Community Detection in Spatial Networks - a Systematic Literature Overview

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Abstract. *Community detection in spatial networks is a critical research area that explores the complex relationship between network structures and spatial contexts. Understanding the structure and evolution of these networks is essential across various disciplines. To address this, a comprehensive Systematic Literature Review (SLR) was conducted following the PRISMA protocol [Page et al. 2021], ensuring a rigorous and transparent process for identifying, categorizing, and analyzing relevant studies. The review examines key themes, including spatial network characterization, empirical observations, models, and processes. Findings indicate that most studies rely on real-world data, with China and the United States being the most analyzed regions. However, there is limited availability of source code and a lack of research on dynamic or temporal aspects. This review introduces a novel classification for spatial community detection, encompassing network perturbations, modularity index, and detection algorithms. By integrating insights from multiple disciplines, it enhances the understanding of spatial constraints and network dynamics, providing valuable contributions to various applications and fields.*

1. Introduction

Complex systems are composed of interacting parts whose behavior is more than the simple sum of their parts, like ants in colonies or the interplay of neurons in a brain [Newman 2011]. Complex networks correspond to graphs representing such systems

[Barabási and Pósfai 2016]. The Graph theory dates back to the 18th century when Leonhard Euler proposed a mathematical framework to investigate the well-known problem of the seven bridges of Königsberg. Important authors like Paul Erdős and Alfréd Rényi, with their investigation on random networks [Erdös and Rényi 1959], and M. S. Granovetter with the discussion about the strength of weak ties [Granovetter 1973] paved the way for the network science as we know. However, only at the turn of the 20th century to the 21st the area gained momentum, with essential contributions of A. Barabasi and R. Albert on scale-free networks [Barabási and Albert 1999], and D. Watts and S. Strogatz on small worlds [Watts and Strogatz 1998], in addition to the availability of different network maps such as Protein-Protein Interactions, Hollywood actors, the WWW and others [Barabási and Pósfai 2016]. Nowadays, networks are ubiquitous, being studied in various disciplines like computer science, sociology, biology, and transportation, to name a few.

A graph (G) is a set of vertices (V) and edges (E) [Bollobás 1998], where vertices can form groups, known as communities or clusters, that reveal underlying network structures. Community detection algorithms generally assume that groups emerge from the network itself, with denser connections within a community, a path between any pair of nodes, and links exceeding random expectations (modularity) [Barabási and Pósfai 2016]. Key algorithms include Infomap, Louvain, Girvan-Newman, Walktrap, and Ravasz, which may be agglomerative, divisive, and/or based on random walks. Fortunato [Fortunato 2010] reviews the field, noting that besides modularity, methods like Stochastic Block Models and random walks are used to evaluate graph partitions, with recent approaches utilizing embeddings to identify community structures.

Geoinformatics is a multidisciplinary field that integrates geography, computer science, and technology for data acquisition, analysis, and visualization, using tools like satellite imagery, GPS, and digital mapping platforms [Awange and Kiema 2013, Karimi 2014]. Within this field, geoprocessing focuses on practical techniques for handling geographic data [Upton et al. 1985, Burrough et al. 2015]. Spatial networks, a subset of complex networks, have nodes with positions in 2D or 3D space and edges that represent real, physical connections with location, length, and sometimes weight. The topological aspects of these networks are linked to spatial features like node positions or edge sizes [Barthelemy 2010, Crucitti et al. 2006, Dale et al. 2010].

[Santos et al. 2017] introduced the concept of (geo)graphs, where nodes are assigned geographical coordinates and edges display spatial dependence, allowing for the effective representation and analysis of geographical networks. These graphs are compatible with GIS, where vertices are represented as points and edges as line shapefiles, enabling seamless manipulation within GIS environments. [Barthelemy 2010] conducted a review of the relationship between networks and spatial dynamics, discussing topics such as spatial network characterization, empirical models, and processes like disease spread and resilience. This work highlights how spatial constraints influence network structures and provides an interdisciplinary understanding of complex systems. In [Boguna et al. 2021], the role of geometry in understanding complex networks is examined, focusing on how analytical tools from statistical physics have revealed network self-similarity and latent hyperbolic geometry. These insights have led to new methodologies for analyzing complex systems and have significantly contributed to their modeling.

