts characterised by spatially distributed entities and interaction-based organisation.

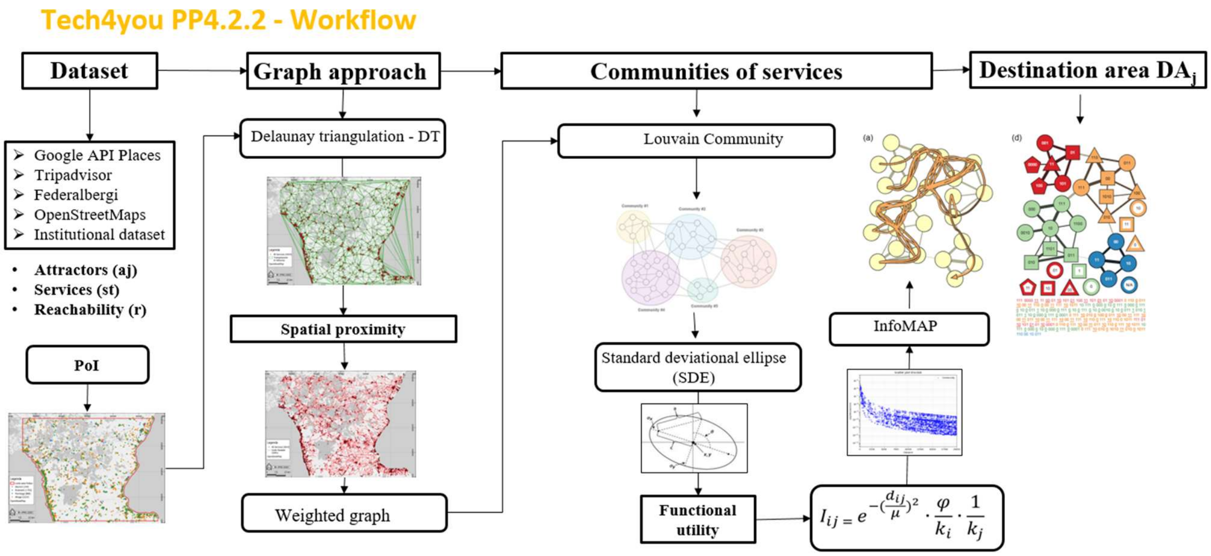

Figure 4 Network-based workflow for Destination Area detection. The figure presents the main steps of the proposed framework, from the construction of the geolocated dataset to the spatial graph, community detection and identification of emergent Destination Areas.

3.1 Google Places API for building the territorial knowledge base

The definition of a territorial knowledge base represents the first task of this doctoral research. The mapping of tourism-related phenomena and their local-scale dynamics has therefore been developed through a methodology designed to ensure generalizability and methodological transparency, with the explicit objective of supporting future data-driven spatial analyses.

Ministerial geoportals and regional spatial data infrastructures, although traditionally employed within territorial planning practices, present significant structural limitations. The main issues concern the fragmentation of information across multiple platforms, the heterogeneity of territorial classification systems, and the lack of standardized data-sharing formats, which would be addressed at the European level through the INSPIRE Directive. Moreover, these platforms often lack systematic updating procedures. As a consequence, they fail to adequately represent the rapid evolution of territorial processes, rendering them insufficient for the dynamic management and interpretation of spatial systems. Such limitations directly affect the analytical validity of spatial modelling. When datasets are fragmented, outdated, or structurally inconsistent, the capacity to infer spatial processes from observed patterns is significantly reduced. This constrains both the reliability of spatial projections and the interpretative strength of statistical analyses, particularly in contexts characterized by fast-changing socio-economic dynamics such as tourism systems.

For these reasons, alternative data sources were adopted, particularly those provided by platforms such as OpenStreetMap (OSM) and the Google Maps Platform. These services are characterized by high update frequency, extensive territorial coverage, and strong interoperability through Application Programming Interfaces (APIs). Their structured architecture enables the extraction of georeferenced and attribute-rich data in a reproducible manner, thus reinforcing the methodological shift toward a network-based and data-driven representation of territorial configurations.

In particular, the Google Places API provides access to detailed information on commercial activities and points of interest, enriching the analytical framework with attributes such as geographic location, functional categories, opening hours, and user-generated reviews. The integration of these otherwise difficult-to-access components allows the research to overcome the fragmentation and obsolescence that affect conventional institutional datasets. More importantly, it enables the construction of a granular territorial knowledge base suitable for modelling spatial proximity, interaction structures, and emergent service communities. Although the use of private datasets raises concerns related to privacy, data governance, and potential biases in representation, these sources constitute an indispensable resource for investigating complex territorial phenomena. When treated critically and methodologically controlled, such data allow the identification of spatial correlations, the detection of relational structures, and the anticipation of evolving dynamics.

An API, acronym for *Application Programming Interface*, is a set of rules and protocols that enables the structured exchange of information between different software systems. It is an interface that allows one program to access functionalities or data from another program, without requiring in-depth knowledge of how the latter has been developed. This level of abstraction enables developers to use APIs without writing specific code for each application, thereby simplifying access to remote resources. Each request made through an API follows a defined syntax, established and documented by the service provider. Such documentation guarantees a standardized method for reading and writing data to and from available resources, ensuring that the process is transparent and replicable.

Google APIs are programming interfaces that allow interaction with the various services developed within the Google ecosystem. Through structured service calls, they enable the integration of advanced functionalities into applications, including computing services, data storage, networking, map access, data analysis, and identity and security management. The Google Maps Platform – Places API is a service that provides detailed information about physical places, such as restaurants, hotels, museums, shops, points of interest, and other commercial or geographical entities. Through this API, users can access the same data available within the Google Maps application. Examples of retrievable information include the name of the place or service, geographic location (coordinates), reviews, opening days and hours, photographs, and additional descriptive attributes. From a technical perspective, the Google Places API operates through an interface that mediates communication between the user and Google's servers. It is necessary to register a project within the Google Cloud Console and obtain an API Key. This key is used to authenticate requests and monitor application usage. Data retrieval is subject to a fee-based model, although Google provides a monthly free quota that allows limited access to the available functionalities.

API calls are regulated through a quota system based on the number of requests performed within a given time period. Costs depend on the type of service used and on the volume of data requested. The pricing model is structured on a pay-per-use basis and is organized through *Stock Keeping Units* (SKUs), which represent billing categories associated with specific API products and functions (e.g., Places API – Place Details; Places API – Autocomplete per request). Each SKU is billed according to usage tiers defined by request volume. The Google Places API allows targeted requests, enabling the classification of query types according to their functionality. Before describing the different features, it is necessary to clarify how Google Maps identifies places. The API assigns a unique *Place ID* to each location within the Google Places database. This identifier ensures unambiguous recognition of each place. Beyond the Place ID, the returned data can be enriched with additional attributes that provide more detailed information about the characteristics of the location, resulting in a structured and comprehensive dataset. Place Search allows users to retrieve locations within a specific geographic area or based on selected keywords (e.g., restaurants or tourist attractions within a given area). The search can be spatially constrained by specifying latitude and longitude coordinates and defining a place type.

The Places API offers two search modalities:

- Text Search: allows the specification of a free-text query string. The search can be refined by including parameters such as price levels, operational status, ratings, or specific place types. It can also be biased toward a particular geographic area.
- Nearby Search: allows the definition of a geographic region through a circular buffer defined by a central coordinate (latitude and longitude) and a radius expressed in meters. Results are returned based on proximity to the specified point.

The principal difference between the two modalities is that Text Search is on arbitrary textual query, whereas Nearby Search requires a clearly defined spatial boundary. The Place Details function provides additional information for a single location identified by its Place ID. Available attributes include name, address, reviews, photographs, rating scores, and opening hours. This functionality enables the retrieval of highly specific information related to a point of interest. In addition, the API provides Place Autocomplete and Query Autocomplete functionalities, both based on intelligent search auto-completion mechanisms. Place Autocomplete generates suggestions for geographically referenced locations, including businesses, addresses, and points of interest, as the user types. Query Autocomplete, instead, predicts general search phrases or keywords without necessarily incorporating a geographic constraint. The functionalities offered by the Places API are particularly suited to the objectives of this research. Given that the aim is to construct a territorial knowledge base for the selected case studies, the Place Search functionality was adopted in order to map services within the study areas.

Text Search proved limiting for the objectives of this research. Therefore, the most appropriate solution was the use of Nearby Search, which returns results based on geographic proximity to a reference coordinate. This function enables the identification of places within a specified radius and ensures spatial coherence in the construction of the dataset. In addition to geolocation, the research required the extraction of descriptive attributes associated with each place. The Place Details function allowed the retrieval of a broad range of additional information linked to each Place ID, such as full address, contact details, user ratings, and reviews. The integration of these detailed attributes is essential for constructing a structured and analytically robust dataset. Data requests were performed using Google Colab, an open-source platform for Python-based application development. Google Colab facilitates the use of external libraries and code repositories, providing a flexible and collaborative environment suitable for reproducible computational workflows.

```
API_KEY = *ApiGoogleCloudConsole*
url = "https://maps.googleapis.com/maps/api/place/nearbysearch/json"

params = {
    "key": API_KEY,
    "location": "40.85342,15.85404",
    "radius": 50000,
    "type": "restaurant"
}
```

In the first line, the personal API Key generated through Google Cloud Console is defined. This key authenticates the requests and tracks service usage. The second line calls the Nearby Search function. This function requires a reference point and a search radius. The location parameter specifies the latitude and longitude of the central point, while radius defines the search extent in meters (up to a maximum of 50 km). The type parameter filters results according to predefined place categories provided by Google.

When performing a Nearby Search or Place Details request, it is necessary to explicitly specify which fields should be returned. There is no predefined default list of fields; if no fields are specified, no data are returned. Place types represent categories that describe the characteristics of a location. The classification system is structured into two tables:

- Table A: standardized macro-categories designed to facilitate interaction with geolocated data and support spatial analysis applications.
- Table B: includes additional attributes and more detailed classifications that allow deeper analytical exploration.

Each macro-category contains multiple subcategories reflecting the variety of identifiable place types. These categories are primarily used to filter search results and assign a functional classification to each location.

In this research, only place types relevant to tourism service provision were retained. Institutional, administrative, commercial, and non-tourism services were excluded. According to the adopted taxonomy, a physical place can be considered part of a tourism destination only if it satisfies specific characteristics associated with the concept of Destination Area.

The selected categories were:

- Lodging: accommodation structures such as hotels, B&Bs, and motels.
- Restaurant: food and beverage establishments, included generically to avoid excessive sub-classification.
- Transit station: transport-related nodes such as railway stations, extra-urban bus stops, and intermodal terminals.

For each place type, relevant data fields were specified to construct a structured dataset. The following attributes were extracted:

```
place_info = {
    "ID": place.get("place_id", ""),
    "Name": place.get("name", ""),
    "Type": place.get("types", []),
    "Rating": place.get("rating", ""),
    "N_ratings": place.get("user_ratings_total", ""),
    "Location": place.get("geometry", {}).get("location", "")
}
```

The selected fields include:

- `name`: official name of the place
- `types`: all associated place types, including the primary type
- `rating`: average user rating
- `user_ratings_total`: total number of user reviews
- `location`: geographic coordinates

All other attributes were excluded through field masking to avoid unnecessary costs and to maintain analytical focus.

The joint consideration of rating and number of ratings is methodologically relevant. A high rating based on a limited number of reviews cannot be considered statistically comparable to a slightly lower rating supported by a substantial volume of evaluations. Although these parameters are not directly employed in the subsequent modelling phase, they were retained to preserve dataset completeness for future analytical developments.

The Nearby Search function of the Places API is an extremely versatile tool that can be integrated into a wide range of applications. It is most commonly used within navigation systems, particularly those connected to Google Maps, to facilitate the identification of nearby locations for users. In tourism-oriented applications, it can support travelers in exploring a city or a region by suggesting points of interest such as historical monuments, museums, parks, and other attractions. By specifying parameters such as the place type "tourist_attraction" or keywords like "museum," these applications are able to return relevant locations in real time, enhancing the user's spatial awareness and exploratory experience. In more critical contexts, the Nearby Search function can also be implemented in emergency-support applications, assisting users in locating hospitals, pharmacies, or police stations in their immediate surroundings. The ability to rapidly identify essential services in real time is crucial for ensuring prompt and targeted responses in situations of need. The use of the Nearby Search function proved particularly effective for constructing a detailed database of tourism-related services. By defining a central coordinate and a search radius, it was possible to systematically map services within the study areas, thereby creating a spatially coherent and territorially bounded dataset.

This approach makes the process automated and replicable. By optimizing data retrieval procedures and ensuring the extraction of standardized, complete, and uniquely identifiable information, the resulting dataset becomes readily integrable into advanced analytical tools and computational workflows. In the specific case examined in this study, the methodology may also be further developed to support interactive platforms capable not only of informing territorial planning development plan, but also of serving for data-driven decision-making in the tourism sector. Such applications could include the production of thematic maps, the simulation of future development scenarios, or the implementation of continuous monitoring systems for territorial dynamics. The capacity to integrate structured geospatial data with analytical and modelling tools contributes to a more informed and sustainable management of territorial resources. It supports strategic, evidence-based interventions and responds to the needs of planners, stakeholders, and policy-makers engaged in the governance of tourism systems

3.2 The graph-based approach

In line with the conceptual framework outlined in the previous sections, where territorial systems are interpreted as relational and interaction-based configurations, this section introduces the operational model developed for this doctoral research, grounded in graph theory. Within the Spatial Interaction Model proposed in this thesis, the territory is conceptualized as a network of interdependent entities. Graph structures are therefore employed as an embedding framework to represent services as nodes and spatial proximity as edges. This transformation enables the explicit modelling of interdependencies and functional relationships across the tourism system, allowing a deeper interpretation of spatial organization and territorial dynamics (Rey et al., 2024). Graph theory is a mathematical discipline that studies the properties and applications of graphs — structures composed of vertices (or nodes) connected by links. These links may be directed (having both direction and orientation), in which case they are referred to as arcs and the graph is defined as directed, or undirected, where links simply connect two nodes without direction (Hamilton, 2020). Graphs are typically represented visually as points (nodes) connected by segments or curves (edges). In directed graphs, edges are associated with arrows indicating direction.

In the present research, the graph structure adopted is undirected, since spatial proximity between services is reciprocal. However, as will be described in the methodological steps, attributes are associated with both nodes and edges in order to construct a weighted graph, consistent with the interaction-based logic of the model. This approach overcomes the limitations of traditional two-dimensional cartographic representations, which capture spatial distributions but fail to explicitly model relational structures. In particular, conventional representations do not account for territorial morphology, network constraints, or interaction intensities — elements that are central in a spatial interaction framework. Starting from a given dataset, multiple triangular mesh configurations can be generated. However, not all possible triangulations

are capable of adequately representing territorial structure or the interactions between spatial entities. Selecting the most appropriate configuration is therefore not a trivial task.
This leads to a methodological question:

"How can we determine which vertices should be connected in order to obtain a representative graph structure, capable of effectively modelling spatial relationships and territorial topology?"

