A geographic knowledge integrated computation framework based on grid graph modelling

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Abstract

Managing dynamic geographic knowledge effectively is hindered by fragmented tools lacking holistic integration, particularly when handling the heterogeneous and evolving nature of real world spatio-temporal data. Traditional knowledge graphs and databases struggle with efficient representation, storage, and reasoning over such complex information. This paper propose an integrated computation framework built upon Grid Graph Modelling to make geography computable. This framework provides an end-to-end solution encompassing knowledge representation, storage, querying, and spatio-temporal reasoning. It synergistically integrates three core components: the Grid Augmented Geographic Knowledge Graph (AugGKG) for unified grid based representation with computable spatial relations; the Grid Graph Database (GGD) for spatially aware storage and efficient grid algebra based computation; and the Grid Neighborhood-based Graph Convolutional Network (GN-GCN) for advanced reasoning by learning from semantic, spatial grid, and temporal dimensions. This cohesive architecture transforms diverse geographic data into actionable knowledge, enabling efficient querying and complex reasoning, paving the way for next generation intelligent geospatial systems, including empowering foundation models, enhancing smart cities, creating digital twins, and reasoning geographic event evolution.

1. Introduction

The modern era is characterized by an unprecedented deluge of geographic data, originating from diverse sources such as Earth observation satellites, in situ sensor networks, mobile devices, and volunteered geographic information (Gao et al., 2024; Janowicz et al., 2019). This wealth of data holds immense potential for understanding and managing our increasingly complex and dynamic planet, addressing critical challenges in areas like climate change, urbanization, and resource management. However, transforming this raw geographic data into actionable geographic knowledge requires sophisticated frameworks capable of handling its inherent complexities, coupled with the intricate interplay of semantic attributes, spatial configurations, and temporal evolution (Zheng et al., 2021; Ma, 2022).

Current approaches to geographic knowledge management often suffer from significant fragmentation. Existing tools and systems typically excel in specific niches, such as semantic web technologies for ontology modelling (Kokla, and Guilbert 2020), geographic deep learning for spatial analysis, spatial database technologies for storage, but they lack a unifying, end to end architecture (Alam, Torgo, and Bifet 2022). This fragmentation leads to cumbersome workflows, data interoperability issues, information silos, and substantial computational inefficiencies, hindering the ability to perform holistic analysis and reasoning over dynamic geographic phenomena (Wang et al., 2024).

Meanwhile, traditional Knowledge Graphs (KGs), while powerful for representing static relations and semantic facts (Chen, Jia, and Xiang 2020), encounter fundamental difficulties when extended to the spatio-temporal domain. Accurately representing continuous space and time within discrete graph structures, unifying diverse geospatial data types, modeling dynamic processes and evolving relations, and enabling efficient spatio-temporal querying and reasoning remain open challenges (Huang et al., 2019). Simply adding coordinate pairs or timestamps as literal attributes to graph nodes or edges often fails to capture the rich structure and computability inherent in geographic space and time (Mai et al., 2021).

Conventional database systems also present limitations. Relational databases struggle with the complex; often non-hierarchical relations found in geographic networks and the schema evolution required for dynamic data. Key value stores, though scalable, lack the semantic richness and optimized spatial query mechanisms needed for sophisticated geospatial analysis (Puangsaijai, and Puntheeranurak 2017). Standard graph databases, while naturally suited for relationship modeling, typically lack native support for spatio-temporal indexing, query operators (e.g., range queries, nearest neighbor searches), and embedded computational geometry, leading to performance degradation when handling large scale, geographically explicit datasets (Malinverni et al., 2020; Bernardino, and Fernandes 2018). The need for specialized indexing and processing paradigms is evident (Tian et al., 2022).