In this study, we conducted a Systematic Literature Review (SLR), which involves identifying, categorizing, and analyzing relevant literature on a specific research topic, as detailed by [Tranfield et al. 2003]. Here, we collected studies in the field of spatial networks exploring community detection. To the best of the authors' knowledge, it is the first SLR on this topic.

2. Method

To ensure transparency and replicability, this review followed the methodology of [Okoli and Schabram 2010] and the PRISMA guidelines [Moher et al. 2015]. Okoli and Schabram's approach provides a pragmatic, step-by-step process for conducting systematic reviews in information systems, while PRISMA, though designed for health-related reviews, has been widely adopted across disciplines [Liao et al. 2017] [Ansyori et al. 2018] [Larsson and Brostr"om 2019]. According to [Okoli and Schabram 2010], a comprehensive Systematic Literature Review (SLR) involves eight steps: defining the review's purpose, protocol and training, literature search, practical screening, quality appraisal, data extraction, study synthesis, and review writing.

Broadly, this review aimed to assess the advancement in research directed towards enhancing spatial networks. Specifically, this review aimed to: (i) identify studies using real-world data; (ii) identify the most frequently studied regions; (iii) examine studies utilizing dynamic data; (iv) identify the most commonly used community detection algorithms; (v) explore the most prevalent application domains; (vi) determine the percentage of studies providing accessible artifacts; and (vii) identify journals with the highest number of publications on spatial networks.

3. Protocol

3.1. Search Strategy

The search was carried out on the CAPES Journals Portal [1] on November 9, 2023. After applying filters based on the authors' formulated query, 34 papers were retrieved. The query employed in this research was: ("geographical network" OR "spatial network" OR "geographical graph" OR "spatial graph" OR "geospatial graph") AND ("community detection").

3.2. Criteria and procedures

The review included only peer-reviewed English articles published up to November 2023, sourced from the CAPES Journal Portal database. Articles were selected based on inclusion criteria, excluding those without community detection. The data extraction process involved recording relevant information from each study in a spreadsheet or database [Petticrew and Roberts 2008]. The fields for article analysis include title, actual data usage, community detection methods, dynamic data, domain, public code/artifacts, public data, study area, journal, publication year, and geographical network (whether networks used geographic nodes).

4. Results of the Review

This section specifies the fields employed in the systematic review, statistical description, and review outcomes.

