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Article

# Spatial networking analysis to capture local innovation flows towards inclusive transition

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**Abstract:** The economy is a complex system, and the interactions between different agents are still not easy to quickly see-through. This complexity should reflect in a spatial dimension; in this way, tracking the tradeoffs opens a new window to the nexus of place and flow. Due to the fact, the economic systems often go through transitions and end up in another state, and this evolution is embedded in cities as the new motor of paradigm shift. To adequately represent and study these dynamics, we aim to develop an integrated method based on network analysis science and geographic economy synthesis to detect a multiscale navigator to track the transition from regional to the local level. This paper seeks to explore the specialization of regional clusters and their innovative behaviour in a particular lagging region, hence unfolding the innovation ecosystem to the smallest granularity then simulating the emergence phase of this complex system. First, our findings reveal that the local scale is relevant to start a bottom-up planning approach on policy implementation. Second, the global challenges could be addressed on a regional scale if we investigate the local complexity to unfold the innovation flow over its complex ecosystem and lead the knowledge as a critical element for inclusive transition, most probably into cities. Finally, the innovation network is an existing fact which can translate as a host for prosperity; In this line of reasoning, we intend to spatialize the track of the innovation flow to achieve transition hotspots and respond adequately to upcoming world concerns.

**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 is getting much more complex. In the last decade, studies on economic complexity ensued the 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 the conditions that would allow complexity to emerge in order to generate growth and prosperity* [3]. The economic complexity theory and methods have been acquiring interest within a broader perspective on the global system whilst the sustainability and social inequalities cast light on the uncertainties for the future[4–7].

These complex systems contain unexpected properties and often respond in a non-linear way to shocks or changes[2]. The systems should self-organize, learn, and adapt to

shocks to absorb this complexity towards new sustainable trajectories [4], in other words, being “resilient” [1,5–7]. In this paper, we argue that to achieve sustainability and resilience, the system can no longer be “locked into” a particular trajectory of economic development [8,9]. Hence, it is argued that new technological pathways that deviate from past practices and attempt to deploy new technologies should be implemented [2]. The urgency of environmental sustainability [10] and the need for reductions in greenhouse gas emissions (GHG) became encapsulated into the Paris convention (accelerated recently by the 26th UN Climate Change Conference of the Parties in Glasgow) with commitments of the EU, member states as well as many local authorities. Such commitments went well beyond obligations in carrying out excellent research but now comprise also transformative innovations for so-called “systemic transitions” including also non-technological driven innovation, diffusion, experimentation, regulation, new business models, behavioural changes, etc. It was encapsulated in the concept of “missions” and the notion of mission-oriented innovation policy [11,12]. Prosperous cities have led much of the growth of Europe over the last decade [13] and prosperous cities tend to have many advantages in responding to climate change. Cities are responsible for two thirds of global energy consumption and also generate some 70% of GHG emissions [14,15]. Indeed, Heating and air conditioning systems in buildings today alone contribute about 7% of global emissions [16]. However, cities are also critical to finding potential solutions to the current environmental challenges [13,14]. The fact that Europe is so urbanized, with the whole EU population living in less than 5% of the total European land area, means that that urban focused policy actions and interventions intended to foster sustainable growth can potentially reach a large share of the EU economy and population by being targeted over relatively very small geographical areas. The combination of city-level decision-making, local stakeholder engagement and dense populations means that these types of settings can provide ideal testbeds where new innovations aimed at enhancing sustainable growth and inclusive growth can be piloted [14].

Local Systems of Innovation have not been the focus of academic studies for long time, even it is widely recognised that the transition starts and happens at local level [15,17,18]. As cities try to push long term strategies and accelerate their pursuit of participatory processes to define recovery plans [19,20], strengthening and extending the access to digital equipment becomes a crucial feature of recovery and resilience [15,21]. Do et al. (2018) argue that institutions need innovation to improve their production and service delivery to attain superior performance for dealing with turbulence in the external environment [22,23]. Zivlak et al. argue that digital services based on big data analysis are highly used in high growth manufacturing firms [24]. These authors further claim that digital services would trigger manufacturing firms to enhance their servitization process and increase their competitiveness and performance [25,26]. However, the digital divide makes people and places are unequal regarding teleworking and many cities have been initially providing measures to reduce the gap [27,28]. During the pandemic, digitalization in the emergency has pushed many cities to systematize the use of smart city tools more permanently [27]. These tools and the changes in habits they entailed will remain a permanent component of cities’ recovery phase and increased preparedness for any future shocks [28].

Recent studies are concentrated on evaluating the ability of a geographical system, mostly regionally, to absorb the complexity inherent in the ecological transition or the advanced technological capacity that we can define as green [1,2,29–32]. However, the development of sustainable technological change claims for different dimensions of challenges [33], which are correlated to the context concerning the innovation ecosystem’s level of preparedness [34]. These conditions, in turn, reflects the inclusive character that sustainable transition requires to avoid the drawbacks of new capitalism based on green economic growth [35] that can increase inequalities and exclusion [36]. The paper proposes a different interpretation of the context starting from territorial units close to the urban dimension to identify the interconnection network as a generator of innovation

flows to be strengthened with a view to sustainable transition. The case study is a European region with long-lasting structural issues of development and growth. The cluster-based analysis is adopted to spatialize economic cluster at local level. Since each firm has interactions composed of people, materials, freight, and information [37], networking analysis would help understand the structure of all industries and the interplay between all relevant parts [38,39]. As a consequence of that, in recent years, scholars tend to carry out economic investigations employing network science [40–44]. Based on this premise, we focus on economic networks at local level to investigate how the interconnections inside each cluster can display a path for transition. Starting from cluster spatialization at local level, we use the economic spatial network analysis technique to examine how the structure of interaction in regions' sectors is ready to absorb the complexity for technological change. Then in line with the cross sectorial perspective we investigate the whole system benefiting a novel inverse adjacency matrix to take an overall picture from regions' network as a complex system to understand Which sectors in this innovation ecosystem are ready to play the global role to respond to international megatrends?

The paper is articulated as follows. First, we start with economic networks and cluster theories. In this way, the history behind network studies, network analysis and problem-solving by networks approach will be considered. Then two perspectives of "*space of place*" and "*space of flow*" will be introduced as the root for spatial studies. Connecting mentioned concepts help ease of reasoning on spatial economic network necessity as a tool for measuring complex issues at the urban level. After forming the theoretical framework for a novel networking analysis tool, we will detail the complexity and the innovation ecosystem to take a close look at a new window to economic growth opportunity.

Next, the methodology behind this paper will be presented in a section. We will precisely explain the spatial unit of study, the approach of proximity between spatial units benefiting knowledge flow and applying this study in an Italian southern region Calabria well elaborated. To analysis the case, we investigate data in three interconnected layers. First, we look at the case under the lens of a particular cluster to see if there is a meaningful pattern for couplings. Lastly, in this chapter, we check the system results in diversification; so-called emerging industries will be demonstrated in a multi-mode network.

We believe the investigation results could be considered initial steps for a pioneer data-driven place-based structural analysis model. We report results as images (graphs), and we call for contribution to elaborate this tool for a brighter future. The paper finishes with a reasonable conclusion about the possible next steps on statistical analysis application, urban network formation, enriching futuristic data for decision-makers to implement inclusive policies in line with the digital and ecological transition.

## 2. Overview of economic network and Cluster theory

Economic networks are a particular form of social network [45]. However, financial networks' history started to shape more than half a decade after studying social networks back in the 1920s [38,46–48]. Perhaps it is no coincidence that the increased interest in economic networks in recent years corresponds to the emergence of computational social sciences as an appreciation of phenomena outside the natural sciences [48–50].

Emmert-Streib et al. claimed economic networks are based on how their nodes are defined [38]. Nodes in network theory represent the elements of a system; in this way, connection (links) means the interrelatedness of each part and the system itself can illustrate as a Network, this system can form a simple monolayer connection or in economic networks as an example due to high degree of nodes connectivity [49]. Networks have been an essential tool for understanding regional economics and economic geography [50]. In the economic geography debate, there was a question of which is more relevant for the competitiveness of firms, the places, or the networks [51].