Discrete Global Grid Systems (DGGS) offer a compelling alternative, providing a globally consistent, hierarchical framework for partitioning the Earth's surface (or volume) into uniquely identifiable cells (Gibb et al., 2022; Zhou et al., 2024). DGGS facilitate seamless data integration across different sources and resolutions, provide efficient indexing mechanisms, and enable optimized spatial analysis through grid or voxel based operations (Robertson et al., 2020). Leveraging the potential of DGGS, this proposes a Geographic Knowledge Integrated Computation Framework based on Grid Graph Modelling. This framework is architected as a cohesive, end to end system designed to manage the full lifecycle of dynamic geographic knowledge. This paper details the unifying grid graph model, elaborates on the functionality and synergistic integration, explores promising future applications unlocked by this architecture, and concludes by summarizing the contributions. The framework's core innovation lies in its tightly coupled, grid centric design, aiming to overcome the fragmentation and computational limitations of prior methods, thereby enabling more robust, scalable, and efficient management and reasoning over complex geographic knowledge.

2. Grid Graph Model

The Grid Graph Model serves as the conceptual and computational underpinning of geographic integrated framework. Its adoption is motivated by the need to overcome fundamental limitations in traditional geographic information handling, where representing and computing spatio-temporal relations across large, dynamic, and heterogeneous datasets is often inefficient. Traditional coordinate-based systems make deriving spatial relations computationally intensive and querying spatio-temporal ranges slow (Lei et al., 2022). Integrating diverse data types also remains challenging (Li, McGrath, and Stefanakis 2021).

This model employs the DGGS system to discretize space and time. This discretization provides a unified structure for representing varied geographic entities and phenomena, mapping them to sets of grid cells within specific time slices . Significantly, the structure of GeoSOT codes that we employed allows spatial relations like adjacency and proximity to be computed efficiently through grid coding algebra (Zhai et al., 2021), transforming geographic space into a computable domain. These codes also function as highly effective spatio-temporal indices, enabling rapid data access and optimized range queries (Han, and Qu 2024; Lei et al., 2023). Furthermore, the inherent hierarchy supports seamless multi scale analysis and aggregation (Qian et al., 2019; Han et al., 2022).

By placing the grid at its core, our approach treats space and time not merely as attributes but as fundamental, computable organizational structures. The framework synergistically integrates three specialized components developed in our previous research. As shown in Figure 1, the overall architecture of the integrated framework is built directly upon this grid model. Data flows sequentially through the components, leveraging the grid structure at each stage. Initially, raw data is processed by the AugGKG layer, which performs grid encoding to create standardized knowledge quadruplets. Subsequently, these grid encoded quadruplets are managed by the GGD layer, which utilizes the grid codes for optimized storage exploiting spatial locality and rapid retrieval. Finally, the GN-GCN reasoning layer interacts with the GGD, efficiently accessing grid encoded facts. This reasoning layer uniquely exploits the semantic graph structure, the spatial neighborhood structure inherent in the grid, and the temporal sequences defined by the framework. In essence, the spatio-temporal grid acts as the unifying thread, providing the common data structure and computational foundation that enables seamless integration and powerful reasoning across the framework's components.

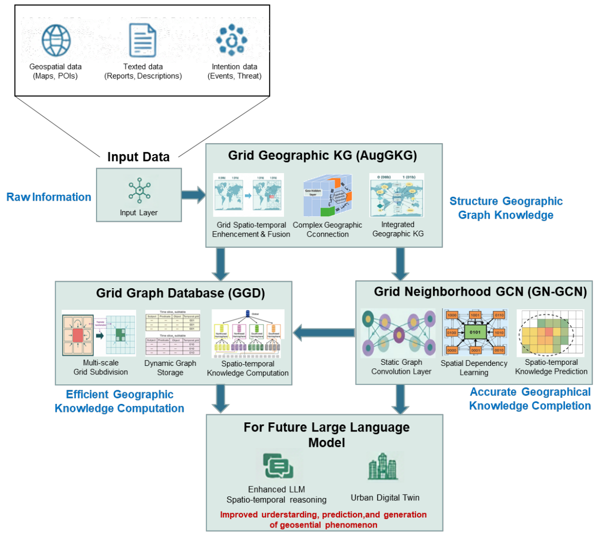

Figure 1. The Schematic diagram of the geographic knowledge integrated computation framework based grid graph modelling.