[1] https://www-periodicos-capes-gov-br.ezl.periodicos.capes.gov.br/

4.1. Search Results

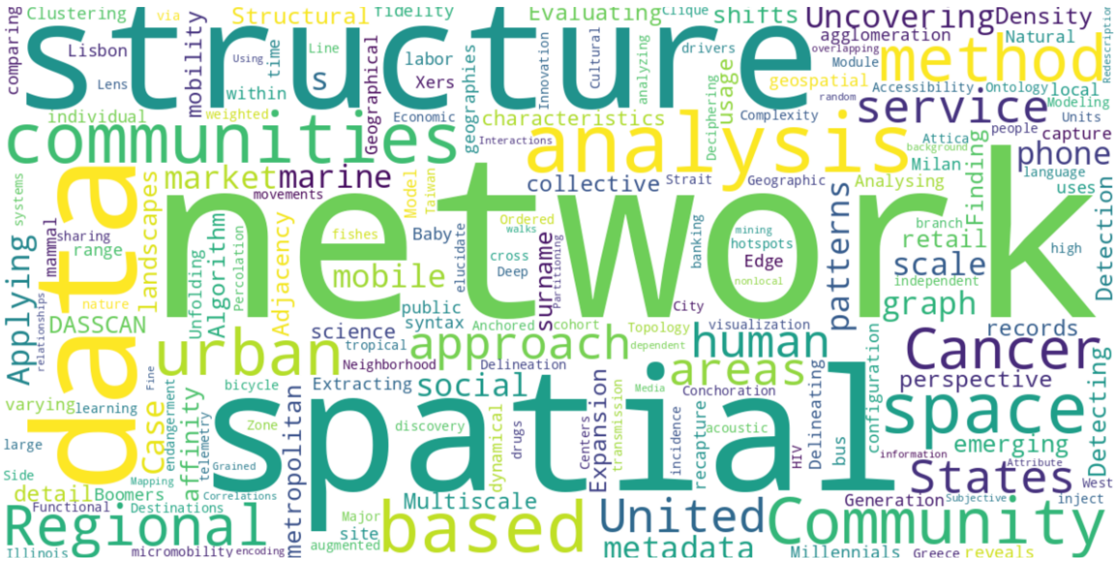

Figure 1. Word cloud formed by the words found in the titles of the works.

The research was conducted using a query based on keywords from the search strategy, and Figure 1 shows the most frequent words in the paper titles, including network, spatial, structure, data, analysis, and communities. Guided by the search strategy outlined in Section 3.1 and detailed in Section 3.2, the database exploration resulted in 58 findings. After screening titles and abstracts, 24 articles were excluded for not meeting the research objectives, leaving 34 articles for in-depth analysis.

Figure 2 illustrates a collaboration network of authors in spatial networks, where each node represents an author, and edges indicate jointly published works. The node size reflects the total number of publications, and edge thickness shows the number of shared works. Node color represents the average appearance year (AAY), with a gradient displayed in the lower right corner. Several disconnected components are visible, with isolated nodes representing individual publications. The largest connected component, in yellow, consists of 12 authors from the paper [Clipman et al. 2022]. Six authors appear in two papers, shown as larger nodes, while the rest are featured in only one.

The co-citation network in Figure 3 links articles by citations, arranged chronologically. Each node is labeled with the first author's last name, and first names are added for clarity if needed. Articles with one citation are green, two are blue, three are yellow, and more than three are red, while articles with no citations are gray. Most articles are from 2022, with [Expert et al. 2011] being the most cited. This paper, which introduced a distance decay factor to the modularity model, also ranks highest in external citations. The second most cited article, [Evans and Lambiotte 2010], presents a method for detecting overlapping communities in weighted graphs. [Clipman et al. 2022] corresponds to the largest connected component in Figure 2.

4.2. Analyses - Descriptive Insights

In this section, descriptive statistics are presented through charts constructed using the columns of the table containing information about the articles.

