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Spatializing Social Networking Analysis to Capture Local Innovation Flows towards Inclusive Transition

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Abstract: The location of the local network of firms impacts, positively or negatively, their economic performance. The interactions between different sectors in a territory are still not easily observable. We test the complexity of the economic structure at a local level, given the availability of data at a very granular scale. This could greatly assist in observing sectors or/and locations that play a dominant role in the regional economy. Thus, in order to interpret the economic structure of a territory, we used cluster-based analysis. The analysis helps in evaluating the interconnections among sectors that constitute a cluster. A novel method of describing the territorial economic structure is presented by applying Social Network Analysis (SNA) within cluster-based analysis to characterize the importance of both location and economic interconnections. In this study, we focus on the industrial agglomerations in Calabria, Italy, to underpin the potential of the region's industries by using social networking analysis metrics. This research put forward new interpretations of SNA metrics that describe regional economic compositions. Our findings reveal that territorial social networks are a potential instrument for understanding interactions in regional systems and economic clusters and might help in highlighting local industrial potentials. We believe that this study's results could be considered as the initial steps for a pioneer data-driven place-based structural analysis model.

Keywords: spatial analysis; innovation flows; urban transition; inclusive; clusters; lagging regions; network analysis; data city

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1. Introduction

The economy is a system of individuals and enterprises bound together in markets, policies, laws, public services, and regulations [1,2]. As the scale of the world economy continues to grow, the system becomes more complex. In the last decade, studies on economic complexity led to interdependences between the level of income dictated by the complexity of their productive structures and sustained growth, "indicating that development efforts should focus on generating conditions that would allow complexity to emerge in order to generate growth and prosperity" [3]. The economic complexity theory and methods have acquired interest within a broader perspective on the global system, whilst sustainability and social inequalities cast light on uncertainties for the future [4,5]. These complex systems contain unexpected properties and often respond in a nonlinear manner to shocks or changes [2]. The systems should self-organize, learn, and adapt to shocks to direct this complexity towards new sustainable trajectories [6]; in other words, systems should become "resilient" [1,4,7,8]. In this paper, we argue that, in order to achieve sustainability and resilience, the system can no longer be "locked into" a particular trajectory of economic development [9,10]. Hence, it is argued that new technological pathways that deviate from past practices and attempt to deploy new technologies should be implemented [2]. Zivlak et al. claimed that digital services would trigger manufacturing firms to enhance their servitization processes and increase their competitiveness and performance [11,12].

However, the digital divide renders people and places unequal regarding teleworking, and many cities have initially provided measures to reduce gaps. During the COVID-19 pandemic, digitalization has pushed many cities to systematize the use of smart tools more permanently [13]. For instance, remote patient monitoring devices [14] and drones were employed to disinfect locations [15]. These tools and the changes in habits they entail will remain as permanent components of a city's recovery phase and increase preparedness for any future shocks [16]. However, lagging regions lack technological capabilities to access essential services and economic opportunities. The development of sustainable technological change introduces different challenges [17], which correlate with the context concerning the innovation system's level of preparedness [18]. These conditions, in turn, reflect the inclusive character that sustainable transition requires to avoid the drawbacks of new capitalism [19] that can increase inequalities and exclusion [20]. Pinheiro et al. claimed that the constraints and opportunities of regions to move to more complex innovation and industrial systems are based on the following: (i) the region's income levels, (ii) the level of the complexity levels, (iii) population density, and (iv) whether the regions belong to old or new EU member states [21].

We aim to investigate the level of complexity of the local economic structure within lagging regions. The transition begins and occurs at the local level [22–24]. The combination of city-level decision making, local stakeholder engagement, and dense populations means that these types of settings can provide ideal testbeds in which innovations are aimed at enhancing sustainable growth and inclusive growth can be piloted [25]. Thus, we adapt the concept of granularity in our study to observe, in detail, the pieces of the economic structure that a region can take as a basis for smart specialization [26]. Specifically, our research question is the following: how can the local competitive potential of lagging regions be measured? The question is tackled by analysing industry agglomeration and the industry's interconnection in the Local Labour Market Areas (LMAs) in one of the lagging regions in Southern Italy: Calabria. We focus on industry agglomeration and firm clustering identified by Porter [27]. Cluster-based analysis is a tool for obtaining an improved and deeper understanding of the regional economy. It allows the interpretation of the economic structure of a territory according to the interconnections among sectors that constitute a cluster [28]. Social Network Analysis (SNA) is applied to understand the cluster's structure and to trace complexity within the region. Investigating the interconnections inside each cluster could help pave a path for transition. We formed a network by considering economic sectors within a cluster in a specific territory as nodes. We aim to identify the flow of knowledge in a broader sense by examining benefiting employees participate in the same cluster or establishments in the same cluster as a proxy of interaction. Consequently, in line with the cross-sectorial perspective, we investigate whole-system benefits by using SNA within the cluster-based analysis to obtain an overall picture of regions' networks.

The case study is a European region with long-lasting structural development and growth issues. The paper is articulated as follows. First, we start with cluster-based analysis and SNA. In this manner, the theoretical background of network studies, network analysis, and SNA metrics will be considered. Then, two perspectives of "space of place" and "space of flow" will be introduced as the root for spatial studies. Connecting the mentioned concepts helps render reasoning a tool for measuring complex issues at the urban level with respect to spatial economic network necessity. After forming the theoretical framework for a novel networking analysis tool approach, this paper's methodology will be presented. We will precisely explain the spatial unit of study in the Calabria region in Southern Italy. To analyse the case, we investigate data in three interconnected layers. First, we examine the region's economic composition. Second, we examine the point under the lens of a particular cluster to observe if there is a meaningful pattern for couplings. Finally, we verify the system's results in diversification; the so-called Emerging Industries will be demonstrated in a multimode network.

2. Overview of Cluster-Based Analysis and Social Network Analysis

Industry agglomeration has been helping in understanding how and why firms group within specific sectors [29]. A set of clustering algorithms was implemented to generate a set of cluster definitions. The definitions are based on inter-industry linkages based on the co-location patterns of employment and establishments, input–output linkages, and shared labour occupations [30]. In 1990, Porter identified the reason behind firm clustering and its importance. He introduced the concept of clusters as "geographic concentrations of industries related by knowledge, skills, inputs, demand, and/or other linkages" [30]. Porter summarized that clusters have a broad impact on competition [27]. It helps increase firms' productivity based in the cluster by driving innovation and its pace, reinforcing productivity growth.