3. Geographic Knowledge Integrated Framework based on Grid Graph Modelling

The proposed framework integrates three specialized components: AugGKG, GGD, and GN-GCN, to build upon the common foundation of the grid graph model. This integration facilitates a seamless flow from data representation to storage, querying, and advanced reasoning.

3.1 Geographic Knowledge Representation and Integration (AugGKG)

The Grid-Augmented Geographic Knowledge Graph (AugGKG) model serves as the crucial first step, transforming diverse and often unstructured geographic information into a standardized, computable format (Han et al., 2023). Its core function is to represent geographic entities, events, and their attributes within a discrete spatio-temporal framework provided by GeoSOT and time slicing. AugGKG defines primary node types including Locgrid (encoded spatio-temporal girds), Entity (geographic objects), Heading (movement direction), Event (significant occurrences), and Attribute (node properties). These nodes provide a structured vocabulary for describing the elements within a geographic scene. These nodes are then connected by relations within time sliced subgraphs. AugGKG distinguishes between Explicit Relations, which are directly stored facts representing basic connections like temporal continuity, spatial location, or semantic links, and Implicit Relations. Implicit Relations encompass spatio-temporal relations such as distance, direction, topology, and influence, which are generally too numerous to store exhaustively for all pairs of entities or events.

3.2 Geographic Knowledge Storage and Computation (GGD)

Once geographic knowledge is represented by AugGKG in the form of grid encoded quadruplets, the Grid Graph Database (GGD) provides a specialized architecture for its efficient storage, retrieval, and computation (Han et al., 2025). GGD's design addresses the specific needs of storing and querying large scale, dynamic spatio-temporal graph data, overcoming inefficiencies found in generic database solutions.

The storage architecture of GGD employs a five-table structure tailored to the AugGKG model: Node Table, Edge Table, Spatial Grid Table, Quadruplet Table, and Triplet Table. This structure separates static definitions (like entity types or grid definitions) from dynamic spatio-temporal facts (stored primarily in the Quadruplet Table) and purely semantic facts (in the Triplet Table). The Quadruplet Table, holding the bulk of the dynamic spatio-temporal facts, is meticulously organized. It is partitioned by time slices. Within each time slice partition, quadruplets are spatially sorted based on the Z order curve derived from the spatial codes of their subjects or objects. This ordering ensures that data points close in space and time are also stored closely together physically, enhancing data locality.

Computation within GGD is accelerated by leveraging grid coding algebra, enabling efficient execution of spatio-temporal operations directly within the database. Operations fundamental to spatio-temporal analysis, such as displacement calculation, distance derivation, direction finding, topology determination (overlap, adjacency, separation), and set operations, are implemented using optimized operations on the binary grid codes rather than relying on external geometric libraries. This embedded computational capability allows GGD to handle complex spatio-temporal queries, including K nearest neighbor searches and range queries, much faster than traditional approaches by exploiting the structure and algebra of the grid.

Furthermore, GGD is designed for scalability using a spatially distributed parallel optimization strategy. The inherent partitioning provided by the GeoSOT grid is used to distribute the Quadruplet and Spatial Grid tables across a cluster of servers. Each server becomes responsible for the data associated with specific spatial regions defined by code prefixes. A cluster addressing mechanism maps queries to the appropriate nodes based on the grid codes involved. This approach maintains spatial locality within partitions while enabling parallel query processing and computation across the cluster, ensuring the framework can handle massive datasets efficiently.

3.3 Geographic Knowledge Spatio-temporal Prediction and Reasoning (GN-GCN)

Building upon the representation provided by AugGKG and the efficient storage and querying capabilities of GGD, the Grid Neighborhood-based Graph Convolutional Network (GN-GCN) serves as the framework's intelligent reasoning and prediction engine (Han, Qu, and Jiang 2025). Its primary function is spatio-temporal knowledge graph completion, aiming to predict missing entities or relations in spatio-temporal quadruplets ((s, p, o, t)) by learning complex patterns and dependencies.