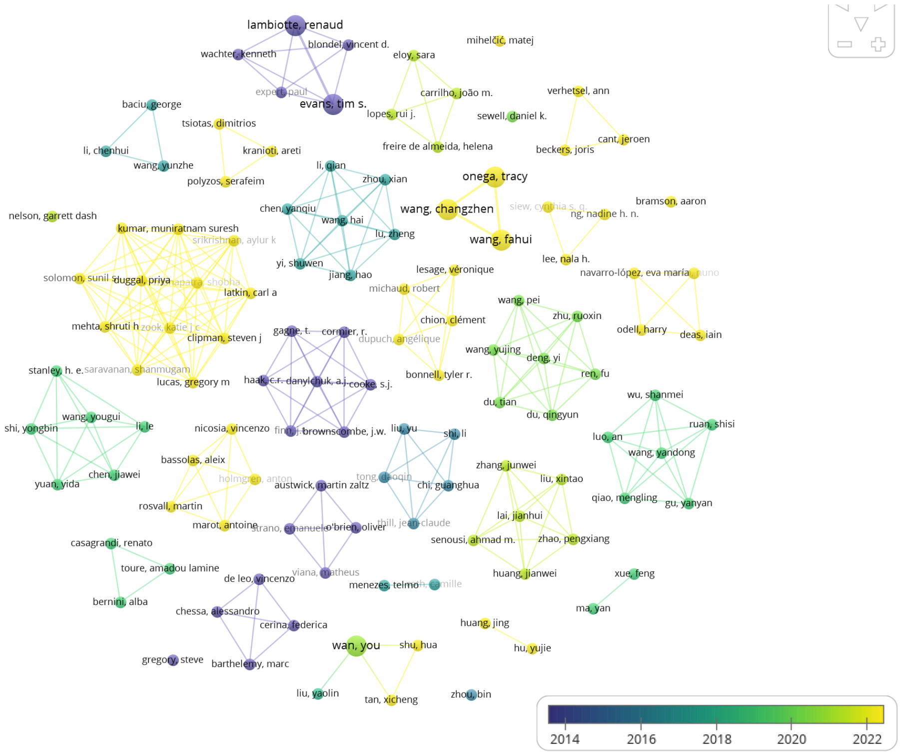

Figure 2. Co-authorship network using the VOSviewer (https://www.vosviewer.com/) tool [Van Eck and Waltman 2010]. In this graph, each node represents an author, and the edges connecting the nodes represent works developed with co-authorship.

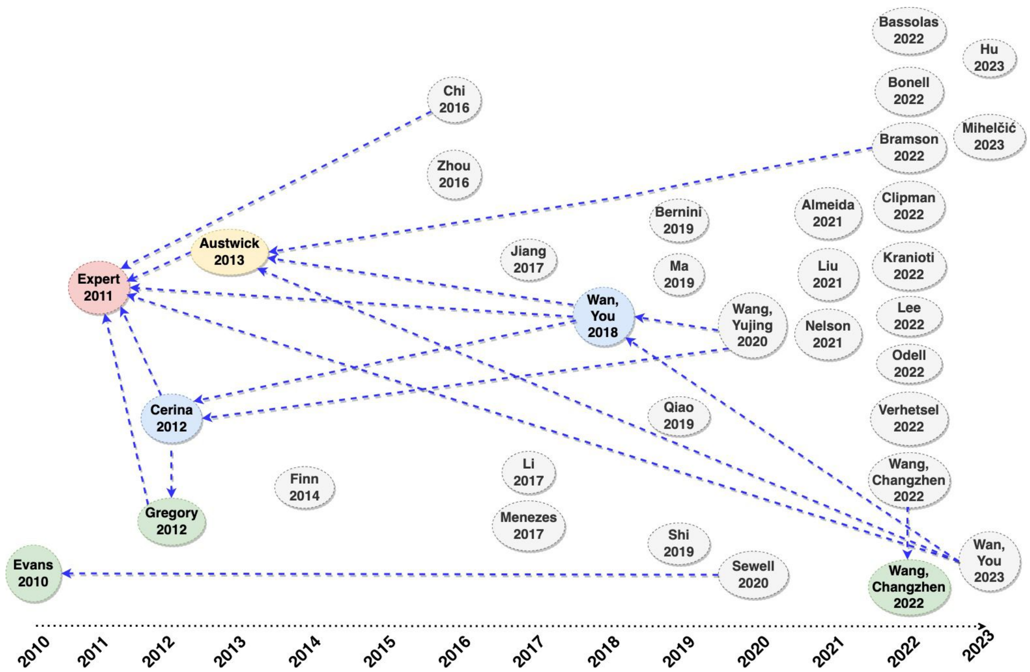

Figure 3. Co-citation network among the papers returned in the search. In this graph, each node represents an article, labeled with the name of the first author, and the directed edges represent a citation from one work to another.