Moreover, it stimulates new business, expanding and empowering the cluster [31]. Clusters "have powerful roles in the diagnostics design and delivery of effective policies to contribute to the number one objective of achieving more jobs, growth, and investments" [32]. The economic relationships that emerge within clusters create a competitive advantage for the firms in a specific region [33]. Then, this advantage becomes a temptation for investors and suppliers of those industries to develop or relocate to that region [34]. Therefore, developing industrial clusters has become critical to regional and economic development planning, strategies, and policies [35]. An increasing number of regions worldwide have modified their economic development strategies to focus more on and capitalize on industrial clusters where they wish a competitive advantage [36]. Over time, regions with cluster portfolios have proved to be innovative leaders, while it was proved that regions with no clusters are still behind [37]. Porter identified 67 clusters, and they are divided into two categories: "traded" and "local" clusters, with 51 and 16 clusters, respectively [38]. The European Cluster Observatory encompasses the structure of 51 clusters in the European context as a critical dimension of the current policy agenda. This paper focuses on the 51 traded clusters, their performance, and relationships within the case study region. The traded clusters are the clusters "that concentrate in particular regions but sell products or services across regions and countries" [39]. They empower the region's resistance by three main properties: (i) clusters enhance the region's specialization and therefore its productivity, (ii) dynamic clusters tend to easily deal with shocks through their ability to transfer capacity into new market fields, and (iii) regions with clusters have many interconnections and overlaps that boost their diversification and specialization [37]. This state of complexity is the primary source of growth in the region.

Clusters provide a fertile ground to promote industry transformation and the development of emerging industries [32]. From here comes another study on emerging industries carried out in this article. The European Cluster Observatory identified that emerging industries face megatrends [40]. Emerging industries can be understood as either new industrial sectors that are emerging or existing industrial sectors that are evolving or merging into new industries [41]. Emerging industries often have high growth rates and further market potential, essential for future competitiveness and prosperity [42]. In the latest document published by the European Cluster Panorama, it was highlighted that the collaboration between business, research, and government within and between clusters is helping to build a robust recovery plan during the COVID-19 pandemic in regions across Europe [43].

This paper seeks to address the sectors' interconnections by applying network analysis to cluster spatialization. Networks have been an essential tool for understanding regional economics and economic geography [44]. They allow for understanding direct and indirect linkages that are part of an economic system. They also allow for understanding the interaction between firms and markets [45]. Network analysis has recently advanced in economic geography and regional sciences [46,47], but it is still developing [48]. The network can itself be described in terms of its node sizes (which in our study indicate the size of the industry in the region), density (proportion of interconnections between sectors) [49], centrality (the extent to which the network revolves around any single node) [50], closeness (the role of proximity for on innovation) [51], and betweenness centrality (the impact of some nodes in "transforming" the knowledge) [52] (Table 1). Interest in cluster research and network analysis has expanded in recent years [53–56], evident from burgeoning academic literature. For example, some articles have applied social networks to study the evolution of firms within clusters [48,57], assessing the connectivity of the urban system through spatial connections of clusters by network analysis visualization tools [58], investigating the impact of economic crisis by using the SNA to [59] the regions' structural understanding via networks [60,61], and the influence of spatial proximity on the knowledge flow [62,63]. However, the aspect of adding the location into the social network has still not been widely tackled.

In the economic geography debate, there was a question of which is more relevant for the competitiveness of firms: the places or the networks [64]. The concepts of "space of places" and "space of flows" are both crucial when it comes to cluster analysis [65]. The idea of "space of places" expresses that location matters for learning and innovation [66]. In addition to this, the concept of "space of flows" highlights the role of networks as the necessary form for transferring and diffusing knowledge [67]. Therefore, it is essential to underpin and visualize the clusters' network and then contextualize the flow to investigate the location's role in creating the whole system. In this study, we not only generate industry networks that only reveal flows of inputs and outputs between firms, but we added a special dimension to the network to identify and anticipate locations' impact on the industry. We focus on territorial social networking analysis, as the cluster literature has claimed that regions are drivers of innovation and economic development [68]. Firms in groups benefit automatically from knowledge externalities through labour mobility, informal networks, buyer–supplier relationships or R&D cooperation [69]. This is because tacit knowledge moves easier across short distances, and shared institutions at the cluster level facilitate the effective transfer of knowledge [70]. Within the region, we shed light on Local Labour Market Areas (LMAs) (Figure 1) as the spatial unit and the intra-regional development unit of analysis.

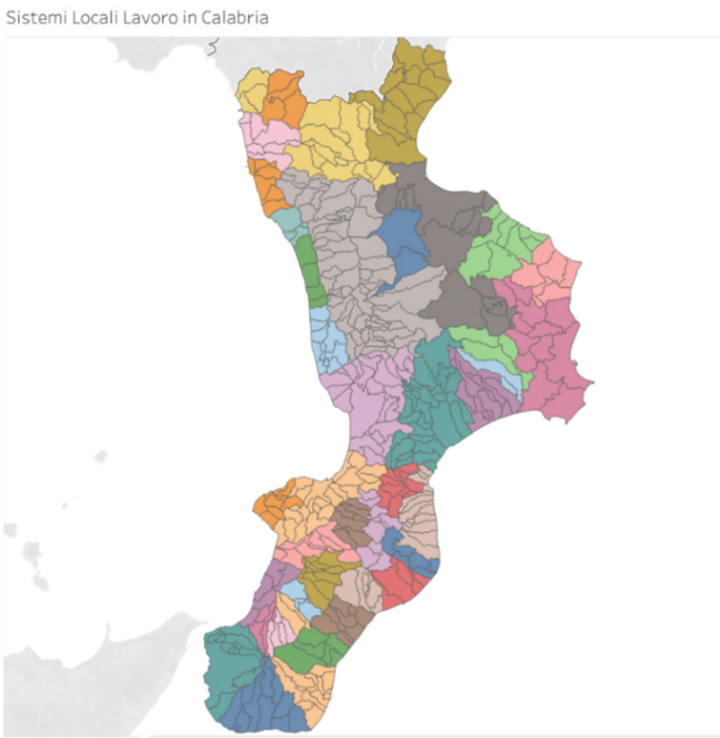


Figure 1. Calabria region Local Labour Market Areas (LMAs). Source: http://osservatoriosviluppolocale.regione.calabria.it/web/sll-calabria-aggiornamento-2021/ (accessed on 28 February 2022).

