Spatio-Temporal Knowledge Graphs: Approaches and Challenges

Philipp Plamper[1,*], Anika Groß[1]

[1]Anhalt University of Applied Sciences, Department Computer Science and Languages, Köthen (Anhalt), 06366, Germany

Abstract

Knowledge graphs capture interconnected information by representing entities and their relationships to each other within graph structures. Specifically, spatio-temporal knowledge graphs gain increasing interest. They enable detailed modeling of many real-world systems in which time and space often play a crucial role, such as ecology, climate change and both local and global infrastructures. Previous relevant research in this area is diverse and influenced by different, rather distant research communities such as computer science and geography, making it challenging and complex to review the field. Due to the diversity of research and the complexity of spatio-temporal knowledge graphs, there are still many gaps that need to be explored to gain a more comprehensive understanding along their whole life cycle including the modeling, creation, management and analysis. On the one hand there is a need for generic concepts and methods, while on the other hand applications can have complex and varying requirements specific to a domain. Our goal is to develop spatio-temporal knowledge graphs and analysis methods with a focus on the requirements in the field of ecology and restoration in agricultural landscapes. In this paper, we initially provide a historical overview of key influences in the development of spatio-temporal knowledge graphs. We then outline challenges and give an overview of our approach and planned research in this field.

Keywords

Knowledge Graph, Spatio-Temporal Knowledge Graph, Knowledge Representation, History

1. Introduction

In many domains knowledge graphs are used to represent inherently interconnected systems in a graph structure, e.g. social networks, computer networks or chemical networks [1] as illustrated in Figure 1. Modeling information in a knowledge graph preserves the relationships between entities and provides a semantically enriched network representation to support interoperability and improved querying. Often knowledge graphs are represented based on the property graph model or the Resource Description Framework [2] and are used for many network analysis tasks, including the emerging field of deep learning on graphs [3] e.g. for completion, recommendation or question answering.

Spatio-temporal knowledge graphs (STKG) additionally cover spatial and temporal properties. They thus form a combined approach of spatial [4] and temporal [5] knowledge graphs allowing to represent systems, which are influenced by both properties. There is a wide field of possible applications of STKG such as urban networks to predict traffic flow patterns in a city [6], medical networks to model the progression and spread of infectious diseases [7] and ecological networks to predict forest fire in different regions [8]. Due to their complexity, the modeling, construction, evaluation and analysis of STKG of high-quality based on real-world data is a challenging process, and requires in-depth research.

So far urban networks [9] receive particular focus in STKG research as complex systems with well-known nodes and relationships on the spatial scale and continuous changes in this space such as traffic and transportation on the temporal scale. In contrast other domains, such as ecology, are less frequently investigated, since there are still large parts of the complex system or network unknown making it difficult to model nodes and edges with high coverage and quality. Moreover, much of

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*Corresponding author.

philipp.plamper@hs-anhalt.de (P. Plamper); anika.gross@hs-anhalt.de (A. Groß)

0009-0000-9663-7361 (P. Plamper); 0000-0002-2684-8427 (A. Groß)

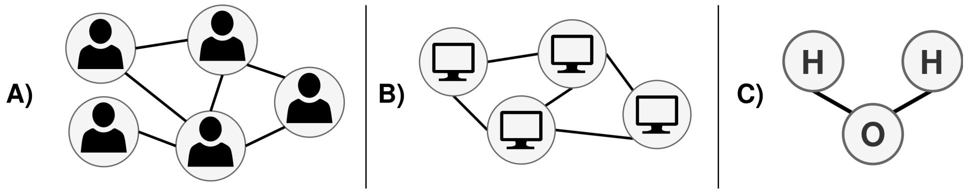

Figure 1: Three use cases of knowledge graphs. (A) Relationships between users in a social network. (B) Connections between computers in a computer network. (C) The bonds between atoms in a molecule.

the knowledge collected in ecosystem research remains unstructured in publications or is difficult to access in researchers' studies. A possible benefit of a STKG in ecology could be the linking of domain knowledge and experimental data to support data integration and analysis e.g. for uncovering unknown relationships, interactions or patterns. In this context, there is a significant need to develop new methods and interdisciplinary approaches. The "AgriRestore" project, for instance, seeks to investigate a deep understanding of key indicators for more resilient ecosystems and landscapes [10]. To this end, researchers from different disciplines (ecology, agriculture, data science) are working together to investigate ecological relationships across various spatial and temporal scales.