4.2.1. Domain

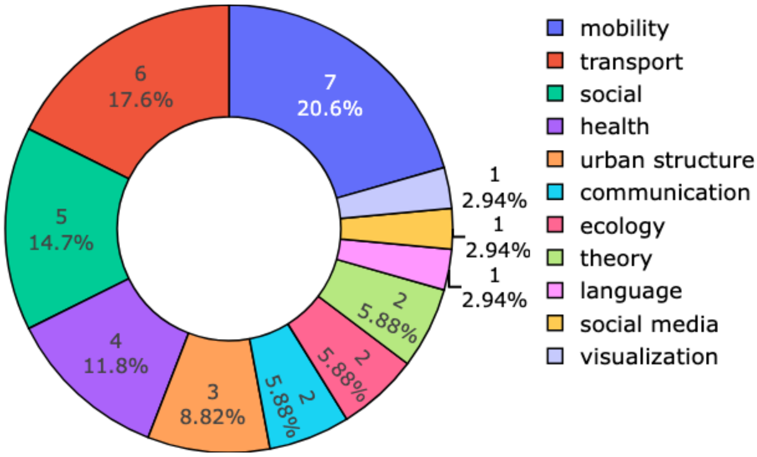

Figure 4. Domains of study chosen to categorize the papers.

The domain of application refers to the specific field where research addresses real-world problems, helping to identify the target audience and guide the implementation of solutions. The study domains are categorized into: “mobility” (human mobility), “transport” (networks for transportation of people/goods), “social” (social sciences), “health”, “urban structure” (organization of urban areas), “communication” (mobile networks), “ecology”, “social media”, “theory” (theoretical network studies), “language”, and “visualization” (network visualization), with these categories reflecting the focus of the respective studies. Broader studies on transportation and mobility address issues such as designing more efficient transportation networks and making transportation more accessible and affordable for all, as shown in Figure 4. This prevalence highlights the importance of the field in shaping cities, economies, and the environment.

Among the set of examined studies, no works about the subject of rainfall, hydrology, and related topics were identified. Nevertheless, for discussion, we have included two studies that explore the interplay of spatial networks with the aforementioned themes. [Ceron et al. 2019] presents a study on detecting communities within high-resolution meteorological networks using a (geo)graph approach. The authors apply this approach to model a dataset derived from radar-based precipitation and analyze the topological properties of the network. They discover a spatially well-defined community structure that aligns with topographic and land-use data. [Jorge et al. 2023] presents Graph4GIS, a tool designed for constructing geographical graphs from spatially gridded data, with a specific emphasis on weather radar datasets. Utilizing graph-based networks facilitates the identification of inherent relationships and structural patterns in natural systems such as weather and climate. Through node representation of time series and the establishment of links based on predefined similarity criteria, the tool offers diverse similarity measures and criteria for network construction, as demonstrated by the results obtained from applying different network structures to a watershed.

4.2.2. Real Data and Study Area

Using real data enhances the reliability and credibility of studies, enabling meaningful conclusions and the application of findings in real-world situations. It also allows for result verification and replication, ensuring the validity of scientific discoveries. Among the 34 papers reviewed, only one explicitly stated it did not use real geographical data. The studies primarily focused on China and the United States, each featured in 9 papers. Belgium appeared in 3 works, while Canada and the United Kingdom were referenced in 2 papers each. Additionally, Greece, India, Italy, Japan, and Portugal were cited once, with some studies considering multiple countries, and 2 papers not specifying a country of focus.

4.2.3. Dynamic Data

Dynamic data in geographical networks refers to the variation of attributes associated with nodes and edges over time. This type of data provides valuable insights into network behavior, enabling the identification of temporal patterns and a deeper understanding of spatiotemporal dynamics. It facilitates the analysis of temporal dependencies, and the identification of temporal communities, and clusters. The incorporation of dynamic data enhances decision-making processes by enabling the assessment of changes, prediction of future states, and development of adaptive strategies in dynamic spatial networks

Approximately 76% of the selected papers employed temporally varying data. However, only 11% of the papers explored the data through temporal analyses.