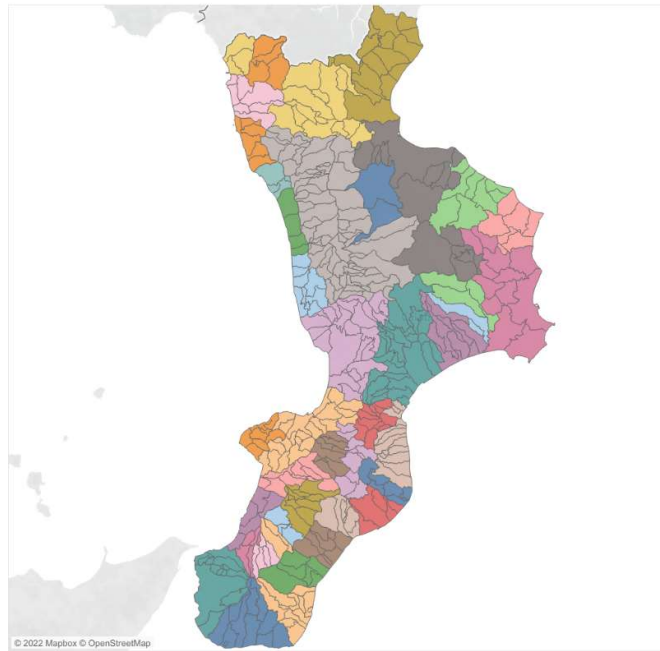
The concepts of "space of places" and "space of flows" are both crucial when it comes to cluster analysis [52]. The idea of 'space of places' expresses that location matters for learning and innovation [53]. In addition to this, the concept of 'space of flows' highlights the role of networks as the necessary form for transferring and diffusing knowledge [54]. Therefore, it is necessary to underpin and visualize the network of firms in traded clusters, then contextualize the flow to investigate the location's role to create the whole ecosystem. The cluster literature claimed that regions are drivers of innovation and economic development [39]. Firms in groups benefit automatically from knowledge externalities that are in the air [55]. This is because tacit knowledge moves easier across short distances, and shared institutions at the cluster level facilitate the effective transfer of knowledge [56]. These interactions between different actors or sectors in the market differ from one place to another [57]. Regions have become increasingly important at the economic and political levels in the past 30 years, reflected in the European Union and regional trade agreements [58]. Regions, like firms, need to innovate to remain competitive and, therefore, thrive [59]. Hence, our focus in this paper is on a Southern Italian region, the Calabria region.

As stated earlier, the enriching complexity of a system leads it to a more adaptive and creative status. In this way, the application of new technologies is considered a path to any regional economic development. Moreover, innovation is crucial to enriching productivity, and higher productivity is linked with innovation [60]. Thus, tracking innovation structure (network of flow) is a key to absorbing the complexity. Therefore, the intra-regional spatial dimension is relevant. Although a knowledge-based economy helps sustain economic growth and boost competitiveness [61], regions need to foster a creative, fast, and flexible system to move towards an innovation-driven economy [62]. The characteristics of this innovation-based competitiveness should be creative in generating new feasible ideas, fast in getting these new ideas to market, and flexible in adjusting to market circumstances [63]. Competitiveness is affected by the geographic location through the impacts on productivity and productivity growth [64]. For a reason that location proximity establishes intimate interaction with nearby firms and research institutions and creates unique access to other aspects of the business environment [65]. This highlights the crucial role of spaces, the operation of multi-scalar processes, and the spatial politics of transition. In 1990, Porter introduced the concept of clusters as groups of interconnected firms, suppliers, related industries, and specialized institutions in particular fields present in specific locations [66]. Porter summarized that clusters have a broad impact on competition. It helps increase firms' productivity based in the cluster through driving innovation and its pace, which reinforces productivity growth.

Moreover, it stimulates new business, which expands and empowers the cluster [64]. The economic relationships that emerge within clusters create a competitive advantage for the firms in a particulate region [67]. Then this advantage becomes a temptation for investors and suppliers of those industries to develop or relocate to that region [68]. Therefore, developing industrial clusters has become critical to regional and economic development planning, strategies, and policies [69]. An increasing number of regions worldwide have modified their economic development strategies to focus more on and capitalize on industrial clusters where they wish to have a competitive advantage [70]. There are 67 clusters, and they are divided into two categories; "traded" and "local" clusters, 51 and 16 clusters, respectively [71]. This paper focuses on the 51 traded clusters, their performance, and relationships within the case study region. Another study that is carried out in this article is the so-called "emerging industries". They are defined on their Cross-sectoral structure as presumed emerging industries built on traded industries (cluster sectors). They can be understood as either new industrial sectors – as emergence - or existing industrial sectors that are evolving or merging into new industries [72]. Emerging industries often have high growth rates and further market potential, essential to future competitiveness and prosperity [73]. We can say that they are cross-border and cross-sectoral clusters. Here comes an essential role for networking. It would help understand how the emerging industries were defined and their cross-sectoral linkages (see Figure 5).

We formed innovation network, considering economic sectors within a cluster in a specific territory as nodes in first phase. Employees, as physical carriers, and enterprises as a hub in a specific territory prompt the transfer of knowledge, wealth, workforce, and opportunities within a region. Therefore, we aim to identify the flow of knowledge and innovation in a broader sense by taking either the number of employees who participate in the same group of economic sectors (cluster) or establishments in the same cluster as a proxy for spatial interaction (drawing the links). This article uses the so-called Labor Market Areas (LMAs) (Figure 1) as the spatial unit and the intra-regional development unit of analysis. To be more clear about LMAs, they 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) [74]. Therefore, the population's social and economic relationships and home/work trips are used to identify the borders of 45 LMAs.

Sistemi Locali Lavoro in Calabria



**Figure 1.** Calabria Region Labour Market Areas (LMAs) source: <http://osservatoriosviluppocale.regione.calabria.it/web/sll-calabria-aggiornamento-2021/>

In a nutshell, in one hand, the new paradigm for the global economy is required to have relied on the urban economy. On the other hand, digital and the ecological transition is the promising approach towards a sustainable post-carbon future by helping to reduce the gap between the left behind and pioneer regions [75]. The technology-driven system allows the lagging areas to remain competitive in the marketplace while being clean [76,77]. In order to understand the methods and trajectory of these lagging regions, we investigate a new instrument to highlight local (urban level) potentials. Adding spatial network analysis can "absorb" the complexity by understanding the interactions in the regional systems and economic clusters.

Furthermore, it reveals a spatial dimension's accurate and complete structure for the innovation network to track the knowledge flow. From this point of view, we believe that the network analysis method could be a tool to measure a local system's resilience capacity. At the same time, a new perspective for predictive knowledge flows rate modelling. Additionally, through dynamic studies of spatial networks, we will better understand the

evolution of networks across time and space, translating to the cross-sectorial nature of Emerging Industries.

### 3. Methodology

We have considered Knowledge Diffusion Structure as the center point of this research, as a deep source for the shifting dynamics from supply-demand carbon to provide and support services [78]. Porter claims that today's local clusters are typical because competitive advantages increasingly lie in local things, such as knowledge, relationships, motivation, enabling continuous innovation [79]. The local pool of knowledge regarding a local labour market of experts and skilled labour is significant [64]. In the period of knowledge categorization, we can claim that knowledge is easier to understand than diffuse. Thus, tacit knowledge may be foreknowledge of undiscovered things and their implications, for example, in science [80]. Knowledge is thus easier to diffuse within a community made up of agents who can read the codes (the language) [81], but, in general, it is cheaper to transfer codified knowledge than tacit knowledge [81]. As we know, the community is interchangeably used by social scientists as the term network as an alternative to traditional conceptions of the community as locally bounded [82]. As long as we discovered there is no concrete definition for the knowledge economy, as mentioned earlier, it could play a critical role for territories to learn their economic potentials, relied on the *"knowledge economies are not defined in terms of their use of scientific and technological knowledge (...). Rather, they are characterized by exploiting new knowledge to create more new knowledge"* [83]. The mentioned statement demonstrates the fact of complexity, and a complex system is the source of exponential growth for its property. In other words, we can claim knowledge is easier to create and diffuse in a complex ecosystem; thus, the productivity of a territory (Local) in this paper is firmly correlated to the level of complexity of the economic network.

