

From Scalar Rankings to Territorial Structures: A Topological Data Analysis Framework for Regional Competitiveness

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Abstract

Existing approaches to measuring regional competitiveness rely predominantly on composite indices that compress multidimensional territorial characteristics into scalar rankings. This paper proposes a topological data analysis framework. This paper examines EU regional competitiveness not as a single composite score, but as a multidimensional and relational territorial space. The purpose is to test whether a topological perspective can reveal structural configurations that remain hidden when competitiveness is reduced to scalar rankings. The analysis uses Eurostat data for NUTS 2 regions over 2015–2024. It constructs a seven-indicator feature space covering labour-market performance, development level, investment capacity, digital access, social vulnerability, weak labour-market attachment and human capital. Methodologically, the paper applies a topological data analysis framework combining persistent homology and Mapper. The selected Mapper specification is then re-applied to 2018–2022 in order to test robustness. The results show that EU regional competitiveness is not organised as a single smooth hierarchy. It is structured through segmented and partially overlapping configurations. Persistent homology reveals a strong H0 signal and a more moderate H1 signal. Mapper identifies core, intermediate and peripheral regional roles, together with uncovered territories outside denser local structures. The robustness analysis further shows that these patterns are not confined to a single year. The article offers a novel topological data analysis framework for regional competitiveness research. Its main contribution is to show that competitiveness can be analysed as a territorial structure.

JEL classification: R11; R12; C55

Introduction

Globalisation and market integration have further stimulated governments' growing interest in the concept of competitiveness, both at firm, regional and national levels. (Sánchez, et al., 2019). Regional competitiveness remains one of the most debated and policy-relevant concepts in contemporary territorial analysis. It stands at the intersection of regional development, innovation, productivity, institutional quality and social resilience. In the European context, this debate has acquired additional importance because regional disparities continue to shape the effectiveness of cohesion policy, the uneven capacity of territories to absorb structural change and the differentiated ability of regions to respond to digital, green and geopolitical transitions. For this reason, the question is no longer only whether regions differ in their performance, but how such differences should be conceptualised and measured in the first place (European Commission, 2023; Eurostat, 2026b; Ketels and Porter, 2021).

A substantial part of the existing literature addresses this problem through composite indicators, scoreboards and ranking systems. Such approaches have clear analytical value. They provide comparability, facilitate benchmarking and offer an accessible summary of multidimensional territorial information. This is precisely why the measurement of regional competitiveness continues to attract strong scholarly and policy interest, including recent work devoted to alternative index construction and comparative ranking techniques at the European level (Charles et al., 2019; Ferrarini et al., 2024;

Moirangthem and Nag, 2022). At the same time, the use of scalar indices imposes a specific logic on the phenomenon under study. It compresses multidimensional territorial differences into one ordered score, and in doing so it may understate overlap, transition and structural heterogeneity across regions. The analytical cost of this reduction becomes more visible precisely when competitiveness is treated not as a single outcome, but as a configuration of interacting territorial capacities and vulnerabilities (Zarotiadis and Halkos, 2016; Ferrarini et al., 2024).

Recent contributions reinforce this point by showing that regional competitiveness is deeply connected with broader territorial conditions and policy environments. Research in Competitiveness Review has examined the role of economic complexity in the dynamics of regional competitiveness, the significance of regional innovation policy and digital transformation, the contribution of universities to regional competitiveness policy-making and the institutional context of regional development (Bahrami et al., 2023; Hervas-Oliver et al., 2021; Aranguren and Magro, 2020; Melo et al., 2023). Taken together, this line of work points toward a more complex view of regional competitiveness. It suggests that regional advantage is not merely the result of one aggregate level of performance, but is shaped by the interaction of development level, innovation capability, institutional quality, connectivity, labour-market structure and social conditions. Yet even where the determinants become more sophisticated, the empirical representation of competitiveness often remains scalar.

This article starts from the view that this is a limitation. The problem is not that composite indices are useless. The problem is that they are insufficient for a research question concerned with territorial structure. If regions differ not only in level but also in the internal composition of their strengths and weaknesses, then a one-dimensional ranking captures only part of the phenomenon. What remains less visible in standard approaches are the relations between regions in a multidimensional space: which regions are structurally close, which occupy intermediate or branching positions, which are more peripheral and whether such patterns are stable over time. These are precisely the questions addressed here.

