GIS Analysis Model Integration and Service Composition Prospects

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Abstract

In the context of rapidly evolving geospatial technologies, this study provides a comprehensive review of GIS model integration and service composition, emphasizing their critical roles in enhancing spatial analysis accuracy, decision-making efficiency, and cross-domain interoperability. Model ensemble techniques, rooted in machine learning and data mining, address limitations of single models by combining predictions from multiple base learners, thereby improving robustness and reducing overfitting. GIS model integration involves combining diverse spatial algorithms—such as buffer analysis, network analysis, spatial regression, and machine learning models—to tackle multifaceted geographic challenges. Key algorithms are systematically integrated to optimize outcomes in urban planning, disaster management, and precision agriculture. For instance, land-use change prediction synthesizes spatial regression, machine learning, and remote sensing, while natural disaster systems merge meteorological models with post-disaster assessments. The fusion of industry-specific models with GIS enhances location-based decision support by embedding spatial variables into domain workflows. Cloud-native architectures and AI-driven automation emerge as pivotal trends, offering scalable, real-time GIS solutions via platforms like serverless computing and SaaS. These innovations promise self-learning agents capable of automated spatial pattern recognition, real-time alerts, and optimized resource allocation. Despite progress, challenges persist in model selection, interpretability, and robustness. Future research directions emphasize large language model (LLM)-powered agents for intelligent geospatial processing, cloud-GIS hybrid platforms for elastic resource management, and industry-tailored SaaS solutions. By bridging traditional GIS tools with intelligent service ecosystems, this evolution aims to drive digital transformation, enhance cross-sector competitiveness, and unlock new potentials in spatial decision-making.

1. Introduction

1.1 General Instructions

In the fields of machine learning and data mining, model ensemble has gained widespread attention and application in recent years as an effective technique to improve prediction performance. Single predictive models often fail to achieve ideal results due to data complexity, noise, or the limitations of the model itself. To address this issue, model ensemble methods combine the predictions of multiple base learners to significantly enhance prediction accuracy, improve model robustness, and reduce overfitting. The core idea behind model ensemble is derived from the concept of "wisdom of crowds," which suggests that the combination of multiple relatively simple individual models can yield a result superior to that of any single model. Early ensemble methods, such as Bagging (Bootstrap Aggregating) and Boosting, have already achieved notable success in various applications by combining models in different ways. For example, Random Forest improves classification and regression accuracy by constructing multiple decision trees, while AdaBoost combines multiple weak classifiers with weighted adjustments to create a strong classifier. With the development of deep learning and big data technologies, more complex and computationally intensive models have emerged, making ensemble learning an indispensable part of many real-world applications. In recent years, ensemble methods have not only been widely applied to traditional machine learning tasks but have also expanded into GIS field (LI et al., 2016, Yue et al., 2024).

However, despite the significant improvement in prediction accuracy achieved through model integration, effectively selecting integrated models, reducing computational costs, and improving model interpretability remain key challenges in practical applications. In recent years, many new ensemble methods have been proposed, such as stacking and adaptive ensemble methods, which aim to flexibly select model combinations and reduce unnecessary computational overhead through optimization algorithms (Wang et al., 2011, Zeng et al., 2021).

2. GIS Model Integration

Model integration is an important research direction in the field of artificial intelligence, involving the combination of multiple different models or algorithms to improve predictive accuracy, enhance performance, or deal with complex problems. With the increase in data scale and the improvement of computing power, model integration techniques have been widely applied (LI et al., 2016, Noorollahi et al.,2008, Batty et al.,2011). Model integration involves forming a whole from multiple different models to enhance performance or address complex issues.

2.1 GIS Algorithm Model

The GIS algorithm model is a mathematical model and program used for processing and analyzing geospatial data. It is widely applied in Geographic Information Systems (GIS) to solve various spatial problems. Common algorithms include buffer analysis, distance measurement, topological relationship

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judgment, spatial interpolation, network analysis, and geographically weighted regression. as shown in the table below:

1. Buffer algorithm: Used to determine the buffer zone range of geographic features. Based on geographic features such as points, lines, and areas, it generates buffer polygons according to a set distance. For example, a buffer with a radius of 5 kilometers can be generated for a factory as a point feature to analyze the pollution impact range of the factory; a buffer of 50 meters on each side can be generated for a river as a linear feature to define the scope of a river ecological protection zone.