The experimental research method first forms the local innovation network based on the Porter cluster-based analysis algorithm. Then by introducing labour (employees) commuting to work/home in the same cluster as a proxy of the tacit/codified knowledge transfer emphasis on the unnegotiable dimension of the local units by connecting the nodes in the first level. The second stage is to contextualize the nodes based on their geographical coordination to create a georeferenced model (see Figure 4) having nodes assigned with two properties form a multiplex network formation. Finally, the nodes will connect as a proxy to an interaction (transferring knowledge in this paper). In the next chapter, we will detail the possible connection scenarios and the network structure due to the research perspective.

In essence, this paper performs a thorough sequential analysis of the Economic Network of Calabria as a case study to reveal its undiscovered complexity. Social Network Analysis (SNA) is both a theoretical perspective on how the interactions of individual autonomous actors form the social structures of a community and a set of analytical tools to analyze those interactions and social systems as networks of nodes (actors) and ties (relationships). Some earlier scholars questioned the claim that SNA represents a distinct body of theory [84,85]. There are many different coherent definitions elaborated by [85], but the gap in this theory is the analytic application. To go more in detail, SNA is customarily applied to the so-called Newman [86] definition of four 'loose categories' from those technological networks that will be considered for this research. This approach focuses on the structure and possible connections to form a graph to ease mathematical modelling and possible algorithms for network measuring. What makes SNA suitable for innovation investigation is rigorously perspective to the interaction and complexity of the system [87].

Networks may be modelled using dots or "nodes" to represent actors in the web and lines between the dots to define the relationships or "ties" between actors. Actor attributes are associated with the nodes, and the complete set of actor attributes is the network composition [82]. The pattern of all the ties between actors in the network structure [84]. In this structure, we are encouraged to investigate the flow, and historically the flow model

is based on a pathway and the thing which transfer between a node to be more evident in this research; we are tracking the knowledge (knowledge flow) between the LMA and local business to demonstrate an appropriate form of local potentials in global calls for digital and ecological transition.

### 3.1. Forming Spatial Economic Networking Analysis (SENA)

The reasoning in this research follows Porter efforts on the Cluster mapping project [88], which uses Cluster-Based analysis and recent European Panorama of Clusters and Industrial Change [72] to investigate the economic structure of a local area. Thus, we aim to demonstrate a novel classification model for the innovation structure of a region. Following this aim, we try to map the network in local dimensions, and the expected result would be the critical nodes both in the Economic layer and local dimension. To generalize our tool, we consider the cluster mapping methodology as a comparable defragmenter strategy where we can claim each single "Cluster" of this structure could be set side by side to the same one in another territory in this way. There are opportunities for applying the following levels of this methodology to compare regions or even possible ranking tables. To describe more in detail in this strategy, the economic sectors are grouped based on the algorithm as mentioned earlier to construct the traded (export) clusters which for us hereafter named proxy of "innovation", then, these nodes will be considered as a hinge between LMAs where the labour (the transformers of knowledge) commute and sharing those in the same time (a temporal unit such as a specific year) hereafter we call this proximity as temporal proximity in the innovation network. In short, two (or more) LMAs are connected when they share the labour force inside a so-called cluster in a specific sector (4 digits) in the same year. The proposed tool, Spatial Economic Networking Analysis (SENA), is compound by the networking structure for analyzing the system's complexity as an a-dimensional model to capture the spreading nature of the innovation. The so-called graph consists of nodes (2 modes) of LMA as spatial dimension and sectors of a cluster (4 digits) as the bridge to the economic structure of the same territory. The next step is grouping sectors and forming a distribution layer of the named cluster in a specific year. Aforementioned leads to the following:

#### 1. Spatiotemporal analysis: Network of all clusters of a region

This model is a vast panel data analysis form suggested in this research; to create this, we conduct a three-fold investigation in the same spatial dimension. At first glance, sectors are fragmented and act solely in the territorial unit (maximum granulite of network components). The LMA are connected if they share labour who commute for having served in a sector simultaneously. In this definition, the nodes and the connections (the strength and degrees) have the potential to sort and classify. To compare the actual classification with the standard clustering algorithm (Porter), we run the simulator, where the larger the number of overlaps, the better-shaped network to transfer the innovation. In other words, when the network forms the same cluster patterns (coupling the same group of economic sectors together) based on the referenced list (51 Clusters table) in iterations (500 turns), we evaluated this as the high probability of innovation network formation in the region. Then, we applied the time as dynamic criteria of the system to check whether the nodes tend to form spatial clusters? It means if the same pattern of nodes connection is remaining steady in 7 successive years. From this perspective to the proposed network, one could confidently define system failures such as hemophilia (coupling to the same sort of nodes in different layers based on a unique connection characteristic [89]), isolations, locked-in, and other structural bugs of the network. (See Figure 4) At the final stage, this analysis could identify the most influencing cluster of the territory that we will explain later.

#### 2. Intra-cluster analysis: Investigate specific cluster over local units

This dynamic study can demonstrate the significance of a node (either spatial unit or economic sector) inside a cluster, this type of analysis could simulate the network in a way to experience a shock facing the selected local area and track the cluster behaviour and its

components via scoring general distribution of specific innovation network over the region benefiting from time sequences. This model is proposed to check a region's innovation network considering the most potent/weakest sector(s)/spatial nodes of a region. In this experience, the unique identity of the cluster and its contribution to the LMAs are examined, then, as mentioned earlier, by highlighting the centerpiece, the potential for opening new windows for robustification [90] of the structure can be implemented. The next step for this exploration will be a selection method for sectors or LMAs ready to emerge to be considered nodes for emerging industries.

### 3. Emerging industries : Cross-Sectorial selection of the nodes due to the emergence theory [91]

This level for sorting sectors is highly dependent on a novel perspective to the interconnection between economic sectors of territory and complex system theory [92]. To capture this level of complexity, the model investigates the two mentioned stages simultaneously; then, by suggesting the best choices, we can examine the model accuracy with the actual trained sorted list of so-called Emerging Industries. The higher overlapping concerning the complete possible network, the more accurate the model is. Emerging industries are a possible futuristic contribution of this method to the innovation structure. One can evaluate this method to claim these industries as a response to global megatrends where the novel economic structure is struggling within the transitional phase. In other words, since the future shocks are yet to encounter, their response is structural. Thus, the most flexible, pioneer, and cross-sectoral economic structure formation could be considered a response.

It is essential to mention that we are aware that the local identity, historical background, and entrepreneurship process could bias the model results. However, this first step is only a novel perspective and yet calls for elaboration.

#### 3.2. Case Study: SENA of Calabria Region

Forming a data frame is an essential stage to conduct this experiment. To respond to this requirement, we extract the economic data (Number of enterprises and labour force in those enterprises) from The Italian National Institute of Statistics (ISTAT); To be more precise and follow the research line of reasoning, first, we aggregate the city level data to LMAs based on the geographic distribution of them over the Calabria region. In this way, 44 LMAs are created, named, and placed as the vertical axis of the data frame. Next, Cluster's data is aggregated based on the LMAs. Both the number of enterprises and the number of employees are taken into consideration for each period; in this way, the horizontal axis of the data frame is formed. Finally, the data frame for the first year (2012) of 51 clusters (Porter methodology) is elaborated. This data frame demonstrates the local level data over the 2012–2018-time span annually (Table 1).