To be more precise, LMAs started when the American concept of Standard Metropolitan Areas was introduced [71]. This attempted to describe the pattern of people's activity within an urban area based on their work trips. In other words, LMAs are based on a territorial unit whose boundaries, regardless of the administrative organization of the territory, are determined using the flows of daily home/work trips (commuting) [72]. The LMA concept has been widely used for administrative and research purposes and has been successfully applied in Italy [73]. Furthermore, LMAs are crucial to understanding the performance of the labour markets and one of its distinct constituent elements [71]. They represent the local labour pool in which the transfer of knowledge and technology is easy between firms [61,74].

In this study, we apply spatial coordination with SNA to data in 2019 for industrial clusters in Calabria, Italy, to investigate the importance of social network and spatial location in exploring the complexity level within the cluster-based analysis.

Table 1. Descriptive analysis of network graph characteristics [75].

Domain	Characteristics	Annotation	Definition	Equation	Note
Node	Degree	d_v	the degree d_v of a vertex or node v, in a network graph G = (V,E) counts number of edges in E incident upon v.	$\{d_1, \ldots, d_{Nv}\}$	Degree varies among Direct and Undirect networks based on In/Out degree distinction.
Node and Network	Closeness Centrality	C_{Cl}	The standard approach lets the centrality vary inversely with a measurement of the total distance of a vertex from all others where dist.(v,u) is the geodesic distance between the vertices u,v ∈ V.	$C_{Cl} = 1/\sum_{u\in V} \mathrm{dist}(v,u)$	Often, for comparison across graphs and with other centrality measures, this measure is normalized to lie in the interval [0, 1].
Node and Network	Eigenvector centrality	C_{Ei}	This definition of centrality seeks to capture the idea that the more central the vertex's neighbourhood is, the more central the vertex itself is.	$c_{Ei}(v) = \propto \sum_{\{u,v\}\in E} cEi(u).$	The convention is to report the absolute values of these entries, which will automatically lie between 0 and 1 by orthonormality of eigenvector.
Network	Degree Distributions	f_d	Given a graph G, define fd as the fraction of ver-tices v ∈ V with degree dv = d. The collection {fd}d ≥0 is called degree of distribution of G and is simply the histogram formed from the degree sequence, with bins of size one, centred on non-negative integer.	$\{f_d\}_d \geq 0$	The degree distribution provides a natural summary of the connectivity in the graph. In practice, degree distribution is arguably interesting as descriptors for large graphs.
Network	Density	den(G)	Cliques are subsets of fully cohesive vertices in the sense that edges connect all vertices within the subset.	$\mathrm{den}(H) = \frac{\lvert EH\rvert}{\lvert VH\rvert(\lvert VH\rvert-1)/2}$	The value of den(H) will lie between zero and one and provides a measure of how close H is to be a clique.

3. Methodology

3.1. Area of Study

Our case study is the Calabria region in southern Italy. Calabria is one of the EU's least developed regions, with Gross Domestic Product (GDP) at about 60% of the EU average and unemployment at around 20%. Moreover, its population is small, at only about 1,860,601 inhabitants in 2021. Calabria is a statistics NUT III Region and integrates 5 provinces (NUTS III), Catanzaro, Cosenza, Crotone, Reggio di Calabria, and Vibo Valentia, that contain 45 LMAs (Figure 1). Table 2 shows the LMAs' populations, which influence the results. COVID-19 has substantially impacted the regional economy, drastically reducing the turnover of small and medium-sized private enterprises that represent 97% of regional configuration. Additionally, tourist flows at regional accommodation establishments have suffered a sharp fall after years of growth. According to data from the Tourism Observatory of the Calabria Region, attendance in 2020 decreased by more than 50%. Looking ahead, the regional economy could draw impetus from public programs launched in response to the pandemic crisis, including in particular the National Recovery and Resilience Plan, especially if these manage to aid with the delays affecting the Calabrian production system, with regard, for example, to the provision of infrastructures and the levels of digitization [76].

Table 2. Local Labour Market Areas' population in 2019 (https://www.istat.it/en/labour-market-areas, accessed on 5 January 2022).

LMA	Population in Thousands	LMA	Population in Thousands
Acri	22.9	Gioia Tauro	58.9
Amantea	27.5	Locri	38.6
Belvedere Marittimo	21.9	Marina Di Gioiosa Ionica	20.3
Cariati	17.7	Melito Di Porto Salvo	34.2
Cassano All'ionio	49.3	Oppido Mamertina	7.2
Castrovillari	59.9	Polistena	43.5
Cetraro	13.7	Reggio Di Calabria	215.0
Cosenza	259.3	Roccella Ionica	18.2
Mormanno	16.7	Rosarno	29.2
Paola	31.3	Sant'eufemia D'aspromonte	7.4
Praia A Mare	13.5	Stilo	8.7
San Giovanni In Fiore	21.6	Taurianova	18.3
San Marco Argentano	30.7	Cirò Marina	25.8
Scalea	25.5	Crotone	119.0
Catanzaro	146.9	Mesoraca	6.6
Chiaravalle Centrale	14.8	Petilia Policastro	17.6
Sellia Marina	29.4	Serra San Bruno	15.1
Soverato	41.4	Soriano Calabro	12.5
Lamezia Terme	130.4	Tropea	22.2
Bianco	15.4	Vibo Valentia	101.9
Bovalino	26.2	Corigliano-Rossano	99.4
Delianuova	5.8	Nova Siri	13.7

3.2. Methods and Materials

In order to investigate the economic structure in Calabria that is dealing with a sustainable transition and its complexity, we have implemented a merged methodology by spatializing SNA metrics at the territorial level. In this way, we benefit from cluster-based analysis to illustrate the region's economic structure from a novel perspective. In the first step, we aimed at picturing the region's industries under the lens of cluster-based analysis to interpret the economic structure of LMAs according to the interconnections among sectors that constitute a cluster. This first step was carried out through the economic sectors aggregated into 51 clusters and the territorial unit over the case study area. In the next step, we spatialized clusters using the SNA tool to highlight the clusters' compositions. Finally, we used SNA as a practical tool to define how the interactions of sectors form the economic structures.

Moreover, it has a set of analytical features that analyses those interactions within a network of nodes (actors) and ties (relationships). In the next subchapters, we will detail different levels of industries' agglomeration and the network structure aligned with the research perspective. In essence, this paper performs a sequential analysis of the cluster network of Calabria to reveal its undiscovered aspects of complexity.