The article therefore asks three connected questions. First, can EU regional competitiveness be represented more adequately as a multidimensional feature space rather than as a single composite ordering? Second, does this space display non-trivial topological structure rather than a smooth and homogeneous continuum? Third, do the resulting territorial configurations persist beyond one benchmark year? To address these questions, the paper uses Eurostat data for NUTS 2 regions over 2015–2024 and constructs a seven-indicator feature space covering labour-market performance, development level, investment capacity, digital access, social vulnerability, weak labour-market attachment and human capital. Methodologically, the analysis applies a topological data analysis framework combining persistent homology and Mapper. The benchmark cross-section is 2021, selected on a complete-case basis, and the selected Mapper specification is subsequently re-applied to 2018–2022 in order to test robustness.

The contribution of the article is threefold. First, it contributes conceptually by treating regional competitiveness as a multidimensional territorial structure rather than only as a scalar rank. Second, it contributes methodologically by introducing a topological framework that captures segmentation, overlap and structural position without prior aggregation into a composite index. Third, it contributes empirically by showing that EU regional competitiveness is organised through recurrent and partially overlapping regional configurations that cut across simple national or hierarchical classifications. In this sense, the article does not reject existing competitiveness measures. It complements them by adding a different type of evidence: one that is sensitive not only to level, but also to configuration, adjacency and territorial structure.

Literature Review

Regional competitiveness

The concept of regional competitiveness is widely used in the economic literature, but at the same time remains theoretically ambiguous and multidimensional. Early contributions to the understanding of regional competitiveness, related to the work of Porter (1996), emphasize the comparison of nations based on the competitive advantages they have. As factors for the development of competitive advantages of nations, Porter reduces to: macroeconomic factors; efficient allocation of production factors; effective policies; as well as cultural factors that favor the relationship between government and production. McCann and Ortega-Arguiles (2013) assume that regional competitiveness is a significantly more complex phenomenon than a summary of the economic and cultural factors of individual regions. They link the competitiveness of regions to the interaction between innovation, productivity, innovation and the level of institutional quality. Similarly, Rodriguez-Pose (2013) emphasizes not on institutions, per se, as a factor of regional competitiveness, but on the interaction of institutional factors and a number of other factors such as education, training, skills and innovation, which in an effective combination can positively influence the economic development and competitiveness of regions.

Budd, et.al (2004) perceive regional competitiveness as a combination of the competitive advantage of firms and the comparative advantage of the regional economy. In considering the regional economy, Capello (2016) places emphasis not so much on space as a passive zone, but on the territory as a system of interconnected resources and assets that are potential factors for regional development. Such an approach draws attention to the fact that regional competitiveness should be analyzed as a result of a combination of these interconnected characteristics, and not solely through aggregated indicators of economic performance.

In a similar vein, with an emphasis on territorial measurement, Camagni (2017) considers regional competitiveness as a multidimensional territorial structure that is directly related to and dependent on territorial capital, which represents the availability of stocks of single types such as: location, size, quality, internal and external interactions. Territorial capital has been identified as a key driver for improving regional competitiveness and largely depends on its efficient and effective use. (Panić, et al.

2025). Territorial capital is the result of the interaction of multiple economic, social and institutional factors. That is why regional competitiveness should not be reduced to considering it only as a set of economic results, but also as territories that generate sustainable growth through the use of local assets. These understandings further develop the ideas of Krugman (1991) about the differences in the development of regions as a result of the spatial concentration of economic activities. In this context, competitiveness should be considered as the result of the set of territorial factors and the interrelationships between them, and not as the result of the action of individual factors. (Krugman, 1991)

Collectively, the considered meanings of regional competitiveness show that it depends on multiple factors. In this context, a more comprehensive understanding of regional competitiveness is provided by Kouskoura, et al., (2024), who, through an analysis of published research in the field over a five-year period, identify ten main factors and areas on which regional competitiveness depends, namely: economy; labor market; poverty and social inclusion; healthcare; educational infrastructure; environmental considerations; transport infrastructure; science and technology; high-tech industries and innovations. Regional competitiveness is widely recognized as a multidimensional concept, yet its measurement as such remains a methodological challenge.

Measuring regional competitiveness

The examination of the definitions of regional competitiveness raises the question of its measurement, since it is a component element in the preparation of policies to address regional imbalances and divergences.