2. Overlay analysis algorithm: Multiple spatial data layers are overlaid to perform operations such as intersection, union, and erasure of spatial features to extract new information. For example, polygon overlay algorithm, by overlaying two or more polygon layers, can obtain the intersection, union, and difference results between polygons. It is commonly used in land use planning to analyze the overlap and change areas of different land use types.

3. Network analysis algorithm: Analysis is conducted in various network data such as transportation and communication networks. For example, the Dijkstra algorithm is used to find the shortest path in a network and can be applied in navigation systems to plan the best driving routes; the Floyd-Warshall algorithm can calculate the shortest paths between all pairs of nodes in a network and is often used to analyze the accessibility and shortest distances between nodes in a transportation network.

4. Slope and Aspect Calculation Algorithm: Calculates the slope and aspect of the terrain based on Digital Elevation Model (DEM) data. Commonly used algorithms include differential methods based on a 3×3 window. By performing differential calculations on the elevation values surrounding each grid point in the DEM data, the slope and aspect information for that point can be obtained. This provides fundamental data for topographic and geomorphologic analysis, as well as land use planning.

5. Watershed Analysis Algorithm: Determines the boundaries of a watershed and the distribution of its hydrological network. For example, watershed and hydrological network extraction algorithms based on DEM data involve steps such as depression filling, flow direction calculation, and flow accumulation calculation. These steps help identify the boundaries of watersheds and the distribution of hydrological networks, which are crucial for water resource management and flood control and disaster reduction.

6. Line-of-Sight Analysis Algorithm: Determines whether there is a clear line of sight between two points or between a point and an area. Based on DEM data, it calculates the intersection points of the line of sight with the terrain surface to determine visibility. This is commonly used in fields such as military lookout point selection and communication base station siting.

7.Coordinate Transformation Algorithm: Used for converting between different coordinate systems, such as the transformation between geographic coordinates (latitude and longitude) and plane rectangular coordinates, as well as between different projected coordinate systems. Common algorithms include the Gauss-Kruger projection transformation algorithm and the UTM projection transformation algorithm, which enable the unified expression and analysis of spatial data in different geographic frameworks.

8. Data Interpolation Algorithm: When the spatial data values of a limited number of discrete points are known and it is necessary to infer the values of unknown points, interpolation algorithms are used. For example, the Inverse Distance Weighting (IDW) algorithm assigns weights to known points based on their distance from the interpolation point, with closer points having greater weights. The Kriging interpolation algorithm, on the other hand, takes into account the spatial autocorrelation of the data and performs interpolation based on the theory of the variogram, which can more accurately reflect the trends in spatial data changes. It is commonly used for interpolating meteorological and soil data.

9. Data Compression Algorithm: To reduce the storage and transmission volume of spatial data and improve data processing efficiency, data compression algorithms are employed. For example, the Douglas-Peucker algorithm simplifies curves by removing points that have a smaller impact on the shape of the curve, thereby reducing the data volume while maintaining the basic shape of the curve. Run-length encoding is another method that encodes sequences of repeated values by representing them with a single value and a count of repetitions, and it is often used for compressing raster data.

10. Spatial Regression Algorithm: Spatial regression analysis algorithms are designed to model and analyze spatial data while accounting for spatial dependence and heterogeneity. Unlike traditional regression models that assume independence among observations, spatial regression models consider the spatial relationships between data points. such as Spatial Autoregressive (SAR) Model and Geographically Weighted Regression (GWR).

11. Spatial Clustering Algorithm: Spatial clustering analysis algorithms group spatial data points into clusters based on their spatial proximity and similarity in attributes. These algorithms help identify spatial patterns and hotspots in the data. Such as, K-Means Clustering, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and Hierarchical Clustering.

In addition, machine learning algorithms such as Support Vector Machines (SVM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Random Forests, and Decision Trees, especially deep learning models based on neural networks, have become important development directions in GIS applications. Neural networks have demonstrated excellent performance in tasks such as remote sensing image processing, land use classification, and vegetation type identification.

2.2 Model Integration

Model integration is a commonly used technique that combines multiple different analytical models to better handle the complexity and diversity of geographic spatial data. Therefore, model integration in GIS usually requires a comprehensive consideration of factors such as the spatial attributes of the data, heterogeneous data sources, and analytical objectives (Goodchild et al.,1994) .