3.2.1. Forming Territorial Social Networking (TSN) of Calabria Region

Forming a data frame is an essential stage in conducting this experiment. To respond to this requirement, we extracted the economic data (number of establishments and labour force in those establishments) from the Italian National Institute of Statistics (ISTAT). To be more precise and follow the research line of reasoning, first, we aggregated the city-level data to LMAs based on their geographic distribution over the Calabria region. LMAs are territorial units blurring the administrative boundaries of a city to include its surroundings where the labour moves and knowledge flows. Thus, Calabria's 45 LMAs are placed as the vertical axis of the data frame. Next, the clusters' data are aggregated based on the LMAs. Both the number of establishments and the number of employees of each economic sector (399 sectors) are utilized for each year; in this way, the horizontal axis of the data frame is formed. Finally, the data frame for all years for the 51 clusters is elaborated (Table 3).

Table 3. The data framework of the case study.

Cluster Name		
Selection Period	**Year (2012–2019)**	
NUTS Level ISTAT (National Census Bureau) Italia (NUT 1) Region (NUT 2) Municipality (NUT 3)	Number of Establishment NACE 4 digits per cluster and LMA	Number of Employees NACE 4 digits per cluster and LMA
ATECO Code (2007)	Sectors NACE 4-digit aggregation based on Traded Cluster and Emerging Industries	
Italy Southern Italy Calabria LMAs		

The next step is data preparation for spatial networking analysis. This level consists of extreme detection, data validation and data frame transfer to create an adjacency matrix (A), (Table 4).

Table 4. LMA and Sectors Adjacency Matrix.

Sectors	**1801**	**1802**	**.**	**.**	**.**	**1845**
510	1	1	.	.	.	0
610	1	0	.	.	.	0
620	0	1	.	.	.	1
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
9329	0	0	.	.	.	0

At this step of the experiment, connections of the regional network are being investigated. We tried to draw a big picture of the structure by testing the adjacency matrix to understand the network statistics. Figure 2 illustrates the LMAs' connection probability, which relies on transforming the adjacency matrix to a logical incidence matrix (Ai) as (1):

$$\forall\, a_{ij} \in A \rightarrow a\prime_{ij} = 0 \leftrightarrow a_{ij} = 1 \quad (1)$$

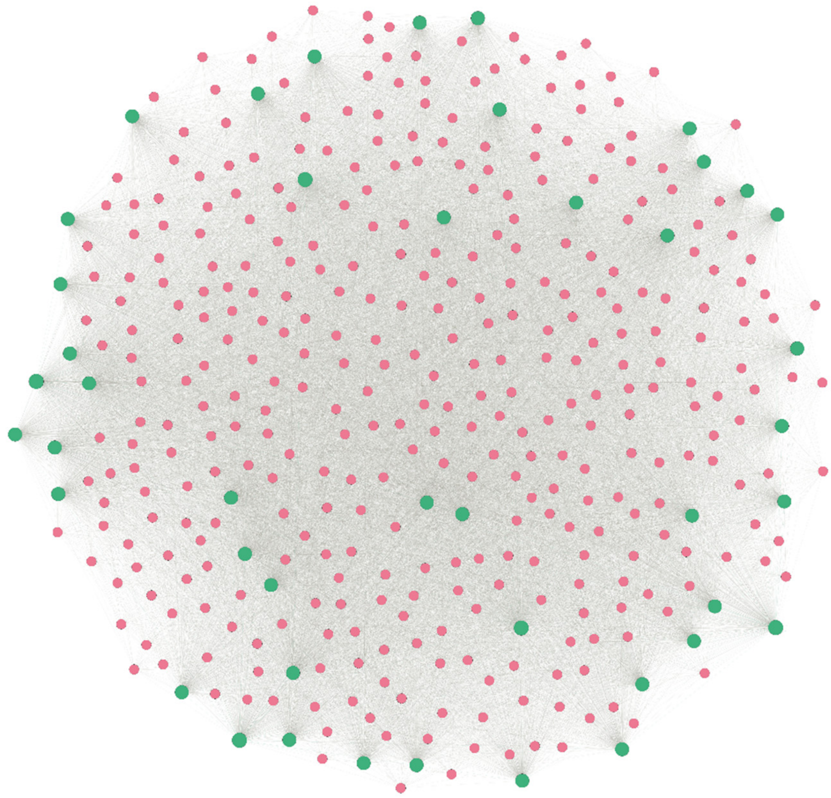


Figure 2. TSNA of all sectors in Calabria in 2019. Pink nodes = sectors, and green nodes = LMAs.

To develop a comprehensive network, we checked all anomalies and extremes of the data frame. To some extent, the data were precise, but some cities belonged to overlapping LMAs or experienced the sudden shutdown of an industry in a specific year and reopening in further years, where the issues require special attention and we must avoid relying solely upon automatic algorithm development. To elaborate the matrix, two forms of connection are taken into consideration. On the one hand, we investigated whether the nodes (v) are connected into a network and then evaluated the network total size (total of vertex pairs). On the other hand, we calculated the node's degree, network diameter, network density and traditional networking analysis metrics such as centrality [77]. The following algorithms are conducted to form an interpreted, visualized, and robust structure. Force Atlas 2 [78] is a force-directed layout: it simulates a physical system to specialize a network. Nodes repulse each other like charged particles, while the edges attract nodes like springs. These forces create a movement that converges to a balanced state. This final configuration is expected to help interpret the data [79]. Though it may require some adjustment, the Fruchterman–Reingold [80] layout works well for many large social networks. The algorithm uses an iterative process to adjust the placement of the vertices to minimize the system's fluctuations. Due to the iterative nature of this layout, it runs repeatedly, each time incrementally changing the position of each vertex based on the last part.

3.2.2. Random Sampling TSN in Calabria

At this stage, we wanted to take a more advanced step by locating the LMAs in the network. Therefore, we retrieved their geographical coordinates from ISTAT thanks to the software (Gephi™) [81] that handled the visualization of the economic structure with respect to geo-located LMAs in a reasonable time. In the first stage of forming the network, we randomly selected 8 clusters in different sizes to analyse the connectivity for 2019. Then, to enumerate the connection weights, we relied on the reported number of employees and establishments and replicated the links and the node sizes based on mentioned numbers.

Subsequently, to import the matrix into the software, we considered the numbers (matrix digits) as string data types due to the average commuter from LMA X to sector Y. These numbers are imported by one decimal. The connections are considered indirect since the relationship between two nodes is regarded as coincident in the conceptual TSNA system and has no priority. The Geo layout algorithm was applied to connect LMA nodes to their geographic position in this network. The nodes were partitioned by their relative degree (number of connections). The connectivity was investigated and demonstrated by the line weight. The economic sectors and LMAs were divided by colour.

