ANALYZING THE SPATIAL INTERACTIONS IN THE NATIONWIDE REGIONAL CAPITALS NETWORK OF GREECE

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Abstract

This paper studies the spatial interactions of the nationwide regional (NUTS III) capitals network in Greece, using complex network analysis and comparative methods. The study detects the topological characteristics of the nationwide spatial network composed of regional capitals and to examine how this network serves and promotes regional development. The analysis highlights the impact of spatial constraints on the network, provides information on the major infrastructure projects that have developed in the road transport sector and affected the country's transport capacity, and outlines the gravitational dimension of the nationwide spatial interconnectivity phenomenon. Overall, the paper highlights the effectiveness of complex network analysis in the modeling spatial networks and transport systems, and promotes the network paradigm in spatial and regional economics' research.

Keywords: spatial networks; centrality; complex network analysis; transport development.
JEL Classification Codes: R4, R41, R42.

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1. Introduction

The study of spatial networks has engaged researchers for decades and has been particularly fruitful in many disciplines, including regional science, economic geography, spatial analysis, transport planning, spatial planning, and the social and natural sciences. The relevant literature (Barthelemy, 2011; Rodrigue et al., 2013; Tsiotas, 2017, 2021; Stavara and Tsiotas, 2024) suggests that spatial networks can be analyzed using complex network analysis methods and can provide insights regarding their centrality, connectivity, structural configuration, and functionality. The study of network topology, conceived as the structural organization and connectivity between spatial nodes (locations, cities, prefectures), can provide insights into the spatial coherence, the efficiency of movements, and the resilience of a network to different types of disturbances. Such an analysis can contribute to detect hub cities (Berthelemy, 2011; Tsiotas and Polyzos, 2024; Khan et al., 2024), identify areas with limited connectivity, and guide decisions on infrastructure improvements. This knowledge is particularly useful in areas related to urban and regional policy and planning (Polyzos, 2019; Ruxho and Ladias, 20222; Polyzos, 2023), sustainable development strategies (Ruxho et al., 2023; Pescada et al., 2024; Sequeira et al., 2024), and crisis management (Beha and Ruxho, 2024; Ruxho et al., 2024) in the event of economic crises and natural disasters.

One of the modern scientific fields that is becoming proficient in providing modeling methods towards this direction is complex network analysis (Brandes and Erlebach, 2005; Easley and Kleinberg, 2010; Barthelemy, 2011), which has evolved into the so-called Network Science (Brandes et al., 2013). The network paradigm drives into representing communication systems as graphs (Easley and Kleinberg, 2010; Borgatti and Halgin, 2011; Tsiotas, 2017, 2021), namely as bipartite sets consisting of a collection of interconnected units (the nodes) and their interconnections (the edges). The study of network topology using graph theory and complex network analysis contributes to the understanding of the architecture, structural characteristics, and functionality of spatial networks; and the detection of hierarchy patterns (Tsiotas and Tselios, 2024), nodes of privileged connectivity, and their overall growth dynamics. A topological analysis can also provide insights into the coherence and functionality of the network, as well as its resilience to failures.

According to the network perspective, a nationwide system of spatial interconnection between regional capitals can be represented as a network (graph), in which nodes express (at the interregional scale) the regions of origin and destination (Tsiotas and Polyzos, 2013), whereas edges express distance and flow information. The study of the topology of a network connecting the regional capitals nationwide is a critical and interesting subject for various disciplines, as such a network reflects the way in which the nationwide spatial, socio-economic and transport fabrics are structured (Polyzos, 2019, 2023; Tsiotas and Polyzos, 2024). Understanding the structure of a nationwide regional capitals network can reveal information about the spatial pattern of commercial connectivity (Ruxho et al., 2022; Teixeira et al., 2024), population interaction, and service interconnection across the country, suggesting directions for optimizing spatial connections.

The study of centrality in a nationwide prefecture capital network allows also identifying the most influential or connected cities. The term “centrality” (Crucitti et al., 2006; Estrada and Bodin, 2008; Wang et al., 2011; Tsiotas, 2021) is a general concept depending on geography and functionality, and is specialized according to its use by scientific fields (Algebra, Geometry, Statistics, Physics, Geography, Regional Science). For any given geographical area there is a unique geometric or spatial center, whereas several functional centers can be traced in functional (topological) spaces depending on the volume (intensity) of the activity being under study (Tsiotas and Polyzos, 2013; Tsiotas, 2021). The common feature in each definition of centrality concerns, however, the location resulting from the optimization of a topological property. Centrality is an essential concept in understanding the structural and topological properties of both physical and immaterial systems that interact with the social and economic environment (regions, regional capital cities, cities) and contribute to the shaping of human behavior and the evolution of socioeconomic life.

The concept of centrality was introduced in Regional Science along the lines of Crystaller and Losh (Capello, 2016; Polyzos, 2019, 2023), but it has become a fundamental concept for network analysis (O’Connor, 1992) and a popular research field, following the explosive utility that social networking induced in everyday life (Kalantzi and Tsiotas, 2011). Graph Theory is a key tool in network analysis because it predominantly studies topics involving the concept of location. Graph Theory can be seen as an algebra of ordered pairs $G(V,E)$, between a countable set of vertices (or nodes or points) V and a countable set of edges (or ties or lines) E, and is part of the broader discipline of Discrete Mathematics. Essentially, Graph Theory is a calculus that focuses on the geometric position of an object, just as algebra focuses on its size (Diestel, 2005), which makes it particularly useful in the spatial and geographical disciplines.

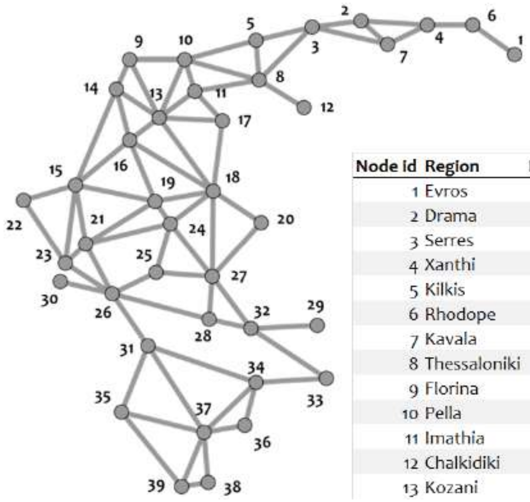
Various studies to date have measured networks centrality by spatial (geographical) reference, using Graph Theory. Some initial approaches include the study of Irwin and Hughes (1992) on the structure of urban systems, the work of Fleming and Hayuth (1994) who examined spatial characteristics of transportation hubs, the research of Crucitti et al. (2006) who worked on the centrality of urban street networks, and the study of Estrada and Bodin (2008) who used measures of network centrality to study and manage landscape. Further, Wang et al. (2010) examined the structure and centrality of air transport network nodes and the relationship (2011) between street centrality and intensity in land use. More recently, the study of Tsiotas (2021) highlighted the potential of using network metrics as economic indicators of spatial interaction and spatial pattern detection, and Tsiotas and Tselios (2024) pointed out the direction of using network measures of interregional connectivity to assess spatial patterns and the degree of cohesion in the EU. Within the aforementioned conceptual framework, this paper studies the topology of the nationwide network of regional capitals in Greece (GRCN), i.e. the network configured between the capitals of the land NUTS III Greek regions. The characteristics of this network are examined both individually, in terms of the topology and functionality of the network being constructed, and comparatively to detect time changes in centrality.