4.2.4. Public Code / Artifacts

When authors make their developed code publicly available in articles, they promote transparency, reproducibility, and research collaboration. Code sharing facilitates validation, learning, and improvement of their work. Publicizing the code fosters open science, enabling replication, extension, and the growth of a strong scientific community. Six out of the 34 papers explicitly declared the availability of the codes and artifacts produced in their respective studies. Regarding the studies utilizing public data or publishing independently collected data, there are 18 papers, contrasting with 16 that did not.

4.2.5. Papers by Journals

The pie chart in Figure 5 shows the distribution of articles by journal. The Applied Network Science Journal had the highest number of articles. Additionally, there are 21 articles labeled as "Others," each from different journals, including titles like "American Journal of Physical Anthropology", "Cancer Research Communications", "Ecological Modelling", and many more.

It is worth mentioning that there are publications in traditional Geoinformatics journals, such as "International Journal of Geographical Information Science: IJGIS" and

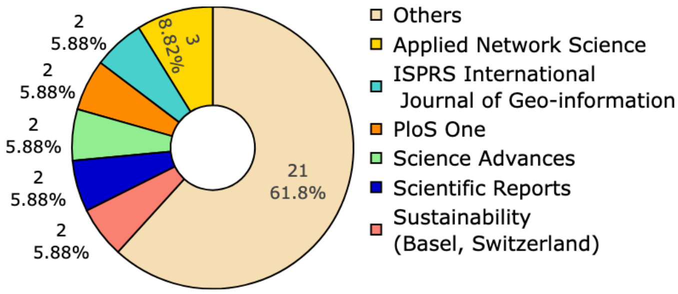

Figure 5. Pie chart illustrating the distribution of papers within the study sample across different journals.

"Transactions in GIS", as well as papers in journals from different application areas, ranging from "Cities" to "Cancer Research Communications" and "Ecology and Evolution".

4.2.6. Community Detection

Community detection is crucial in geographical networks, as it helps uncover structures and patterns that provide valuable insights. Modularity, introduced by [Newman and Girvan 2004, Justel et al. 2014], quantifies the strength of division within networks, assessing their structure in terms of communities. Higher modularity values indicate better network partitioning, reflecting a more effective division into communities, whose formula is described as follows:

$$Q = \frac{1}{2m} \sum_{ij} (A_{ij} - P_{ij}) \delta(C_i, C_j), \tag{1}$$

where, m (number of edges); A_{ij} (indicates the existence of edges between nodes i and j); P_{ij} (number of edges existing between nodes i and j in the null model); δ = 1 if C_i and C_j (communities of nodes i and j) are the same, or 0 otherwise.

Among the Community Detection algorithms cited and employed in the studies, the most frequently mentioned are Infomap (12%) and Louvain (19%), followed by Leiden and Fast-Greedy.

[Expert et al. 2011] discussed the concept of geographic consistency in the context of spatial networks. They argue that modularity optimization in spatial networks is often blind to spatial anomalies and fails to uncover modules determined by factors other than mere physical proximity. Therefore, they propose a method to detect patterns that are not solely due to space and go beyond standard network methodology to uncover significant information from spatial networks. [Austwick et al. 2013] describe how basic spatial models can be used to highlight the most frequently used routes. They also use community detection techniques to identify networks that are more strongly connected than what would be expected based on spatial proximity.

Considering original contributions to community detection in spatial networks, we propose a classification considering three classes: Network (Perturbating the network itself); Modularity (Perturbating the index of modularity); Community Detection (Perturbating the algorithm for community detection).