Integration of Multiple GIS Analytical Models: GIS algorithm integration involves combining different types of spatial analysis algorithms to fully leverage the strengths of each algorithm in processing spatial data, thereby enhancing the accuracy and efficiency of spatial analysis and decision-making (Karimi et al., 1996, Ungerer et al., 2002). Commonly used algorithms in GIS include spatial analysis, spatial interpolation, network analysis, spatial statistics, and geographically weighted regression, each with unique application scenarios and advantages. By integrating different algorithms, more comprehensive and precise analysis results can be obtained. In GIS, it is often necessary to use various spatial analysis methods to solve practical problems. For example, land use change prediction can simultaneously utilize spatial regression models, machine learning algorithms, image recognition models, and other tools. Model integration can effectively combine the results of these different methods, thereby improving the reliability of the analysis (Zeng et al., 2021). In natural disaster early warning systems, traditional meteorological analysis models, geographic spatial models, and post-disaster assessment models can be integrated. The integrated results can be used to predict the likelihood of disasters and provide accurate emergency response information to decision-makers.

Integration of Industry-specific Models with GIS: Industry-specific models are designed to meet the business needs of particular industries or fields. By integrating and analyzing industry-specific data, they help industry practitioners optimize decision-making and improve management efficiency (Engel et al.,1993). These models typically incorporate a wide range of industry-specific knowledge and experience, enabling the simulation, prediction, or optimization of various scenarios within the industry. The integration of industry-specific models with GIS combines spatial data with industry data to provide more precise analysis and decision support. GIS (Geographic Information System) visualizes spatial data, helping industry experts gain a deeper understanding of various geographical phenomena and business processes, thereby achieving business optimization based on geographical location (Fedra et al.,1993, Srinivasan et al.,1994). For example, urban planning models use GIS to analyze land use and traffic flow, precision agriculture models combine GIS for land suitability analysis, and water resource management optimizes resource allocation through GIS analysis of water distribution and watershed information. The application fields of this integration are very broad, including but not limited to urban planning, transportation, environmental monitoring, agricultural management, disaster emergency response, real estate analysis, and energy management. In these fields, the combination of industry-specific models and GIS significantly enhances the precision and efficiency of business operations, helping decision-makers make more scientific judgments. Through in-depth analysis of spatial data, industry-specific models can optimize resource allocation and improve management levels while providing decision support, ultimately achieving a dual improvement in economic and social benefits.

3. GIS Service Composition

Encapsulate the analytical model as a reusable component or service for easy sharing and invocation in different GIS applications. The networked service of spatial data is an important development direction, so spatial service composition is a networked application of model integration. Spatial service composition involves describing existing services semantically and dynamically combining them to offer more complex functions to solve real-world problems. Spatial service composition mainly includes two parts: data flow and control flow. The data flow defines the input and output of the data, while the control flow consists of numerous operator models that form the smallest units of spatial services and support the dynamic selection of operator models (WANG et al., 2011, Argent et al., 2004).

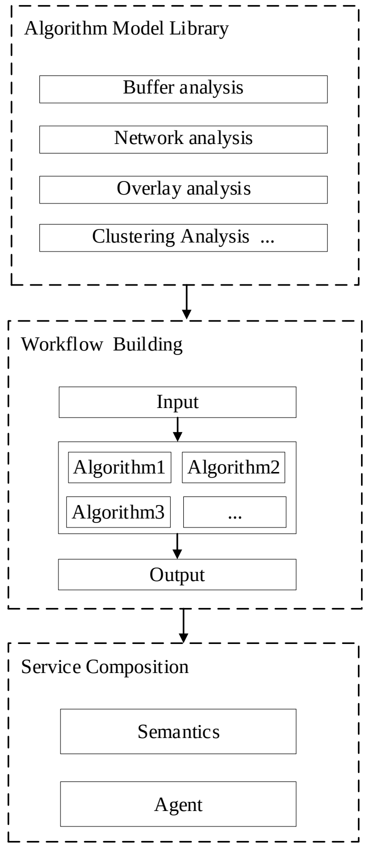

Figure 1. GIS service composition workflow

3.1 GIS Service

GIS services are a web-based software application model that allows users to access and use geospatial data and related geographic analysis functions through the Internet or other network connections via standard protocols and interfaces, without the need to install a complete GIS software locally (Tsou et al., 2002). It publishes the functions and data of GIS in the form of services for different users and applications to share and invoke, achieving the sharing, interoperability, and integration of geographic information. It is widely used in many fields such as urban planning, resource management, environmental protection, transportation, and disaster early warning.