A possible answer is provided by the principle known as the Delaunay criterion. The Delaunay criterion establishes a geometric rule to determine whether a pair of adjacent triangles represents an optimal connection. In this context, Delaunay triangulation guarantees that the resulting structure satisfies this condition. Its importance has been recognized since the 1930s, with the pioneering work of Delaunay (1934), who formalized the definition and properties of this triangulation. Since then, it has become a widely adopted approach in spatial analysis and computational geometry (Yan et al., 2019). The use of tools and software implementing Delaunay triangulation allows rapid construction of a graph structure based on this criterion. However, since the objective of this research is to analyze how tourism services interact across the territory, it is useful to briefly describe how the triangles are constructed.
The construction of triangles must satisfy the Delaunay condition, which states that no point in the dataset should lie inside the circumcircle of any triangle in the mesh. The Delaunay triangulation algorithm connects points based on geometric independence.
The resulting triangulation presents several desirable properties:

- Maximization of the minimum angle of all triangles
- Minimization of long and narrow triangles
- Generation of circumcircles that contain no other vertices of the mesh except the three defining vertices

This latter property represents the key element of the Delaunay triangulation.

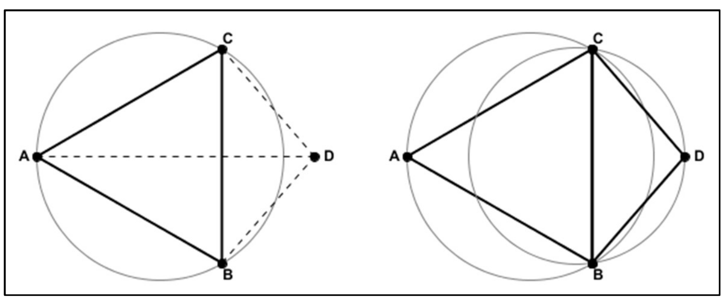

Figure 5 Valid Delaunay configuration. Point D lies outside the circumcircle of triangle ABC; therefore, the triangulation satisfies the empty circumcircle condition.

Considering a triangle with vertices A, B, and C, and a fourth vertex D located outside the circumcircle of triangle ABC: if D is connected to form triangle CBD, the resulting network remains optimal according to the Delaunay criterion. Conversely, if vertex D lies inside the circumcircle of triangle ABC, the resulting triangulation would violate the Delaunay condition and therefore would not be optimal.

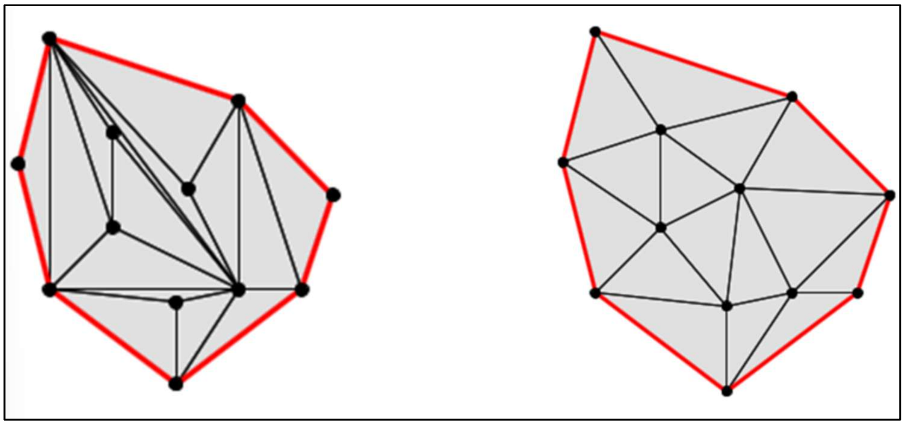

Figure 7 Non-valid Delaunay configuration. Point D lies inside the circumcircle of triangle ABC; therefore, the triangulation violates the empty circumcircle condition and is not optimal according to the Delaunay criterion.

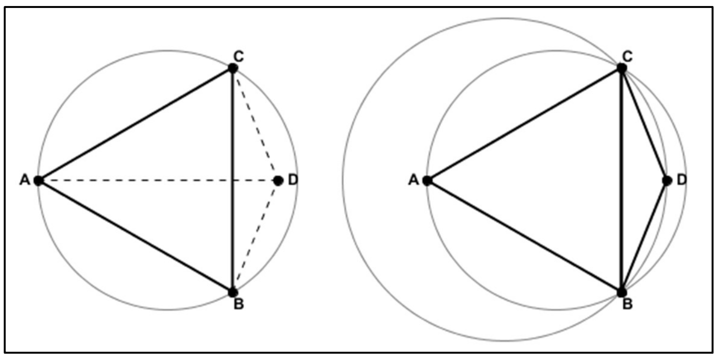

Figure 6 Arbitrary connections versus Delaunay triangulation. The figure shows how arbitrary point connections can distort local spatial relationships, while Delaunay triangulation provides a structured graph that better preserves neighbourhood relations among spatially adjacent points.

As illustrated in the referenced figures, when points are connected arbitrarily rather than according to the Delaunay criterion, spatial proximity relationships may be distorted. Vertices generated randomly and added sequentially can produce a triangulation in which nearby points are separated by intermediate edges. In contrast, a Delaunay-based triangulation preserves local neighborhood relationships by directly connecting spatially adjacent points.

Another important advantage of Delaunay triangulation is its relationship with the construction of Voronoi polygons. Specifically, it can be used to generate a Voronoi diagram, which partitions the plane into regions based on distance from input points. Voronoi diagrams are widely applied in spatial clustering and territorial partitioning analyses. Having theoretically defined the Delaunay triangulation, it is now necessary to explain how it has been applied in this research and why it proved useful for achieving the objectives of the study.

In this thesis, Delaunay triangulation was applied to all services present in the study areas. Here, “services” refers to all tourism supply components, including accommodation services (lodging and restaurants) and accessibility-related services (transit stations and parking areas).

To automate the modelling procedure, the Delaunay triangulation across all points in the study areas was generated using the same open-source coding environment adopted for data retrieval (Google Colab), through Python programming language and commonly used external libraries.
The following code illustrates the function used to compute the adjacency matrix, which corresponds to the

matrix representation of the Delaunay triangulation. The matrix form is particularly useful for subsequent analytical processing.

```
def calcola_matrice_adiacenza(punti):
    # Perform the Delaunay triangulation
    triangolazione = Delaunay(punti)

    # Initialize adjacency matrix with zeros
    num_punti = len(punti)
    matrice_adiacenza = np.zeros((num_punti, num_punti), dtype=int)

    # Populate adjacency matrix with triangulation results
    for simplex in triangolazione.simplices:
        # Each simplex represents a triangle in the Delaunay graph
        for i in range(len(simplex)):
            for j in range(i+1, len(simplex)):
                # Set adjacency between points i and j
                matrice_adiacenza[simplex[i], simplex[j]] = 1
                matrice_adiacenza[simplex[j], simplex[i]] = 1
    return matrice_adiacenza
# Import point layer
punti = pd.read_csv('/content/Services_reachability.csv')
```

The point layer, stored in CSV format, contains all service-related attributes discussed in the previous chapter. Since the algorithm operates within the topological space of the graph, only the spatial coordinates (latitude and longitude) are used for constructing the Delaunay triangulation. Functional attributes are not considered at this stage. The Delaunay triangulation represents one possible configuration of an undirected graph network, composed of nodes and edges. Each node may have multiple edges; these edges represent connections to neighboring nodes identified according to the Delaunay criterion. However, using the geometric distance derived directly from Delaunay adjacency to weight the graph would be conceptually incorrect in this case. The distance between connected nodes corresponds to Euclidean distance (straight-line distance), which does not account for territorial morphology or real-world movement constraints. It does not incorporate the actual transport network that would be used for travel between two services. Therefore, the weight of connections must be represented by the “real” distance between points — that is, the distance computed along the road network connecting them. This network-based weighting procedure is described in the following section.

Starting from the undirected and unweighted graph — where each edge has a unit value representing a simple topological connection between nodes — the second step consists of weighting the graph based on the road network.

Since one of the objectives of this research is to automate the entire analytical process, the calculation of distances between points was also performed within the Colab coding environment. In this specific case, the Python library OSMnx was employed. OSMnx is an open-source Python library designed to facilitate the acquisition, analysis, and visualization of street networks and urban infrastructure data derived from OpenStreetMap (OSM). It allows users to download, manipulate, and analyze road network graphs and other geospatial infrastructures, providing tools to compute metrics such as network connectivity, node distances, and shortest path analysis. OSMnx supports multiple operations, including the creation of directed or undirected graphs, visualization of georeferenced maps, and spatial analysis over large geographic areas. The library retrieves data through OSM APIs and integrates them with advanced network analysis functionalities.

Below are the main steps and analytical choices adopted for implementing the procedure.

```
# install libraries
```

```
!pip install osmnx
import osmnx as ox
```

After installing the OSMnx library and importing pandas, the next step consists of downloading the graph corresponding to the road network.

In this research, the road network was selected because the two study areas, as previously described, are characterized by significant infrastructural deficiencies, particularly with respect to public transport systems (both local and extra-urban). As a result, accessibility to tourism-related locations depends predominantly on private vehicles. This condition reinforces the importance of modelling effective reachability between Destination Areas within the analyzed territories. In marginal areas where infrastructural improvements are constrained by limited demand and scarce resources, it becomes essential to develop solutions that maximize the efficiency of existing services. A realistic modelling of road-based accessibility therefore represents a fundamental component of the spatial interaction framework.

The retrieval of the road network graph can be performed through different query types in OSMnx: by city name, polygon, or bounding box. Given that the study focuses on large territorial contexts, the bounding-box query was selected as the most appropriate method.

```
# bounding box [spatial window for downloading the road network graph]
north = 40.3237   # Northern latitude - Pollino
south = 39.55212  # Southern latitude - Pollino
east = 16.83960   # Eastern longitude - Pollino
west = 15.5614    # Western longitude - Pollino
# Create bbox tuple
bbox = (north, south, east, west)
bbox
```

The bounding-box coordinates for the Pollino areas are reported above.

Moreover, OSMnx allows the assignment of travel speeds to different road categories in order to calculate travel times accurately.

```
# Configure speeds for each road type
hwy_speeds = {
    "motorway": 110,      # highways
    "trunk": 90,          # major roads
    "primary": 70,        # state roads
    "secondary": 50,      # municipal roads
    "tertiary": 30,       # urban roads
    "residential": 10     # residential streets
}
```

As shown in the code, each road category is assigned an average speed (in km/h), based on typical speed limits established by national traffic regulations. Assigning speeds is crucial because OSMnx calculates shortest paths based on travel time. Consequently, the algorithm selects routes minimizing travel time rather than purely geometric distance. In most cases, faster roads (e.g., highways or primary roads) are preferred over slower urban streets, reflecting realistic mobility behaviour.

The Shortest Path Analysis represents a central step in this phase, as it determines the weight assigned to the edges derived from the Delaunay triangulation. The weight associated with each edge corresponds to the road-network distance (in meters) between two connected services.

The following code excerpt illustrates this process:

```
# Iterate through each row to compute travel time and distance
for index, row in Connessioni_input.iterrows():
    # Extract origin and destination coordinates
    orig_lat, orig_lon = row['lat'], row['lng']
    dest_lat, dest_lon = row['lat_2'], row['lng_2']

    # Identify nearest nodes in the road network graph
    orig_node = ox.distance.nearest_nodes(Gp, orig_lon, orig_lat)
    dest_node = ox.distance.nearest_nodes(Gp, dest_lon, dest_lat)



    # Compute shortest path based on travel time
    if orig_node != dest_node:
        shortest_time_route   =   ox.shortest_path(Gp,   orig_node,   dest_node,
weight="travel_time")

    # Check that route is valid
    if shortest_time_route is not None:
        # Compute total distance
        total_distance = sum(
            ox.utils_graph.get_route_edge_attributes(Gp,    shortest_time_route,
"length")
        )
```

The origin and destination coordinates used in the shortest path computation do not correspond exactly to the original service points, but rather to the nearest nodes in the road network graph generated by OSMnx. This simplification does not significantly alter spatial accuracy, as the road network graph is highly detailed and composed of numerous closely spaced nodes. Furthermore, this procedure avoids potential computational loops, particularly in dense urban areas. The shortest path is calculated based on travel time, taking into account the assigned road speeds. Once the optimal route is identified, the total distance along that route is computed and used as the weight of the connection. One limitation, although not critical, of performing point-to-point shortest path calculations using this library concerns processing time, particularly when handling large datasets. However, the management of input and output data remains relatively straightforward, and the integration of OSMnx within the automated workflow ensures methodological coherence and replicability.

3.3 Mapping of the tourism service communities

The third methodological step aims at delimiting the communities of tourism service provision starting from the undirected graph with weighted edges. When referring to service communities, we mean a set of services located close to one another, characterized by strong spatial interaction and sharing the function of supporting one or more specific tourism attractors, thereby increasing their overall utility. Considering exclusively the services related to tourism supply, which include both accommodation services and reachability services, these services are treated as individual point entities located within the territory and connected in some way to nearby points. In this step, the objective is to define a rule for the aggregation or subdivision of communities. The concept of proximity in the study of social sciences assumes the meaning of spatial, temporal, or conceptual relationship between elements or phenomena. In a strictly geographic sense, proximity denotes the physical closeness between two points in space. It may also indicate the intensity and frequency of interactions between individuals or groups in social, economic, and cultural contexts. Within the concept of spatial proximity, distance decay describes how the relationship between two entities weakens as the distance between them increases. Distance decay is one of the most studied concepts in spatial interaction models and is expressed in the First Law of Geography:

“Everything is related to everything else, but near things are more related than distant things” (Tobler, 1995).

Researchers have been inspired by the relationship between interaction and distance, as studied by Tobler (1995), in simple arithmetic form based on observations such as the tendency of Irish emigrants to move predominantly to the closest counties of Great Britain. Distance decay describes how the strength of a relationship between people, places, or systems decreases as separation increases. The strength of the relationship is generally measured by similarity between entities in a spatial process. To distinguish interaction from similarity, we can consider the following example (Hasova & Wolf, 2022): interaction may refer to trade between countries or connections in social networks within a city; similarity may refer to how the temperature in one garden is similar to that of a neighboring garden.