The origins of STKG trace back to early research in graph theory. Over time graph models have evolved from simple graphs to semantically enriched knowledge graphs. Similarly, basic graph algorithms have evolved into comprehensive deep learning architectures. Research on graphs and networks has been conducted simultaneously and independently of each other in different domains such as mathematics, computer science, physics, biology and geography. This resulted in a lack of standardization and inconsistent terminology. A historical overview is helpful in order to understand the origins of STKG and develop a holistic understanding for deeper insights. Examining contributions from various disciplines fosters a comprehensive understanding of STKG and promotes interdisciplinary collaboration to improve their development. The main contributions of the paper are:

- A brief outline of the origins of STKG, including knowledge, temporal and spatial graphs.
- A high-level overview of our approach and planned research on STKG in the domain of ecology.

The remainder of this paper is organized as follows: Section 2 presents the origins of spatio-temporal knowledge graphs. In Section 3 we introduce our approach for spatio-temporal knowledge graphs within the project "AgriRestore". Section 4 summarizes and concludes this work.

2. Origins of Spatio-Temporal Knowledge Graphs

To gain a comprehensive understanding of the origins of spatio-temporal knowledge graphs, it is helpful to look beyond individual contributions and consider the overall development of the field over time. Table 1 presents a timeline highlighting years alongside selected publications and concepts introduced during those periods. The timeline serves several purposes: it highlights important trends and changes in the field, provides a condensed historical context and helps to develop a conceptual understanding of how today's modern approaches emerged. It also underlines the interdisciplinary nature of the field, as spatio-temporal knowledge graphs are not only applied in different areas, but the basic research has also been driven by several disciplines, including computer science, physics and geography. This timeline is not intended to be exhaustive. Rather, it highlights selected milestones that we believe are relevant for understanding the historical development of the field.

Graph theory dates back to the 18th century, when Leonhard Euler published an answer to the "Königsberg bridge problem" [11]. Two hundred years later, the research area gained broader interest again. A starting point of modern graph theory was the idea of "random graphs", a graph model where edges are generated on a fixed set of nodes based on probabilistic processes [12]. At the same time, fundamental algorithms were also proposed. These include, for instance, the "Dijkstra" algorithm [13], a shortest path algorithm within weighted graphs that has also been adapted for temporal graphs [33] and is still relevant for spatio-temporal knowledge graphs [34].

Table 1
An outline of the origins of spatio-temporal knowledge graphs.

1736	“Seven Bridges of Königsberg”, Euler [11]
1959	“Random Graphs”, Erdős and Rényi [12]
1959	“Shortest-Path” Algorithm, Dijkstra [13]
1969	Book “Network analysis in geography”, Haggett and Chorley [14]
1969	Network Database Model “CODASYL”, Bachman et al. [15]
1972	Foundational Book “Graph Theory”, Harary [16]
1978	Centrality Measures, Freeman [17]
1990s	Considerations on Temporal Network Models
1993	Ontologies in Computer Science, Gruber [18]
1998	“PageRank” Algorithm, Page and Brin [19]
1998	“Small-World” Networks, Watts and Strogatz [20]
1999	Spatio-Temporal Graph Model, Renolen [21]
1999	“Scale-Free” Networks, Barabási [22]
1999	Draft RDF-Standard, Lassila and Swick[a]
2001	Introducing “Semantic Web”, Berners-Lee et al. [23]
2002	Community Detection, Girvan and Newman [24]
2002	Statistical Mechanics on Networks, Albert and Barabási [1]
2009	Graph Neural Networks (GNN), Scarselli et al. [25]
2010	Property Graphs, Rodriguez and Neubauer [26]
2011	Survey Spatial Networks, Barthelemy [4]
2012	Cross-domain Survey on Temporal Networks, Holme and Saramäki [5]
2012	Introducing “Knowledge Graph” (KG), Google[b]
2016	Revival of GNN by introducing Graph Convolutional Networks, Kipf and Welling [27]
2016	Survey on KG, Paulheim [28]
2017	Survey on KG Embeddings, Wang et al. [29]
2020	Survey on KG Completion, Chen et al. [30]
2023	Property Graph Queries added in SQL:2023 standard[c]
2024	Survey unification KG and LLM, Pan et al. [31]
2024	Survey Deep Learning on STKG, Zeghina et al. [32]

[a] https://www.w3.org/TR/1999/REC-rdf-syntax-19990222/, last visited: 10.09.2025
[b] https://blog.google/products/search/introducing-knowledge-graph-things-not/, last visited: 10.09.2025
[c] https://www.iso.org/standard/79473.html, last visited: 10.09.2025

Soon after, the first books on graph theory have been published, describing numerous basic graph models and methods, including simple, weighted, labeled, directed and multigraphs. One of these fundamental books is “Graph Theory” by Frank Harary [16]. At the time, graphs were also being used to analyze geographical networks, reflected for instance in the book “Network analysis in geography” by Haggett and Chorley [14].