In this regard, a number of econometric studies of regional competitiveness apply different methodological approaches, with a significant part of them using scalar indices. A typical example of a scalar approach is the approach adopted by the European Commission (EC) to measure regional competitiveness in the EU, namely the use of the European Regional Competitiveness Index (RCI), which is a general index and provides a summary view of regional competitiveness for NUTS 2 regions. Building on this model, Bilbao, et al. (2019) complement it with several environmental indicators to also examine the sustainability of competitiveness. The use of composite indices, which provide a summary measure of multiple indicators, and subsequently allow the results to be ranked and compared, is treated as a useful tool to support business, policy and economics. (Berger, 2011).

Other studies (Ferrarini, 2024) apply the technique of preference order of similarity to the ideal solution (TOPSIS), taking into account different distance measures and two levels of analysis, to provide a comparative and comprehensive measurement of regional competitiveness in Europe.

However, a disadvantage of using such aggregate indicators is often the inability to take into account the structural characteristics of the regions. Also, Boschma (2004) questions the usefulness of comparative

analyses of regional competitiveness, since there is no specific model of regional development that can be perceived as the most successful and a basis for the development of other regions.

Despite the widespread use of traditional approaches to measuring regional competitiveness, they face a number of challenges related to their limited ability to identify complex, nonlinear relationships and underlying structural patterns that determine development trajectories. The limitations of these methods lie in their inability to preserve and analyze the topological and geometric structure of multidimensional data. This is especially evident when using noisy, high-dimensional and incomplete data, where a significant part of the structural information can be lost. (Revista, 2025) This makes it difficult to analyze the way regions are organized in the multidimensional space of competitiveness. All this necessitates the search for alternative approaches to analyzing regional competitiveness that can reveal hidden dependencies and the multidimensional structure of the data. One such approach is the topological data analysis Topological Data Analysis – TDA, which allows for the study of regional competitiveness through the value of individual indicators and the connections between regions in structural terms.

Topological Data Analysis and Regional Competitiveness Research

The limitations of the traditional and scalar approach, which are based on statistical assumptions or linear projections, necessitate the search for alternative analytical methods with which to analyze data of different types. Topological data analysis allows to examine the overall structure of the data by capturing the inherent geometric and topological characteristics of the data by identifying components, contours and empty spaces. This allows to reveal stable structural dependencies (Kumar et al., 2025). Important advantages of the obtained topological information are its invariance to the impossibility of deformation and computerization, as well as its flexibility, explained by the abstract origin of algebraic topology. (Zia, et. al, 2024). Topological data analysis offers a promising approach, as it involves the study of the connected components of a space (Carlsson, 2009; Ghrist, 2008), which allows to discover structural patterns. This allows to evaluate and position regions more clearly not only as independent units with the corresponding individual results, but also to evaluate them in relation to their structural connections with other regions.

In addition, another advantage of the topological method over traditional methods for measuring regional competitiveness is, for example, that it can be used to detect early warning signals of impending market failures and to investigate complex economic structures. (Gidea, 2017). The application of topology in economic analysis allows it to be used as a mechanical tool through which some parts of economic models can be simplified. (Pagano, et al., 2019)

Despite the multitude of theoretical and empirical studies of regional competitiveness, a large part of them are challenged by the analysis of data of different types. All this necessitates the application of an alternative, building-on approach, such as the topological approach, through which it is possible to assess regional competitiveness also in structural terms.

Topological data analysis is increasingly used in the analysis, especially of complex systems, but its application to the analysis of regional competitiveness remains insufficient and limited. The present study has despite the increasing use of TDA in the analysis of complex systems, its application to regional competitiveness remains limited. In this context, the present study aims to bridge **this gap** by proposing a topological framework for the analysis of the structure of regional competitiveness of the EU.

Methodology

This study analyses EU regional competitiveness as a multidimensional feature space rather than as a single composite index. This is not a secondary stylistic choice, but a methodological one. A substantial part of the competitiveness literature relies on composite indicators, scoreboards and rankings, including the European Regional Competitiveness Index (RCI), which measures the major determinants of competitiveness for NUTS 2 regions and defines competitiveness as the capacity of a region to provide an attractive environment for firms and residents to live and work (European Commission, 2023; European Commission, 2019). Such approaches are useful for comparison, but they also impose additive aggregation, fixed weighting structures and scalar ordering. In this way they may conceal structural heterogeneity across territories and blur transitional or mixed regional profiles. Recent work on territorial competitiveness likewise shows that regional spaces are internally heterogeneous and are not always well represented by a single summary score (Fantechi, 2024).