“Separation” is usually defined according to the type of relationship studied. In the case of interaction, the relationship concerns trade and separation may correspond to shipping cost; in the case of similarity, simple geographic distance may be sufficient. The definition of distance decay is based precisely on these abstract concepts of relationship and separation. The concept of similarity is particularly useful in the context of service communities, since through distance decay analysis it is possible to describe how nearby elements relate more strongly than distant ones. This principle is useful in defining agglomeration economies, where services arranged in a compact manner tend to develop more specialized and synergistic functions, improving efficiency and the overall attractiveness of a center. In the case of similarity, distance decay may be correlated with the idea of spatial autocorrelation, which applies more generally than distance decay in interaction studies, since similarity-based decay is not limited to interaction contexts such as trade.

For this thesis, the intention is to emphasize the distance between neighboring entities; therefore, the concept of distance decay is particularly useful. Numerically, distance decay can be imagined as a parameter that assumes high values for short distances and low values for large distances. In our model, connections between nodes on the road graph are weighted according to distance, using the concept of distance decay, which assigns higher weights to closer connections and lower weights to more distant ones. This approach naturally reflects the reduction of interaction between two entities as the distance separating them increases.

However, in order to ensure a more accurate representation, it is essential to correctly calibrate edge weights, avoiding underestimation of nearby connections or overestimation of distant ones. The focus therefore remains on optimizing the model so that it realistically reflects spatial interaction dynamics between nodes.

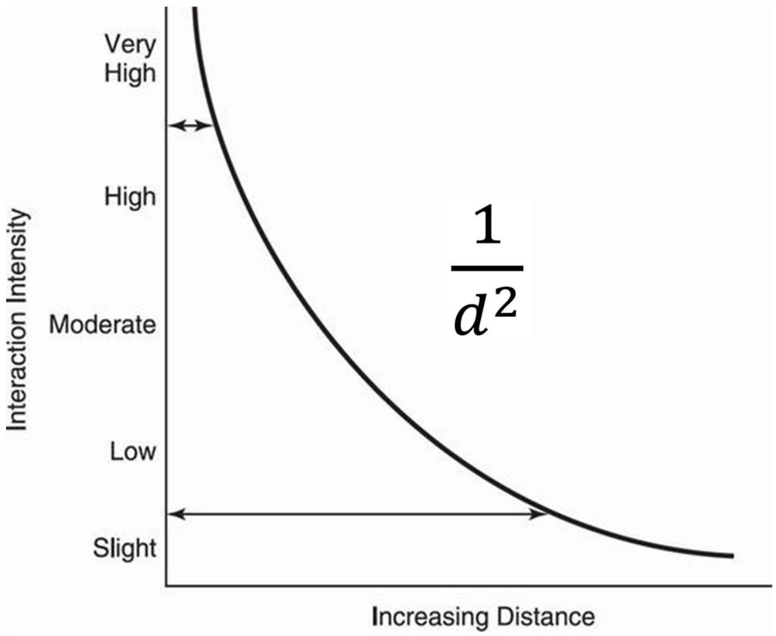

Figure 8 Inverse-square distance-decay function. The figure shows how interaction intensity decreases as distance increases, assigning stronger weights to nearby nodes and weaker weights to distant ones.

As shown in the graph, where the difference between the inverse of distance (1/d) and the inverse of squared distance ($1/d^2$) is reported, in this case the latter is used because the function tends toward zero more rapidly, which is useful in reasoning about interaction between nearby entities.

The following code was used to weight the graph with the appropriate parameter:

```
# GRAPH WEIGHTING BASED ON DISTANCE DECAY
# Apply transformation 1/distance^2 to 'distance'
data_transformed['distanza'] = (1 / (data_transformed['distanza'] ** 2))
```

Distance decay is therefore an important element for parameterizing the graph and identifying the appropriate partition for constructing communities. The algorithm used to partition communities is the Louvain Community Detection Algorithm, an analytical method useful for extracting community structure in a network. It is a heuristic method based on modularity optimization (Blondel et al., 2008).

The algorithm operates in two phases.

In the first phase, each node is assigned to its own community. Then, for each node, the algorithm searches for the maximum positive modularity gain by moving the node into all neighboring communities. If no positive gain is obtained, the node remains in its original community.

The modularity gain obtained by moving an isolated node *i* into a community *C* is calculated as:

$$\Delta Q = \frac{k_{i,in}}{"m} - \gamma \frac{\Sigma_{tot} * k_i}{2m^2}$$

where m is the size of the graph, $k_{i,in}$ is the sum of connections from i to nodes in C, k_i is the sum of weights of edges incident to node i, Σ_{tot} is the sum of weights of edges incident to nodes in C, and γ is the resolution parameter.

The first phase continues until no individual movement can further improve modularity.

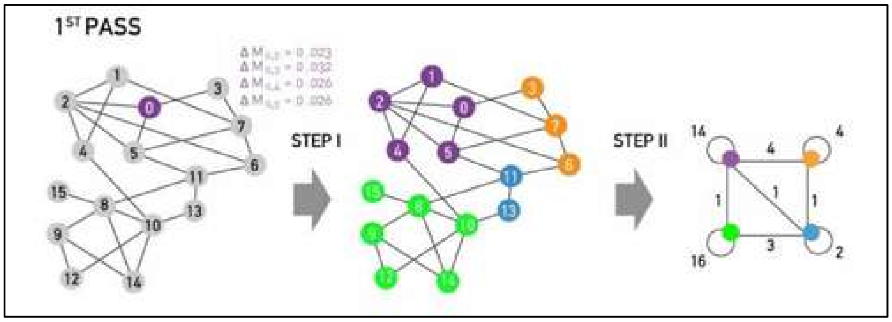

Figure 9 First phase of the Louvain algorithm. Nodes are iteratively moved between neighbouring communities to maximize modularity gain.

The second phase consists of building a new network in which nodes correspond to the communities identified in the first phase. The weights of edges between the new nodes are given by the sum of weights of edges between nodes in the corresponding communities.

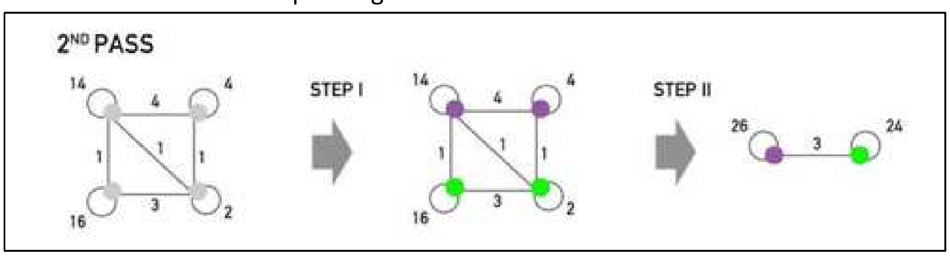

Figure 10 Second phase of the Louvain algorithm. The detected communities are aggregated into new nodes, producing a reduced network for the next optimization step.

The two phases are cyclical and are repeated until no further increase in modularity is possible.

The Louvain algorithm identifies high-modularity partitions in large networks in a short time and reveals a complete hierarchical community structure, allowing access to different resolutions of community partitioning (Clauset et al., 2004). This algorithm presents several advantages. First, its steps are intuitive and easy to implement, and the result is unsupervised, which is consistent with the approach pursued in this thesis. The order in which nodes are considered may influence the final output, since ordering occurs through random reshuffling. Moreover, the algorithm is extremely fast even for large networks, making it suitable for extensive territorial contexts.

The following code was used to generate communities in the study areas starting from the weighted connections:

```
# Detect communities with Louvain
```

```
communities = community_louvain.best_partition(G_transformed, weight='distanza',
resolution=2.5)

# Format results

community_data_louvain = pd.DataFrame(list(communities.items()), columns=['Node',
'Community'])
```

To detect communities, the edge weight considered is the distance between nodes. The "resolution" parameter is the only user-defined parameter. If the resolution is lower than 1, the algorithm favors larger communities; if greater than 1, it favors smaller communities.

By iterating the entire process across different resolution values and validating the results against known areas characterized by service concentration and compactness a resolution value of 2.5 was selected. This value has also been widely adopted in the literature (Dugué & Perez, 2015).

3.4 New geographies of tourism ecosystems: mapping of the Destination Areas

The final methodological phase aims at defining the Destination Areas, which, as discussed previously, represent territorial entities composed of at least one cultural attractor, at least one accommodation service, and at least one reachability service. The service communities obtained through the methodology described in the previous section include both accommodation and reachability services. In this phase, a new methodology is introduced to determine which tourism service communities interact with the cultural attractors present in their surroundings in order to form a Destination Area. The network connecting all cultural attractors and all communities must be represented as a weighted graph, that is, a network in which links (edges) between nodes are associated with a weight. This weight reflects the intensity or relevance of the interaction between two entities, enabling a more detailed analysis of relationships within the system. In this case, the interaction between two entities is quantified using a specific formula, developed to accurately represent the connection between cultural attractors and service communities, taking into account the key factors influencing these relationships.

The interaction between the two entities is defined as:

$$I_{Att\_Com} = e^{-(\frac{d_{ij}}{\mu})^2} \frac{\varphi * 1}{k_i * k_j}$$

The formula has been structured to incorporate all the variables involved in the study, namely the service communities (k_i), the cultural attractors (k_j), the distance (*d*), (μ) the mean distance. The parameter characterizing tourism service communities is k_i.

Since communities are composed of a set of points with different numerosity and spatial extent, but sharing the common feature of belonging to the same community, they are considered in this methodology as point entities incorporating a fundamental characteristic: the degree of dispersion of the community. This characteristic measures the compactness or, conversely, the spatial dispersion of services within the community. Communities with high dispersion values exhibit a fragmented and poorly structured distribution of accommodation and reachability services, making access more difficult for potential users. The presence of compact and well-structured service clusters is crucial for ensuring that local economic operators can effectively meet the needs of users, including residents, tourists, and other territorial actors. Compact service systems improve resource efficiency, reduce access time and costs, especially in peripheral or disadvantaged areas, and push synergies among services, generating agglomeration economies.

Conversely, highly dispersed communities may penalize accessibility and social cohesion, particularly in the case of essential territorial services such as educational, healthcare, and institutional facilities (Corrado, Santopietro, et al., 2024). Such fragmentation may increase territorial inequalities, reduce system efficiency, and increase management costs. From a tourism perspective, service dispersion may compromise the overall visitor experience, reducing the attractiveness of the community and negatively affecting local economic competitiveness. For this reason, the formula uses $1/k_i$ rather than k_i. The objective is to privilege compact communities (low dispersion values). For small dispersion values, $1/k_i$ produces large values, whereas high dispersion values generate smaller values. Therefore, compact communities are considered more relevant than dispersed ones.

To represent the entire service community, a representative point must be defined. Several geometric parameters may be used; in the proposed methodology, both the mean center (centroid) and the median center were considered. The centroid presents a limitation related to its geometric position, as it may not be fully representative of the "imaginary polygon" defining the community boundary.

The median center, instead, takes into account the spatial distribution of services within the community, as its position depends on how services are arranged. It is influenced by higher service concentrations and therefore better represents the structure of the community. To compute these geometric attributes and community characteristics, Python coding was used to automate this phase, starting from a service layer containing a field specifying the community ID.

The following code calculates the mean and median centers for each identified community:

```
# Calculate mean (centroid) and median center for each community

def calculate_centers(group):

    mean_center = centrography.mean_center(group[["X", "Y"]])

    med_center = centrography.euclidean_median(group[["X", "Y"]])

    return pd.Series({"mean_center": mean_center, "med_center": med_center})
```

To compute community dispersion, the following code was used:

```
# Calculate dispersion for each identified community

def dispersion_centers(group):

    disp_mean_center = centrography.std_distance(group[["X", "Y"]])

    disp_med_center = centrography.std_distance(group[["X", "Y"]])

    return pd.Series({"mean_center": disp_mean_center, "med_center": disp_med_center})
```

The parameter characterizing cultural attractors is k_j, defined as the sum of two components:

$$k_j = k_{Source} + k_{Rarity}$$

The parameter k_j was structured to assume values categorized between 3 and 10. The first component, k_{Rarity}, represents the importance of the cultural attractor. This value is determined according to the source that identifies the asset as a cultural attractor. An ordinal scale was defined, assigning different weights to each source based on its authority and relevance.

The second component, kRarita`k_{Rarità}kRarita`, is related to the study area and represents the rarity of a given cultural attractor within that area, thus assigning higher values to rarer attractors.

Rarity is inversely proportional to frequency:

$$k_{Rarity} = \frac{1}{Frequency}$$

Since k_{Rarity} must range between 3 and 10, rarity values were normalized to obtain values between 0 and 1 using:

$$k_{Rarity,norm} = \frac{k_{Rarity,attr} - k_{Rarity,min}}{k_{Rarity,max} - k_{Rarity,min}}$$

By summing the two components, the final $k_{Rarity,norm}$ value for each type of cultural attractor was obtained. The assignment of k_j values to each attractor type was performed within the GIS environment.

The interaction between communities and cultural attractors depends not only on their intrinsic characteristics but also on the physical distance d separating them. In the formula, distance appears in the denominator because interaction is inversely proportional to it: stronger interactions occur at short distances, while interaction decreases as distance increases. To further emphasize this effect, distance is squared, following the same methodological principle adopted for service community construction. Each cultural attractor within the study areas is connected to all communities; therefore, once again, the system is represented as a graph network. Although conceptually different from the previously constructed graph, connections are again weighted according to distance. In this case, Euclidean distance was adopted. Using road-network distance would have been conceptually inappropriate, since the point representing the community corresponds to the median center of the ellipse in which services are located. It is therefore not a real territorial point but a representative geometric location.

To compute these connections, a distance matrix was used, producing an N × M matrix (where N corresponds to the number of cultural attractors and M to the number of identified communities), containing distances between each pair of entities. The final parameter included in the interaction formula is a constant accounting for the size of the study area. This constant ensures representativeness and renders the interaction value dimensionless. It corresponds to the maximum diagonal distance of the study area. Each attractor is therefore connected to *n* communities, with a number of connections equal to the total number of communities within the study area. To determine which communities are linked to each attractor in order to form a Destination Area, graphical representations of interactions and distances were produced for each macro-category of attractors, based on their source: UNESCO Sites, Museums (MiBACT), "Borghi più Belli d'Italia," and Protected Cultural Assets.

The resulting structure is a weighted bipartite network, where one layer represents cultural attractors and the other represents service communities. Edges are weighted by the interaction value I_{ij} which incorporates distance decay, rarity, compactness, and attractiveness components. No edges exist within the same node set; all connections occur between attractors and communities, consistent with the formal definition of bipartite graphs.

To detect Destination Areas as emergent territorial subsystems, the Infomap algorithm was applied. Infomap is a community detection method grounded in information theory and based on the Map Equation framework (Edler, 2026). Rather than optimising modularity—as in Louvain or Leiden approaches—Infomap minimises the expected description length of a random walker's trajectory on the network.