3.2.3. Education and Knowledge Creation Cluster TSN and Blue Growth TSN in Calabria

The data collection to constitute the 51 clusters within the Calabria regional context, together with the ten emerging industries, allows for configuring the granularity performance according to the rationale behind the cluster-based analysis concerning the changes over the observation period of 2012–2019. As the first result of the proposed methodology, we show the potential of the territorial SNA applied for the education and knowledge creation cluster and Blue Growth emerging industries in the last update year, 2019. Furthermore, the network density as a general characteristic of the graph [82], the degree distribution of the nodes as the level of beneficiation of the network, and the eigenvector centrality [75] are calculated and stored in an elaborated data frame. The next chapter will detail the particular findings in the complex network elaborated based on the abovementioned data frame.

The cluster and the emerging industry selected to display how the TSNA methodology operates can provide grounds for reasoning on the industrial change claimed to accelerate industrial modernization towards a sustainable transition. Tables 5 and 6 contain the specific sectors aggregated for the "Education and knowledge creation" cluster and Blue Growth emerging industry, respectively.

Table 5. Education and knowledge creation cluster sectors [40].

Cluster	NACE	Industry Name
Education and knowledge creation	72.11	Research and experimental development on biotechnology
	72.19	Other research and experimental development on natural sciences and engineering
	72.20	Research and experimental development on social sciences and humanities
	85.41	Post-secondary non-tertiary education
	85.42	Tertiary education
	85.52	Cultural education
	85.59	Other education n.e.c.
	85.60	Educational support activities
	94.12	Activities of professional membership organisations

Table 6. Blue Growth industry sectors [40].

Emerging Industry	NACE	NACE Name
Blue growth industries	03.11	Marine fishing
	03.12	Freshwater fishing
	09.10	Support activities for petroleum and natural gas extraction
	10.20	Processing and preserving of fish, crustaceans and molluscs
	22.19	Manufacture of other rubber products
	25.99	Manufacture of other fabricated metal products n.e.c.
	28.11	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
	28.22	Manufacture of lifting and handling equipment
	30.11	Building of ships and floating structures
	30.12	Building of pleasure and sporting boats

Table 6. *Cont.*

Emerging Industry	NACE	NACE Name
Blue growth industries	03.11	Marine fishing
	33.15	Repair and maintenance of ships and boats
	35.11	Production of electricity
	35.12	Transmission of electricity
	36.00	Water collection, treatment and supply
	42.91	Construction of water projects
	46.14	Agents involved in the sale of machinery, industrial equipment, ships and aircraft
	49.41	Freight transport by road
	50.10	Sea and coastal passenger water transport
	50.20	Sea and coastal freight water transport
	50.30	Inland passenger water transport
	50.40	Inland freight water transport
	52.10	Warehousing and storage
	52.22	Service activities incidental to water transportation
	52.23	Service activities incidental to air transportation
	52.24	Cargo handling
	52.29	Other transportation support activities
	71.12	Engineering activities and related technical consultancy
	71.20	Technical testing and analysis
	72.19	Other research and experimental development on natural sciences and engineering
	73.11	Advertising agencies
	77.32	Renting and leasing of construction and civil engineering machinery and equipment
	77.34	Renting and leasing of water transport equipment
	79.11	Travel agency activities

4. Results and Discussion

4.1. Forming Territorial Social Networking Analysis (TSNA)

This chapter presents the findings of TSNA results from four perspectives. First, the outcome of the investigation in Calabria as a single territorial dimension hosting all 399 sectors of 51 clusters will be explained. Graph (Figure 2) consists of nodes (two modes): (i) LMA as a spatial dimension and (ii) sectors of clusters (four digits) and ties as links between territorial units and economic sectors that form the economic structure. In this view, we look over the small granularity level of the network to capture the complexity of economic structure in terms of which economic sectors are influencing the structure and provide significant potential for change. The European observatory of clusters classified 399 industrial sectors. However, Figure 2 shows that only 358 sectors exist in Calabria. This could be interpreted as a 10% lack in economic sectors in traded clusters. Moreover, A total of 21 LMAs out of 45 have less than 10% connectivity, which can explain the lagging performance of the region (Figure 3). We then report network density; Figure 4a shows the left skewness in the degree distribution, which means a few sectors are dominant. Furthermore, the same pattern in the eigenvector centrality shows the tendency of the dominant nodes to connect each other (Figure 4b). The structure is sparse. There are (358×45) 16,110 records; among them, less than 16% non-zero pairs found.

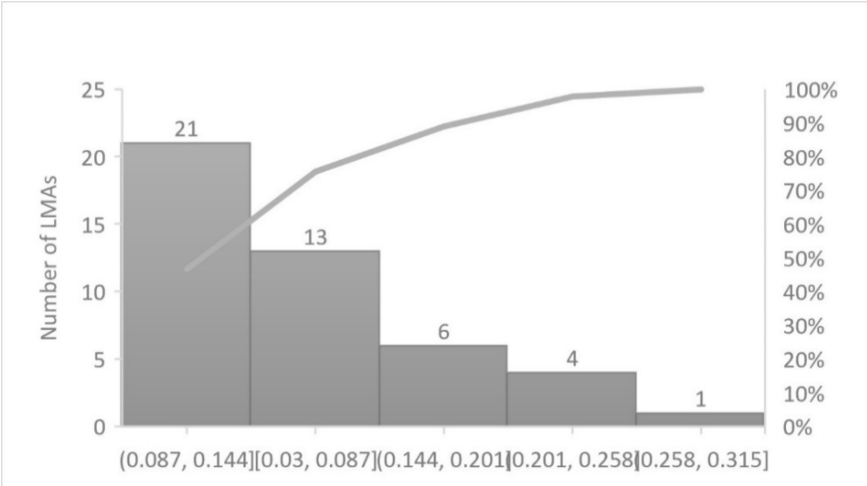
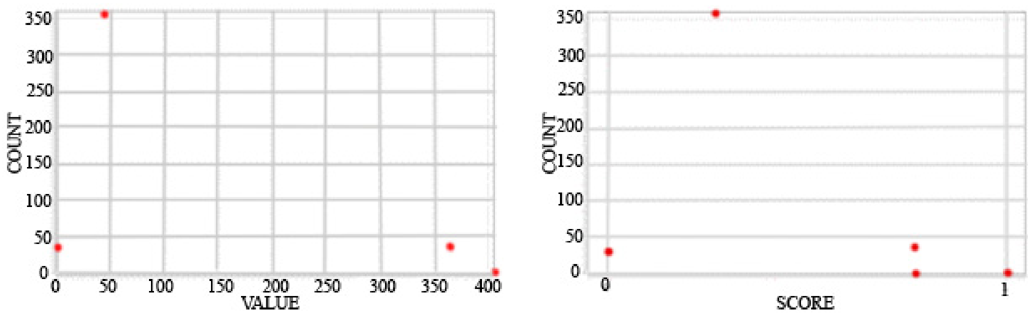


Figure 3. Connection probability chart of inverse network (Calabria region).