The empirical strategy addresses this limitation through Topological Data Analysis (TDA), combining persistent homology and the Mapper algorithm. Persistent homology is used to recover the global structure of the regional feature space across scales. Mapper is used to derive an interpretable graph representation of dense local regional configurations and their overlaps. The value of this combination lies precisely in the fact that the two procedures do not do the same thing. Persistent homology identifies features that persist across filtrations rather than at one arbitrary threshold, while Mapper summarises high-dimensional data through projection, cover construction and partial clustering (Carlsson, 2009; Edelsbrunner and Harer, 2008; Singh, Memoli and Carlsson, 2007).

The empirical dataset is drawn from the Eurostat regional database and is organised at the NUTS 2 level. The panel covers the period 2015–2024 and includes multiple annual observations for 117 regions, although data availability differs across indicators. This territorial scale is appropriate because NUTS 2 regions are defined by Eurostat as the basic regions for the application of regional policies, and because the regional database is specifically designed to provide harmonised and comparable territorial statistics for European regional analysis (Eurostat, 2026a; Eurostat, 2026b).

The study works directly with a theoretically selected seven-variable feature space. The aim of this selection is to capture the main structural dimensions associated with regional competitiveness without imposing prior aggregation. More specifically, the variables reflect labour-market performance (employment rate), development level (gdp_pc), investment capacity (fixcap), digital access (house with

internet), social vulnerability (social_exclusion), weak labour-market attachment at household level (low intensity), and human capital and knowledge capacity (hrst). The selected variables also preserve recent cross-year comparability and stronger complete-case coverage.

The methodological workflow combines four connected elements. First, the dataset is preprocessed in order to retain complete observations for the selected indicators and thus construct an internally consistent regional feature space. Second, the selected variables are standardised using z-scores because both topological procedures and distance-based clustering are scale-sensitive. Third, the standardised feature space is analysed through persistent homology and the Mapper algorithm, which make it possible to recover both the global topological structure of the data and an interpretable graph representation of local clustering and overlap (Carlsson, 2009; Edelsbrunner and Harer, 2008; Singh, Memoli and Carlsson, 2007). Fourth, the selected Mapper specification is re-applied across adjacent years in order to test robustness and determine whether the observed structure is recurrent rather than year-specific. The workflow is implemented in Python.

Empirical analysis

Data preprocessing and benchmark-year identification

The first stage of the empirical analysis consists in preprocessing the regional dataset so as to construct an internally consistent analytical space for the selected seven indicators. Since the analysis is based on topological methods and distance-sensitive procedures, missing values would distort both the geometry of the regional point cloud and the graph structures derived from it. For this reason, only complete observations for the full seven-variable specification are retained.

The complete-case audit shows a clear variation in usable regional observations across years. The number of complete cases is 89 in 2015, 99 in 2016, 99 in 2017, 108 in 2018, 108 in 2019, 108 in 2020, 117 in 2021, 114 in 2022, 9 in 2023 and 0 in 2024. These values show that 2021 provides the strongest recent cross-section for the selected feature space, since it is the only year in the relevant period with full coverage for 117 NUTS 2 regions. The benchmark year is therefore selected on the basis of data completeness rather than ex post visual convenience.

After restricting the data to 2021 and removing incomplete observations, the analytical matrix retains 117 regions and seven variables. This yields a fully observed seven-dimensional regional feature space for the benchmark year. The variables are then standardised using z-scores so that no single indicator dominates the geometry of the space because of scale differences alone. The resulting standardised matrix contains 117 regional observations in a seven-dimensional point cloud.

Persistent homology results

The second stage applies persistent homology to the standardised 2021 regional point cloud through a Vietoris–Rips filtration, with attention focused on homology dimensions H_0 and H_1 (Carlsson, 2009; Edelsbrunner and Harer, 2008). The purpose of this step is to determine whether the regional competitiveness space displays non-trivial topological structure across scales rather than behaving as an undifferentiated cloud of observations. The corresponding results are presented in Fig. 1.

The persistence output contains a considerable number of topological features, and the dominant signal is located in H_0 . In substantive terms, this means that multiple connected components emerge at relatively low filtration values and merge only gradually as the distance threshold increases. This is consistent with a regional space that is internally differentiated and segmented into several local configurations rather than collapsing immediately into a single homogeneous structure. In this sense, H_0 provides the strongest topological signal in the benchmark cross-section.