The remainder of the paper is structured as follows: section 2 presents the methodological framework, and in particular the modeling assumptions, the graph modeling, and the network analysis methods that are used. Section 3 presents the results of the analysis and discusses them in the light of regional science, focusing on the transport sector. Finally, section 4 presents the conclusions of the research.

2. Methodological Framework

2.1. Network modeling

The GRCN (Figure 1) is a network with a more economic and less physical interpretation. This spatial model represents an aspect of the nationwide road network expressed at an interregional scale (NUTS III). The construction of the GRCN essentially attempts to represent the functions and spatial land communication relationships that develop between the Greek NUTS III regions, to study the topology and economic dynamics shaped by this system of spatial and economic interactions. More specifically, the GRCN is represented in L-space (Barthelemy, 2011; Tsiotas and Polyzos, 2013; Tsiotas, 2021) as an undirected graph $G(V,E)$ with spatial weights (spatial network), whose set of nodes V represents the capitals of the Greek NUTS III regions, while the set of edges E expresses the existence of the possibility of direct land connections between the NUTS III regions of Greece. The nodes positions of the GRCN on the map (Figure 1) correspond to the geographical coordinates of the capitals of the Greek NUTS III regions, while the edges lengths represent the Euclidean kilometric distances between nodes. The choice of this particular type of nodes is made due to the economic importance of regional capitals in Regional Economics, as places of significant population concentrations (Capello, 2016; Polyzos and Tsiotas, 2020, 2023; Tsiotas and Polyzos, 2024). Due to its configuration, the resulting GRCN is a model with significant economic impact.



Node id	Region	Node id	Region	Node id	Region
1	Evros	14	Kastoria	27	Phthiotis
2	Drama	15	Ioannina	28	Phocis
3	Serres	16	Grevena	29	Euboea
4	Xanthi	17	Pieria	30	Lefkada
5	Kilkis	18	Larissa	31	Achaea
6	Rhodope	19	Trikala	32	Boeotia
7	Kavala	20	Magnesia	33	Attica
8	Thessaloniki	21	Arta	34	Corinthia
9	Florina	22	Thesprotia	35	Elis
10	Pella	23	Preveza	36	Argolis
11	Imathia	24	Karditsa	37	Arcadia
12	Chalkidiki	25	Evrytania	38	Laconia
13	Kozani	26	Aetolia-Acarnania	39	Messenia

Figure 1. Topological layout of the nationwide Greek Regional Capitals Network (GRCN), represented in *L-space* as an undirected graph with $n=39$ nodes and $m=71$ edges (the nodes in the graph represent the capitals of the NUTS III regions).

The GRCN is a *connective* network (one component), consisting of $n=39$ regional (NUTS III) capital cities (nodes) of the mainland and $m=71$ spatial links (edges) between them (Figure 1). The term *connectedness* represents the existence in the graph of at least one path between any two nodes (Diestel, 2005; Bathelemy, 2011; Tsiotas, 2021). The spatial weights $w_{s,ij} = d(e_{ij})$ of the GRCN edges express the actual kilometric distances of the shortest paths (km) connecting the regional capitals. Each edge corresponds to bi-directional segments, resulting in a symmetric adjacency matrix. Further weights in the GRCN are spacetime distances between nodes, which express the required time (min) to cover a given kilometric distance between two network locations. These values can provide an indirect indicator of the efficiency of this interregional network, since the average transit time of a route represents the quality of the road infrastructure of the network (Barthelemy, 2011; Tsiotas, 2021). From a technical viewpoint, the distances between any pair of nodes in the graph are collected in two weight matrices of the form D^{39x39}, where each element d_{ij} represents the spatial costs (Diestel, 2005; Crucitti et al, 2006) from node v_i to v_j. The first matrix includes time distances (time required to cover a given link) $D_t = [d_{ij}]$ (min) and the second of kilometric (road) distances $D_s = [d_{ij}^{E}]$ (km), between regional capital cities P_i and P_j (or nodes v_i and v_j) with $i,j = 1,...,39$.

The spatial data (geographic coordinates) used for the construction of the GRCN were obtained from Google's digital mapping services (2024), while the data of kilometric distances and time distances were obtained from the works of Tsiotas (2021) and Tsiotas and Polyzos (2013). The available data of time distances correspond to two time states (snapshots) of the inter-prefecture Greek network. The first one includes data from the year 1988, which describes the state of the national road network in its most recent past, namely in the initial stage of its modern form. The second includes data from 2010, which represents a more modern picture of the network, following the integration into the country's road infrastructure of the key upgrading projects of the *Rio-Antirrio Bridge* (set in operation in 2004) and the *Egnatia Motorway* (set in operation in 2009).

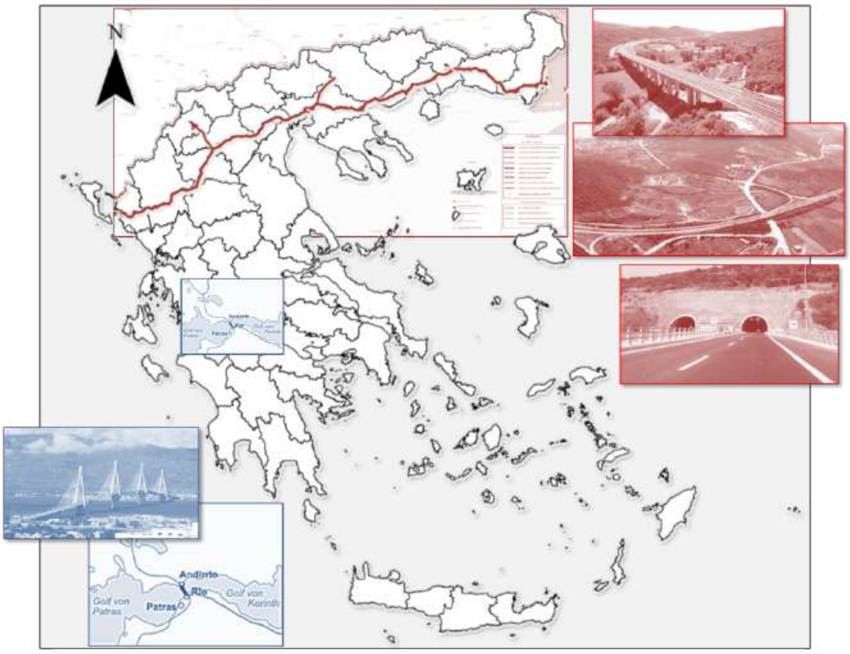


Figure 2. Map layout of Greece highlighting the location of the Rio-Antirrio Bridge and the Egnatia Motorway's path (indicative photos are included).

2.2 Network analysis

The measures of network topology used in the GRCN analysis are shown in brief in Table 1.