Conceptually, the algorithm interprets network flows as information flows. A random walker moves through the graph following edge weights; modules are identified by compressing the description of this movement. If the walker tends to remain within a subset of nodes for longer periods before transitioning elsewhere, that subset can be encoded as a module with shorter codewords. The optimal partition is therefore the one that minimises the overall description length of the walk. In this sense, communities are not defined purely by topological density but by flow persistence.

Formally, the Map Equation:

$$L(M)=q\curvearrowright H(Q)+i=1\sum mp\circlearrowright iH(Pi)$$

quantifies the average per-step code length needed to describe movements across and within modules. The algorithm seeks the partition MMM that minimises L(M)L(M)L(M). This probabilistic perspective is particularly coherent with spatial interaction systems, where functional connectivity is better interpreted as flows of potential interaction rather than static adjacency.

Infomap presents several methodological advantages for the present research:

1. Weighted networks: It directly incorporates edge weights, thus preserving the quantitative structure of interaction intensities.
2. Bipartite compatibility: It can operate on bipartite structures without requiring projection onto one mode, thereby avoiding information loss.
3. Hierarchical detection: It identifies multilevel modules, revealing nested territorial configurations.
4. Flow-based logic: It aligns with the conceptualisation of tourism systems as networks of functional interdependencies.

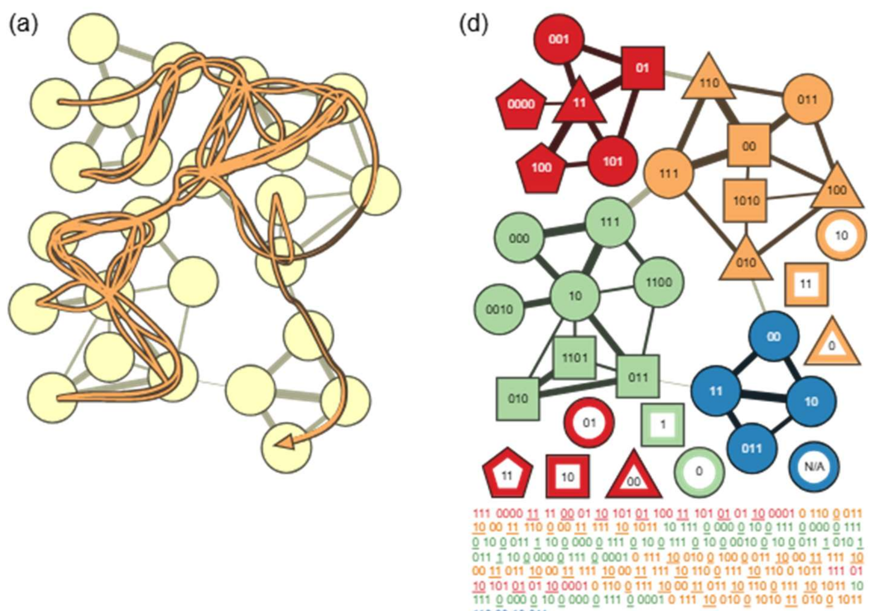

Figure 11 Flow-based community detection in the Infomap approach. The figure illustrates how Infomap identifies modules by modelling movements or flows across the network, grouping nodes that are frequently visited together and separating areas connected by weaker flows.

The algorithm was applied to weighted bipartite network of attractors and service communities. The resulting modules are associated with groups of attractors and communities with a high intensity of internal interactions and with comparably low external interactions. These modules have been understood as Destination Areas (DAs). Notably, Infomap was executed in its multilevel configuration, which made it possible to identify hierarchical modules. It is a multiscale structure that indicates the inherent nestedness of the territorial systems. Broad Destination Areas are produced at level 1, sub-configurations at level 2, sub-specialisations and internal differentiation at level 3.

Analytically, the Destination Area is thus neither an administrative unit that is preset, nor a morphological cluster. It is a new functional subsystem which is characterized by the flow of interaction between cultural assets and communities of service. The DA is a spatial arrangement that is based on the relational intensity and not the geometric proximity. The fact that Infomap is applied to the bipartite interaction graph empowers the main thesis of the paper: territorial systems are better visualised in network-based representations that help to reveal unseen relational patterns underlying obvious spatial patterns. By integrating:

1. granular representative PoI,
2. spatial proximity modelling (Delaunay + Louvain),
3. functional interaction modelling (distancedecomay utility),
4. and probabilistic community detection (Infomap),

the methodology develops a multi-layered analytical system which has the capacity to identify the emergent geographies of tourism.

This process leads to the identification of Destination Areas that effectively asses the spatial organisation of the cultural tourism system. Some areas emerge as compact hubs characterised by a high degree of consolidation between tourist attractors and service communities, where interaction intensity is reinforced and spatial impedance plays a limited constraining role. These hubs display strong internal cohesion and tend to act as organising cores within the broader tourism system. In contrast, other areas appear as peripheral subsystems marked by low functional cohesion. In these configurations, interactions between attractors and service communities are weaker, more fragmented, and often spatially dispersed, reflecting structural discontinuities in service provision and reduced systemic integration. Finally, the analysis reveals intermediate or mixed regions characterised by asymmetric interaction patterns, where certain attractors exhibit strong ties to specific communities while remaining weakly connected to others. These asymmetries indicate partial integration processes and suggest transitional territorial conditions, in which emerging clusters coexist with structurally fragile components.

Through this network-based appraoch, Destination Areas thus represent functional geographies that reflect the logic of interaction flows within the cultural tourism ecosystem. These arrangements cannot be seen instantly on administrative lines or traditional zoning. By doing so, the methodology approach enhances the development of Spatial Interaction Models by incorporating them in the current network science and information-theoretic society detection. It is the complex adaptive structure of hierarchies, flows and modularity.

4 Results

4.1 Mapping of the tourism supply system in the Pollino area

The construction of the territorial knowledge base for the Pollino area begins with the explicit presentation of the dataset composing the tourism ecosystem. The dataset is organised into two principal components: (i) tourism-related infrastructure and services, and (ii) tourist attractors.

The tourism infrastructure layer consists of 5,059 georeferenced point features, functionally differentiated into:

differentiated into:

- 2,206 accommodation facilities,
- 1,558 restaurants,
- 143 transit stations,
- 888 parking areas,
- 264 trekking-related facilities.

This dataset composition reveals a strong concentration of hospitality and food-service functions, which together constitute the structural backbone of the tourism supply. Accessibility-related services (transit stations and parking areas) provide the reachability points of the system, while trekking facilities is the environmental and specialized tourism orientation of the Pollino area, particularly within and around the National Park perimeter.

The attractor layer includes 777 certified tourist attractions, subdivided into:

- 406 cultural attractors,
- 295 nature-based attractors,
- 57 eno-gastronomic attractors.

The balance between cultural and natural assets confirms the hybrid territorial vocation of the Pollino area, where heritage, landscape, and environmental resources coexist as co-structuring elements of the tourism system. Although quantitatively smaller, the eno-gastronomic component represents a specialised layer with potential integrative effects in network dynamics.

Overall, the dataset comprises 5,836 geolocated entities, forming a spatially explicit and functionally articulated empirical base. The absence of preliminary spatial aggregation ensures that local heterogeneity and fine-grained spatial patterns are preserved, in coherence with the epistemological stance adopted in this research.

The spatial configuration of tourism infrastructure is illustrated in the following figure:

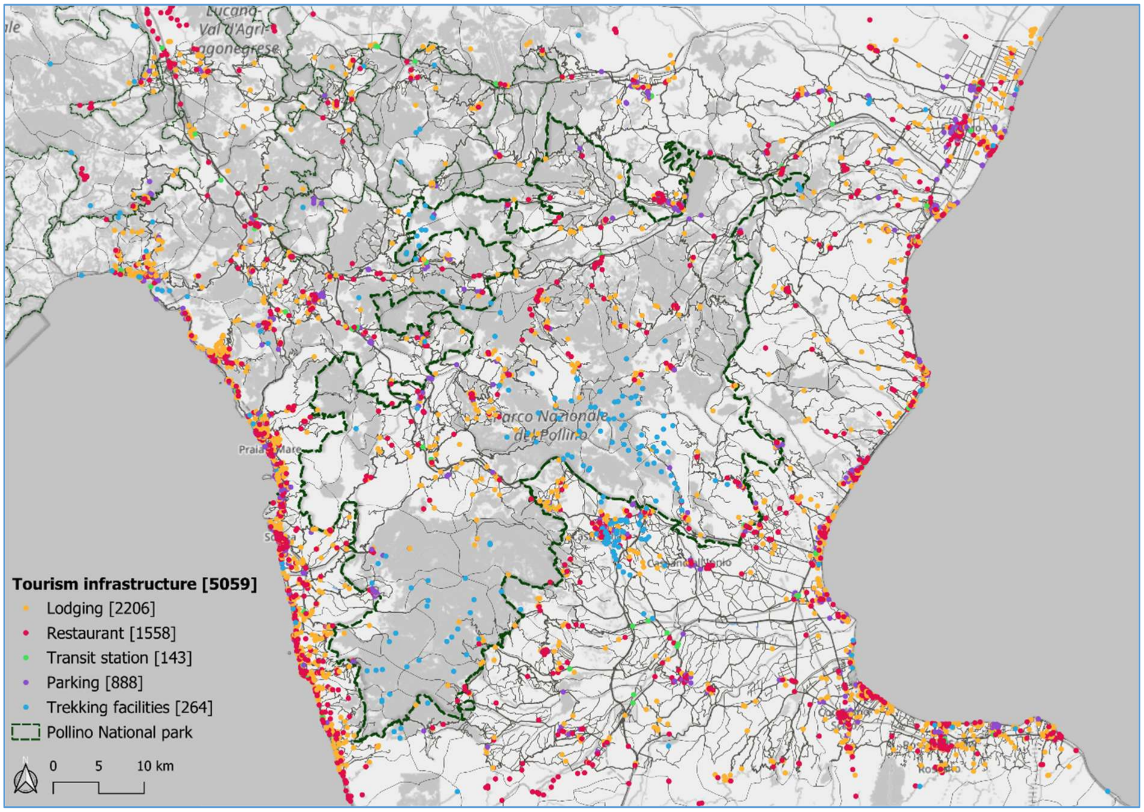

Figure 12 Tourism infrastructure in the Pollino area. Spatial distribution of accommodation, restaurants, transport-related facilities, parking areas and trekking infrastructures.

The map highlights the distribution of accommodation, restaurants, transit stations, parking facilities, and trekking infrastructures across the Pollino area. A clear concentration pattern emerges along the main urban centres along the coastal settlements, where hospitality and restaurant functions are densified. In contrast, the mountainous area of the Pollino National Park exhibits a more dispersed configuration, characterised primarily by trekking facilities and selective hospitality nodes.

This uneven distribution reflects both morphological constraints and settlement structure. The clustering of services around consolidated urban systems anticipates the emergence of compact service communities in the subsequent proximity-based network analysis.

Moreover, the spatial distribution of tourist attractors is presented in next figure:

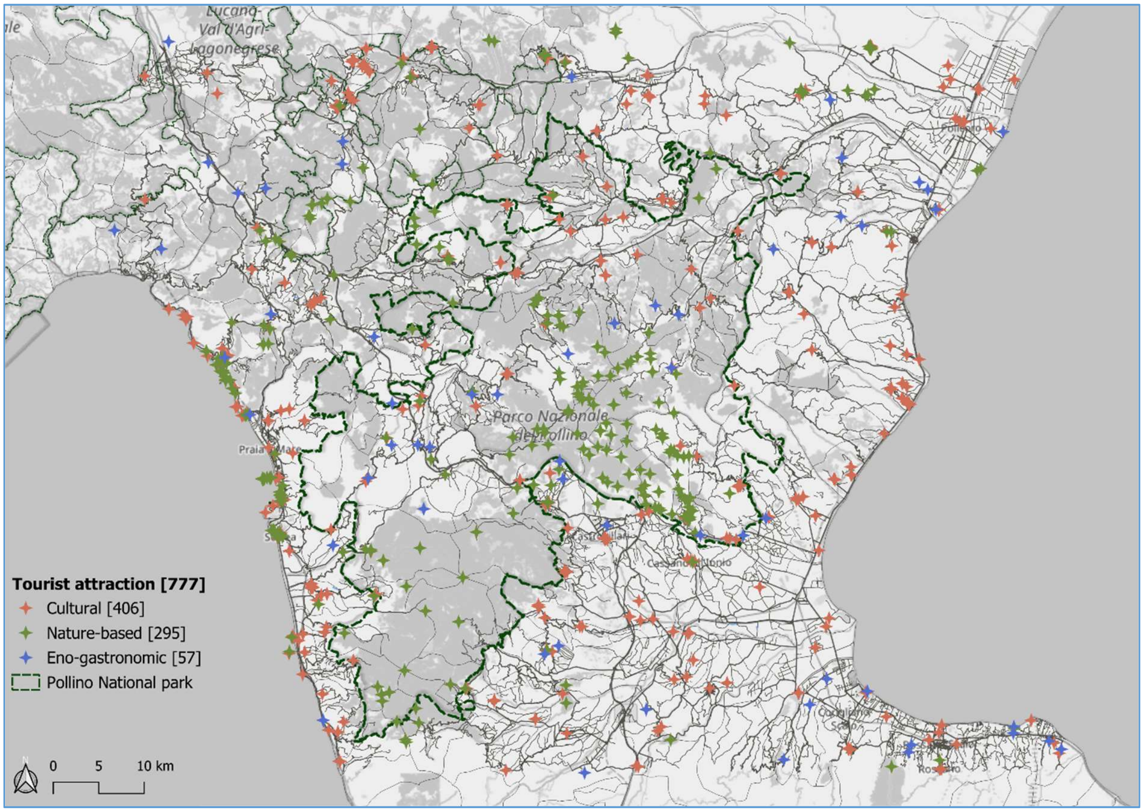

Figure 13 Tourist attractors in the Pollino area. Spatial distribution of cultural, nature-based and eno-gastronomic attractors across the Pollino territorial system.

Cultural attractors display a widespread distribution, often aligned with historic centres and settlement nuclei. Nature-based attractors, by contrast, are more prominently located within and around the Pollino National Park boundary, reinforcing the environmental vocation of the area. Eno-gastronomic attractors appear spatially selective and frequently associated with small inland settlements. From a spatial-analytical perspective, the attractor layer exhibits a less centralised configuration compared to services. This structural asymmetry between supply (services) and territorial resources (attractors) constitutes a critical condition for the subsequent interaction modelling. The mismatch between dense service clusters and dispersed environmental assets is expected to influence interaction intensity, flow persistence, and the modular configuration of Destination Areas.