GN-GCN adopts a unique tripartite learning architecture designed to explicitly capture semantic, spatial, and temporal context. It integrates three modules synergistically. First, a Static Graph Neural Network (GNN) module processes the semantic graph structure within each time slice subgraph provided by AugGKG. It learns embeddings that reflect the semantic relations between entities and concepts, similar to traditional KG embedding techniques but applied dynamically at each time step.

Second, the Neighborhood Grid Calculation (NGC) module introduces spatial awareness by directly leveraging the grid map associated with the AugGKG. When dealing with entities or events associated with Locgrids, this module learns not only from their semantic graph neighbors (via the static GNN) but also simultaneously from their spatial neighbors within the grid. It employs a message passing mechanism that considers grid adjacency and topology to capture spatial dependencies that are often ignored in standard GNNs. The NGC module effectively fuses the semantic embeddings from the static GNN with spatial context derived from the grid, producing rich spatio semantic embeddings. This fusion can be conceptually represented as combining semantic and geographic context factors:

$$\vec{e}^{\,l}_{o,t} = \lambda_1 \vec{e}^{\,l}_{GRAPHo,t} + \lambda_2 \vec{e}^{\,l}_{GEOo}, \tag{1}$$

$$\vec{e}^{\,l}_{GRAPHo,t} = f\left(\frac{1}{c_o}\sum_{(s,p)\in\sigma_t} W^{l-1}_{neighbor}\left(\vec{e}^{\,l-1}_{s,t} + \vec{p}_t\right) + W^{l-1}_{self}\vec{e}^{\,l-1}_{o,t}\right), \tag{2}$$

$$\vec{e}^{\,l}_{GEOo} = f\left(\frac{1}{c_o}\sum_{(s,Adj)\in\sigma} \overline{W^{l-1}_{neighbor}}\left(\vec{e}^{\,l-1}_{GEOs} + \vec{p}_{GEO}\right) + \overline{W^{l-1}_{self}}\vec{e}^{\,l-1}_{GEOo}\right), \tag{3}$$

Then, the Time Evolution Unit (TEU) module, implemented using a GRU like architecture, models the temporal dynamics. It processes the sequence of spatio semantic embeddings generated by the NGC module across consecutive time slices. By incorporating information from previous time steps, the TEU learns temporal patterns, trends, and dependencies, producing final evolutionary embeddings that encapsulate the state and likely trajectory of entities and relations over time.

By explicitly modeling and integrating semantic connections, spatial grid adjacencies, and temporal sequences, GN-GCN achieves superior accuracy and interpretability in spatio-temporal reasoning tasks compared to models that neglect one or more of these critical dimensions.

4. Future Applications about Grid Geographic Knowledge Integrated Framework

The integrated computation framework, synergizing AugGKG, GGD, and GN-GCN on foundation, opens up numerous possibilities for advanced geospatial applications by providing a robust, scalable, and computationally efficient way to manage and reason over dynamic geographic knowledge.

4.1 Foundation Models and Geographic AI

The rise of foundation models, especially Large Language Models (LLMs), presents exciting opportunities for more intuitive human computer interaction with complex data (Liu et al., 2024). However, their inherent limitations in precise numerical computation, factual consistency, and spatio-temporal grounding hinder their direct application in critical geospatial domains (Meyer et al., 2024). Our framework can establish a synergistic relationship with these models, enhancing their capabilities in both upstream prompt engineering and downstream result validation, which could be shown in.

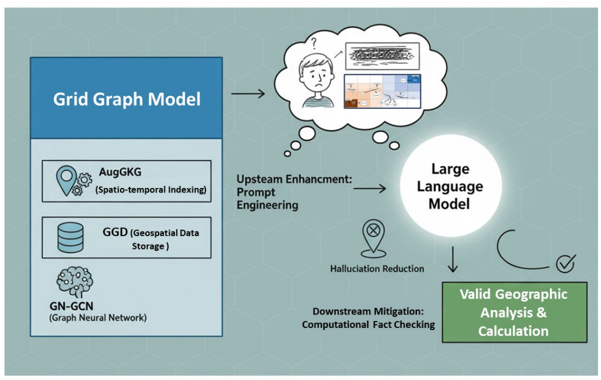

Figure 2. The function of grid graph model for upstream and downstream of foundation model.