**Table 1.** This is a table. Tables should be placed in the main text near to the first time they are cited.

Data Source	Elaboration	Territorial Unit	Observation period	Cluster	N° Establishments	N° Employees
ISTAT (National Census Bureau) Municipality (NUT 3) Region (NUT 2) Italia (NUT 1)		LMA – 45 (Calabria Region)	2012-2018	NACE 4 digit aggregation based on Traded Cluster and Emerging Industries	NACE 4 digit per cluster and LMA	NACE 4 digit per cluster and LMA

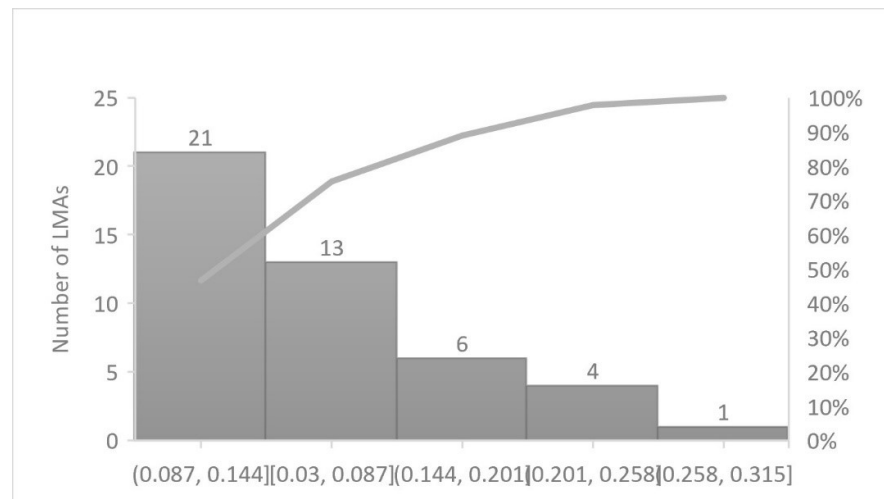
The next step is data preparation for spatial networking analysis. This level consists of extreme detection, data validation and data frame transfer to create an adjacency matrix. (Table 2).



**Table 2.** LMA and Sectors Adjacency Matrix.

Sectors	1801	1802	.	.	.	1845(5555)
510	1	1	.	.	.	1
610	1	1	.	.	.	1
620	1	1	.	.	.	1
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
9329	0	0	.	.	.	1

The real adjacency matrix's inverse (full rank transpose) matrix is illustrated. Due to the multisector nature of the region, the structure is sparse. There are  $(384 \times 45)$  17280 records among them less than 20 per cent non-zero pairs found (Figure 2). The weight (redundancy) for those paired connections is above the local (same cluster) average, which could interpret as a few nodes playing significant roles in the global (all clusters) network.

**Figure 2.** Connection Probability chart of Inverse Network (Calabria Region)

To develop a comprehensive network, we checked all anomalies and extremes of the report. To some extent, data was precise, but some cities belonged to overlapped LMA or sudden shutdown of an industry in a specific year and reopening in further years where the issues are required special attention and avoid relying solely upon automatic algorithm development. To elaborate the matrix, two forms of connection are taken into consideration; on the one hand, we investigate whether those nodes are connected into a network and then evaluate the network total size (total of vertex pairs) [93] and on the other hand figuring the connection weight, node diameter and classic networking analysis attribution such as centrality, degree and etc. [40]. We decided to do both. However, the permutation adjacency matrix could be considered as big data due to more than 17000 observations. However, thanks to the nature of the binary analysis, the Software (Gephi™) [94] did handle them in a reasonable time. To enumerate the weights of connection, we made good the reported number of employees and enterprises and replicated the connections and the node diameter based on mentioned numbers, respectively.

To import the Matrix in the software, we considered the numbers (matrix digits) as a string data due to the average commuter from LMA X to Sector Y, these numbers are flows by one decimal. The connections are considered undirect since the relationship between two nodes are considered as coincident in conceptual spatiotemporal system and has no priority whatsoever. After importing the data, a year (2013) due to random selection by

automatic bot of Python™ taking into consideration for cluster selection we select purposefully Education sectors to demonstrate the knowledge infrastructure of the context. To form an interpreted, visualized, and robust structure, the following algorithms are conducted. Force Atlas 2 [95] is a force-directed layout: it simulates a physical system to specialize a network. Nodes repulse each other like charged particles, while edges attract their nodes, like springs. These forces create a movement that converges to a balanced state. This final configuration is expected to help the interpretation of the data[95]. The Fruchterman-Reingold [96] layout works well for many large social networks, though it may require some adjustment. It is an example of a force-directed algorithm that uses an analogy of physical springs as edges that attract connected vertices and a competing repulsive force that pushes all vertices away from one another, whether connected. It typically results in relatively similar edges in length, though the size of advantages has no specific meaning in most network visualizations. The algorithm uses an iterative process to adjust the placement of the vertices to minimize the “energy” of the system. Due to iterative nature of this layout, it runs repeatedly, each time incrementally changing the position of each vertex based on the last part. Then to connect LMAs nodes to their geographic position, the Geo layout algorithm applied. The nodes are partitioned by their relative degree (number of connections), the connectivity investigated and demonstrated by the line weight and the economic sectors and LMAs are divided by the color.

At the final step, the network diameter as a general characteristic of the graph [97], the average degree of the nodes as the level of beneficiation of in innovation network [98] and bridging centrality (BNC) [98] are calculated and stored in an elaborated data frame. Over next chapter we will go more in detail about the particular findings in the complex network elaborated based on abovementioned data frame.

#### 4. Results and discussion

In this chapter, we present the regions’ innovation network results from 3 perspectives. First, the outcome of the investigation on Calabria as a single territorial dimension will be explained; in this view, we look over the spatiotemporal level of the network to capture the complexity of innovation network in terms of which economic sectors are influencing the technological change and in an inclusive term how the region’s structure is prepared to absorb the complexity? (Figure 3)

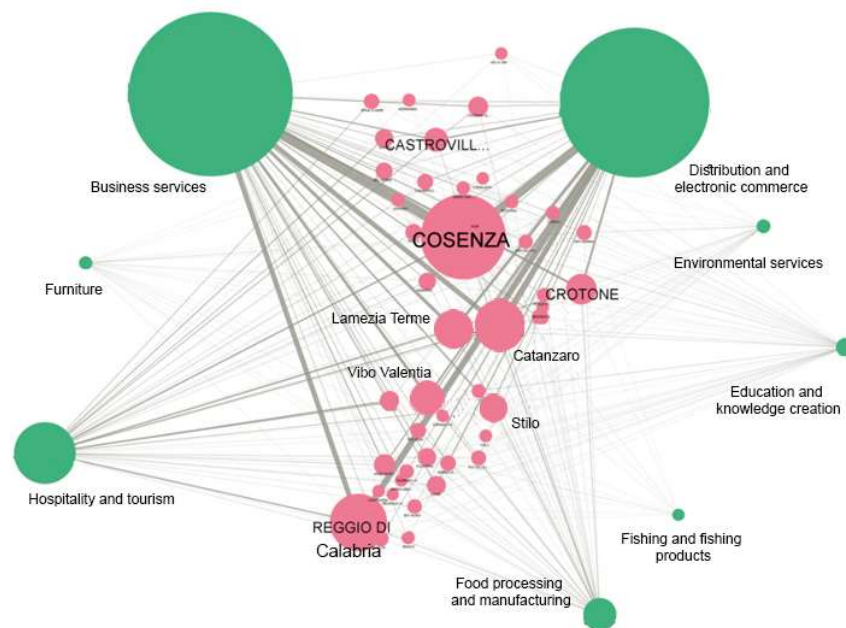
Next, the education cluster, as an example in this case study, has been illustrated to highlight hubs [99], weak points [100] topologies mentioned earlier. This type of analysis helps us find the possible path for transition inside a single network (See Figure 4). Lastly, in the final subchapter, we will focus on the emerging industry as the future forecast of the research, which is the contribution of the complex network of each region to the global megatrends. In this way, the future forecasting nature of the network formation will be addressed (Figure 5).

##### 4.1. SENA Calabria region Innovation Network

To see the phenomena from a different perspective, we generate a new network model (See Figure 3), importing all Clusters (51) existing in the Calabria and crossing them to temporal proximity as mentioned earlier in methodology. In this experiment, the green nodes (the cluster) size is proportional to the proximity established with LMA(s), where the line weight advocates the number of employees is sharing simultaneously. As expected, although the central city engines (Cosenza and Reggio Calabria) are engaged where this model highlights other medium-size cities playing fairly positive roles. The disparity (North-South) is no more vivid; hence, the Lamezia Terme, Catanzaro, Vibo Valentia, Crotona and Castrovillari established reliable connections to the region’s main active clusters, respectively. Clusters are not evenly facilitated due to local resources, scarcities and possible knowledge miss diffusion, However, as a national habit the business and Hospitality are among the top 5 influencing clusters of Calabria, but it is essential to name "Distribution and electronic commerce" as a well-functioning economic potential of

the territory. Due to the territorial resource in the Blue Economy, the time series (Dynamic) networking analysis on the "Food production" cluster is highly recommended for future studies as underlying by European union on the new studies on the emerging industries along with maritime ecological, logistics and food supplies as blue growth. As mentioned earlier, although Hospitality is historically forming among the best industries in Italy and Calabria as the province, it is a large gap between the essential potentials of the region and the degree of betweenness (contribution to innovation network) of Hospitality and tourism as a cluster of services. This lag can be described in the digitalization phase, where the accommodation, advertisement and quality auditing services are radically changed.