4.2 Definition of the network: delaunay triangulation

The resulting analytical phase involves the formal construction of the service network. In principle, tourism infrastructure can be viewed as a constellation of distinct spaces. Consequently, the fundamental question for the methodology is to identify the relational structure that links these entities. Spatial adjacency was operationalised using Delaunay triangulation, in line with the proximity-based logic described in Chapter 2. The first stage involves finding an undirected graph that is based on the Delaunay criterion. The complete point layer of tourism infrastructure was triangulated in the Pollino area, but tourist attractors were excluded. The input data thus includes 5 059 service points that are formed as a result of the combination of accommodation facilities, restaurants, transit facilities, parking facilities, and trekking facilities.

Delaunay triangulation guarantees that no point occurs on the inside of the circumcircle of any triangle by construction (Preparata and Shamos, 1985). Spatially, it produces a planar graph maximising proximity-based connectivity and eliminating arbitrary threshold distances. The resulting structure provides a rough estimation of local spatial neighbourhoods without earlier defined buffers or distance cut-offs.

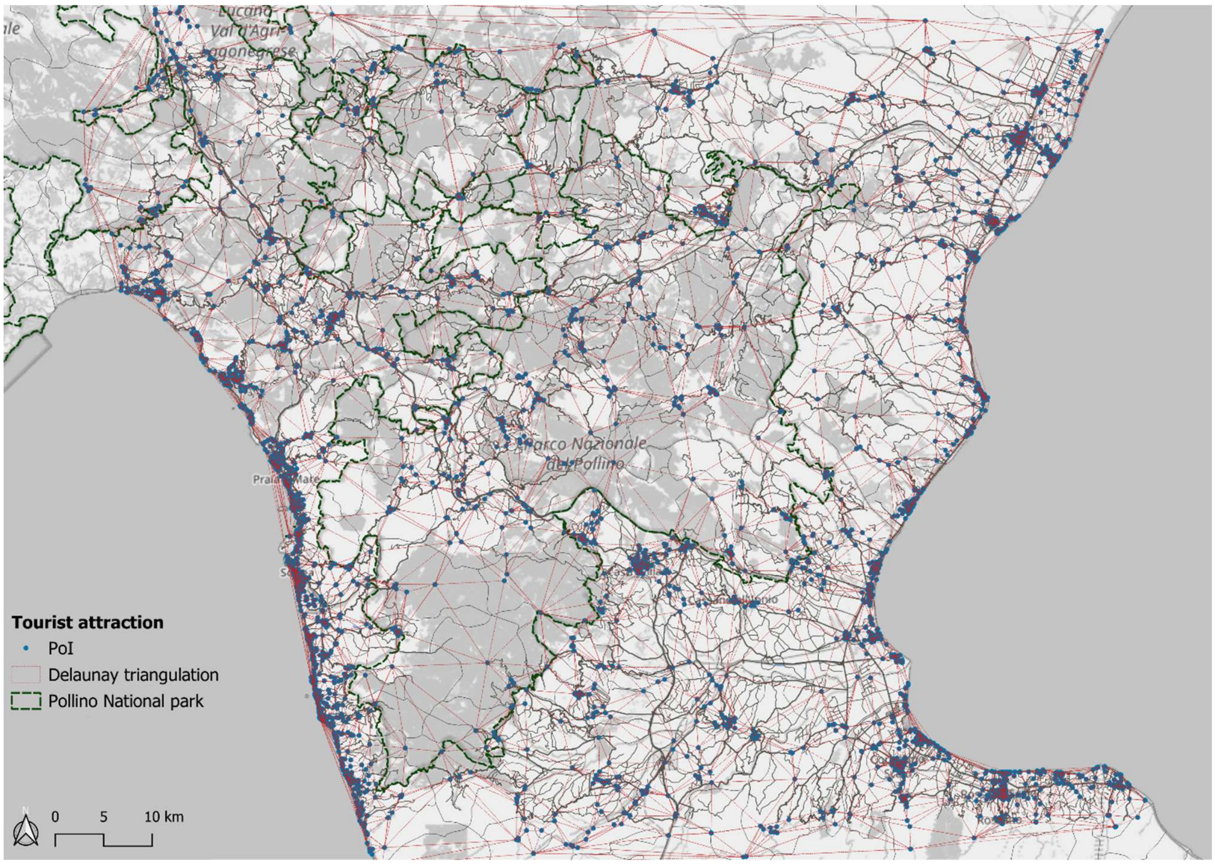

Figure 14 Proximity-based service network. Delaunay triangulation applied to tourism services to define local spatial neighbourhoods.

On a visual level, the triangulated network seems thick and incoherent because of the huge number of generated edges. This was the reason why the graph was formalised computationally by building an adjacency matrix. The matrix is square and symmetric; rows and columns are nodes, the values in the cells take a binary character (1 = connection; 0 = no connection).

The full adjacency matrix with 5059 nodes is too large to compute, but the concept is easy to understand. The matrix was copied as an edgeList format consisting of three columns to allow further processing:

- Node ID (origin),
- Node ID (destination),
- Connection value (1).

Active connections (value=1) remained, which drastically reduced dimensionality and produced a manageable edge list, which is the unweighted Delaunay graph. This step is when topology but not impedance is encoded: all edges look the same structurally.

The second step involves a metric differentiation, which is to assign a weight to every edge. Although Delaunay triangulation reflects geometric proximity, it fails to represent the real accessibility situation. This is why edge weights were computed based on road-network distance as obtained through openstreetmap. The street network was automatically accessed through the Python library OSMnx (Boeing, 2017) that allows extraction and analysis of street graphs on OpenStreetMap directly. The Pollino area road network obtained is shown in the following figure.

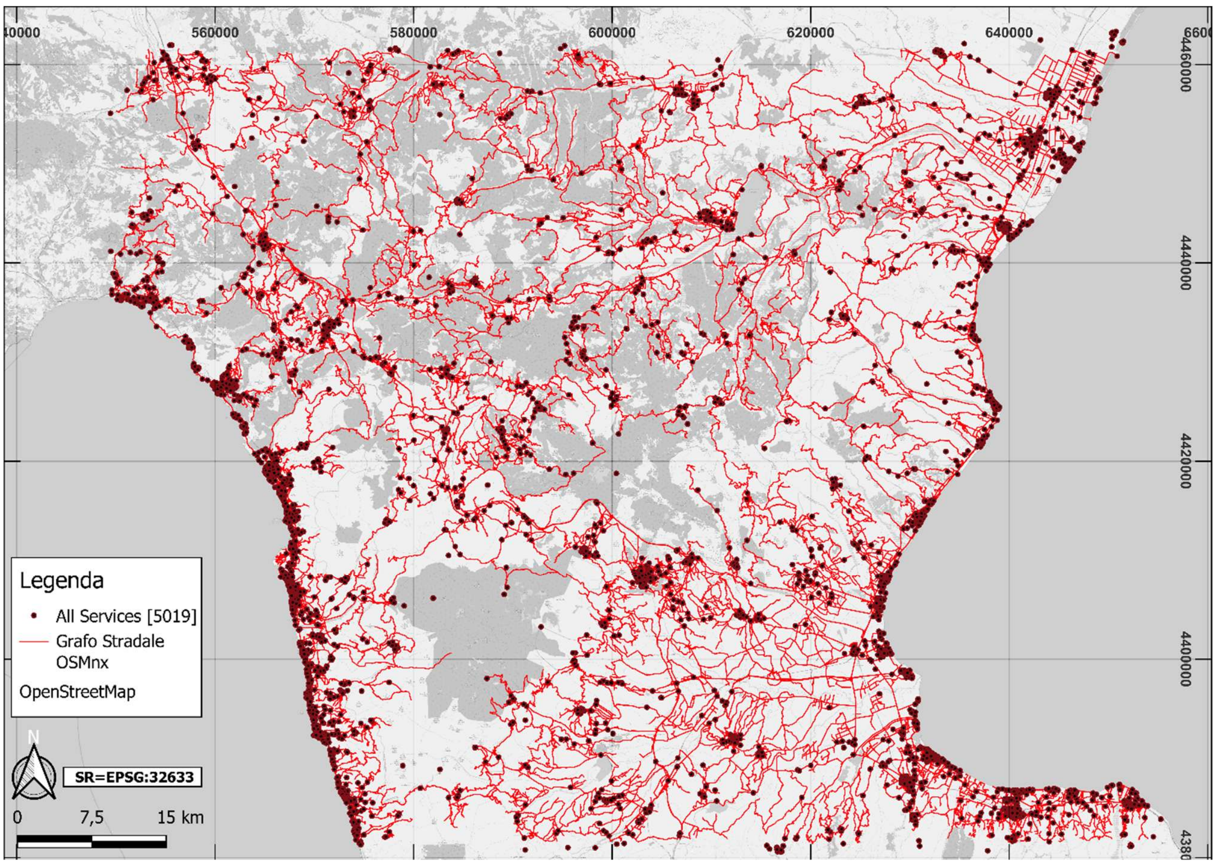

Figure 15 Road-based distance network. Road network used to assign metric distances to the edges of the service graph.

OSMnx builds a routable graph that uses intersections as nodes and weighted edges (distance in metres). The shortest line through the road network was calculated between every pair of nodes in the Delaunay graph and a realistic value of spatial impedance was assigned to each connection, in the form of metric distance.

The result of this step is a revised edge list in the form of:

- Node ID (origin),
- Node ID (destination),
- Distance (metres).

The connection is no longer topological as before; it now has weight based on road distance. The edge weight is now an indication of real world conditions of reachability, not an abstraction by Euclidean geometry. This is a methodologically relevant difference: whereas Delaunay triangulation defines the possible neighbourhood structure, OSMnx-based weighting projects that structure to functional proximity. The weighted graph, which is the result of Step 2, is the input to the next community detection process (Louvain), in which a modularity optimisation is used to detect service communities based on spatial proximity and impedance. Analytically, this two-step process, which does geometric triangulation followed by network-based weighting, is used to ensure that the resulting graph reflects spatial adjacency as well as accessibility of tourism infrastructures nodes.

4.3 Service communities of the tourism supply

The third analytical task attempts to determine the communities of tourism services resulting out of the weighted spatial network developed in the previous stage. Similar to the above phases, the output of Step 2(the weighted graph based on the Delaunay triangulation and road-network impedance) is the input to the current analysis. Communities of services are determined by the Louvain Community Detection algorithm (Blondel et al., 2008), a modularity -optimisation scheme designed to detect groups of nodes sharing more internal connectivity as compared to the rest of the network. Here, modularity is calculated on the weighted graph; hence, the topological adjacency and road-network distance affect the partitioning. The algorithm allocates each service point to a particular community, thus generating a partition of the 5059 nodes of the infrastructure into spatial clusters. In the case of the Pollino area, 264 service communities were identified through the procedure. The label of community membership that has been given by the algorithm. When these communities are mapped then their spatial distribution can be directly visually interpreted.

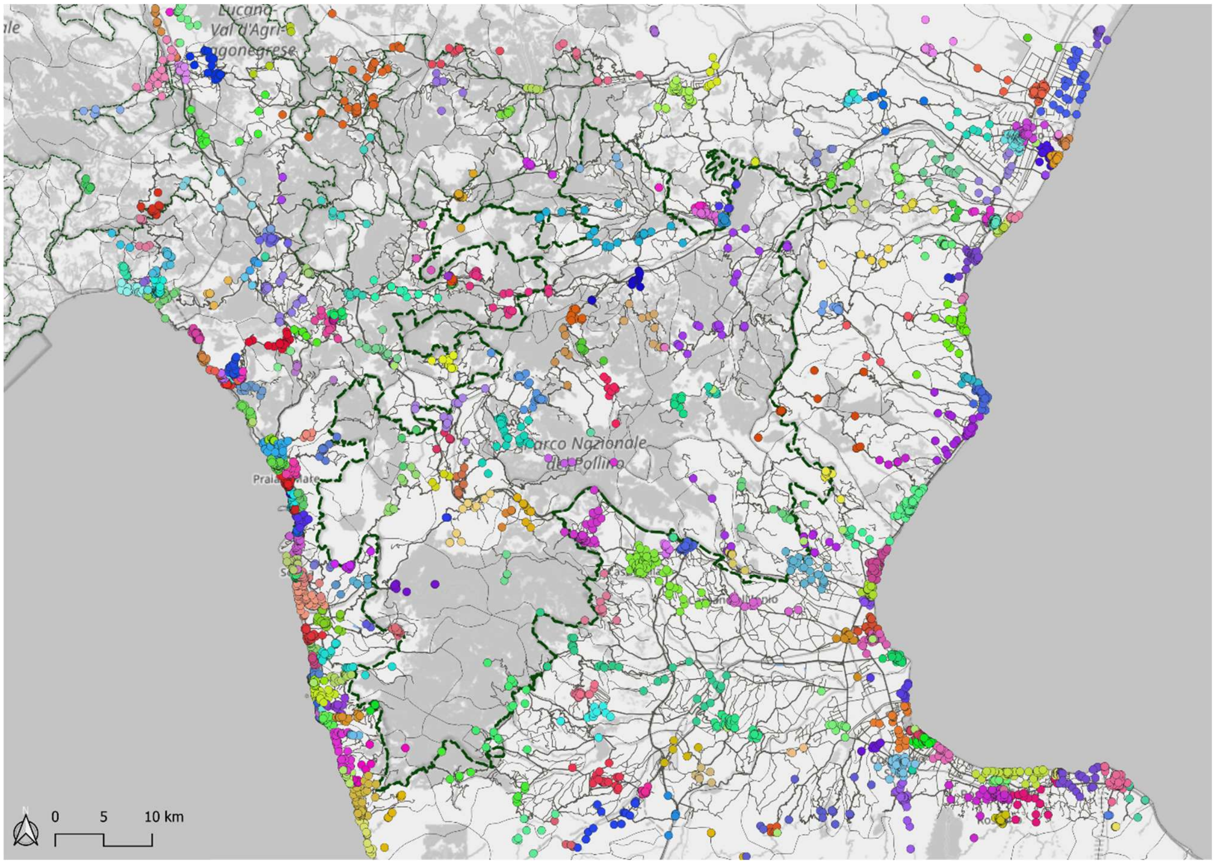

Figure 16 Service communities in the Pollino tourism system. Spatial distribution of tourism service communities identified from the road-distance weighted proximity graph.