4.1.1 Upstream Enhancement: Grid Grounded Prompt Engineering

Providing clear, unambiguous context is crucial for eliciting accurate responses from LLMs. Our framework significantly enhances prompt engineering for geospatial tasks by leveraging the structured, grid based knowledge representation. Instead of relying on potentially ambiguous place names or descriptions, prompts can incorporate precise spatio-temporal references using grid codes and time slice identifiers managed by AugGKG and GGD.

For example, a prompt asking an LLM to generate a risk assessment could be formulated as: "Assess the flood risk for infrastructure assets located within GeoSOT level 16 grid cells during time slice, considering terrain elevation [Attribute query to GGD] and predicted rainfall intensity [Event data query to GGD]". The explicit grid codes define the exact area of interest, while queries to GGD retrieve verified, current data attributes, providing precise grounding that standard LLMs lack.

Furthermore, complex spatio-temporal patterns or relations pre computed by GN-GCN (e.g., predicted traffic flow bottlenecks) can be summarized and included in the prompt, enriching the LLM's contextual understanding beyond simple geographic coordinates. This grid grounded approach reduces ambiguity and focuses the LLM on the relevant spatio-temporal context, leading to more accurate and relevant generated text or analysis.

4.1.2 Downstream Mitigation: Computational Fact Checking and Hallucination Reduction

LLMs are known to occasionally "hallucinate," generating plausible but factually incorrect information (Meyer et al., 2024). In geospatial contexts, where decisions can have real world consequences, ensuring factual accuracy is paramount. Our framework acts as a powerful downstream validation engine to detect and correct spatio-temporal inaccuracies in LLM outputs. When an LLM makes a specific geospatial claim (e.g., asserting a specific travel time, predicting the location of a dynamic entity, or describing the impact radius of an event), this assertion can be translated into a query or computation task for our framework. GGD can retrieve ground truth data for the relevant location and time, while the GN-GCN reasoning engine can perform independent calculations or predictions.

For instance, if an LLM predicts a certain travel time between two locations, GGD can retrieve the relevant road network grid codes and associated real time traffic data, potentially using GN-GCN to simulate the journey based on learned patterns, yielding a computationally derived travel time. This result can then be compared against the LLM's assertion.

Similarly, if an LLM predicts the impact zone of a simulated environmental event, GN-GCN's event evolution capabilities can generate a grid based prediction for comparison. By leveraging the framework's ability to store verified facts and perform reliable spatio-temporal computations, inconsistencies and hallucinations in LLM outputs related to locations, distances, times, or dynamic processes can be identified and flagged or corrected (Stephen et al., 2024). The framework essentially provides the spatio-temporal "calculator" and "fact checker" that LLMs intrinsically lack. Integrating these components allows for a system where LLMs handle natural language interaction and high level conceptual understanding, while our framework ensures the spatio-temporal accuracy and computational rigor.

4.2 Smart Cities and Traffic Management

Urban environments, characterized by dense populations and complex infrastructure interactions, generate vast amounts of dynamic spatio-temporal data (Bao et al., 2023). Our framework can significantly enhance smart city operations. For intelligent transportation systems, integrating real time data streams from traffic sensors, vehicle GPS, public transit systems, and incident reports can be seamlessly achieved by AugGKG mapping these sources onto the grid representing the road network. GGD provides efficient storage for this high volume, rapidly changing data. Subsequently, GN-GCN can leverage this integrated information for tasks like predictive traffic flow modeling. By learning from the semantic graph structure (road connectivity), the spatial grid neighborhood (how congestion propagates between adjacent road segments represented by grid cells), and temporal patterns (recurring rush hours), GN-GCN can forecast congestion with high granularity and accuracy.

For example, upon detecting an accident (an Event) in a specific Locgrid, the model could predict the spatio-temporal spread of the resulting traffic jam through adjacent Locgrids, enabling proactive traffic rerouting advice or dynamic traffic signal adjustments based on predicted conditions, as shown in Figure 3. Similar principles apply to optimizing public transport schedules based on real time demand prediction or planning emergency vehicle routes considering predicted traffic (Wang et al., 2021).