Table 1

Network Measures used in the GRCN's analysis

Measure	Description	Math Formula
Graph	A pair set consisting of a node-set V and an edge-set E. In graph $G(V,E)$, n is the number of nodes, and m is the number of links.	$G(V,E)$
Graph density (ρ)	The fraction of the existing (m) to the number of possible graph connections. It expresses the probability of meeting a link between two randomly chosen nodes in the network.	$\rho = m \Big/ \binom{n}{2} = \frac{2m}{n \cdot (n-1)}$
Network diameter (dG)	The longest shortest path $p(i,j)$ in a network.	$d(G) = \max\{p(i,j) \mid i,j \in V\}$
Node Degree (k)	The number of graph edges being adjacent to a given node i. It expresses the communication potential of a node.	$k_i = m(i) = m_i = \sum_{j \in V(G)} \delta_{ij} = \sum_{j \in V(G)} \delta_{ij}$, where $\delta_{ij} = \begin{cases} 1, \text{ if } e_{ij} \in E(G) \\ 0, \text{ otherwise} \end{cases}$
Node strength or weighted degree (s)	The sum of weights (w_{ij}) of the links (e_{ij}) being adjacent to a given node i. The δ_{ij} operator is the Kronecker delta function yielding one for links belonging to a graph G.	$s_i = s(i) = \sum_{j \in V(G)} \delta_{ij} \cdot d_{ij}$, where $d_{ij} = w(e_{ij})$ in km
Closeness Centrality (CC)	Is computed on the average path-lengths $d(i,j)$ originating from a given node i to all other nodes j in the network. It measures accessibility.	$CC(i) = \frac{1}{n-1} \cdot \sum_{j=1, i \neq j}^{n} d_{ij} = \bar{d}_i$
Betweenness Centrality (CB)	The proportion that is defined by $\sigma(i)$ shortest-paths that pass through a given node i to the total shortest-paths σ in the network. It expresses intermediacy.	$CB(i) = \sigma(i)/\sigma$

Measure	Description	Math Formula
Local Clustering Coefficient (*C*)	The probability of a node *i* to have *E*(*i*) connected neighbors. It is computed on the number of triangles configured by node *i* to the number of the total triplets $k_i(k_i-1)$ shaped by this node.	$C(i)=\frac{E(i)}{k_i\cdot(k_i-1)}$
Modularity (*Q*)	The objective function expresses the potential of a network to be divided into communities. In its mathematical formula, g_i is the community of node *i*, $[A_{ij}-P_{ij}]$ is the difference of the actual minus the expected number of edges falling between a particular pair of nodes *i,j*, and $\delta(g_i,g_j)$ is an indicator function returning 1 when $g_i=g_j$.	$Q=\frac{\sum_{i,j}[A_{ij}-P_{ij}]\cdot\delta(g_i,g_j)}{2m}$
Average path length $\langle l\rangle$	The average of the path lengths $d[p(i,j)]$ computed for all accessible pairs (*i,j*) of network nodes.	$\langle l\rangle=\frac{\sum_{v\in V}d\left(p\left(i,j\right)\right)}{n\cdot(n-1)}$

Sources: Koschutzki et al. (2005); Barthelemy (2011); Tsiotas (2021)

In addition to these basic measures, the *omega* (*ω*) *index* of Telesford et al. (2011) is computed in the GRCN analysis to detect the small-world *S-W* property (Watts and Strogatz, 1998) and the presence of lattice-like characteristics or random-like characteristics. The measure compares the empirical network's average clustering coefficient $\langle c\rangle$ with that of an equivalent lattice $\langle c\rangle_{latt}$ and the average path length of the empirical network $\langle l\rangle$ with that of an equivalent random graph $\langle l\rangle_{rand}$, according to the relationship (Tsoulias and Tsiotas, 2024):

$$\omega=\left(\frac{\langle l\rangle_{rand}}{\langle l\rangle}\right)-\left(\frac{\langle c\rangle}{\langle c\rangle_{latt}}\right) \qquad (1)$$

Values of the ω-index close to zero indicate the small-world property, positive values indicate the existence of random-like characteristics in the network, while negative values indicate the existence of lattice-like characteristics (Tsiotas, 2021; Tsoulias and Tsiotas, 2024). The null models used to compute the above relationship are generated using the randomization algorithm of Maslov and Sneppen (2002), and the latticization algorithm of Sporns and Kotter (2004). Both are *iterative* algorithms and preserve the degree distribution of the empirical network. The randomization algorithm is applied in two steps: first, four nodes are randomly selected whose edges are bisected, assigning half an edge to each node, and then half the edges are randomly connected (Rubinov and Sporns, 2010). Sporns and Kotter's (2004) *latticization algorithm* applies the same procedure, imposing the constraint that half-edge rewiring only occurs when the resulting adjacency matrix has its non-zero entries closer to the main diagonal compared to its initial state. This condition approximates the topology of a lattice network, since in lattices it is unlikely that connections of distant nodes can be made (Sporns and Kotter 2004; Rubinov and Sporns, 2010). In general, the *S-W* property is rigorously tested on an available graph family when it is detected that $\langle l\rangle$ does not grow faster than logarithmically as the number of nodes tends to infinity (Porter, 2012), that is when $\langle l\rangle_{bin}$=O(*logn*) as *n*→∞. Since collecting a family of different longitudinal versions of the GRCN to test the *S-W* property based on this definition is not usually available, in this paper we choose to test the small-world property using the approximation based on the ω-index (Tsoulias and Tsiotas, 2024). This approach provides further insights into whether the typology of the considered network is governed by random network or lattice network characteristics.

2.3. Centrality analysis

Three different measures of centrality (Koschutzki et al., 2005; Barthelemy, 2011; Tsiotas, 2021) are used to study the GRCN's centrality: degree, closeness and straightness centrality. These measures are calculated in the 39 land NUTS III regions of Greece, as they were defined by the *Kapodestrian* administrative division (Act.2539/1997). The overall approach aims to highlight the geographical transformation of the Greek transport network during the last twenty years (1988-2010) and to evaluate the policies related with the Greek transport infrastructure sector.

Degree centrality (C^D) follows the general principle that the most valuable nodes in a graph or network $G(V,E)$ have the largest number of adjacent edges relative to the other nodes in a graph. Degree centrality is an enumeration of the edges that are adjacent to a given node, expressed by the relation (Koschutzki et al., 2005):

$$C^D = \sum_{i=1}^{n} a_{ij} \Big/ (n-1) = \sum_{j=1}^{n} a_{ij} \Big/ (n-1) = k_i / (n-1) \quad (2)$$

where k_i is the degree of node *i*, a_{ij} expresses the element of the adjacency matrix at location *ij*, and *n* the number of nodes in the set *V*.

Closeness centrality (C^D) is defined as the total geodesic distance of a given node to all others, according to the expression (Koschutzki et al., 2005):

$$C_i^C = (n-1) \Big/ \sum_{j=1, i\neq j}^{n} d_{ij} = \left(\sum_{j=1, i\neq j}^{n} d_{ij} \Big/ (n-1) \right)^{-1} = (\bar{d}_i)^{-1} = 1 / \bar{d}_i \quad (3)$$

where d_{ij} is the distance between nodes *i* and *j* and $\sum_{j=1,i\neq j} d_{ij}$ is the sum operator of the minimum length of the possible edges interposed between nodes *i* and *j*. The concept of closeness centrality describes the degree to which a node *i* is close to all others along a geodesic path and practically illustrates the transport cost required to overcome spatial constraints between different regions and activities. Essentially, closeness centrality expresses the *inverse average distance of* a vertex *i* to all others.