Graphically, communities are well defined and geographically small. The division brings out a nonhomogenous system: certain communities are represented as extremely focused on urban centres, whereas others are more decentralized and are indicative of peripheral conditions (Inner areas). Communities (264) indicate the concentration of services and the size of the Territorial area (Pollino). Another analytical step goes to the internal composition of every community. Through the examination of the allocation of service typologies in each cluster, one can differentiate between very diversified (balanced accommodation, restaurants, parking, etc), or functional specialised clusters, aor even weakly organised societies with low service differentiation. From a planning perspective, compact and diversified service communities may indicate areas where tourism supply is already structured and potentially suitable for integrated destination management. Conversely, dispersed or weakly diversified communities may reveal areas where the tourism offer is fragmented and where accessibility or service integration should be strengthened.

To further investigate the internal structure of service communities, the following table reports the composition of selected Destination Areas (DAs) in terms of both attractors and service typologies

DA	Most Beautiful Villages	Museums (MiBACT)	Local heritage sites	Accommodation	Restaurants	Parking Areas	Transit Station
48	1	1	12	82	17	30	1
58	0	0	2	18	3	2	0
59	0	0	2	16	16	7	0

Each row represents a Destination Area (DA) identified through the interaction model, while columns describe its internal composition. Specifically, cultural attractors are distinguished according to their source (e.g. Most Beautiful Villages, MiBACT museums, local heritage sites), while services are grouped into accommodation (lodging), restaurants, and accessibility components (parking areas and transit stations).

The table allows a direct comparison of the internal configuration of different territorial subsystems. For instance, DA 48 shows a highly structured and diversified profile, combining multiple types of cultural attractors with a dense and articulated service system (82 accommodations, 17 restaurants, 30 parking areas). This configuration is indicative of a consolidated and potentially central tourism node. In contrast, DAs such as 58 and 59 exhibit a more limited and less diversified service base, with fewer accommodation and accessibility elements. These configurations suggest weaker territorial integration and may reflect more peripheral or less developed tourism subsystems.

Before proceeding to the definition of Destination Areas, it is necessary to characterise the internal spatial structure of the service communities identified in the Pollino area. Community detection reveals where clusters exist; dispersion analysis explains how they are spatially organised.

For each community, a centrographic analysis was performed in order to compute its spatial dispersion. Specifically, the Standard Deviational Ellipse (SDE) was calculated for every cluster, allowing the quantification of:

- spatial spread,
- directional tendency,
- degree of compactness.

The dispersion parameter k_i corresponds to the spatial spread of the community, derived from the ellipse metrics. Communities with low dispersion values are spatially compact and internally cohesive; those with higher values exhibit greater spatial spread and lower internal density.

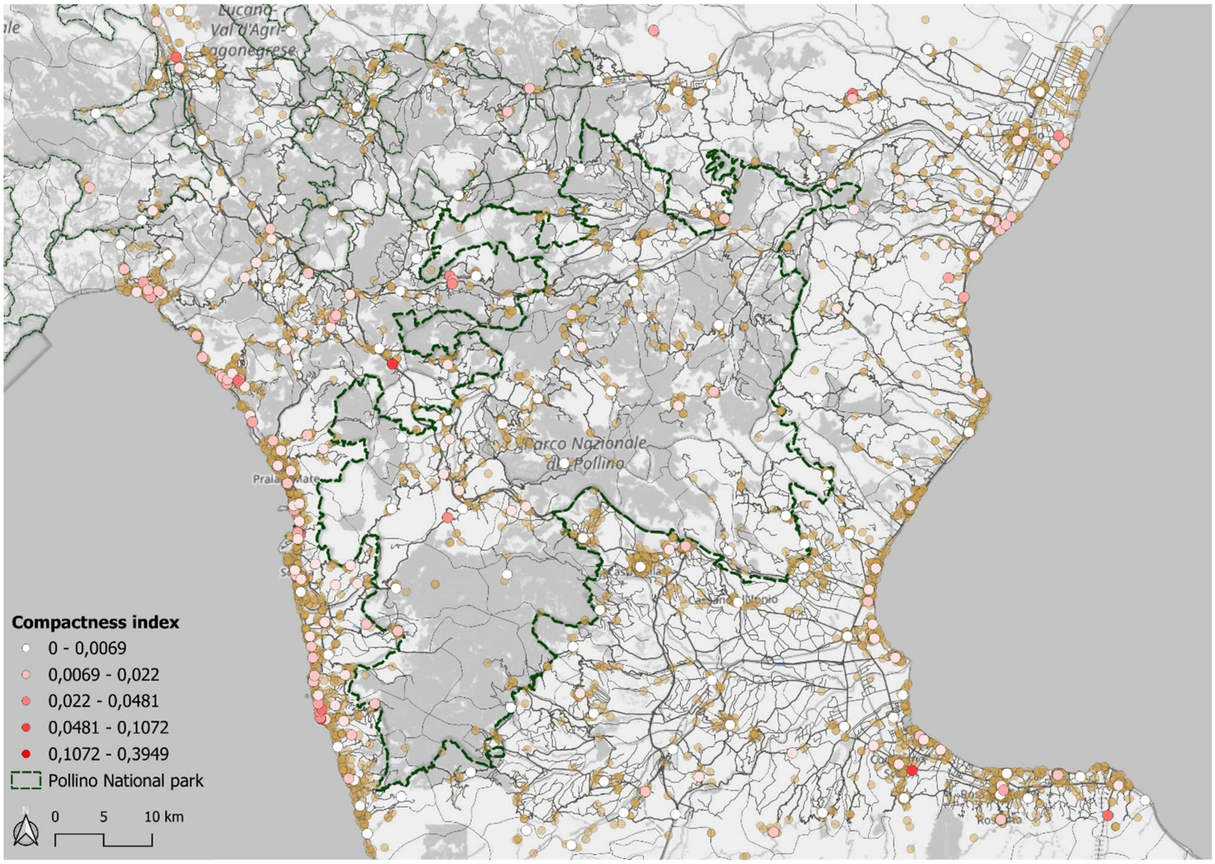

Figure 17 Spatial compactness of tourism service communities. Compactness index showing the degree of spatial concentration or dispersion of service communities across the Pollino territorial system.

Within the functional utility formulation, the inverse value $1/k_i$ acts as a compactness coefficient, meaning that more cohesive service communities exert stronger interaction potential with cultural attractors. Therefore, the capactness values vary significantly across the Pollino territory. Three broad structural configurations emerge:

1. Highly compact communities, typically located in consolidated urban centres or tourism nodes. These clusters exhibit low dispersion and high compactness index values. They represent structurally robust service systems, where accommodation, restaurants, and accessibility services are spatially concentrated.
2. Intermediate communities, characterised by moderate dispersion. These clusters often correspond to small towns or peri-urban systems where services are present but spatially less concentrated.
3. Dispersed communities, generally located in peripheral or morphologically constrained areas (mountainous or low-density settlements). In these cases, services are spatially scattered, and the compactness index is correspondingly low.

This highlights a key structural condition for tourism development: the effectiveness of a territorial system depends not simply on the availability of services, but on their spatial organisation. Compact configurations support stronger interaction patterns and higher system cohesion, while fragmented distributions introduce structural inefficiencies and constrain the emergence of integrated tourism dynamics. This result reinforces the relational perspective adopted in this research, where territorial performance is interpreted as an emergent property of spatial configuration. Compact service communities enhance connectivity and interaction potential, ultimately affecting the formation of Destination Areas.

4.3 Destination Areas: new geographies of tourism ecosystem

The last step of the analytical framework is how the Destination Areas (DAs) can be identified as the emerging structure of the tourism system. Starting from the 264 identified service communities with Louvain detection and characterised by the dispersion within the communities, a bipartite interaction network of each specialised tourism system was created: cultural, nature-based, and enogastronomic. The nodes of the former layer are, in both instances, the service communities (as denoted by their median centres), whereas the second layer entails the attractors pertaining to the particular thematic category of the analysis. The weight of edges between the two layers is based on the interaction value of aij that is weighted with distance decay, community compactness, attractor attractiveness, and scale normalisation of the territory. The resulting structure is a weighted relational graph that encodes the possible flows of tourism resources as well as service systems.

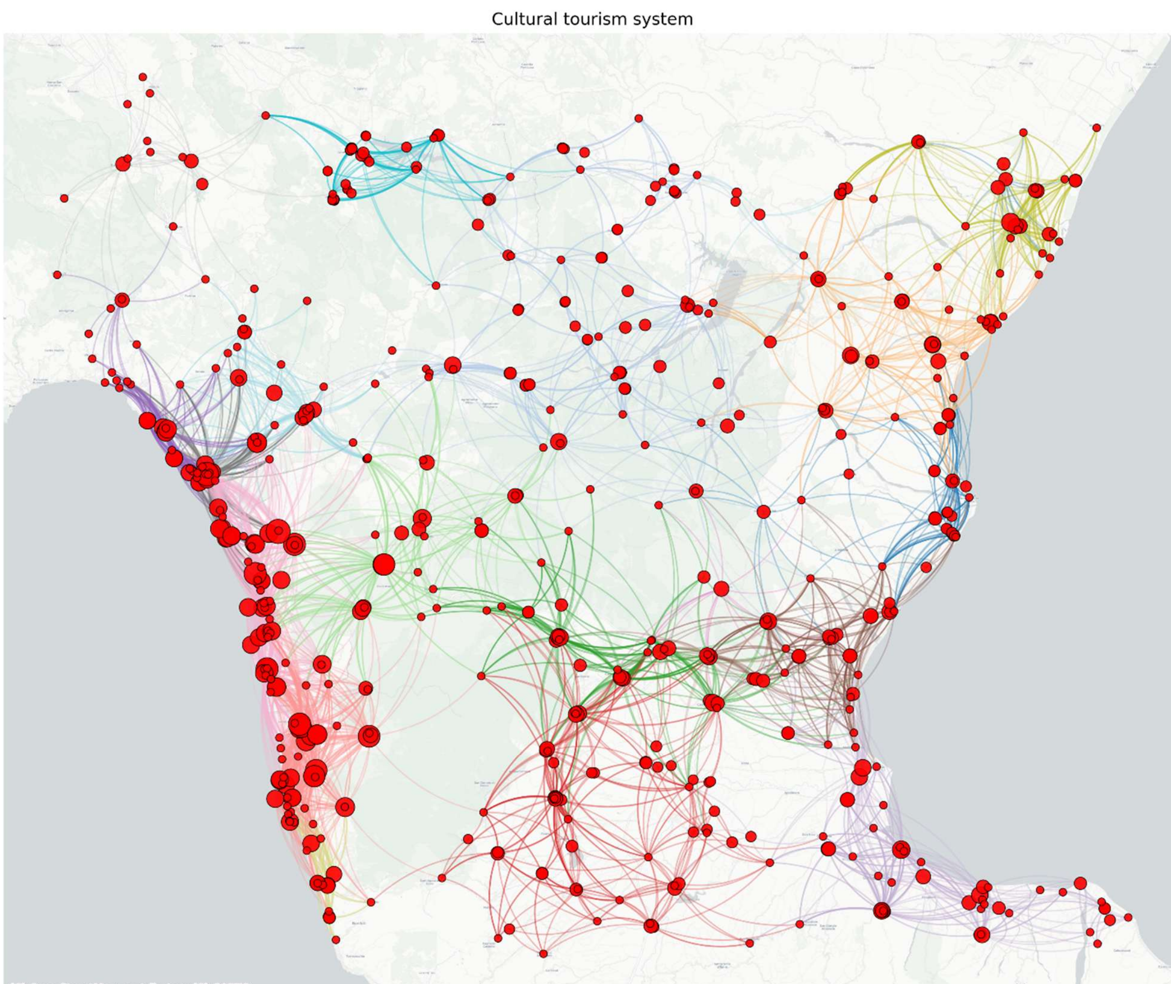

Figure 18 Bipartite interaction network of the cultural tourism system. Weighted connections between cultural attractors and service communities used to model potential tourism interactions.

What comes out is geography of the intensity of interactio. Nodes that seem far apart can be closely related through the support of small community of service and whereas more spatially proximate entities can be weakly tied because of structural dispersion or lack of appeal. Using Infomap on such weighted bipartite graphs permits identifying modules that reduce the length of descriptions of informational flows in the network. Substantively, this implies that they are grouped into the same module when clusters of attractors and service communities have high interaction weights. These modules are defined in our framework as Destination Areas.

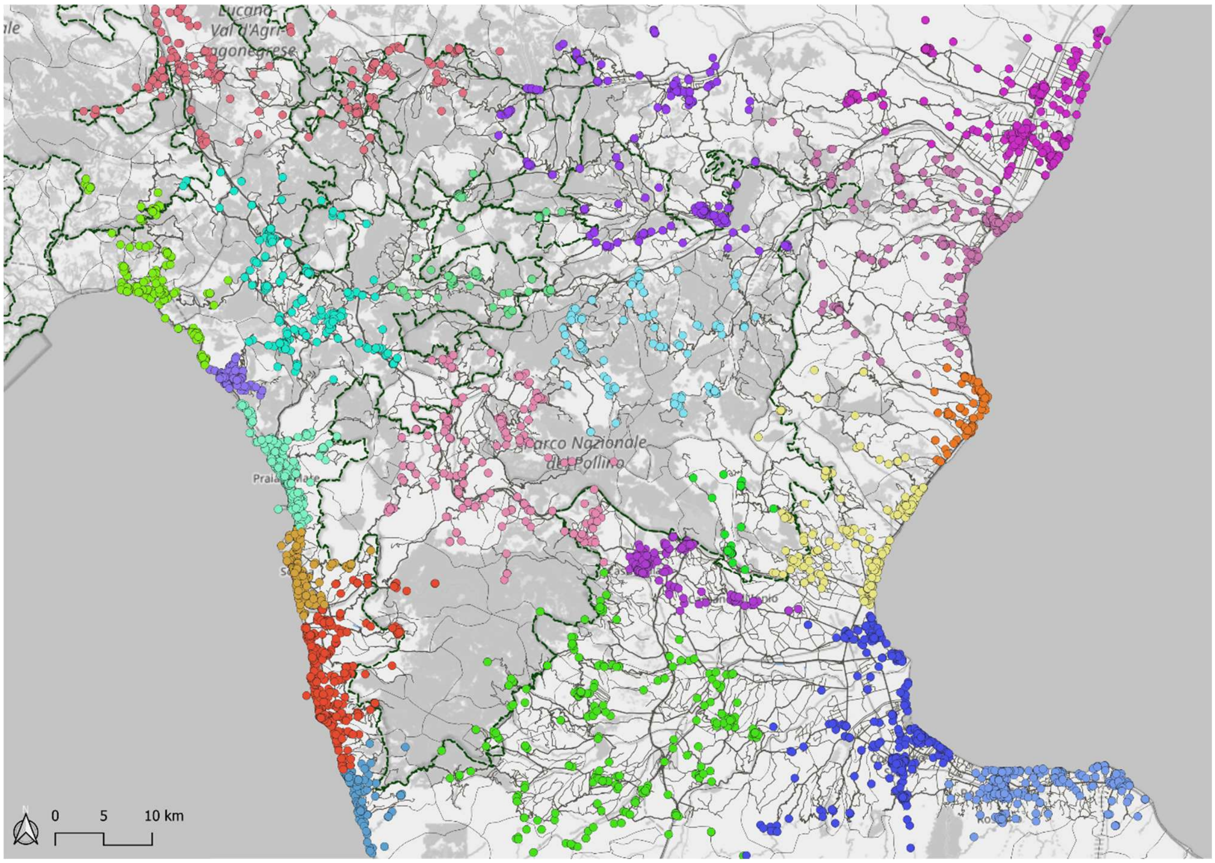

Figure 19 Cultural Destination Areas detected through Infomap. Spatial distribution of flow-based modules identifying emergent cultural Destination Areas in the Pollino tourism system.