H_1 features are also present, but they are more moderate and clearly less dominant than the H_0 structure. This suggests that the seven-dimensional feature space contains some loop-like gaps or uneven transitions between groups of regional profiles, though not in a way that would justify strong claims about dramatic persistent holes. The persistence pattern therefore supports a restrained interpretation. EU regional competitiveness appears to be organised through differentiated local components and uneven proximity relations, while higher-order cyclic structure remains secondary.

This result is important for the conceptual argument of the article. If the regional competitiveness space were adequately represented by a single smooth continuum, one would expect a much weaker component structure and a less differentiated pattern of topological emergence. Instead, the persistence output indicates that the seven selected indicators generate a structured and segmented territorial space. In other words, regional competitiveness is more convincingly understood as a multidimensional configuration than as a scalar ranking.

Mapper analysis for the benchmark year

The Mapper algorithm is then applied to the same standardised 2021 feature space using a two-dimensional PCA lens and alternative clustering-cover specifications (Singh, Memoli and Carlsson, 2007; Madukpe, Ugoala and Zulkepli, 2025). Several parameterisations are examined in order to avoid reliance on a single arbitrary run. The tested configurations include both DBSCAN-based and agglomerative clustering specifications.

The comparison of alternative runs shows that raw coverage alone is not a sufficient criterion for selecting the final benchmark graph. Some agglomerative configurations achieve substantially higher coverage ratios, but they do so at the cost of very large numbers of nodes and edges. The result is a dense and weakly parsimonious graph that is more difficult to interpret substantively. For this reason, the retained benchmark specification uses DBSCAN with $\text{eps} = 1.0$ and $\text{min_samples} = 2$, together with 10

cubes and 30% overlap. This configuration provides a more balanced outcome in terms of local differentiation, graph sparsity, overlap structure and interpretability.

Under the selected specification, the 2021 Mapper graph contains 32 nodes, 28 edges and 70 unique covered regions, corresponding to a coverage ratio of 0.598. In other words, approximately 59.8% of the 117 complete-case regions in the benchmark year are represented in the final graph. This should not be interpreted as a defect of the method. Mapper, particularly when combined with density-based local clustering such as DBSCAN, is not intended to force all observations into a graph. Rather, it identifies the denser and more structurally coherent parts of the feature space, as shown in Fig. 2.

The graph itself exhibits a meaningful internal organisation. It contains a central connected backbone, several branching local profiles and a set of smaller peripheral or weakly connected nodes. This pattern is analytically important because it indicates that the regional competitiveness space is neither random nor reducible to a single linear ordering. Instead, the graph points to the coexistence of overlapping regional configurations, intermediate structures and more marginal positions.

The composition of the nodes reinforces this interpretation. The largest node contains eleven regions, including AT12, AT22, DK03, DK05, ES21, ES22, FI1C and Dutch regions. This is not a simple national grouping. It is a cross-national configuration suggesting a structurally coherent regional profile. Another prominent node groups Czech, Hungarian and Slovak regions, including CZ02, CZ03, CZ05, CZ06, CZ07, HU21, HU22 and SK02, indicating a distinct Central European configuration. Other nodes connect Austrian, Danish, Swedish, Dutch and Spanish regions through partially overlapping memberships, while smaller peripheral nodes include combinations of Bulgarian, Romanian, Croatian, Hungarian and Slovak regions.

Substantively, this pattern shows that the Mapper graph does not merely reproduce country borders. Instead, it reveals cross-national structural proximities and partial overlaps among regional profiles. Some parts of the graph reflect denser and more integrated configurations, whereas others capture peripheral or weakly connected positions. This is precisely the type of multidimensional structure that is difficult to recover through a scalar competitiveness index.

Multi-year robustness

The final stage evaluates whether the benchmark-year topology is specific to 2021 or reflects a broader recurrent structure. To address this, the same Mapper specification is re-applied to the annual cross-sections from 2018 to 2022. The purpose of this exercise is not to obtain identical graphs in every year, but to determine whether non-trivial graph structures continue to emerge when the same analytical settings are held constant.

The results show that Mapper produces structured outputs in every year of the robustness window. In 2018, the graph contains 28 nodes, 29 edges and 56 unique covered regions, with a coverage ratio of 0.519. In 2019, it contains 36 nodes, 33 edges and 67 unique covered regions, with a coverage ratio of

0.620. In 2020, it contains 27 nodes, 31 edges and 58 unique covered regions, with a coverage ratio of 0.537. In 2021, it contains 32 nodes, 28 edges and 70 unique covered regions, with a coverage ratio of 0.598. In 2022, it contains 27 nodes, 19 edges and 62 unique covered regions, with a coverage ratio of 0.544.