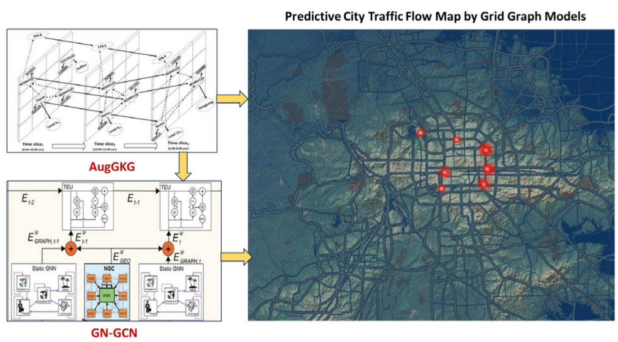

Figure 3. Predictive Traffic Flow Modeling of Grid Graph Model.

4.3 Geographic Entity or Event Evolution Reasoning

Understanding and predicting the movement and behavior of dynamic geographic entities or events, such as ships or aircraft, is crucial for transportation management, maritime security, air traffic control. Our framework provides powerful tools for modeling these entities and reasoning about their future trajectories and intentions. AugGKG represents the path of a vessel or aircraft as a sequence of (Entity, Located in, Locgrid, Temporal grid) quadruplets, augmented with Heading information. GGD efficiently stores these vast trajectory datasets, enabling rapid retrieval of historical paths, associated environmental conditions, and contextual information like designated shipping lanes or airways.

Meanwhile, the GN-GCN engine excels at learning complex movement patterns from this integrated data, and captures spatial constraints, learning how entities typically move within specific geographic contexts (e.g., following shipping lanes, avoiding restricted airspace, reacting to bathymetry or terrain implicitly encoded in grid neighborhoods). It can also learn interaction patterns, such as collision avoidance maneuvers observed between nearby vessels or aircraft. By integrating semantic knowledge (e.g., vessel type, flight plan), spatial constraints learned from the grid neighborhood, and temporal dynamics, GN-GCN can predict the future Locgrid sequence for an entity or entity, effectively forecasting its trajectory. For instance, based on a ship's current position, heading, speed, historical behavior in similar conditions, and nearby vessel traffic, GN-GCN could predict its likely position grid cells over the next several time slices, as shown in Figure 4.

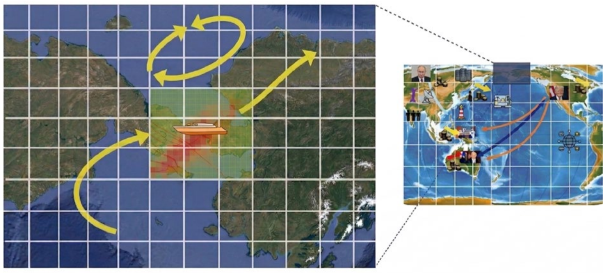

Figure 4. The geographic entity evolution based grid graph modelling.

5. Conclusion

In conclusion, this paper introduced an integrated computation framework designed to effectively manage and reason over dynamic geographic knowledge, addressing key limitations of existing fragmented approaches. By centering the architecture on the Discrete Global Grid System, this paper established a foundation where geographic space and time become inherently computable structures based on grid graph model. This integrated design overcomes critical bottlenecks associated with traditional geographic knowledge graphs and databases, offering superior performance in spatio-temporal querying, and the ability to perform complex deductive reasoning and prediction tasks previously intractable. Furthermore, the explicit incorporation of spatial and temporal structures via the grid lends greater interpretability to the reasoning process compared to purely semantic or black box approaches.

The potential applications of this framework are vast and impactful, ranging from empowering foundation models with robust spatio-temporal grounding for GeoAI, to revolutionizing smart city management and traffic optimization, enabling high fidelity geospatial digital twins, and facilitating sophisticated reasoning about the evolution of geographic entities or events. It lays a critical foundation for building next generation intelligent geospatial systems capable of understanding, predicting, and interacting with our complex and dynamic world.

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