In the case of the cultural tourism system, the graph reveals a differentiated structure characterised by emergent hierarchies. Some service communities act as interaction centres, concentrating strong ties with multiple cultural attractors. These centres are typically associated with consolidated settlement systems, where accommodation, restaurant services, and accessibility infrastructures are spatially clustered.

Around these cores, secondary clusters emerge, forming a multi-scalar organisation of the tourism system. At the same time, peripheral subsystems can be identified—areas where cultural assets are present but remain weakly connected to compact service structures, resulting in fragmented and discontinuous interaction patterns.

The graph of the nature-based tourism system presents a different configuration. In this case, attractors are more widely distributed and often located in morphologically constrained or environmentally protected areas. This spatial dispersion is reflected in the interaction network, where modules appear more elongated and less hierarchically organised. Service communities function less as dense centres and more as access gateways to environmental resources, mediating the relationship between dispersed attractors and the broader territorial system.

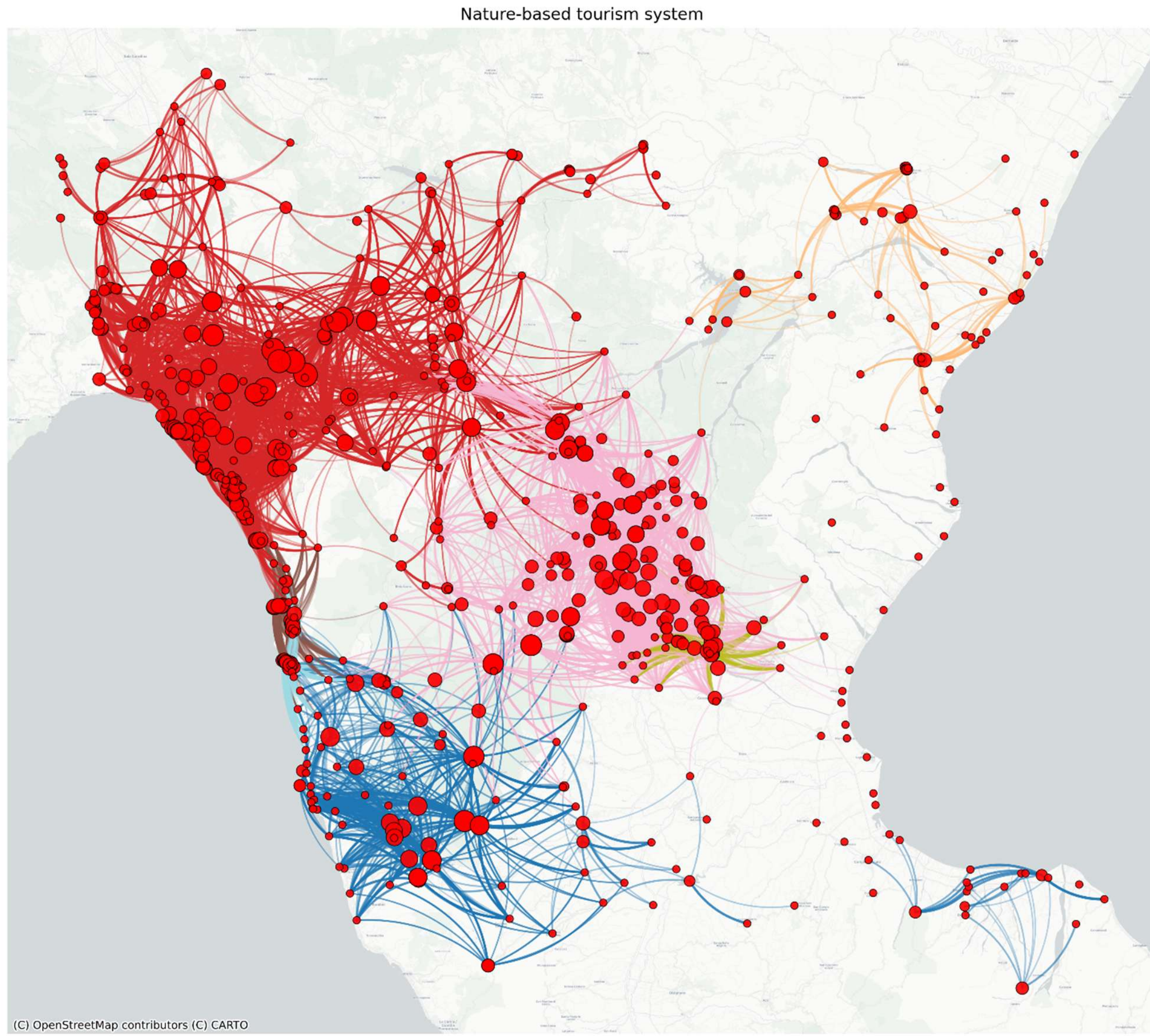

Figure 20 Bipartite interaction network of the nature-based tourism system. Weighted connections between nature-based attractors and service communities used to model potential tourism interactions.

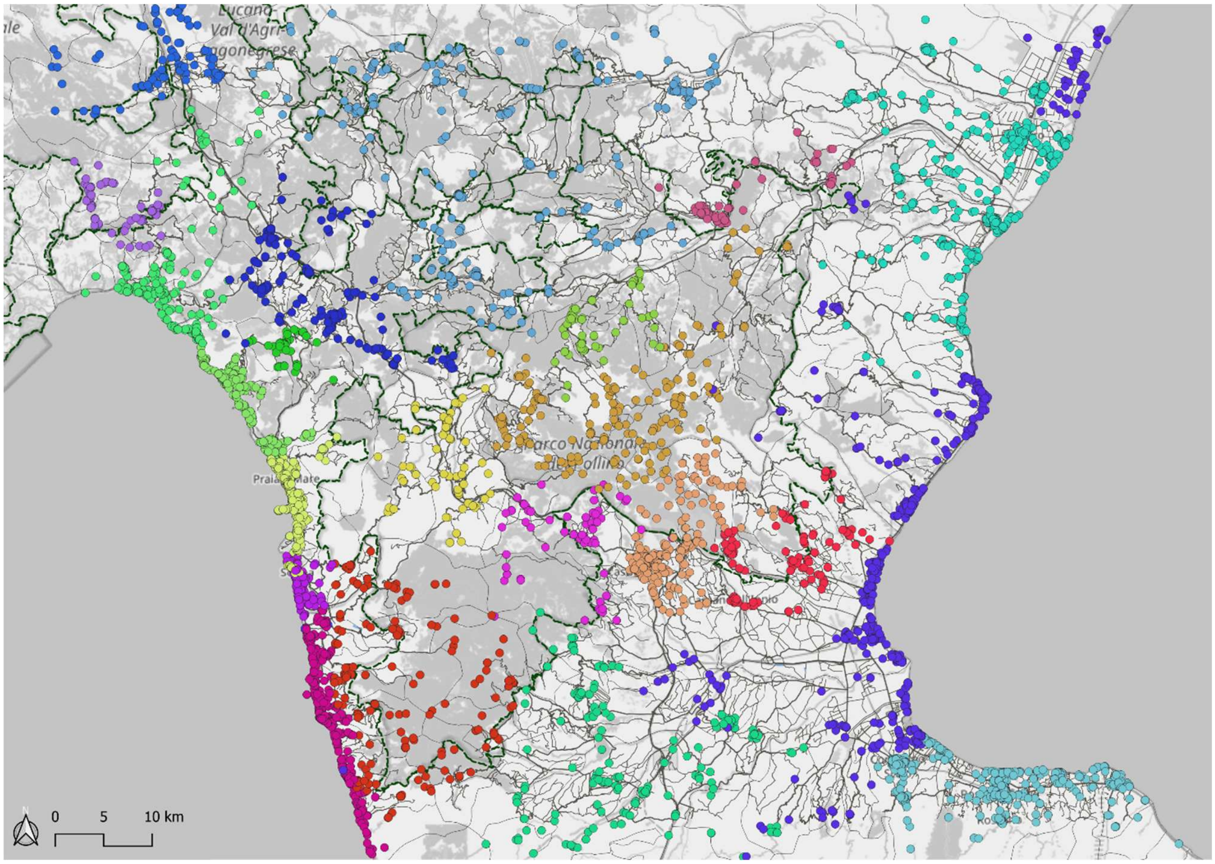

Figure 21 Nature-based Destination Areas detected through Infomap. Spatial distribution of flow-based modules identifying emergent nature-based Destination Areas in the Pollino tourism system.

Another pattern of structure is seen in the event and enogastronomic system. The network is more selective and concentrated given that the number of attractors in this category is smaller. Some inland communities, though not so dominant within the cultural network, gain greater centrality as a result of their specialised identity.

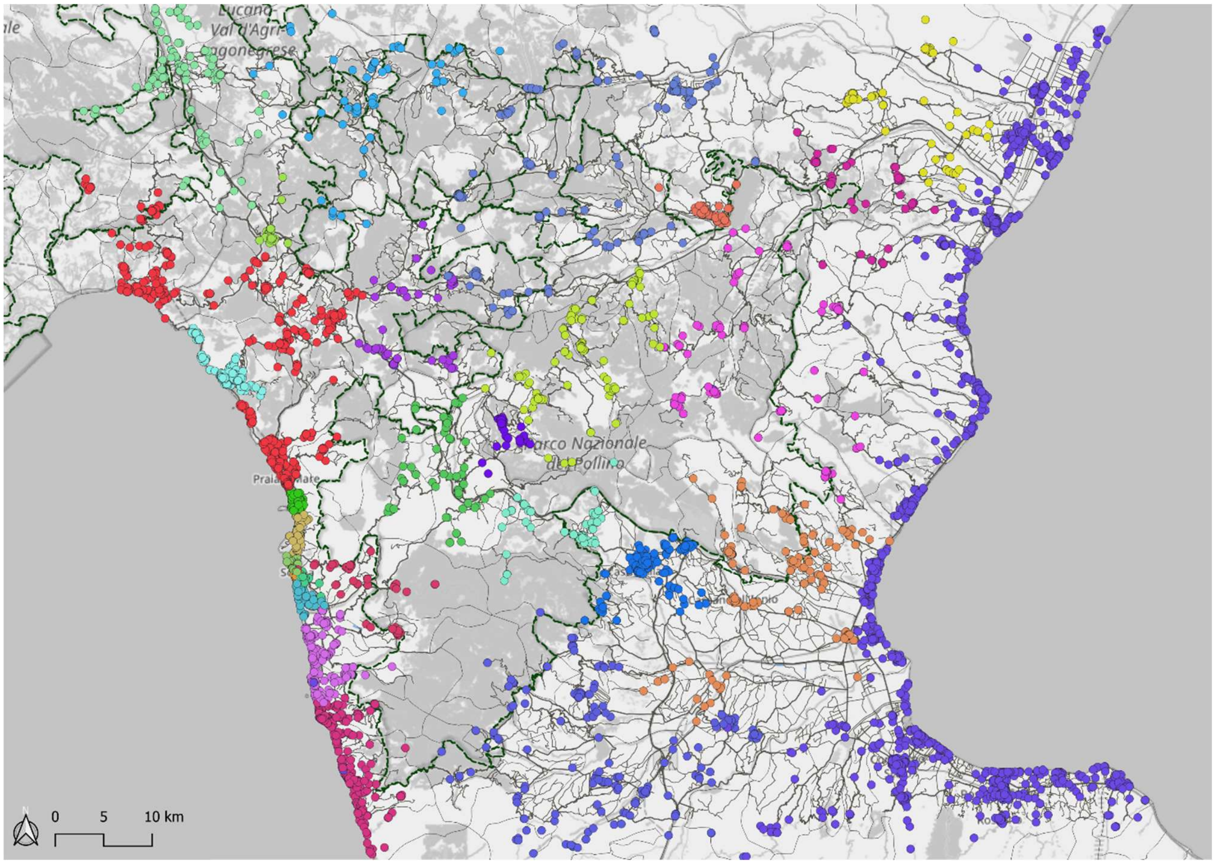

Figure 22 Enogastronomic Destination Areas detected through Infomap. Spatial distribution of flow-based modules identifying emergent enogastronomic Destination Areas in the Pollino tourism system.

What seems especially relevant is that these Destination Areas is that they arise out of the graph structure. Interaction density and flow persistence are therefore used to infer the territorial configuration. Clusters are not plotted in the network representation due to spatial contiguity but rather on the basis of the intensity of the weighted connections which indicates a coherent subsystem. This relational logic is brought to light through the visualisation of the specialised tourism system (as shown in the network figure). Structural consolidation is seen in the densities of edges around some nodes and the weaker integration in the form of sparse and radial patterns. Coastal and lowland regions exhibit more dense network of interactions, which indicates good service-attractor coupling. There are thinner and more fragmented relational structures in inland and mountainous areas, which have abundant environmental and cultural resources. The determination of Destination Areas in this way marks a series of abstractions: of 5,836 discrete points, to 264 service communities, to fewer modules characterized by interaction. The graphical framework of this transformation reveals that the otherwise invisibility processes that structure the tourism system. It reveals hierarchies, asymmetries, and peripheral conditions that are anchored on the fabric of the territory. In that, the Destination Area is not just a cartographic product. It is the map of the network configuration of the system of service capacity, POI attractiveness and reachability conditions. The graph can be the analytical tool to analyze territorial complexity into subsystems at the bottom of which the further discussion of planning implications and strategies of integrated tourism will be based.