In 1969 the “Committee on Data Systems Languages” (CODASYL) developed the first network data model, which enables the declaration of data structures in form of networks [15]. In 1976, CODASYL published the corresponding network database model [35]. The relational data model was proposed in 1970 [36]. During the 1970s the network data model and the relational model were in competition. CODASYL’s model lost to the relational model due to the latter’s greater commercial adoption, still the network data model was one of the earliest data models developed [37].

In research, new algorithms continued to be investigated; overviews of these were published in the 1970s [17]. The "PageRank" centrality algorithm, which was used to rank websites, became very well known around 1998 [19]. Community detection algorithms gained broad interest in the early 2000s, with early approaches aiming to find communities using centrality-based criteria [24]. Both classes of algorithms were adopted for temporal [38, 39] and spatial [40, 41] graphs and are under investigation again in spatio-temporal knowledge graphs [42, 43].

Until the 1990s, graph theory often focused on "random graphs", this changed with the formulation of "small-world" networks [20] and "scale-free" networks [22]. Both network models are based on the assumption that real networks are often not the result of random processes. Small-world networks consist of small groups that are connected by a few hops. Scale-free networks have a few nodes with many edges and many nodes with few edges, i.e. the degree distribution follows the power-law. First major review articles were published shortly afterwards, providing an overview of the numerous network topologies, dynamics, metrics and analysis methods, e.g. [1]. At the same time, the first conceptual models of spatio-temporal graphs were proposed, highlighting their advantages but lacking practical implementation [21].

In the 1990s, there was a shift towards enhancing graph-based technologies and the semantic enrichment of data models. Two approaches that leverage graph structures to represent knowledge are ontologies [18] and the Resource Description Framework (RDF). Ontologies provide a structured and formal way to capture domain-specific knowledge and RDF offers a flexible and generic model for representing information on the web. RDF serves as a foundational technology of the Semantic Web [23]. Both ontology-based and RDF-based knowledge representations have been extended to support the integration of spatio-temporal data [44, 45].

During the 1990s, graph models were developed to incorporate temporal aspects into their structure and semantics. Previously, most examined graphs were static, i.e. changes over time at the nodes or edges are not taken into account. Temporal graph models emerged rapidly and independently across various domains. This led to a lack of standardization and consistent terminology. The topic received a major boost with the first large overview articles, e.g. "temporal networks" from 2012 [5].

Research relevant to spatio-temporal knowledge graphs also originates from geography and geographic information systems (GIS) [46], beginning in the mid-20th century. Spatial graphs, i.e. the nodes and edges are positioned in Euclidean space, experienced a revival of interest in the 2000s. The 2011 survey article titled "Spatial Networks" [4] provides a comprehensive overview of the field's developments.

A commonly used graph model for representing spatio-temporal knowledge graphs is the "Property Graph Model" (PGM). The PGM was examined in more detail in 2010 [26] and integrates several developments in graph modeling into a unified framework, e.g. directed and multiple edges, labels and attributes on nodes and edges. One of the key strengths of the Property Graph Model is its flexibility, making it adaptable across various domains. Along with RDF graphs, it is widely supported by modern graph databases [47].

Since the 2010s, research on graph models and their applications across various domains has significantly increased. Google established the term "Knowledge Graphs" (KG) in 2012. The first overview articles were already published soon after [28]. Other developments that have significantly influenced knowledge graphs include graph neural networks (GNNs), which were introduced in 2009 [25], but gained popularity with a 2016 publication [27] and are currently a major topic within spatio-temporal knowledge graphs [32]. Additionally, "knowledge graph embeddings" [29] aim to represent graphs in a low-dimensional space, for applications like "Nearest-Neighbor" algorithms. "Knowledge Graph Completion" [30] seeks to fill in missing information within a knowledge graph. Furthermore, the integration of Large Language Models (LLMs) has been explored for both constructing knowledge graphs and using knowledge graphs to support LLMs [31]. Moreover, the growing popularity of graph databases and declarative querying of graph structures has led to the integration of Property Graph Queries into the SQL:2023 standard.