**Figure 3.** SENA network of 8 clusters in Calabria in 2018. Pink nodes = LMAs, and green nodes = clusters. The size of LMA node reflects the total no. of units in all clusters found in that LMA, whereas size of cluster's node is the aggregated no. of units in that cluster

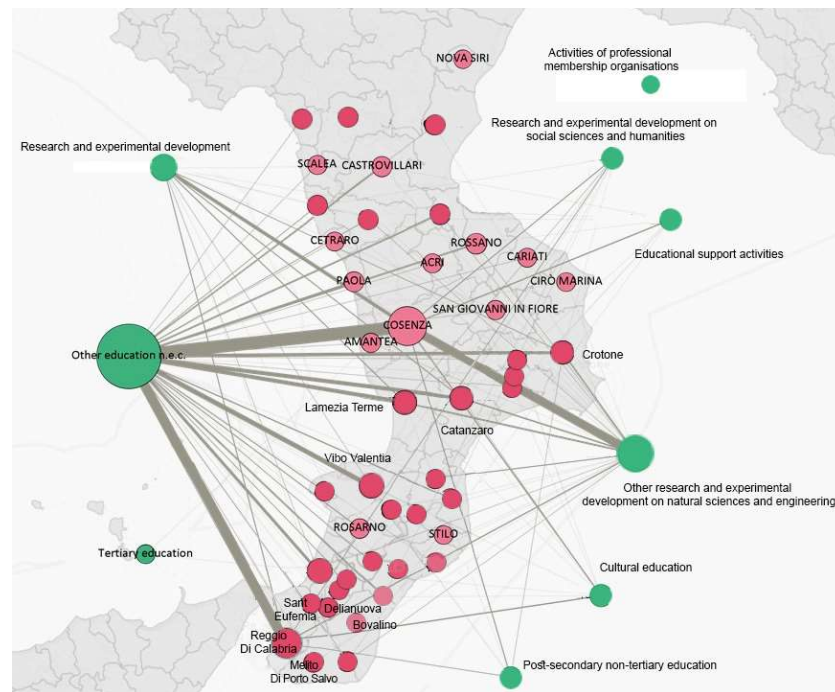


#### 4.2. SENA Education and knowledge creation cluster

This process's first level (intra-cluster perspective) results include 45 interactive network nodes highlighted in red, while nine of the Education 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 well 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", where 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 the Cosenza and Reggio Calabria as the primary hosts of the Calabrian Universities are located, not only university studies but the research sector both complicated/software of the knowledge creation are well connected to them however the Cosenza has strong connection even with other components of the Education clusters.

**Figure 4.** SENA Education and knowledge creation cluster in Calabria in 2013. 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 size of the sector's node is the aggregated no. of establishments in the corresponding sector.



Lastly, for this subchapter, we can stress the digitalization, the high accessibility of online education even before the Pandemic leads the "Other Education" sector to the top rank of this cluster [92] where even the weakest points of this network have some degree of connection to this service. However, contrary to this, the rest of the cluster members are not well performed in network expansion and hub creation.

#### 4.3. SENA Emerging industries: Blue Growth

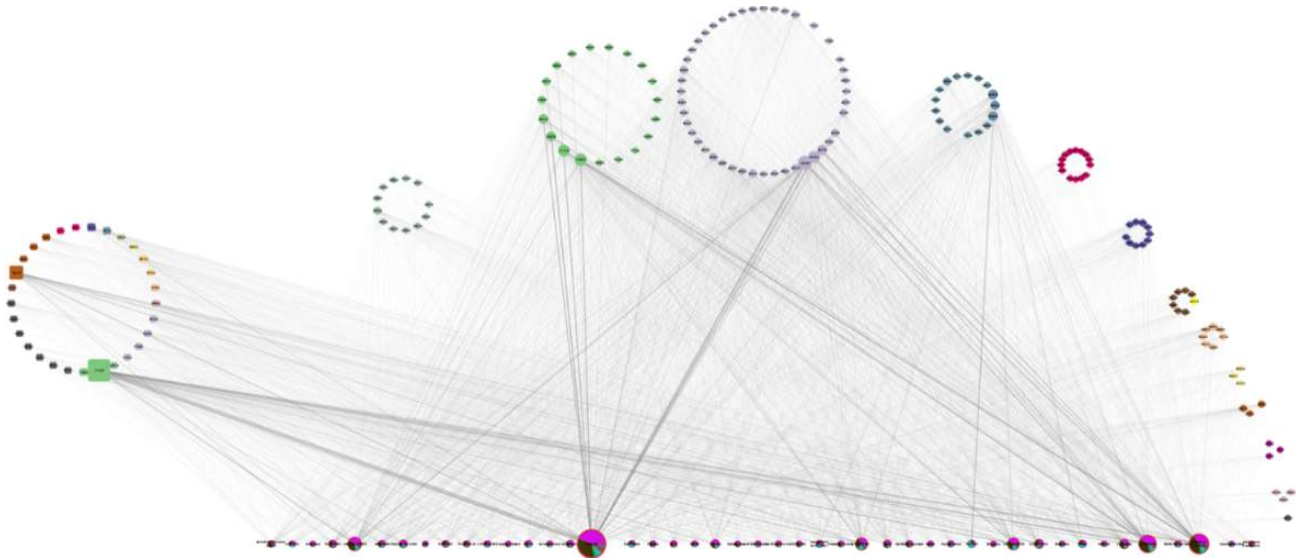
In the last part of this chapter, we investigate the forecasting model for the Blue Growth as one of the emerging industries. The primarily generated graph demonstrates the LMA(s) on the horizontal line; hence an arc of contributing clusters has sounded the region. More precisely, clusters are selective compared to the base economy definition. Thus, this a-dimensional modelling tends to characterize the degree of relevance between the regional preparedness for the transition and the share of each cluster as a critical mass (as one of the cluster strength indicators in specialization). As elaborated earlier, marine life, economy and growth is essential property of the Calabria. The Service sectors in different clusters are creating the backbone for the future of the Blue Growth industries, which can translate as a trend from production to service economy. As illustrated in the network (See Figure 5), the next step for digitalization will surely pass through the eco-digitalization of services. Another exciting fact harvested from this complex structure is, However, Cosenza is considered a hinterland territory, but services' agglomeration made these LMAs the central hub. The variety of the sectors (high number of the contributors) and the homogeneity in the nodes' degree (representing the level of connection) is considered close to a statistically normal distribution, which can be interpreted as a state in which the network is ready to emerge. The environmental service sectors are fully integrated into the system, demonstrating a more interactive, eco-friendly future of this class of industries.

All in all, in this network, it is obvious that emerging industries are the most competitive arena where, However, even more than half of the cluster sectors remain deactivated. However, diversification plays a critical role in the innovation ecosystem. In other words,

the more diversification in this structure, it is easier to capture a higher level of transition waves, thus better performance.

This model is still on the first step for simulation, forecasting and policy estimation frameworks where we can vigorously investigate the future of the complex transition scenarios at the city level; as mentioned in the first chapter, it is essential to respond to the global transition requirements in local (city) level in thus, having a new perspective to cross-sectorial future industries those forming critical mass for megatrends is essential.