(**a**) (**b**)

Figure 4. (**a**) Degree distribution and (**b**) eigenvector centrality distribution.

4.2. Random Sampling TSNA in Calabria

In this experiment, the green nodes' (the clusters) sizes are proportional to the number of establishments. In other words, it is the size of the cluster in the region—the line weight advocates the cluster's number of establishments in the connected LMAs. As expected, although the well-known LMAs (Cosenza and Reggio Calabria) are engaged proportionally to their influential position, this model highlights that other medium-size LMAs are playing relatively positive roles. Lamezia Terme, Catanzaro, Vibo Valentia, Crotone, and Castrovillari establish reliable connections to the region's main active clusters, respectively (Figure 5). The degree of distribution (Figure 6a) highlights that there is a large number of LMAs with less than 12 connections (meaning less than 0.01% of the possible number of links). As a result, there is a geographical disparity in which these dominant LMAs mentioned earlier absorb a significant number of opportunities. The sparsity of the network due to its low density (20%) demonstrates the weakness of the economic structure.

Clusters are not evenly facilitated due to local resources, scarcities, and possible missings knowledge diffusion. As Figure 5 shows, the "Business Services" cluster and "Distribution and electronic commerce" cluster are considered two of Calabria's most important clusters. Still, it is essential to name the "Hospitality and Tourism" cluster as a well-functioning economic potential of the territory. This cluster can be found in all 45 LMAs. The same goes for the "Food processing and manufacturing" cluster. This cluster hosts a small number of establishments, but due to a high degree of connectivity of 100%, it pays an immense contribution to regional resiliency. On the other side, the "Information Technology and Analytical instruments" cluster shows a low connection. This lag can be described in the digitalization phase, where the accommodation, advertisement and quality auditing services are radically changed. We want to emphasize that the size is not the only important aspect, but also a high degree of connection in a sparse network can enhance the territorial resilience (Figure 6b).

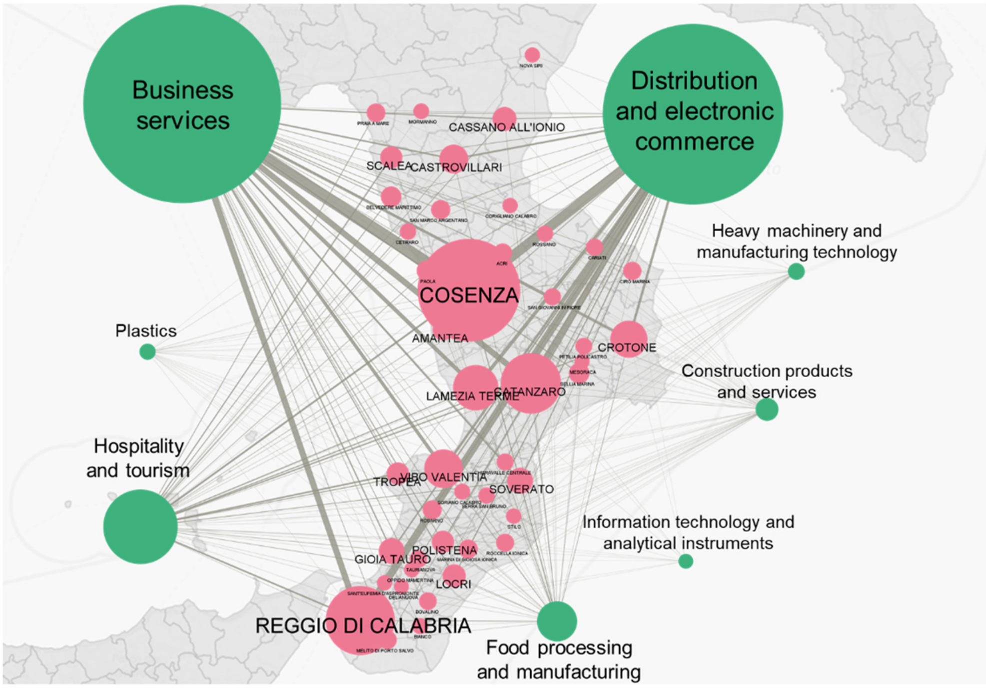
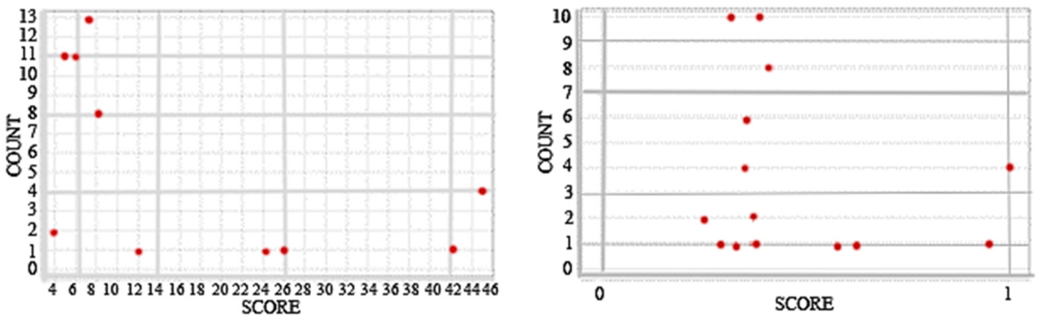


Figure 5. TSNA of 8 clusters in Calabria in 2019. Pink nodes = LMAs and green nodes = clusters. The LMA node size reflects the total number of units in all clusters found in that LMA. Whereas the cluster's node size is the aggregated number of units in that cluster. Edge's width is no. units in each sector in the connected LMA.



(**a**) (**b**)

Figure 6. (**a**) Degree distribution and (**b**) eigenvector centrality distribution.