Last, *straightness centrality* (C^S) generally measures the *efficiency* between nodes *i* and *j* in a communication system. This measure computes network distances and Euclidean distances according to the mathematical expression (Koschutzki et al., 2005):

$$C_i^C = \frac{1}{n-1} \sum_{j=1, i\neq j}^{n} \frac{d_{ij}^E}{d_{ij}} \quad (4)$$

where d_{ij}^E represents the Euclidean distance between nodes *i* and *j* and d_{ij} the original network distances. Straightness centrality captures the degree to which a path between nodes *i* and *j* deviates from the straight-line distance. To the extent that Euclidean distance is the minimum route between any pair of nodes, straightness centrality provides a measure of spatial efficiency. In this study, C^S is used slightly modified. On the one hand, instead of the Euclidean distances, we use kilometric (km) distances between nodes *i* and *j*. On the other hand, we consider as network distance the available time distances (min) of the GRCN. This modification serves as an indicator of the "*quality of road transport infrastructure*", because it calculates the accessibility speed of the GRCN's network edges. The higher the straightness centrality of a node *i* is, the higher its accessibility is. Within this context, a comparative view of the differences in straightness centrality between different periods can to provide insights into which nodes have benefited most from structural changes to the network in the meanwhile period. In the case of the GRCN, the map of the differences in straightness centrality for the available periods 1988 and 2010 can to provide insights into the nodes that benefited most from the Greek transport infrastructure works conducted in the meanwhile period.

3. Results and Discussion

3.1 Network Measures Analysis

In the first part of the analysis, the network measures of the GRCN are calculated and the results of are shown in Table 2.

Table 2

Comparative table with the results of the calculation of the network measures for GRCN and GRCN

Measure	Symbol	Unit	Value GRCN
Number of nodes	n	#[a]	39
Number of edges	m	#	71
Nodes with self-connections	$n(e_{ii} \in E)$	#	0
Number of isolated nodes	$n_{k=0}$	#	0
Linking components	α	#	1
Maximum node degree	k_{max}	#	7
Minimum node degree	k_{min}	#	1
Average degree of nodes	$\langle k \rangle$	#	3.641
Average (spatially) weighted node rank	$\langle k_w \rangle$	km	322.264
Average degree of nearest neighbours	$\langle k_{N(v)} \rangle$	#	3.641
Weighted average nearest neighbours grade	$\langle k_{N(v),w} \rangle$	km	322.26
Average edge length	$\langle d(e_{ij}) \rangle$	km	85.497
Total edge length	$\sum_{ij} d(e_{ij})$	km	3,334.4
Average path length	$\langle l \rangle$	#	4.58
Average path length	$d(\langle l \rangle)$	km	389.045
Network diameter (binary)	$d_{bin}(G)$	#	14
Length of network diameter	$d_w(G)$	km	1,124.4
Graph (planar) density	ρ	net[b]	0.640
Graph density (non-planar)	ρ	net	0.097
Clustering Coefficient	C	net	0.47
Average Clustering Coefficient	$\langle C \rangle$	net	0.422
Compatibility	Q	net	0.566

a. Cardinality
b. Dimensionless number

By definition, the GRCN has no self-connections ($n(e_{ii} \in E)$=0), no isolated nodes ($n_{k=0}$=0), and no more than one component (a_{GRCN} =1). The maximum GRCN node degree is $k_{\text{GRCN,max}}$=7, while the minimum degree is $k_{\text{GRCN,min}}$=1, due to its connectedness. Further, the average degree of GRCN is equal to $\langle k \rangle_{\text{GRCN}}$ =3.641 and is numerically close to the range where the highest frequency of degrees in urban road systems occurs, as described in the study of Courtat et al. (2010). The average path length generally expresses the spatial cost (in steps of separation) required to transport in a network (Tsiotas and Polyzos, 2013; Tsiotas, 2021). For the GRCN, this cost implies that the path between two random network nodes is $\langle l \rangle_{GRCN}$ =4.58 spatial units (steps of separation). This value of is close to the order of magnitude $\mathbf{O}\left(\sqrt{n}\right)=\sqrt{39}$ ≈6.245, expressing the average path length $\langle l \rangle_{latt}$ of an equivalent lattice, providing insights into the relevance of the GRCN to this theoretical model. In addition, the kilometric-weighted average path length of the GRCN equals $d(\langle l \rangle)_{GRCN}$ =389.045km and expresses the average kilometric distance required to randomly travel two nodes in the network. Subsequently, the binary (topological) diameter expresses that the longest binary path that can be traversed inter-regionally in the GRCN consists of 14 edges, while the distance-weighed diameter is d(GRCN)=1,124.40km. The GRCN density ρ, considered as a planar graph equals $\rho_{1,\text{GRCN}}$=0.64, while for the non-plannar case it equals $\rho_{2,\text{GRCN}}$ =0.097. Both these values are extremely small compared to the corresponding empirical values for urban road networks (Barthelemy, 2011). The GRCN clustering coefficient equals to C_{GRCN}=0.47 and indicates a satisfactory clustering in the network structure. Further, the average clustering coefficient equals $\langle C \rangle_{GRCN}$ =0.422, which is remarkably larger than the corresponding value of a random network ER~1/*n*=1/39=0.026, expressing that the network is far from being the result of random processes. Finally, the GRCN modularity score is equal to Q_{GRCN}=0.566, expressing the ability of the GRCN to separate into communities. This value describes a satisfactory divisibility into communities, better at least than the cases of road network partitioning, which in practice usually appear of the order of Q_{bipart}<0.4.

3.2. Network Topology Analysis

To study the degree distribution of the GRCN nodes, we construct and examine the scatter plots (*k*, *n*(*k*)) in Figure 3. These diagrams display a peaked distribution pattern, whose typology is different from a power-law curve corresponding to a hub-and-spoke connection pattern. Also, the mode observed in the value $\langle k \rangle_{GRCN}$~3 suggests the presence of strong spatial constraints (Barthelemy, 2011) in the GRCN structure.

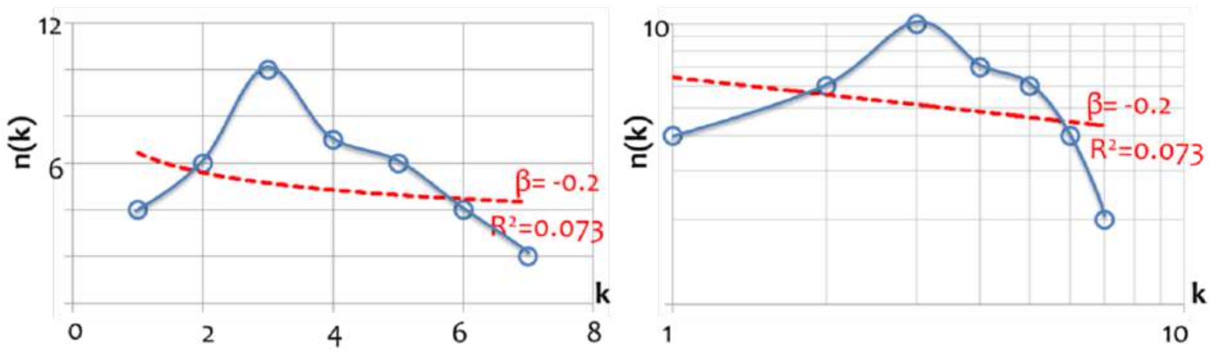


Figure 3. Scatter plots (*k*, *n*(*k*)) of the GRCN degree distribution at metric (ar.) and logarithmic (right) scales.