**Figure 3.** SENA network of all clusters that are contributed to form Blue Growth (BG). The circle on the left shows sectors that shape Blue Growth industries. The other circles identify the clusters in which BG's sectors are from. Horizontal line is the LMAs in a region



## 5. Conclusions

Tables are weak in demonstrating the relations and dynamics between the components in a complex system. Therefore, there is a need for another modelling framework that can better capture these 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 networking analysis techniques potentials in the economic geography for exploring the complexity of context to face an inclusive transition. We saw how the regions' LMAs (as a proxy for local units) and clusters (as a proxy to innovation economy sectors) are integrated and evaluated the level of preparedness of the context (See Figure 3). In a more specific approach, we evaluated the Education network (See Figure 4) as a proxy to the knowledge and research infrastructure of the region; in this way, we examined the competency of the cluster sectors and the connection between cities benefiting the proximity thanks to the sharing same sector employees. We observed the core-periphery image of the network even at the local level, which calls for an inclusive transition to avoid a new era of disparities. We investigate a novel approach to the innovation economy to see how far we can go with networks and to what extent we can get a network of complex systems, emerging industries. 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. (See Figure 5) Proposed Networking analysis methods do not only act as a graph to illustrate a phenomenon but, as demonstrated earlier, are 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. Networking analysis has the potential to overlap layers (different annotation for a node in various

coordination) and create multi-variant functions. Due to the nature of the innovation economy and the evolutionary transition, it has probabilistic results for a large number of applications.

In sum, Networks are an appropriate conceptualization of inter-organizational interaction and knowledge flows. We claim that spatial economic network analysis (SENA) for clusters is a promising tool for future directions in regional research. We believe that in order to understand complex economic networks, one should start with the visualization of the network itself. The visualization of cluster networks is helpful for the management of firms and cluster policies. Our study tried to quantify the structural complexity of the industry clusters and emerging industries 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. Weighted and Bipartite networks help us to allow different node types in the same network and customize the resulting visualization [94]. As in the recent decade, elaboration in computer science and human studies upsurge of interest in the dynamics of networks has been experienced. We examined in our study, but not included in this paper, the intr-organizational interactions and their evolution over time (7 years) and see how the network changed dynamically. We believe spatial network analysis helps predict/highlight different levels of Hubs which reveals the way hubs, markets, and their borders are entangled with one another [99].

For future development, we see that understanding the performance of the industry clusters could be well examined if we add different aspects. For example, they are investigating the innovative behaviour of a cluster of investments trend. Following this point, Multilayer networks or Multiplex networks would be our next step of analyzing and understanding clusters and firms in a region. The following steps could highlight the AI role in this algorithm, forecasting the coupling nodes, the spatial dimension of possible network failure, and the opportunities to develop new sectors for emerging industries reveals. First, a proper model for implementing a policy is critical to estimating, evaluating, and monitoring the outcomes. Network modelling could innovatively play this rule to illustrate and compare the dynamics benefiting from rich literature of statistical analysis of networking data (more than 400 literature highlighted the statistical analysis of network). Third, comparing the future trend with the existing scenario help planners to have a real-time estimation for their decisions. Discovering novel indices based on the network formation leads the urban planning strategies agile enough to respond to the technological shifts towards post-carbon transition.

To build smart cities that can leverage the full potential of innovation for residents' well-being and foster inclusive growth, all levels of government should leverage digitalization to deliver more efficient, sustainable, affordable, and comprehensive local services. To prepare for a sound transition, digitalization should follow its context-specific factors. The one size made remedy will not be effective, and the fundamental for this achievement is understanding the complexity. The complexity neither can be reduced nor neglected but absorbing the dimensions requires a holistic perspective. An inclusive action plan where no one is left behind and forecasting the future struggles to invest wisely, estimate justly and compare rationally. City as a living environment cannot be dealt with as a unilateral built-scape. The city in the transitional phase has already become an era for diversity; as mentioned in this paper, every local unit contributes to the sector (economic agent) to influence the whole network and host the transition. Due to this fact, multidisciplinary planning plays a critical role. As mentioned earlier, this research paper is the first step to sketch a new perspective for inclusive urban planning to pay off its contributions to the ecosystem. Furthermore, the networking analysis is a novel instrument yet to calibrate, adopt and redesign for new scenarios in urban transition modelling. Therefore, AI can be involved in this area of research where we can run complex calculus algorithms to create indices.

In this paper, we illustrated and analyzed different types of economic networks. We consider the visualization of economic networks to be helpful for the investigation of companies and industry clusters in their context and their relation to it. Furthermore, such a visualized network will be helpful to highlight the potential of the developing regions, which will help attract new investors.

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## References

1. Balland, P.-A.; Boschma, R. Complementary Interregional Linkages and Smart Specialisation: An Empirical Study on European Regions. *Regional Studies* **2021**, *55*, 1059–1070.
2. Balland, P.-A.; Boschma, R. Mapping the Potentials of Regions in Europe to Contribute to New Knowledge Production in Industry 4.0 Technologies. *Regional Studies* **2021**, 1–15.
3. Hidalgo, C.A.; Hausmann, R. The Building Blocks of Economic Complexity. *Proceedings of the national academy of sciences* **2009**, *106*, 10570–10575.
4. Loorbach, D.; Rotmans, J. The Practice of Transition Management: Examples and Lessons from Four Distinct Cases. *Futures* **2010**, *42*, 237–246.
5. Hidalgo, C.A. Economic Complexity Theory and Applications. *Nature Reviews Physics* **2021**, *3*, 92–113.
6. Davoudi, S.; Shaw, K.; Haider, L.J.; Quinlan, A.E.; Peterson, G.D.; Wilkinson, C.; Fünfgeld, H.; McEvoy, D.; Porter, L.; Davoudi, S. Resilience: A Bridging Concept or a Dead End? “Reframing” Resilience: Challenges for Planning Theory and Practice Interacting Traps: Resilience Assessment of a Pasture Management System in Northern Afghanistan Urban Resilience: What Does It Mean in Planning Practice? Resilience as a Useful Concept for Climate Change Adaptation? The Politics of Resilience for Planning: A Cautionary Note: Edited by Simin Davoudi and Libby Porter. *Planning theory & practice* **2012**, *13*, 299–333.
7. Davoudi, S.; Brooks, E.; Mehmood, A. Evolutionary Resilience and Strategies for Climate Adaptation. *Planning Practice & Research* **2013**, *28*, 307–322.
8. Garud, R.; Kumaraswamy, A.; Karnøe, P. Path Dependence or Path Creation? *Journal of management studies* **2010**, *47*, 760–774.
9. Lahr, M.L.; Ferreira, J.P. A Reconnaissance through the History of Shift-Share Analysis. *Handbook of regional science* **2021**, 25–39.
10. Organization (WMO), W.M.; World Meteorological Organization (WMO) *Global Climate in 2015–2019*; WMO; Update.; WMO: Geneva, 2020;
11. Mazzucato, M. Mission-Oriented Innovation Policies: Challenges and Opportunities. *Industrial and Corporate Change* **2018**, *27*, 803–815.
12. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Messner, D.; Nakicenovic, N.; Rockström, J. Six Transformations to Achieve the Sustainable Development Goals. *Nature Sustainability* **2019**, *2*, 805–814.
13. Directorate-General for Research and Innovation (European Commission) *EU Research & Innovation for and with Cities: Yearly Mapping Report : September 2017*; Publications Office of the European Union: LU, 2018; ISBN 978-92-79-97736-7.
14. European Commission. Joint Research Centre. *Annual Report 2019 :Joint Research Centre, the European Commission’s Science and Knowledge Service*; Publications Office: LU, 2020;
15. Martinez, C. Monitoring the Transition to a Low-Carbon Economy. 101.
16. Henderson, K.; Pinner, D.; Rogers, M.; Smeets, B.; Tryggstad, C.; Vargas, D. Climate Math: What a 1.5-Degree Pathway Would Take. *McKinsey Quarterly*, April. <https://www.mckinsey.com/business-functions/sustainability/our-insights/climate-math-what-a-1-point-5-degree-pathway-would-take> **2020**.
17. Eraydin, A. “Resilience Thinking” for Planning. In *Resilience thinking in urban planning*; Springer, 2013; pp. 17–37.