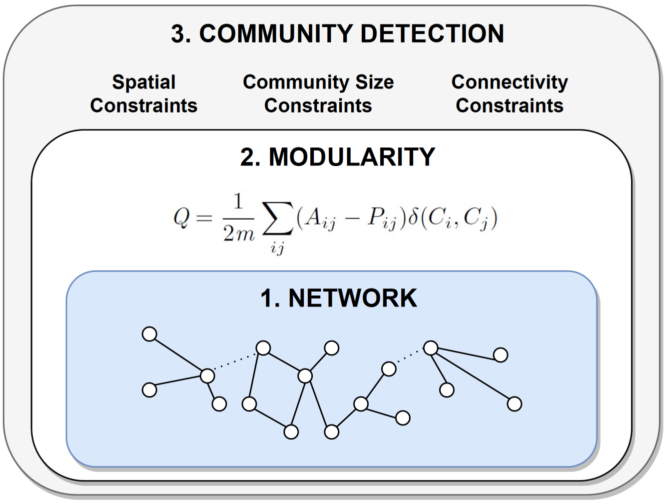

Figure 6. Classifications regarding contributions to community detection in the context of Spatial Networks.

In the first scenario, it is possible to directly incorporate spatial dependency. For instance, this can be achieved by considering spatial connectivity (where polygons touch each other), spatial proximity constrained within a specified distance, or by employing functions that decay with distance, such as gravity models. [Odell et al. 2022] exemplify this approach by utilizing the disparity between actual flows and gravity model-based flow estimations to construct residual networks, facilitating community detection within these networks. In the second case, gravitational models can once again be employed, this time for proposing spatial null models. [Liu et al. 2021] introduces a novel modularity measure based on the difference between actual and gravity model-based flow estimations. [Expert et al. 2011] integrated a distance decay factor into the original modularity model. In the third scenario, key aspects may include, for instance, the utilization of Spatial Constraints, Community Size Constraints, Connectivity Constraints, which will now be applied in the construction of the community detection algorithm, as opposed to the network construction, as is the case in scenario 1. [Wan and Liu 2018] present DASSCAN, which employs shared similarity among nodes' neighbors as clustering criteria, extending the analysis beyond mere consideration of direct connections.

It is noteworthy that each study may adopt more than one approach, as seen in the work of [Qiao et al. 2019], who propose both new weights (based on gravitational models) and include spatial contiguity constraints in the community detection method (in this case, DBSCAN). Furthermore, some methods detect communities without calculating modularity, such as an algorithm based on the evolution of a Markov process on the graph [Jiang et al. 2017] and the Clique Percolation Method, an overlapping community detection algorithm [Zhou 2016].

5. Conclusion

We conducted a systematic literature review of studies on community detection in geographical networks, published up to November 2023, focusing on high-impact journals and conferences. This review offers a comprehensive insight into the research, methods, and progression in the field of spatial networks, and contributes to the development and evaluation of spatial network studies by categorizing and structuring previous work.

The Systematic Literature Review (SLR) focused on papers concerning community detection in spatial networks. In the collaboration and co-citation networks derived from these papers, a notable emphasis emerged on mobility and transport networks, underlining their significance in shaping cities, economies, and the environment. It was observed that the majority of papers relied on real data, with a particular emphasis on data from China and the USA. Intriguingly, 76% of these papers incorporated temporal data, yet only 11% conducted any form of temporal analysis. Moreover, out of the 34 articles analyzed, six made their source code available, contributing to the transparency and reproducibility of the research. This synthesis sheds light on the prevalence of mobility networks and the relatively limited exploration of temporal aspects.

Finally, considering original contributions to community detection in spatial networks, we proposed a classification considering three classes: Network - perturbating the network itself, Modularity - Perturbating the index of modularity, and Community Detection - Perturbating the algorithm for community detection. Our analysis shows that most of the papers used gravitational methods, some of them to change the edges of the network and several to reformulate the null model for spacial interactions.

In future works, we intend to consider additional databases and similar terms on the query and promote topological analysis of the co-citation network, looking for the most relevant research and researchers.

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