In the next part of the analysis, we construct (Figure 4) the spy plots (Tsiotas, 2019) of (a) the GRCN connection matrix and four node-equivalent (n_i=39) (b) scale-free, (c) lattice-like, (d) small-world and (e) random-like null models, respectively. From the comparison of the plots, it is evident that the typology of the GRCN sporadicity pattern is similar to that of the (c) lattice network, but the values of the GRCN connection matrix appear slightly more distant from the main diagonal, compared to the standard case.

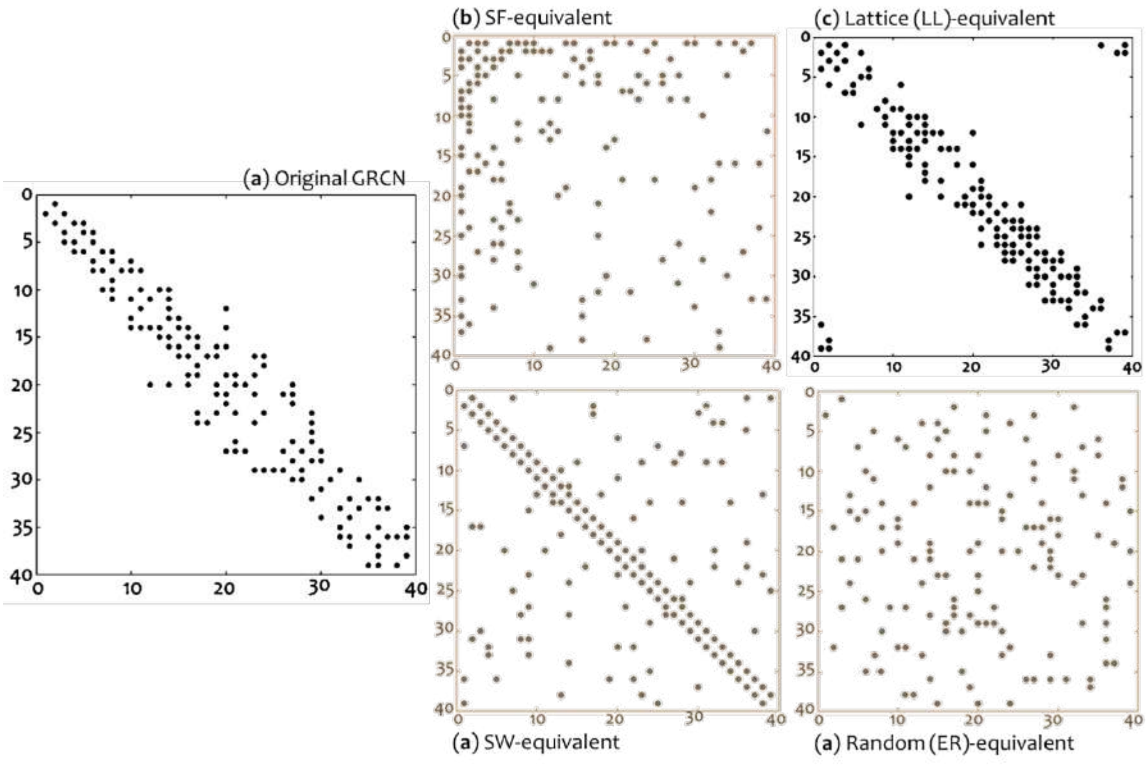


Figure 4. Spy plots of adjacency matrices (a) of the Greek road network (GRCN) and its node-equivalent (n_i=39) (b) scale-free, (c) lattice-like, (d) small-world and (e) random-like null models.

The analysis of the sparsity (spy) plots seems are further verified by the results of the *omega* (*ω*) *index* calculation (Telesford et al., 2011), which are shown in Table 3. As can be seen, the GRCN is more relevant to lattice-like characteristics, which is expected for cases of (spatial) networks subject to strong spatial constraints.

Table 3

Results of the approximate small-world detection analysis for GRCN

Measure	$\langle c \rangle$	$\langle c \rangle_{latt}$	$\langle l \rangle$	$\langle l \rangle_{rand}$	**ω***
GRCN	0.422	0.312	4.580	2.889	***-0.7218***
Indication	Lattice-like characteristics				

*. According to relation (1)

In the next step of the analysis, the major node measures of topology and centrality (degree, betweenness, closeness, clustering, modularity, and spatial strength) of GRCN are calculated. Their spatial distributions are shown in the layouts of Figure 5. First, we consider the spatial distribution of degree (*k*) (Fig.5a), which forms a distinct pattern, with a cluster of strongly connected nodes located in the central core of the GRCN, but also a single hub located in the Peloponnese sub-network. The cluster of the central structure is formed with the hubs of the NUTS III regions of Larissa, Phthiotis, Kozani, Aetolia-Acarnania, and Ioannina, while the Peloponnese hub is located in the prefecture of Arcadia.

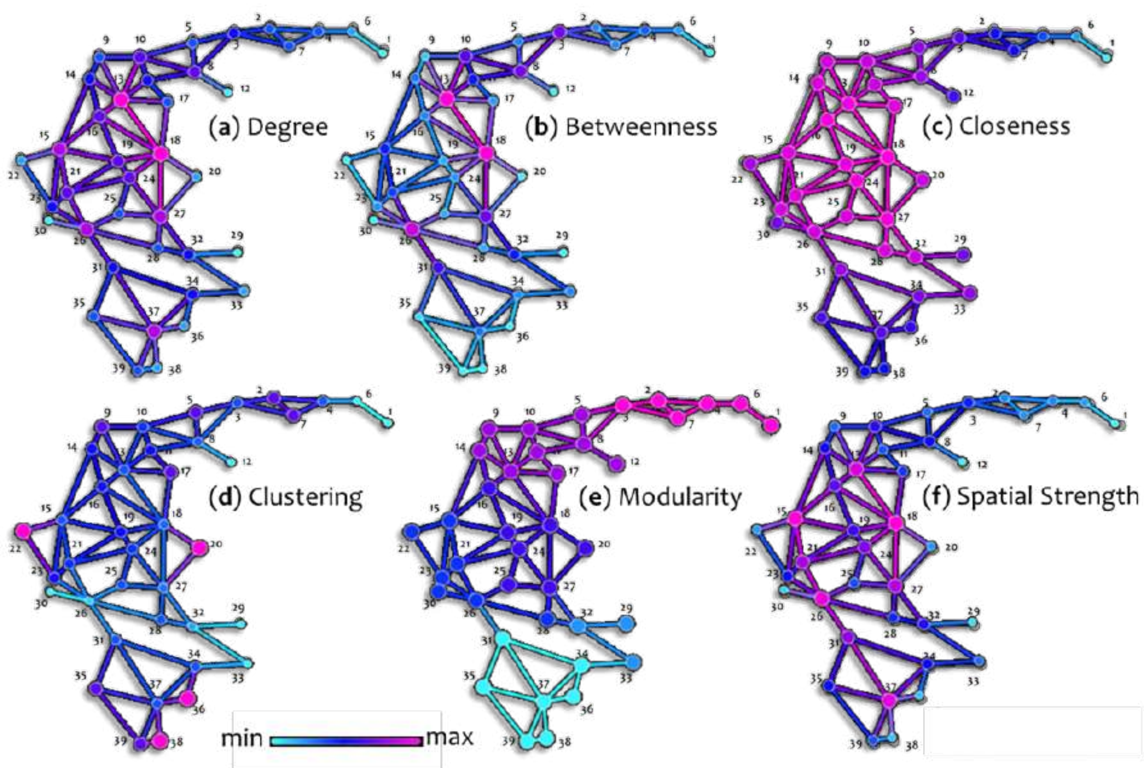


Figure 5. Layouts with the spatial distribution of node measures for GRCN: (a) Degree (b) Betweenness (c) Closeness (d) Clustering (e) Modularity classification and (f) Spatial strength (node labeling as in Figure 1).