18. Geels, F.W.; Schot, J. Typology of Sociotechnical Transition Pathways. *Research policy* **2007**, *36*, 399–417.
19. Barnes, A.; Nel, V. Putting Spatial Resilience into Practice. In Proceedings of the Urban Forum; Springer, 2017; Vol. 28, pp. 219–232.
20. Chelleri, L.; Waters, J.J.; Olazabal, M.; Minucci, G. Resilience Trade-Offs: Addressing Multiple Scales and Temporal Aspects of Urban Resilience. *Environment and Urbanization* **2015**, *27*, 181–198.
21. Andreucci, M.B.; Marvuglia, A. Investigating, Implementing and Funding Regenerative Urban Design in a Post-COVID-19 Pandemic Built Environment: A Reading Through Selected UN Sustainable Development Goals and the European Green Deal. In *Rethinking sustainability towards a regenerative economy*; Springer, 2021; pp. 395–413.
22. Do, H.; Budhwar, P.S.; Patel, C. Relationship between Innovation-Led HR Policy, Strategy, and Firm Performance: A Serial Mediation Investigation. *Human Resource Management* **2018**, *57*, 1271–1284.
23. Jiménez-Jiménez, D.; Sanz-Valle, R. Innovation, Organizational Learning, and Performance. *Journal of business research* **2011**, *64*, 408–417.
24. Medic, N.; Anisic, Z.; Tasic, N.; Zivlak, N.; Lalic, B. Technology Adoption in the Industry 4.0 Era: Empirical Evidence from Manufacturing Companies. In Proceedings of the IFIP International Conference on Advances in Production Management Systems; Springer, 2020; pp. 115–122.
25. Martín-Peña, M.-L.; Sánchez-López, J.-M.; Díaz-Garrido, E. Servitization and Digitalization in Manufacturing: The Influence on Firm Performance. *Journal of Business & Industrial Marketing* **2019**.
26. Ardolino, M.; Rapaccini, M.; Saccani, N.; Gaiardelli, P.; Crespi, G.; Ruggeri, C. The Role of Digital Technologies for the Service Transformation of Industrial Companies. *International Journal of Production Research* **2018**, *56*, 2116–2132.
27. Hassankhani, M.; Alidadi, M.; Sharifi, A.; Azhdari, A. Smart City and Crisis Management: Lessons for the COVID-19 Pandemic. *International Journal of Environmental Research and Public Health* **2021**, *18*, 7736.
28. Cities Policy Responses - OECD Available online: [https://read.oecd-ilibrary.org/view/?ref=126\\_126769-yen45847kf&title=Coronavirus-COVID-19-Cities-Policy-Responses.%20Accessed%2010%20Nov%202021](https://read.oecd-ilibrary.org/view/?ref=126_126769-yen45847kf&title=Coronavirus-COVID-19-Cities-Policy-Responses.%20Accessed%2010%20Nov%202021) (accessed on 10 December 2021).
29. Santoalha, A.; Boschma, R. Diversifying in Green Technologies in European Regions: Does Political Support Matter? *Regional Studies* **2021**, *55*, 182–195.
30. Fröhlich, K.; Hassink, R. Regional Resilience: A Stretched Concept? *European Planning Studies* **2018**, *26*, 1763–1778.
31. Laaha, G.; Skøien, J.O.; Nobilis, F.; Blöschl, G. Spatial Prediction of Stream Temperatures Using Top-Kriging with an External Drift. *Environmental Modeling & Assessment* **2013**, *18*, 671–683.
32. Cumming, G.S.; von Cramon-Taubadel, S. Linking Economic Growth Pathways and Environmental Sustainability by Understanding Development as Alternate Social–Ecological Regimes. *Proceedings of the National Academy of Sciences* **2018**, *115*, 9533–9538.
33. Söderholm, P. The Green Economy Transition: The Challenges of Technological Change for Sustainability. *Sustainable Earth* **2020**, *3*, 6, doi:10.1186/s42055-020-00029-y.
34. Pita, M.; Costa, J.; Moreira, A.C. Entrepreneurial Ecosystems and Entrepreneurial Initiative: Building a Multi-Country Taxonomy. *Sustainability* **2021**, *13*, 4065, doi:10.3390/su13074065.
35. *Green Planet Blues: Critical Perspectives on Global Environmental Politics*; Conca, K., Dabelko, G.D., Eds.; 5th ed.; Routledge: New York, 2019; ISBN 978-0-429-49374-4.
36. Regional Inequality in Europe: Evidence, Theory and Policy Implications | Journal of Economic Geography | Oxford Academic Available online: <https://academic.oup.com/joeg/article-abstract/19/2/273/4989323> (accessed on 11 December 2021).
37. Rodrigue, J.-P.; Notteboom, T. The Terminalization of Supply Chains: Reassessing the Role of Terminals in Port/Hinterland Logistical Relationships. *Maritime Policy & Management* **2009**, *36*, 165–183.
38. Emmert-Streib, F.; Tripathi, S.; Yli-Harja, O.; Dehmer, M. Understanding the World Economy in Terms of Networks: A Survey of Data-Based Network Science Approaches on Economic Networks. *Frontiers in Applied Mathematics and Statistics* **2018**, *4*, 37.
39. Montana, J.; Reamer, A.; Henton, D.; Melville, J.; Walesh, K. Strategic Planning in the Technology-Driven World: A Guidebook for Innovation-Led Development. **2001**.
40. Jackson, M.O. *Social and Economic Networks*; Princeton university press, 2010;
41. Barabási, A.-L. Network Science. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **2013**, *371*, 20120375.
42. Borgatti, S.P.; Mehra, A.; Brass, D.J.; Labianca, G. Network Analysis in the Social Sciences. *science* **2009**, *323*, 892–895.
43. Fang, J.; Wang, X.; Zheng, Z.; Bi, Q.; Di, Z.; Xiang, L. New Interdisciplinary Science: Network Science (1). *PROGRESS IN PHYSICS-NANJING-* **2007**, *27*, 239.
44. Schweitzer, F.; Fagiolo, G.; Sornette, D.; Vega-Redondo, F.; White, D.R. Economic Networks: What Do We Know and What Do We Need to Know? *Advances in Complex Systems* **2009**, *12*, 407–422.
45. Wasserman, S.; Faust, K.; Urbana-Champaign, S. (University of I.W. *Social Network Analysis: Methods and Applications*; Cambridge University Press, 1994; ISBN 978-0-521-38707-1.
46. Freeman, L. The Development of Social Network Analysis. *A Study in the Sociology of Science* **2004**, *1*, 159–167.
47. Hughes, M.; Nagurney, A. A Network Model and Algorithm for the Analysis and Estimation of Financial Flow of Funds. *Computer Science in Economics and Management* **1992**, *5*, 23–39.
48. Smith, D.A.; White, D.R. Structure and Dynamics of the Global Economy: Network Analysis of International Trade 1965–1980. *Social forces* **1992**, *70*, 857–893.