Table I. Multi-year Mapper robustness results, 2018–2022

These annual outputs remain comparable in order of magnitude. Across the five-year window, the number of nodes ranges from 27 to 36, the number of edges from 19 to 33, and the coverage ratio from 0.519 to 0.620. The graphs also remain multi-component in every year. This indicates that the feature space repeatedly generates differentiated local structures rather than collapsing into a single dense block. The persistence of such non-trivial graph outputs under a fixed specification strengthens the interpretation of the benchmark-year result.

This robustness pattern is directly relevant to the empirical argument of the paper. It shows that the 2021 graph is not an isolated artefact produced by an unusually favourable year. Although the exact graph geometry varies across annual cross-sections, as should be expected in a method sensitive to the structure of the underlying data, the repeated emergence of segmented and partially overlapping Mapper outputs across 2018–2022 supports a broader conclusion: EU regional competitiveness is recurrently organised through non-scalar regional configurations rather than through a single uniform hierarchy.

Practical relevance and analytical implications

Beyond its methodological contribution, the proposed framework has direct analytical and practical relevance for the study of EU regional competitiveness. The central implication of the results is clear: competitiveness should not be read only as a scalar rank or as a position in a single ordering. Regions occupy multidimensional and partially overlapping structural positions formed by different combinations of labour-market performance, development level, investment capacity, digital access, social vulnerability, household work intensity and human capital. This matters because regions that appear close in a conventional ranking may still differ substantially in the internal composition of their strengths and vulnerabilities. Conversely, regions from different national contexts may show strong structural proximity within the same topological configuration.

From a research perspective, the framework shifts the analytical focus from simple hierarchical comparison to configurational interpretation. Persistent homology shows that the regional competitiveness space is internally differentiated rather than smoothly continuous. Mapper then identifies which parts of that space form denser and more coherent regional configurations. In this way the approach makes it possible to distinguish between core configurations, intermediate or branching profiles, peripheral positions, and regions that remain outside the denser topological structure under the selected specification. Such distinctions are difficult to recover through composite indices alone, because scalar measures compress multidimensional heterogeneity into a single position.

From a policy perspective, several implications follow. First, benchmarking should not rely only on overall rank, because regions with similar ranks may differ in the actual composition of their constraints and capacities. Second, structurally similar regions may be located in different countries, which means that cross-national comparison may be more informative when it is based on profile similarity rather than only on country grouping. Third, transitional and weakly connected regions deserve particular attention, because they may not fit clearly into standard categories of “high” or “low” competitiveness, but may instead combine elements of both. This is especially relevant for cohesion policy, labour-market policy, digital inclusion policy and innovation support, where the effectiveness of intervention depends not only on a region’s aggregate position, but also on the structure of the disadvantages and strengths that define that position.

More broadly, the framework should be read as a complement to conventional competitiveness measures rather than as a substitute for them. Composite indices remain useful for broad comparison and communication. What the topological approach adds is a different type of information: structural adjacency, overlap, segmentation and relative position within a multidimensional competitiveness space. In this sense, the model helps move the analysis of regional competitiveness away from the narrow question of who ranks higher and toward the more substantively useful question of how regions are structurally positioned in relation to one another.

Conclusion

The analysis shows that EU regional competitiveness can be studied productively as a multidimensional topological space rather than exclusively as a composite index. Using seven Eurostat indicators at the NUTS 2 level, the study identifies a structured regional feature space in which persistent homology reveals clear component differentiation and Mapper uncovers a central backbone, branching subprofiles and peripheral configurations.

The main contribution is methodological and substantive at the same time. Methodologically, the paper demonstrates that a TDA-based framework can recover territorial structure without imposing prior linear aggregation. Substantively, it shows that regional competitiveness in the EU is not organised as a single scalar continuum. Instead, it consists of partially overlapping and recurrent regional configurations whose structure remains visible across 2018–2022.

The approach has direct applicability. It can be used to identify structurally similar regions across national borders, detect transitional territories that do not fit neatly into standard clusters, and complement composite regional indices with a geometry-sensitive representation of territorial heterogeneity. In this sense, the proposed framework is not a substitute for all conventional competitiveness measurement, but a useful extension for situations in which index-based rankings risk oversimplifying multidimensional regional realities.