Secondly, the regional capital cities of Pella and Thessaloniki in Northern Greece, as well as the regional capital cities that form the Grevena-Trikala-Karditsa-Arta arc in Central Greece, show remarkable connectivity. Considering that the level of degree expresses the connectivity (and therefore the ability of the network nodes to communicate), it follows that the spatial distribution of the degree (Figure 5a) highlights the privileged GRCN nodes in terms of connectivity. This advantage highlights the dynamics of central than regional configurations in geographical space, as described in the location theories and new economic geography theories in regional economics (Krugman, 1991; Fujita and Krugman, 2004; Capello, 2016; Polyzos, 2019; 2023; Tsiotas and Polyzos, 2024). Next, the spatial distribution of betweenness centrality C^b (Figure 5b) shows a greater intensity of the maximum values in the eastern part of the GRCN, where more upgraded infrastructure prevails (Polyzos, 2019; Tsiotas and Polyzos, 2024). In contrast, the distribution of closeness centrality values C^c (Figure 5c) shows small values in the borderline regions (Eastern Macedonia, Thrace, Western Peloponnese), while large values are concentrated in the central (continental) part of the country, highlighting the accessibility advantage that central regions have in spatial networks.

Next, the spatial distribution of the clustering coefficient C (Figure 5d) shows the central nodes to be located at the periphery of the GRCN, and particularly in the regions of Elis, Messenia, Laconia, and Argolis in the Peloponnese; in the regions of Thesprotia and Magnesia in the central part of the country; and in the regions of Pieria, Florina, Kilkis, Drama and Kavala in the northern part of Greece. This situation generally expresses that the regional capital cities of Greece have a higher probability of being related to interconnected neighbors, describing their privilege to enjoy network interactions of greater relevance in their content. However, this privilege can also be seen in the long run as a disadvantage, because it indicates a polar co-existence (Polyzos, 2019; Tsiotas and Tselios, 2024) implying the dependence of these nodes on their neighbors. In terms of economic geography (Krugman, 1991; Fujita and Krugman, 2004; Capello, 2015) this spatial distribution outlines a center-periphery pattern providing guidelines for the use of the clustering coefficient as an indicator that can contribute to the detection of this pattern (Tsiotas, 2021). For the GRCN, this context allows interpreting that the network accessibility of nodes with a high clustering coefficient depends on the transport infrastructure of their neighbors, which, due to the high degree of neighbor interdependence, may exhibit similar quality characteristics.

Next, the spatial distribution of modularity classification (referring to the community membership of the GRCN nodes) in Figure 5e appears to be consistent with the spatial networks theory (Guimera et al., 2005; Kaluza et al., 2010; Barthelemy, 2011). In particular, this distribution follows a distinct partitioning into zones (g_1={1-4,6,7}, g_2={5,8-10,12-14,17}, g_3={15,21-23,26,30}, g_4={19-20,24,25,27}, g_5={29,32,33}, and g_6={31,34-39}) of geographical relevance, which verifies the contingency forces ruling the GRCN characteristics. Finally, the spatial strength distribution (Figure 5f) appears more intensive in the center, forming a "*horseshoe*" (U-shaped) arrangement consisting of the regions of Phthiotis, Larissa, Kozani, Ioannina, Arta, Aetolia-Acarnania, and Arcadia. This arrangement resembles with this of node degree (Figure 5a) and implies that, at the interregional scale, spatial strength is more a matter of connectivity (degree k) than of geographical distance.

In the last part of the analysis, we examine the correlations between *node degree k* and *betweenness centrality centrality* C^b; *spatial strength* (s); and *clustering coefficient C*. The results of the analysis are shown in Figure 6.

The fitting curves applies to the pairs (k, $\left\langle C^b|_{k=k_i} \right\rangle$) and ($k$, $\left\langle s|_{k=k_i} \right\rangle$) show the existence of remarkable linearity for both cases, having determination coefficients =0.96 and =0.906 respectively.

The relationship $\left\langle C^b|_{k=k_i} \right\rangle = f(k)$, between degree k and average betweenness centrality per degree $\left\langle C^b|_{k=k_i} \right\rangle$, with i=2,3,...,7, has power-law exponent β_{GRCN} =1.94 and expresses that the network hubs undertake the largest load of the network traffic. In contrast, the exponent β_{GRCN} =1.156 of the relationship $\left\langle s|_{k=k_i} \right\rangle = f(k)$, between degree k and average spatial strength $\left\langle s|_{k=k_i} \right\rangle$, is close to unity (~1) and indicates a smooth hyperbolic decline in the distance connectivity undertaken by hubs, which is approximately described by the pattern $y = f(x) = \dfrac{a}{x}$.

Finally, the relationship C=f(k) indicates the existence of an exponential decline in the GRCN's clustering by degree k, which is consistent with common research practice (Sen et al., 2003; Barthelemy, 2011). This relationship expresses that as the connectivity of a node increases in the network, the probability that this node is associated with interconnected neighbors is reduced, thus highlighting a more centralized connectivity pattern.