4.5 From specialized systems to an integrated tourism framework

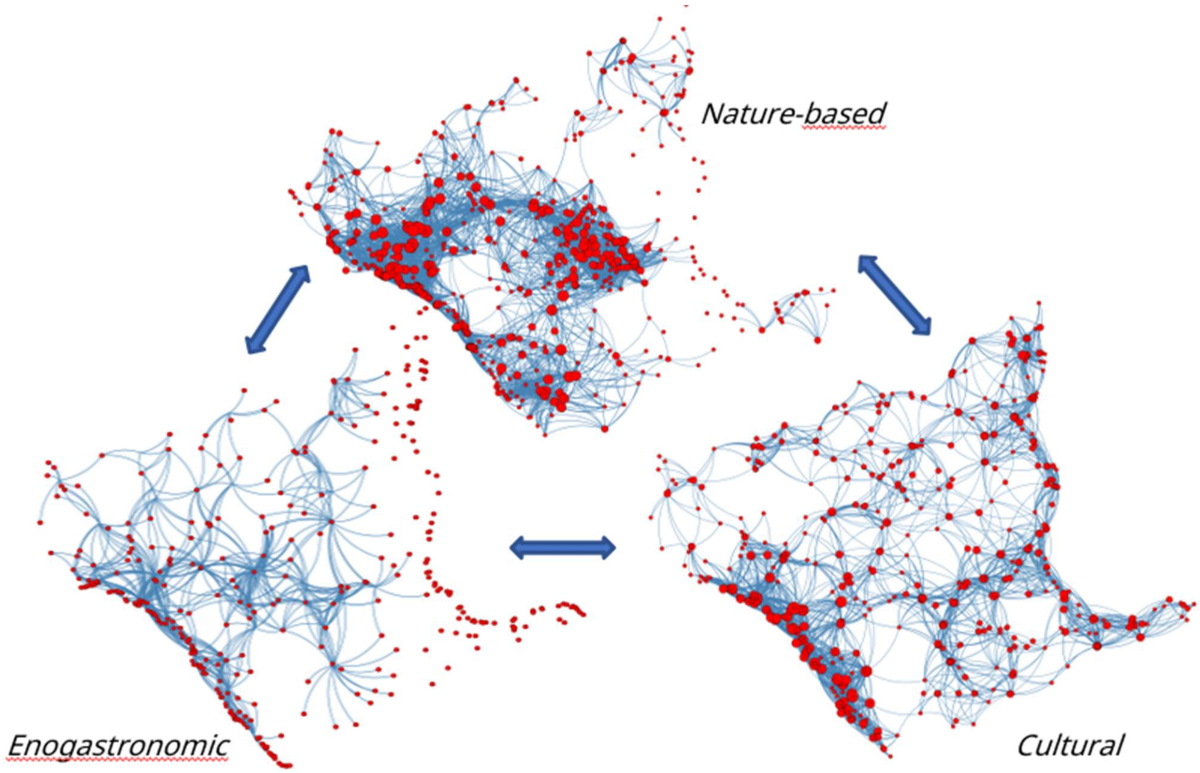

Figure 23 . Integration of specialized tourism systems. Cultural, nature-based and eno-gastronomic networks represented as complementary components of the territorial tourism system.

In the previous paragraph, we have discussed the cultural, nature-based, and event- enogastronomic systems as individual networks of interaction; however, the overall territorial systems, which they describe, can't be analyzed separately. The same groups of service users conduct multiple relationship structures simultaneously, and the attractors representing different thematic segments are found in the common space. This division into specialised systems is very interesting because it aids in identifying thematic hierarchies and asymmetries in architecture. However, when these different structures are discovered, the need to have an integrative perspective is interesting. To the extent that the three networks are analyzed in a coherent manner, service communities appear in the form of multi-relational nodes. Certain communities are central to several specialised systems and act as transversal connectors between cultural, environmental and enogastronomic attractors. On the other hand, there are communities, which are mono-functional, and are located in one thematic layer. This heterogeneity highlights the discontinuous character of the territorial integration and suggests that multifunctionality is not evenly spread across the study area.

Once the structure of the specialised tourism systems has been delineated, the relevant question concerns the nature of the territorial configuration that emerges from the graph. Across the three specialised systems a recurring structural pattern becomes visible. The network does not organise itself randomly, nor does it reproduce administrative boundaries. Instead, it reveals a differentiated and hierarchically articulated territorial structure. In the cultural system, the graph displays a clear tendency toward centralisation. Certain service communities assume the role of structural hubs, concentrating high-intensity interactions with multiple attractors. These hubs are not simply areas with a higher density of services; they represent nodes in which compactness, accessibility, and attractiveness converge. Around them, secondary clusters emerge, forming a multi-level configuration in which peripheral communities maintain weaker but still measurable ties to central nodes. The structure resembles a semi-hierarchical network rather than a flat distribution. The nature-based system exhibits a more reticular configuration. Here, attractors are spatially distributed across environmentally constrained areas, and the interaction network reflects this morphological condition. Modules tend to be less vertically organised and more spatially elongated, often structured along environmental corridors. Service communities function as access gateways rather than dominant hubs, producing a less centralised but still coherent interaction pattern. The enogastronomic system, by contrast, highlights selective centralities. Given the smaller number of attractors, relational intensity is concentrated around specific communities that acquire prominence not because of spatial density but because of thematic specificity. This produces localised micro-hierarchies that partially diverge from those observed in the cultural and naturalistic systems.

After comparing the three specialized structural systems to each other, one thing stands out, namely, the heterogeneity of territorial hierarchies of the thematic strata. The communities which occupy the central place in the network of cultural interaction can lose relative significance when assessed within the nature-based configuration, and the opposite. This point highlights that centrality is not ontological so far as territorially defined units are concerned, but a relational category, and depends upon which interaction structure one uses. On a larger scale, the interaction graph will give a two site territorial architecture. Consolidated settlement systems on the one hand have very dense internal connections and the dynamics of continuous interaction. Conversely, inland areas exhibit fragmented or radially organized structure, in which fluxes of interaction are dilute and reciprocality is reduced. These outlying subsystems lack resource-privilege, but instead they have an exemplified dilution in the larger network. What is important about these configurations is that they are the result of endogenous network processes. By viewing the system with the perspectives of the complexity theory, a tourism system of the Pollino region can be perceived as a modulared architecture with different internal densities, unequal relational strengths, and multi-scale organization. The gradual transformation between discrete spatial points, to service oriented communities and then to interaction defined modules gradually reveals the hidden architecture beneath the apparent spatial configurations.

5 Concluding remarks

We have explored the tourism phenomenon in this paper based on its territorial complexity by adopting a systemic and relational approach of analysis in which the core elements of tourism are granted within a strong taxonomic framework on the basis of three major classes: Destination Areas (DA), Tourism Services (TS), and Tourism Ecosystem Structures (TES). Tourism is therefore not to be thought of as a fixed allocation of locations but rather as an interconnected territorial configuration which arises through spatial proximity, functional dependencies and hierarchical interaction patterns.

Our proposed analytical framework will provide a new approach for identifying tourism geographies of specialized tourism systems on the territorial level. It is an area based not on administrative boundaries or statistical units but on the relational structures identified by network-based spatial interaction modeling. The model is thereby seen to improve the policy of developing territories because it bases strategic decisions on purposeful analytical evidence and enhanced territorial understanding. Starting with a tourism taxonomy based on the principles of complexity theory and sustainable planning, we ran our computational model on chosen case studies, which produced spatial arrangements which illustrate the organization of tourism supply at an extremely fine spatial scale. The findings show various degrees of focus on tourism communities and alternative specializations, which demonstrate that territorial systems are structured according to relational density and intensity of interactions instead of co-location.

From a conceptual perspective, this reinforces the view of territorial boundaries as emergent and relational, consistent with relational geography (Healey, 2004) and with the interpretation of territories as open and interconnected systems (Batty, 2023). We have found that administrative boundaries rarely coincide with tourism system functional boundaries, since tourism flows, infrastructures, and economic-functional interdependencies generally cross the formal jurisdictional boundaries, which supports the importance of interconnected and wider territorial approach to tourism analysis. In the suggested analysis framework, a weighted spatial aggregation of services is determined based on point-to-point reachability and spatial impedance, which results in the identification of service communities based on the principles of interaction by proximity. The concept of a multiscalar perspective views the tourism ecosystem as a constellation of interdependent subsystems along the tourism value chain. Methodologically, the study demonstrates the potential of combining fine-grained PoI data with network-based spatial interaction modelling to reconstruct territorial structures from the bottom up. Scale is thus regarded as an emergent feature of geographically localised networks and sub-networks formed by the attributes of specialised tourism systems but not as an exogenous statistical segmentation (e.g. NUTS levels). The POI-based detailed spatial representation offers a place-based understanding of tourism founded on the relational arrangements of individual services. This approach overcomes the limitations of aggregated representations and the Modifiable Areal Unit Problem (MAUP), enabling a more accurate identification of local specialisations, interaction hierarchies, and functional subsystems. These results have direct implications for territorial planning and policy-making. By identifying Destination Areas as relational configurations, the framework supports more targeted and evidence-based strategies, oriented toward strengthening connectivity, improving accessibility, and enhancing the integration between services and attractors. Moreover, the study contributes to the transition from areal to relational spatial analysis, suggesting that territorial systems should be interpreted as networks of interactions in which scale, hierarchy, and spatial organisation emerge endogenously from the structure of the system.

5.1 Policy implications and practical applications.

Formulation of tourism policies is usually based on general purposes that are supported by aggregate indicators and descriptive analytics. The approach used in this paper offers the capability of giving the public authorities and decision-makers the ability to combine the dynamics of the tourism value chains with those of the territorial development plans using spatially explicit evidence.

By so doing, such alignment could increase local competitiveness by:

1. Finding specialized attractors that are entrenched in dense service communities;
2. Bigger utilization of resources in areas where the tourism systems are based on the robustness of infrastructures;
3. The incorporation of certain services in the territories that are rich with the potential of attractiveness and severely lack service provision.

As the framework focuses on relational forms as compared to aggregated measures, a more accurate picture of the location and the manner of intervention justification is obtained. The recent-setting geography of specialized tourism systems created by the strategy demonstrates a methodological gap in the measurement of phenomena of territories in heterogeneous spatial contexts. Tourism is a phenomenon that is site-specific in nature, and its effects depend on the ability of a territory to react to the demand of goods and services. The relational approach to modelling formulated in this thesis can be applied to other territories and allows their comparison even though they might vary considerably in terms of scale, morphological and institutional form. Since it does not act at the administrative level but at the level of network arrangements, it provides an identical analytic structure that can be tailored to a variety of administrative systems.

The mapping methodology needs a further empirical testing in certain tourism specializations with different or disaggregated value chains like cultural tourism, adventure tourism, coastal tourism, and enogastronomic tourism. This kind of applications would support the flexibility of the method and could helps on industry-specific issues and opportunities. The analytical ability to understand different specialisation in one integrated network-based framework- makes it easy to develop quantitative monitoring systems that have the ability to trace the change of tourism systems over time in a spatial development scenario.

The findings can be utilized to examine the spatial distribution of territorial dynamics along the tourism value chains. The traditional models often ignore the aspect of territory, focusing rather on the market forces or organizational-level design. The combination of sophisticated spatial tools and multiscalar datasets could be used to represent the tourism value chains as complex networks that include actors, services, infrastructures, and public institutions. The attributes represented by each variable are used in the building of a multilayered relational system. This analytical input will help planners and policymakers to find the relevant stakeholders and the structural interrelations that creates the performance of a territory.

Moreover, the study provides a methodological basis of connecting the global value-chain dynamics to regional policies of growth and development, and thus help fill the gap between the global economic processes and the local governance strategies. Over the last few years, unpredictable growth patterns and increasing territorial effects have been observed in the tourism sector, such as overtourism, environmental stress, and displacement. Management of these phenomena requires analytical instruments that can reflect systemic complexity as informational uncertainty condition. The framework that has been created here supports more informed decision-making through the discovery of structural weaknesses, imbalance of services, and hierarchical reliance in tourism systems. It also highlights the need to incorporate environmental and social factors in the process of mapping and assessing the value chains. In this view, the model can be used to identify key nodes and possible points of leverage to induce change and make the targeted intervention more sustainable and coherent in terms of the space, thus promoting more sustainable and territory-scale planning activities by introducing relational measures, including compactness, rarity, and spatial impedance.

5.2 Final consideration and future perspective

The next step of this study can be developed in several and complementary research directions. First, the analysis model can be extended to other tourism specialisation and applied to different case studies in contrasted contexts to determine the robustness of the model in heterogeneous territorial settings. By applying the model to other types of specialised tourism, with different spatial logics and value chains and infrastructural dependencies, the comparative evaluation of the different relational configurations and hierarchical structures would be possible in relation to sectoral specificity and territorial morphology. Comparative applications of this kind would also enhance the external validity of the suggested spatial interaction model and explain its flexibility in various governance and planning contexts.

Second, the modelling architecture should step by step incorporate more complex and evolving datasets over time so as to increase input granularity and statistical power. Such features as longitudinal data, real-time mobility data, and behavioural demand-side data indicators would enable the model to not only represent the fixed configurations but also show changing spatial process. This time enriched identification would assist in the recognition of structural changes, seasonal differences, and new patterns of interactions, which would enhance the explanatory and predictive power of the analytical framework.

Another research direction is on enhancement of uncertainty and sensitivity analysis in spatial interaction modelling. Since the workings of territorial systems are inherently complex, and that the number of parameters at play is vast: spatial impedance, attractiveness values, rarity indices, and compactness measures, it is necessary to critically test the strength of the findings to different assumptions. Enhancing the uncertainty treatment would increase transparency and credibility of the model especially where the decision-support case-based, the policy implications in the model rest on the stability of the interaction structures, and the hierarchies detected.

Lastly but more important, the methodological approach that has been formulated in this study can be extended to other regions in the field that are not related to tourism. The identical logic of relations and network-like form of analytical organization can be applied to environmental systems, economic systems, regional systems of innovation, or any other system of the sector where functional interdependencies and spatial proximity have a decisive role. In this respect, the offered framework has not only a role in tourism studies, but in general in the exploration of the territorial processes, to provide a transferable spatial interaction model to analyze the complex, networked systems in various areas of territorial governance. Therefore, the spatial interaction model indicates generalisability implying that the model can be applied to any field other than tourism to provide a systematic method of analysis of the relationship configuration of complex territory systems.

The finding suggests a different approach to the mapping and analysis of the territorial systems with foregrounding the relational structures, the principles of the spatial interaction and emergent hierarchies. The contribution to spatial interaction modelling consists in the fact that the focus of analytical interest is changed to a network based assessment of territorial configuration. The territory is understood as a dynamic relational system the structure of which is formed under the influence of the interactions in the form of proximity and because of the functional connectivity. In this perspective, particular relevance is given to the identification of the latent relational structure of territorial systems. This structure, once formalized through graph-based representations, provides a coherent analytical basis for moving beyond purely descriptive approaches toward spatially explicit and theory-informed modelling frameworks. By explicitly encoding spatial relations, interaction mechanisms, and structural constraints, the latent network becomes a knowledge base for the development of GeoAI models that are not only data-driven but also grounded in the spatial coherence of territorial systems (Li et al., 2020; Janowicz et al., 2020; Reichstein et al., 2019).

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