4.3. TSNA Education and Knowledge Creation Cluster

This study's first level (intra-cluster perspective) observes a network of 45 interactive geo-coordinated nodes highlighted in red, while nine of the "Education and creation" cluster sectors are illustrated in green (Figure 7). At first glance, it is essential to mention that the network formation's core/periphery nature is evident in both levels. It is clearly shown that the critical LMAs play a significant role in the education knowledge diffusion, while the small share of the others is neglectable. More in detail, we can mention the degree of connection between "Other Education n.e.c.", which primarily relies on the private universities and training centres and the two main hubs of the Calabria region (Cosenza and Reggio Calabria). At this stage, the degree of distribution is commonly proportional to the number of establishments, as 250 establishments were allocated to the "Other Education n.e.c." and considered 65% of the network density. Other highlights are that 13 LMAs out of 45 primarily (more than 70%) rely on the same sector to connect the network. Surprisingly, an LMA, CARIATI, is entirely isolated (has 0 connection). To be more precise, we can group the territory into two vividly separated subsets where the Cosenza and Reggio Calabria are the primary hosts of the Calabrian education centres while the rest have a low connection. The observed situation in this cluster demonstrates the low level of complexity due to the low network density (less than 10%) in the region according to knowledge infrastructures in a way that can be interpreted as a call for particular attention to reinforcing the small-scale cities for hosting education facilities (Figure 8a,b).

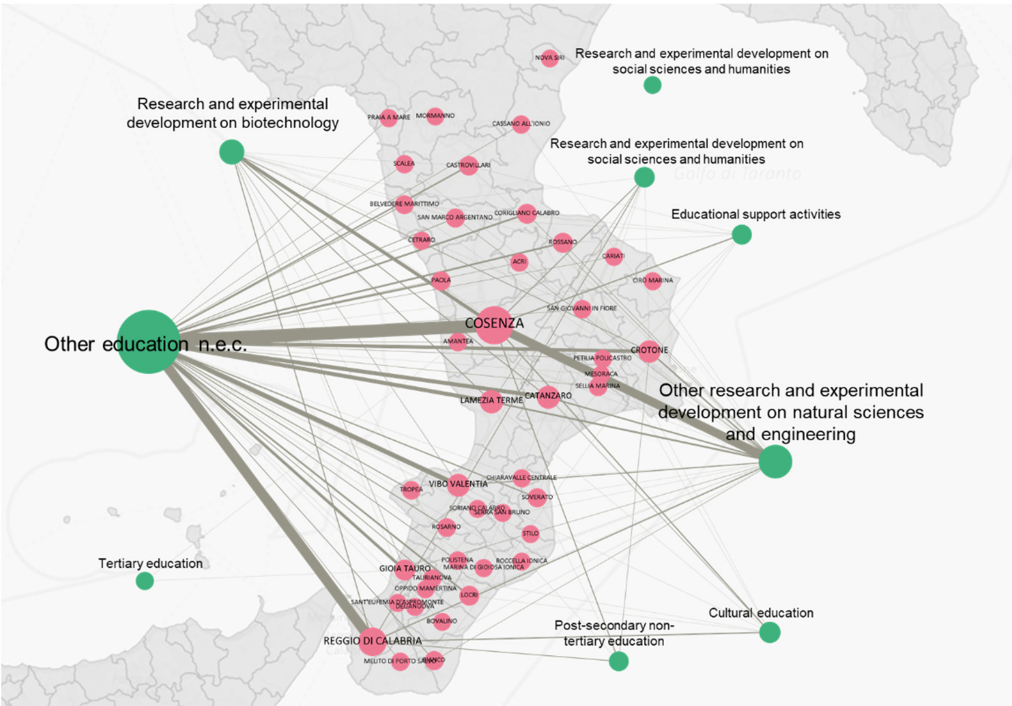
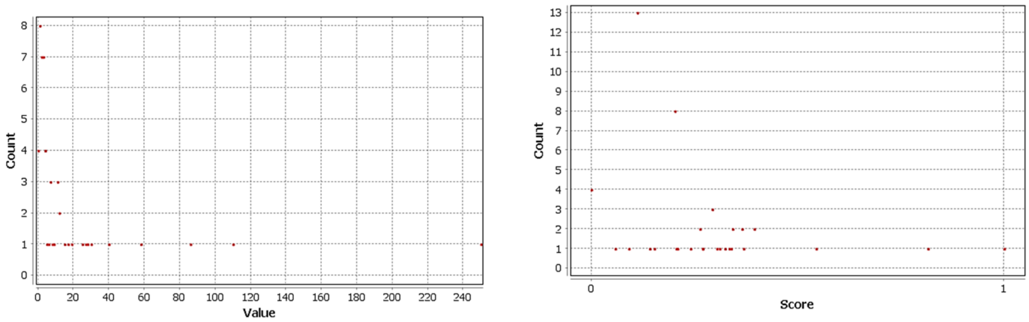


Figure 7. TSNA Education and knowledge creation cluster in Calabria in 2019. Pink nodes = LMAs, and green nodes = sectors. The size of the LMA node reflects the total no. of units in all sectors found in that LMA, whereas the sector's node size is the aggregated no. of establishments in the corresponding sector. Edge's width is no. of units in each sector in the connected LMA.



(**a**) (**b**)

Figure 8. (**a**) Degree distribution and (**b**) eigenvector centrality distribution.

4.4. TSNA Education and Knowledge Creation Cluster

This process's first level (intra-cluster perspective) results include 45 interactive network nodes highlighted in red, while nine of the "Education and creation" cluster sectors are demonstrated in green. At first glance, it is essential to mention the core/periphery network formation level in both levels. It is clearly shown that the critical cities play a significant role in the education knowledge diffusion, while the small share of the others is neglectable. More in detail, we can mention the degree of connection between "Other Education Means", which primarily relies on the private universities and training centres and the two main hubs of the Calabria region. To be more precise in this result, we can group the territory into two vividly separated boundaries where Cosenza and Reggio Calabria, as the primary hosts of the Calabrian Universities, are located. Not only university studies but also the research sector are both complicated/knowledge creation software is well connected to them; however, the Cosenza has a strong connection even with other components of the "Education and creation" cluster.

4.5. TSNA Emerging Industries: Blue Growth

In the last part of this chapter, we investigate the model for the Blue Growth on the most up-to-date dataset (2019). The primarily generated graph demonstrates the LMAs on the horizontal line, and the 13 circles demonstrate contributing clusters (Figure 9). Thus, we see this adimensional modelling tends to characterize the degree of relevance between the territorial potential for inclusive transition and the share of each cluster as a critical mass. Another exciting fact harvested from this complex structure is that Cosenza is considered a hinterland territory, but sector agglomeration made these LMAs the central hub. This can be explained by the fact that Blue Growth has sectors that do not directly interact with the sea, yet they offer services such as advertising and logistics. The variety of the sectors (high number of the contributors) and the consistency in the nodes' degree representing the level of connection compared to the network density is left-skewed. Although 15 clusters form the Blue Growth emerging industry from those, only five construct more than 60% of the establishments in respective clusters and the rest of the economic sectors play an inconspicuous role on a broader image.