49. Lazer, D.; Pentland, A.S.; Adamic, L.; Aral, S.; Barabasi, A.L.; Brewer, D.; Christakis, N.; Contractor, N.; Fowler, J.; Gutmann, M. Life in the Network: The Coming Age of Computational Social Science. *Science (New York, NY)* **2009**, *323*, 721.
50. Chang, R.M.; Kauffman, R.J.; Kwon, Y. Understanding the Paradigm Shift to Computational Social Science in the Presence of Big Data. *Decision Support Systems* **2014**, *63*, 67–80.
51. Beije, P.R.; Groenewegen, J. A Network Analysis of Markets. *Journal of economic issues* **1992**, *26*, 87–114.
52. Boschma, R.A.; Ter Wal, A.L. Knowledge Networks and Innovative Performance in an Industrial District: The Case of a Footwear District in the South of Italy. *Industry and innovation* **2007**, *14*, 177–199.
53. Lentini, L.; Decortis, F. Space and Places: When Interacting with and in Physical Space Becomes a Meaningful Experience. *Personal and Ubiquitous Computing* **2010**, *14*, 407–415.
54. Castells, M. Grassrooting the Space of Flows. *Urban Geography* **1999**, *20*, 294–302.
55. Marshall, A. Distribution and Exchange. *The Economic Journal* **1898**, *8*, 37–59.
56. Marshall, A.; Marshall, M.P. *The Economics of Industry*; Macmillan and Company, 1920;
57. Breschi, S.; Malerba, F. Sectoral Innovation Systems: Technological Regimes, Schumpeterian Dynamics, and Spatial Boundaries. *Systems of innovation: Technologies, institutions and organizations* **1997**, *1*, 130–156.
58. Cayla, J.; Eckhardt, G.M. Asian Brands without Borders: Regional Opportunities and Challenges. *International Marketing Review* **2007**.
59. Cooke, P. Regional Innovation Systems, Clusters, and the Knowledge Economy. *Industrial and corporate change* **2001**, *10*, 945–974.
60. Zeufack, A.; Lim, K.Y. Can Malaysia Achieve Innovation-Led Growth? Available at SSRN 2630131 **2013**.
61. Halim, H.A.; Ahmad, N.H. Transforming Malaysia Towards an Innovation-Led Economy By Leveraging on Innovative Human Capital. *The Winners* **2012**, *13*, 50–57.
62. Collinge, C.; Staines, A. Rethinking the Knowledge-Based Economy. *Built Environment* **2009**, *35*, 165–172.
63. Taranenko, I. Strategic Analysis of Innovation-Based Competitiveness in the Global Economy. **2013**.
64. Porter, M.E. *Clusters and the New Economics of Competition*; Harvard Business Review Boston, 1998; Vol. 76;.
65. Staber, U. Spatial Proximity and Firm Survival in a Declining Industrial District: The Case of Knitwear Firms in Baden-Wu " Rttemberg. *Regional Studies* **2001**, *35*, 329–341.
66. Porter, M.E. The Competitive Advantage of Nations. *Competitive Intelligence Review* **1990**, *1*, 14–14.
67. Tallman, S.; Jenkins, M.; Henry, N.; Pinch, S. Knowledge, Clusters, and Competitive Advantage. *Academy of management review* **2004**, *29*, 258–271.
68. Hill, E.W.; Brennan, J.F. A Methodology for Identifying the Drivers of Industrial Clusters: The Foundation of Regional Competitive Advantage. *Economic development quarterly* **2000**, *14*, 65–96.
69. Nolan, C.; Morrison, E.; Kumar, I.; Galloway, H.; Cordes, S. Linking Industry and Occupation Clusters in Regional Economic Development. *Economic Development Quarterly* **2011**, *25*, 26–35.
70. Development, P.C. for R. Unlocking Rural Competitiveness: The Role of Regional Clusters. **2006**.
71. Ortuzar, G. Industry Clusters and Economic Development. *Indiana Business Review* **2015**, *90*, 7.
72. European Observatory for Clusters and Industrial Change Available online: [https://ec.europa.eu/growth/industry/strategy/cluster-policy/observatory\\_en](https://ec.europa.eu/growth/industry/strategy/cluster-policy/observatory_en) (accessed on 11 December 2021).
73. Tajani, A.; Hahn, J. The Smart Guide to Service Innovation. *Europäische Union, Brüssel* **2012**.
74. Suedekum, J.; Wolf, K.; Blien, U. Cultural Diversity and Local Labour Markets. *Regional Studies* **2014**, *48*, 173–191.
75. Wiseman, J.; Edwards, T.; Luckins, K. Post Carbon Pathways: A Meta-Analysis of 18 Large-Scale Post Carbon Economy Transition Strategies. *Environmental Innovation and Societal Transitions* **2013**, *8*, 76–93.
76. Cabrera, Á.; Cabrera, E.F.; Barajas, S. The Key Role of Organizational Culture in a Multi-System View of Technology-Driven Change. *International Journal of Information Management* **2001**, *21*, 245–261.
77. European Expert Group on Clusters - Recommendation Report - Luxembourg: Publications Office of the European Union, **2021**
78. Geels, F.W.; Schwanen, T.; Sorrell, S.; Jenkins, K.; Sovacool, B.K. Reducing Energy Demand through Low Carbon Innovation: A Sociotechnical Transitions Perspective and Thirteen Research Debates. *Energy Research & Social Science* **2018**, *40*, 23–35, doi:10.1016/j.erss.2017.11.003.
79. Porter, M. The Economic Performance of Regions. *Regional studies* **2003**, *37*, 549–578.
80. Doing, P. Review Essay: Tacit Knowledge: Discovery by or Topic for Science Studies? Michael Polanyi, The Tacit Dimension (University of Chicago Press, 2009), 128 Pp., ISBN 978-0-226-11380-7 (Hbk). *Social Studies of Science* **2011**, *41*, 301–306.
81. Cowan, R.; David, P.A.; Foray, D. The Explicit Economics of Knowledge Codification and Tacitness. *Industrial and corporate change* **2000**, *9*, 211–253.
82. Wellman, B.; Berkowitz, S.D. *Social Structures: A Network Approach*; CUP Archive, 1988; Vol. 2;.
83. Cooke, P. The Regional Innovation System in Wales. *Regional Innovation Systems. The Role of Governances in a Globalized World* **2004**, 245–263.
84. Kossinets, G.; Kleinberg, J.; Watts, D. The Structure of Information Pathways in a Social Communication Network. In Proceedings of the Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining; 2008; pp. 435–443.
85. Scott, J. Methods of Network Analysis. *The Sociological Review* **1991**, *39*, 155–163.

86. Dempwolf, C.S. *Network Models of Regional Innovation Clusters and Their Impact on Economic Growth*; University of Maryland, College Park, 2012;
87. Deguchi, H. *Economics as an Agent-Based Complex System: Toward Agent-Based Social Systems Sciences*; Springer Science & Business Media, 2011; ISBN 978-4-431-53957-5.
88. Huggins, R.; Izushi, H. *Competition, Competitive Advantage, and Clusters: The Ideas of Michael Porter*; OUP Oxford, 2012; ISBN 978-0-19-163598-4.
89. Jackson, M.O. Average Distance, Diameter, and Clustering in Social Networks with Homophily. *arXiv:0810.2603 [physics]* **2008**.
90. Wang, H.; Cui, W.; Xiao, Y.; Tong, H. Robust Network Construction against Intentional Attacks. In Proceedings of the 2015 International Conference on Big Data and Smart Computing (BIGCOMP); IEEE: Jeju, South Korea, February 2015; pp. 279–286.
91. Harper, D.A.; Lewis, P. New Perspectives on Emergence in Economics. *J Econ Behav Organ* **2012**, *82*, 329–337, doi:10.1016/j.jebo.2012.02.004.
92. Ladyman, J.; Lambert, J.; Wiesner, K. What Is a Complex System? *Euro Jnl Phil Sci* **2013**, *3*, 33–67, doi:10.1007/s13194-012-0056-8.
93. Kolaczyk, E.; Csrdi, G. *Statistical Analysis of Network Data with R*; 2020.
94. Bastian, M.; Heymann, S.; Jacomy, M. Gephi: An Open Source Software for Exploring and Manipulating Networks. In Proceedings of the Third international AAAI conference on weblogs and social media; 2009.
95. Jacomy, M.; Venturini, T.; Heymann, S.; Bastian, M. ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software. *PloS one* **2014**, *9*, e98679.
96. Reingold Layout - an Overview | ScienceDirect Topics Available online: <https://www.sciencedirect.com/topics/computer-science/reingold-layout> (accessed on 15 July 2021).
97. Gu, L.; Huang, H.L.; Zhang, X.D. The Clustering Coefficient and the Diameter of Small-World Networks. *Acta. Math. Sin.-English Ser.* **2013**, *29*, 199–208, doi:10.1007/s10114-012-0387-6.
98. W. Liu, M. Pellegrini and A. Wu, "Identification of Bridging Centrality in Complex Networks," in *IEEE Access*, vol. 7, pp. 93123-93130, **2019**, doi: 10.1109/ACCESS.2019.2928058.
99. Berlingerio, M. et al. 'The pursuit of hubbiness: Analysis of hubs in large multidimensional networks', *Journal of Computational Science*. Elsevier, 2(3), **2011** pp. 223–237. doi: 10.1016/J.JOCS.2011.05.009.
100. A Small World of Weak Ties Provides Optimal Global Integration of Self-Similar Modules in Functional Brain Networks | PNAS Available online: <https://www.pnas.org/content/109/8/2825.short> (accessed on 11 December 2021).