The present study, in addition to its empirical application to EU regional competitiveness, also contributes to the proposed framework for a broader understanding of territorial analysis by shifting the

focus from measuring regional characteristics to examining relational structures between territories. To further clarify the question of whether territorial structures represent stable spatial patterns or dynamic configurations that are determined by the dynamics of external shocks and regional capacity, future research could extend this approach by including additional dimensions of territorial development. For example, innovation networks, institutional characteristics, environmental sustainability, etc. could be taken into account.

Declarations

Author Contribution

D.S. and S.R. wrote the main manuscript text ;All authors reviewed the manuscript.

Data Availability

The empirical analysis is based on publicly available Eurostat data at the NUTS 2 regional level. The specific indicators and data sources used in the analysis are described in the manuscript.

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Table

Table 1 is available in the Supplementary Files section.

Figures

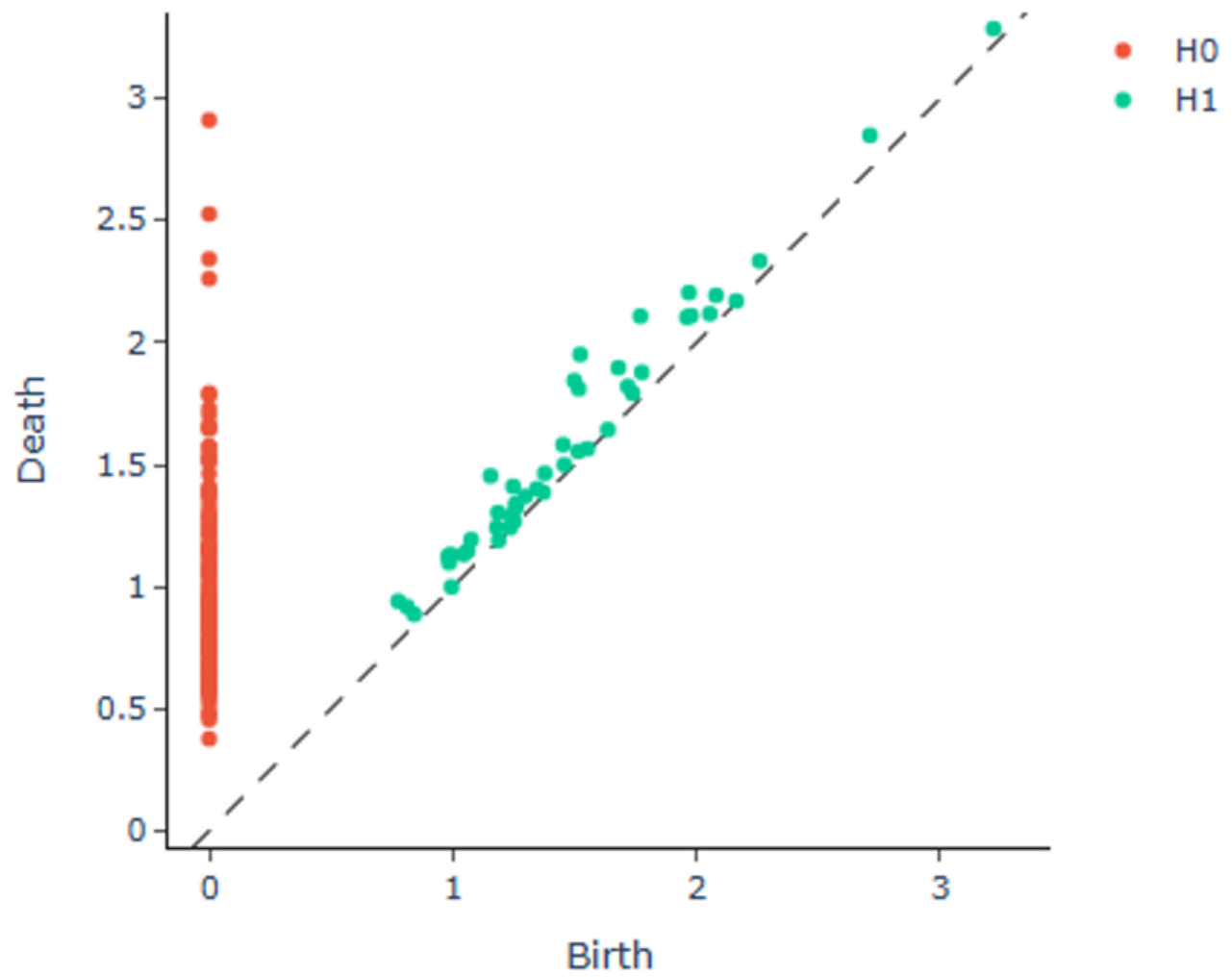


Figure 1

Persistence diagram for the 2021 benchmark cross-section.