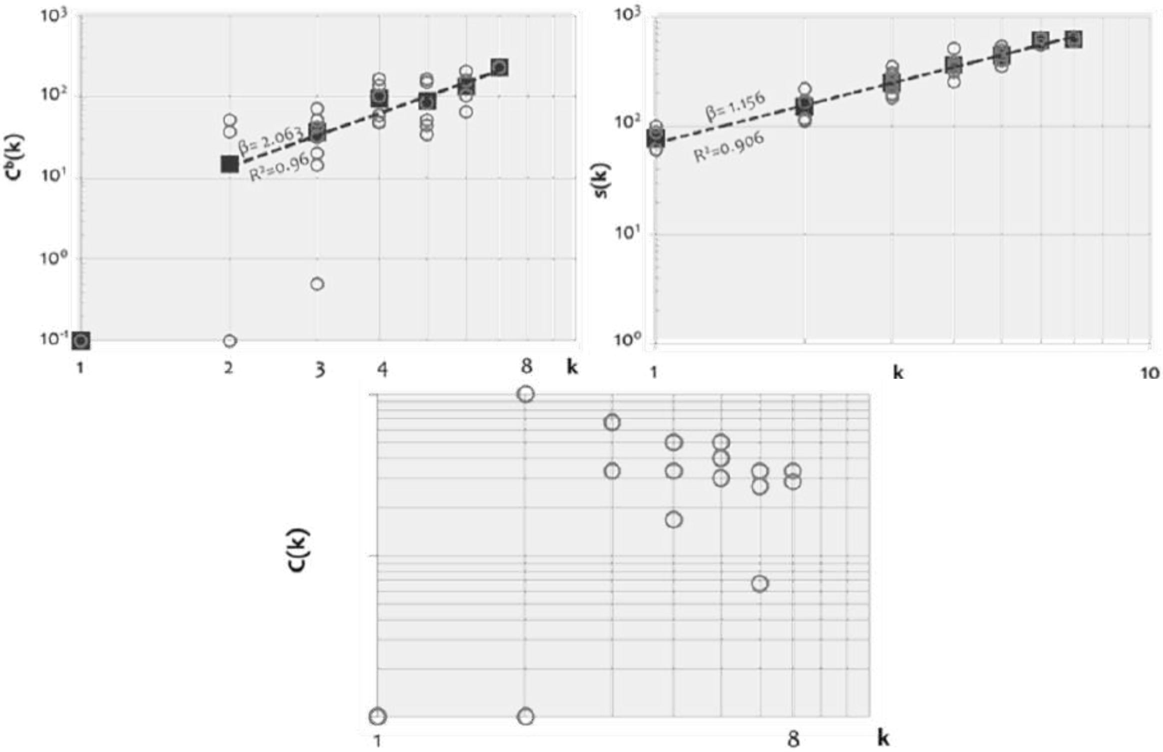


Figure 6. Scatter plots of degree-betwenness centrality (k, C^b); degree-spatial strength (k, s); and degree-clustering coefficient (k, C); for the GRCN. Where applicable, the red squares correspond to the mean values for each degree category.

3.3. Network Centrality Analysis

This section studies GRCN's centrality. Having available for the GRCN spatial and time-distance data, we examine the changes in the spatial distribution of the network centrality for the years 1988 and 2010. Starting with the simplest measure of degree centrality, we first examine changes due to geographical and structural advantages in connectivity of a region during the examined period. In Figure 7 we can observe that the regions Larissa and Kozani are the most central in terms of degree. This fact is attributed to their proximity to the Athens-Thessaloniki major road axis (highway). Further, the Ioannina region appears to be central in western Greece, as is Thessaloniki and to a lesser extent Kozani in northern Greece, and Arcadia in Peloponnese.

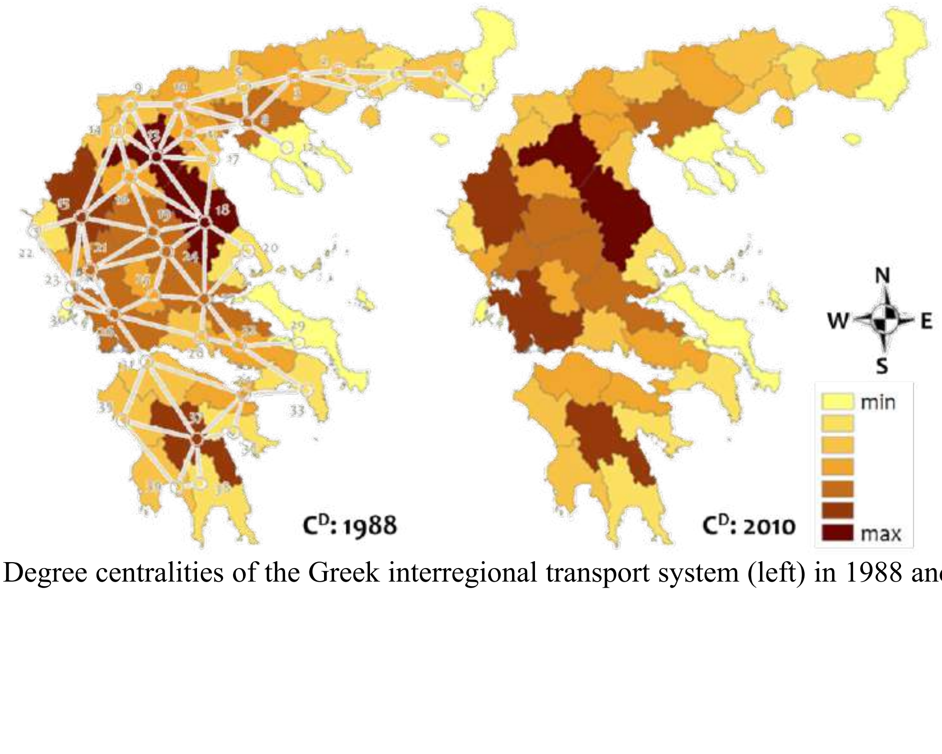


Figure 7. Degree centralities of the Greek interregional transport system (left) in 1988 and (right) in 2010.

The differences observed in degree centrality for the period 1988-2010 can be attributed to the construction of the Rio-Antirrio Bridge (Figure 2), which provided direct road access to the regions of Achaia and Aetolia-Acarnania. As can be seen from the comparison of the two maps, the only difference in network connectivity is for the regions of Aetolia-Acarnania and Achaia, which increased their rank by one connection. This change can be attributed to the construction of the Rio-Antirrio Bridge, which provided direct road access to these NUTS III regions.

The distribution of closeness centrality in 1988 (Figure 8) describes the accessibility of the transport network at that time. The most privileged regional capital cities in 1988 in terms of geographical accessibility were Pieria, Larissa, Magnesia, and Phthiotis, presumably due to their proximity to the Athens-Thessaloniki (highway) road axis. The prefecture of Thessaloniki enjoyed a more central role at that time (1988) compared to the metropolitan region of Attica. The changes in closeness centrality from 1988 to 2010 reveal the relative transformation that transport infrastructures underwent the meanwhile period. As it can be observed, the secondary central Greece regional cluster in 1988 was demoted in terms of closeness in 2010, implying that transport infrastructures upgrade occurred in the meanwhile favored the core connectivity axis of Attica-Thessaloniki. Although this change may be attributed to the construction of the Egnatia Motorway and the Rio-Antirrio Bridge (Figure 2), which enhanced accessibility between Central and Northern Greece, this observation provides insights into the existence of an underlying mechanism of economies of scale in transportation development in Greece, following the "rich-gets-richer" growth model. This interpretation brings into the light the Sisyphus analogy in transportation (Rodrigue et al., 2013; Polyzos and Tsiotas, 2020), according to which large scale transportation infrastructures attract more users and therefore induce derived demand requiring their subsequent upgrade. Overall, the upgrade of the road network that took place in the period 1988-2010 illustrates a major developmental pattern that benefited the wider Central Greece region, where the most accessible areas are clustered. The results of the closeness centrality analysis interprets that accessibility in the current form of the GRCN appears mainly a matter of geographical location rather than infrastructure. The decline in the relative position of the prefecture of Boeotia appears of particular interest, and is probably related to another gravitational effect attributed to the metropolitan prefecture of Attica.