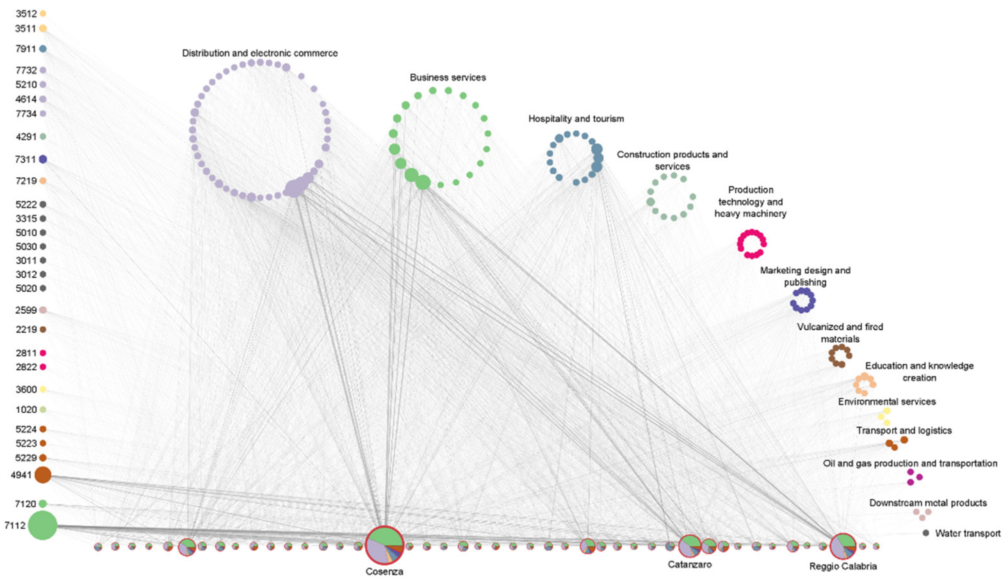


Figure 9. TSNA of all clusters contributed to form Blue Growth (BG) in 2019. Linkages between Blue Growth industries sectors and the parent clusters for the number of establishments in Calabria for 2019. Circles are the parents' clusters, horizontal line is Local Labour Market Areas, and vertical line is Blue Growth sectors.

This model is still in the initial simulation steps; data limitation in transitional indicators is considered an obstacle to forecasting and policy estimation frameworks where we aim to vigorously investigate the future of the complex transition scenarios at the territorial level. As mentioned in the first chapter, it is essential to respond to the global transition requirements at the local level. Thus, having a new perspective on cross-sectorial future industries forming critical mass for megatrends is interpreted as the next steps for this kind of study.

5. Conclusions

On the one hand, understanding industrial clusters within a region is crucial to identifying the local economic structure. On the other hand, there is a need for a new modelling framework that can better capture the systems' relations and their structure. The more complex the system becomes, the more integral the network becomes in order to accommodate this complexity. This paper targets exploration of the network analysis techniques potentials in the economic geography for exploring the complexity of the context to face an inclusive transition. The analysis shows how LMAs and clusters are integrated and evaluates the level of preparedness of the context. The analysis shows the nature of sectors in Calabria.

Furthermore, it reveals the connections between all LMAs. The reasoning in this research follows Porter's efforts on the cluster-based analysis to investigate the economic structure. Thus, we aim to demonstrate a novel classification model for the transition potential of a region. To describe this strategy in more detail, the economic sectors are grouped, and then these aggregations will be considered the first layer of a two-mode network. On the other hand, LMAs construct the second layer of the network. Next, the connection (tie) is defined when two LMAs are connected by hosting the same sector (4 digits) within a cluster in the same year. Finally, the proposed tool, Territorial Social Networking Analysis (TSNA), is compounded by the networking structure as an a-dimensional model. This would help analyse the system's complexity to capture the spreading nature of the knowledge flow.

We examined clusters and the economic structure at a different level. First, we created a single territorial dimension network hosting 358 economic sectors on 45 LMAs. We investigate the economic network density, centrality, and degree distribution. We used these metrics to interpret the case study's economic structure composition. Second, we randomly selected eight clusters of different sizes to examine the connectivity. The results show that having a small number of establishments in a specific cluster does not mean low potential. We found that such clusters as the "Food processing and manufacturing" cluster as well as the "Hospitality and tourism" cluster have at least one establishment in all LMAs. Our interpretation for this is that the more connections the cluster has, the more resilient it is. Third, we started our analysis by examining only one cluster and its linkages. The "education and knowledge creation" cluster's network shows the knowledge and research infrastructure of the region; in this way, we examined the competency of the cluster sectors and the connection between LMAs. We observed the network's core-periphery image, which shows that education infrastructure is fragile.

Meanwhile, the highest number of establishments are in "Other education n.e.c.", which also indicates that the education system's focus is mainly on tutoring and skills training. Fourth, we tried to see how far we could go with networks and to what extent networks could reveal systems' complexity. We selected one of the emerging industries (Blue Growth) to run the examination. Emerging industries arise from clusters as a consequence of megatrends. They were formed from the most vital sectors in each cluster that could compete globally. Network analysis allows us to visualize this formation and put together 15 clusters to see which sectors were considered more innovative and competitive. We can see that the "Fishing and fishing products" cluster, "Electric power generation and transmission" cluster, and "Water transportation" cluster have the highest shares of sectors in Blue Growth industries. Although the European commission already makes this classification for emerging industries, network visualization helps us understand the powerful sectors and the associated clusters.

Proposed Networking analysis methods do not only act as a graph to illustrate a phenomenon, but are also a way to form a complex model. The model has the ability to perform dynamic reactions to real-time data; it follows the complex theory and fits the non-linearity of the system. Furthermore, networking analysis has the potential to overlap layers (different annotation for a node in various coordination) and create multi-variant functions.

In sum, networks are an appropriate conceptualization of inter-organizational interaction and knowledge flows. We claim that TSNA for industrial clusters is a promising tool for future directions in regional studies. The visualization of cluster networks helps us understand the complexity of cluster-based analysis in Calabria. Moreover, networks help to highlight patterns in the data visually. When the nodes are geographically mapped, the interpretation of the networks is enhanced because, for instance, geographic clusters become immediately spottable.

For future development, we see that understanding the performance of the industry clusters could be well examined if we add different aspects. For example, investigating the innovative behaviour of a cluster or the investments trend. Following this point, multilayer networks or multiplex networks would be our next step of analysing and understanding clusters and firms in a region. The complexity can neither be reduced nor neglected, but absorbing the dimensions requires a holistic perspective.

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