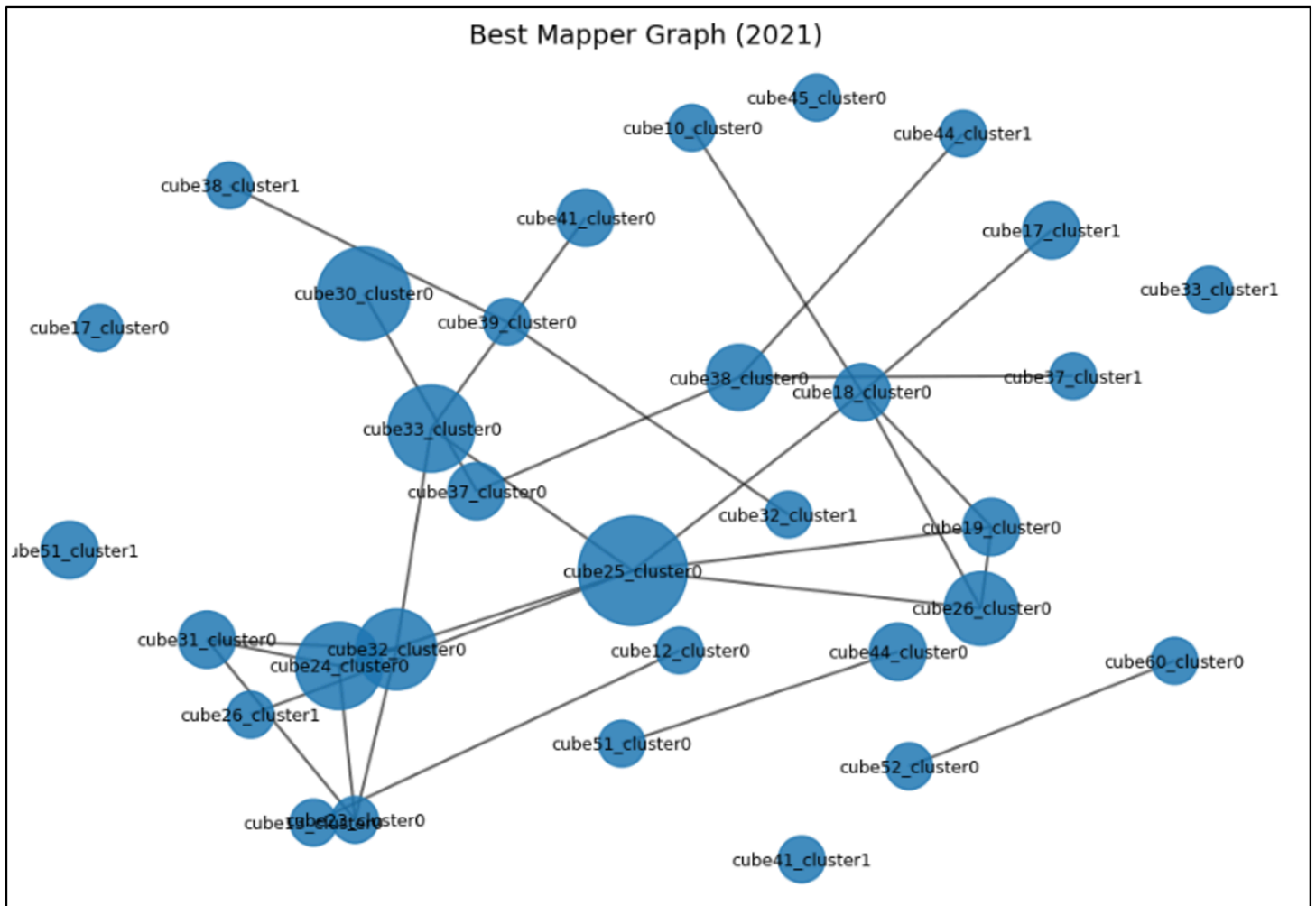


Figure 2

Final Mapper graph for the 2021 benchmark cross-section under DBSCAN (eps = 1.0, min_samples = 2), 10 cubes, and 30% overlap.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Table1.docx](#)