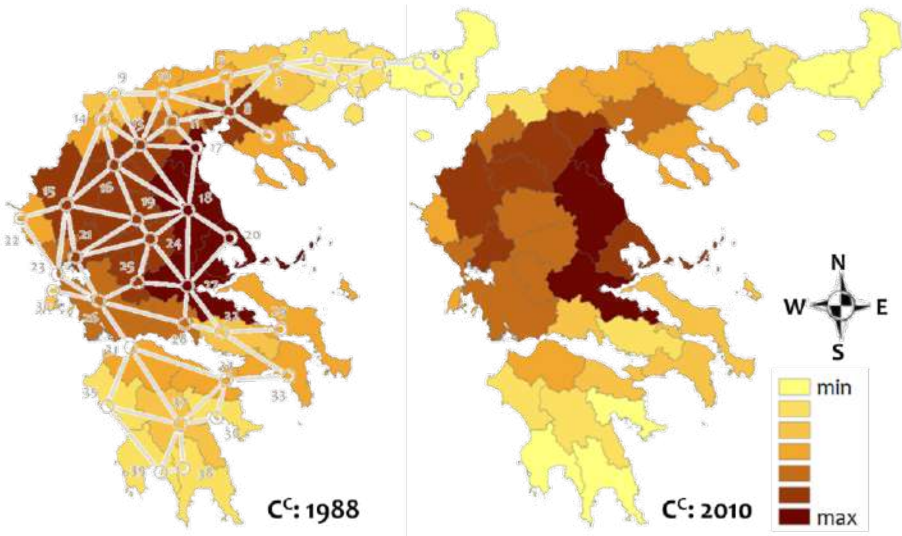


Figure 8. Closeness centrality of the Greek interregional road transport system in 1988 (left) and 2010 (right) (source: own processing)

Finally, the spatial distribution of straightness centrality provides insights into the quality of the country's road infrastructure. Straightness centrality expresses the deviation from spatial directedness between the GRCN regions. Figure 9 depicts the most benefited regional capital cities in transport infrastructure policy, which are Ioannina and Thesprotia. The geographical location of these two regions indicates that they have benefited from both the Rio-Antirrio Bridge and the Egnatia Motorway road projects (Figure 2). The next lowest centrality is shown by the regions Kastoria, Preveza, and Arta, which also have easy access to the Rio-Antirrio and Egnatia Motorway projects. Next in the ranking are the regions Evros and Kavala, in northern Greece; Pieria, Evritania, and Attica, in central Greece; and Arcadia and Laconia and Messenia, in the Peloponnese.

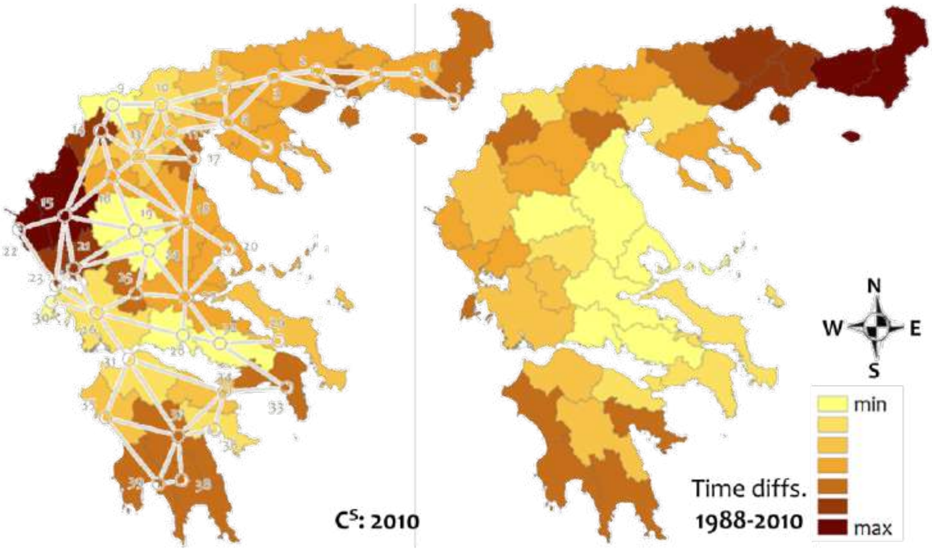


Figure 9. Spatial distribution of (left) centrality of the Greek interregional road transport system in 2010 and (right) differences of average time distances per prefecture for the periods 1988 and 2010 (source: own processing)

The geographical grouping of these NUTS III regions shows the projects that contributed most to their centrality, namely the construction of the Egnatia Motorway (which connects the prefecture of *Thesprotia* with *Evros*) for the northern Greek departments, the Rio-Antirrio Bridge (which connects the prefecture of *Achaia* and *Aetolia-Acarnania*, providing access to and from the Peloponnese from Western Greece) for the Peloponnese and the Athens-Thessaloniki axis for the regions Pieria, Evritania, and Attica in central Greece. The geographical dispersion of the regions Pieria, Evritania, and Attica suggests that there are also secondary apparent causes of increased centrality, such as the Egnatia Motorway for Pieria and the Rio-Antirrio Bridge for Evritania. Next, the geographical distribution of the travel time differences (Figure 9 right) shows the regions that benefited most in terms of travel time from the Greek transport policy of 1988-2010. As shown in the map, the travel time differences distribution shows a clear spatial clustering with the largest values in the periphery and the smallest in the center. In particular, the regional capital cities that showed larger time gains in their interregional travel are mainly the borderline regions Evros and Rhodope, and secondarily the regions Xanthi, Kavala, and Drama. The next most important (in terms of straightness) regions are Serres, Imathia, and Florina, in Northern Greece; Preveza and Lefkada, in Western Greece; and the cluster of the regions Elis, Messenia, Laconia, and Argolis, in the Peloponnese. The positions of the regions included in the aforementioned cases can facilitate correspondences for the infrastructure projects that impacted their reduction of inter-regional travel times.

4. Conclusions

The study of the topology of the Nationwide Network of (NUTS III) Regional Capitals of Greece (GRCN) highlighted the decisive influence of spatial constraints in the network's configuration, revealing particular characteristics that contribute to the understanding of its spatial cohesion and functionality. The topological pattern detected by the pattern recognition distribution analysis (with a peaked distribution and a high concentration of nodes around the main diagonal of the adjacency) revealed that GRCN does not exhibit scale-free characteristics but more resembles to a lattice network. However, the geographical relevance and spatial ordering of the network are enhanced through the small-world property indicated by the ω-index, assigning to the GRCN spatial characteristics found in densely interconnected networks with high local coherence. The centrality analysis identified nodes with high betweenness centrality, implying a geographical structure of GRCN as a heavy center, highlighting areas that play a central role in inter-regional connections. At the same time, the grouping of the network into geographical communities (modularity optimization) highlighted the spatial relevance and the tendency of the network to form regional sets with increased connectivity within them. A finding illuminated by the study is that lattice-like topology is associated with the existence of long-range connections, which are identified by the high value of the power-law exponent ($\beta > 1$). This finding can provide insights into spatial planning to the extent that intercity administrative connections are submitted to latticization spatial dynamics. Moreover, the comparison of the centrality measures of the NUTS III regions between the available years 1988 and 2010 demonstrates the improvement of the country's transport capacities as a result of major infrastructure projects. The changes in centrality highlight the role of national and regional policy, which over the period 1988-2010 sought to strengthen border and remote areas, reducing geographical disparities and promoting development prospects across the country. This targeted direction underlines the importance of public investment in reshaping spatial dynamics and improving accessibility at regional level.

Overall, the study demonstrates the added value of complex network analysis in understanding and improving spatial interactions and provides an important research framework for developing strategies based on evidence-based spatial connectivity models. The GRCN paradigm represents a fruitful application in economic geography and transport sciences, offering insights that can be used in regional and development planning.

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