The timeline represents an intermediate result of our ongoing research aimed at gaining a comprehensive overview of the origins and diverse contexts of spatio-temporal knowledge graphs.

3. Knowledge Graphs for Ecology

This section relates our work on spatio-temporal knowledge graphs to the ecological context of the "AgriRestore" project. Building on this, we summarize the core ideas of our research and outline challenges we want to address.

3.1. Ecological Background and Context

Ecology is a domain that can benefit from detailed modeling of spatio-temporal knowledge graphs. Within ecology there are many complex and dynamic relationships that impact ecosystems. Global change significantly impacts biodiversity and ecosystem functionality in agricultural landscapes, driven by multiple factors such as intensive land use. To counteract the impacts various ecosystem and landscape restoration (ELR) measures were developed. However, there is still a lack of methods and analyses for a deeper understanding of key indicators for the transition to more resilient ecosystems and landscapes. The project "AgriRestore"[1] (full title: "Ecosystem and landscape restoration across spatial and temporal scales to enhance biodiversity and climate resilience in agricultural landscapes") aims to extend the knowledge in restoration science by assessing the effects of temporary and permanent ELR measures in agricultural landscapes. To achieve this, the team of researchers conducts numerous experiments and analyses to identify factors for success or failure of ELR measures at various locations, with varying degrees of granularity (e.g. soil samples, remote sensing) and over different periods of time to achieve a holistic understanding of ecological restoration.

In this context, the suitability of spatio-temporal knowledge graphs, along with new methods for their creation and analysis, needs to be investigated. Spatio-temporal knowledge graphs can help to gain new insights through a comprehensive analysis of results from previous and new data collection. The created graph is intended to be the backbone for data integration and analyses. In addition, it aims to consolidate and assess landscape-level impacts, evaluate the generalizability of findings and identify patterns related to ecosystem and landscape restoration. Ultimately, our goal is to develop a data-driven approach that supports the creation of a knowledge-driven framework for ecosystem and landscape restoration across spatial and temporal scales.

3.2. Approach for Spatio-Temporal Knowledge Graphs

Figure 2 presents an overview of our approach to develop spatio-temporal knowledge graphs for complex systems, with a particular focus on ecosystem research. In addition, we want to introduce knowledge graph based analysis methods designed to uncover new insights, such as previously unknown patterns or relationships relevant to ecosystem dynamics and restoration. We pursue a holistic approach to avoid isolated consideration of individual components and to ensure compatibility and reproducibility.

Figure 2 (1) illustrates the extraction of knowledge graphs from both structured and unstructured data. Depending on the domain or use case, e.g. ecology, researchers often do not initially plan or work with knowledge graphs but build their analyses on structured data like tables or on unstructured data like written documents. Transforming these types of data into meaningful and broadly applicable graphs presents a significant challenge [48]. This is made even more complex when dealing with expressive models like spatio-temporal knowledge graphs. Moreover, the initial modeling of the knowledge graphs, i.e. what is stored where and how, is challenging and should not be neglected, as it influences data management and analysis in the long term. The resulting graph model of this process is influenced by several factors, including the properties to be stored and the type of data, e.g. static, temporal, spatial or spatio-temporal. Large Language Models (LLMs) promise a (semi-) automated knowledge graph creation of data volumes on a large scale [31]. LLMs can be used to create a knowledge graph from structured and unstructured data. However, these methods must be examined in terms of their applicability and quality for different types of data and goals. Further challenges include the traceability

[1]https://agrirestore.de/, last visited: 10.09.2025

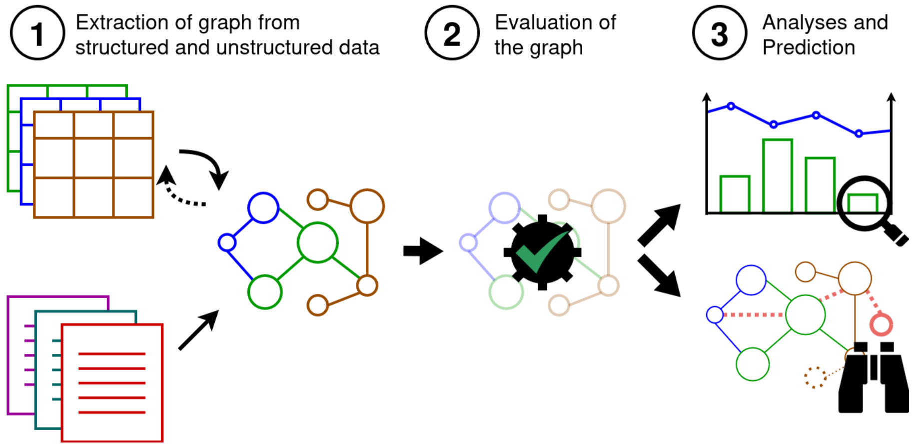

Figure 2: Overview of our approach to a spatio-temporal knowledge graph. (1) Most data is currently not in form of graphs. Therefore suitable methods must be found to transform common structured and unstructured formats into a graph. (2) Graphs must be evaluated to ensure that both the generation and analysis methods deliver meaningful results. (3) Appropriate analyses methods can generate meaningful information from a graph or make predictions possible.

of information obtained from unstructured and structured data. While unstructured data might refer to its origin, methods could be investigated that enable the reconstruction of the original structured data.

Figure 2 (2) addresses the evaluation of knowledge graphs. Suitable evaluation methods for knowledge graphs are a current challenge, i.e. methods that verify the validity of a created knowledge graph [49]. The challenge remains for both small and large knowledge graphs, as well as for those manually conceptualized, generated by LLMs or hybrid approaches. In certain applications of knowledge graphs, e.g. ecological systems or chemistry [50], the inherent complexity of the data can hinder even experts from effectively evaluating the entities and relationships within the graph. In these domains, a crucial challenge is figuring out what evaluations criteria can be used and how to assess knowledge graphs when the truth is not (yet) known. Even when the truth is not fully known, knowledge graphs can still be valuable in these fields by advancing research areas. By providing a holistic view on the considered objects and their relationships, they can help to derive new information and support the planning and design of new experiments.

Figure 2 (3) illustrates the analyses and prediction on top of spatio-temporal knowledge graphs. One of the primary reasons for creating a knowledge graph is to leverage its structure to gain insights. Thus, finding suitable analytical methods that yield meaningful and interpretable results is a significant challenge. The range of methods available for graph analysis is already quite extensive, e.g. link prediction [51], community detection [52] and centrality [53]. Future research could examine whether existing analysis methods are expressive enough for spatio-temporal knowledge graphs or if entirely new approaches are required. Predictive tasks are already showing increasingly promising results on spatio-temporal knowledge graphs, making them a compelling area [32].

Our approach within the “AgriRestore” project will comprise the transformation of structured and unstructured data into a spatio-temporal knowledge graph. A suitable graph model is defined in advance, which should be generalizable and transferable to other fields of application. Further, it is crucial to develop evaluation methods and benchmark data sets for knowledge graphs created within ecology. The methods should not only rely on expert knowledge but also be (semi-) automated and capable of handling data where the truth is not yet known. The spatio-temporal knowledge graph could serve as the initial point of contact for new data obtained from experiments conducted within the project. The graph structure could also help in uncovering connections between data points that have previously remained hidden. Further in-depth analyses could assist in evaluating the various impacts on ecosystems and biodiversity. On a temporal scale, the knowledge graph could be used to trace previous developments and predict future states. On a spatial scale, its applicability to other regions could be evaluated.

4. Conclusion

The paper shows that spatio-temporal knowledge graphs have their origins in an extensive body of literature that has emerged over several decades of graph research. New publications are emerging on a large scale, addressing current challenges and seeking to provide a better understanding of complex systems in time and space. Previously established findings must be acknowledged to prevent the redundant reinvention of existing concepts. There are numerous unresolved and new challenges that need to be addressed. These challenges arise at various stages, starting with the construction of spatio-temporal knowledge graphs and continuing through to their analysis.

In future work, our goal is to adopt a holistic approach that considers all processes in the life cycle of spatio-temporal knowledge graphs in an ecological context. The objective of this concept is to avoid isolating individual components and to ensure compatibility and reproducibility. Furthermore, we will elaborate on specific challenges of spatio-temporal knowledge graphs within ecosystem research, highlighting, among other things, the possibilities and limitations of previous approaches and possible directions for development.

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