Common GIS services include OGC's Web Map Service (WMS), Web Feature Service (WFS), and OGC Web Map Tile Service (WMTS). WMS provides online services for map images, allowing users to obtain information such as map layers, styles, and resolutions. The service returns map images (PNG, JPEG) for display and browsing. WFS provides access to vector data, enabling users to obtain the original geographic information of map data (such as points, lines, and polygons) for analysis, querying, or editing. WMTS provides tiled map services, allowing users to quickly load maps at different zoom levels using tiled images. Users access and utilize GIS services through web browsers or dedicated GIS clients for data querying,

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visualization, and analysis. The server side provides GIS data and processing capabilities through web servers and database management systems. These servers use standard service protocols (such as WMS, WFS, WMTS, etc.) to respond to user requests. Spatial data is stored in geographic databases (Post GIS) and queried and processed through database management systems. GIS services are typically based on protocols such as RESTful API and SOAP, providing web service interfaces to support remote calls and data interaction.

The description of the service includes basic information, functional description, and input and output parameters. The basic information includes the service name, version number, publisher, and service type. The functional description provides a detailed explanation of the specific functions that the service can offer, such as geographic data query, spatial analysis, buffer analysis, and overlay analysis. Input and output parameters: Clearly specify the data types, formats, and parameters required by the service, as well as the type, format, and content of the output results. For example, for a place name query service, the input parameter might be a place name keyword, and the output could be geographic feature data containing place name coordinates, address information, etc.

3.2 Service Composition

Service composition involves combining multiple geographic information services into a service chain according to specific business requirements, following a certain order and logic to achieve complex spatial data processing and analysis. At the same time, the service composition is dynamically adjusted and optimized based on changes in user requirements and the operating environment to enhance the flexibility and performance of the system (Gui et al., 2008, Ma et al., 2008).

Semantic service composition has emerged in the context of the Semantic Web, introducing semantic information into the service composition process (Chen et al., 2003). First, detailed semantic annotations of various aspects of services are made using languages such as the Web Service Semantic Description Language (OWL-S) and the Semantic Annotation Language (WSDL-S). These annotations cover the service's functionality, the data types and semantic meanings of input and output parameters, preconditions for service execution, and postconditions, thereby endowing services with machine - understandable semantic information. Second, domain ontologies are constructed to define concepts, relationships, and rules within a domain, such as hierarchical relationships, equivalence relationships, and dependency relationships. These ontologies provide a semantic foundation and logical basis for service composition (Lutz et al., 2007). Different services can be semantically described based on the same ontology. By leveraging the semantic descriptions of services and the rules defined in the ontology, automatic reasoning and matching can be achieved, enabling more accurate identification of services that meet user requirements.

An Agent is an intelligent entity that possesses characteristics such as autonomy, interactivity, reactivity, and proactivity. It can perceive changes in the environment, reason and make decisions based on its own goals and knowledge, and take corresponding actions to influence the environment (Crooks et al., 2011). In the context of service composition, each Agent can be regarded as a software entity with specific functions and tasks, responsible for interacting with other Agents or external systems to achieve the goals of service composition (Talebirad et al., 2023, Huang et al., 2024, Hong et al., 2024). Service composition based on Agents involves encapsulating various basic services (such as data query services, data analysis services, file processing services, etc.) into different Agents. When a complex business function needs to be implemented, the task is first decomposed into multiple sub - tasks, each of which corresponds to one or more specific services. These services are then combined according to certain logic and processes to form a new service system that can accomplish more complex tasks or meet specific business requirements. The Agents communicate and collaborate with each other through a certain communication mechanism (message passing). The selected Agents execute the corresponding tasks according to the predefined rules and processes, and return the execution results. This forms a new service system that can accomplish more complex tasks or meet specific business requirements.

4. Conclusion and Outlook

This research reviews the commonly used GIS algorithm models, discusses the necessity and methods of model integration, introduces methods for multi-model integration and the integration of industry models with GIS, constructs a toolchain for integrating multiple models oriented towards business needs, and ultimately applies it through the integration of GIS services. It is pointed out that GIS services built on cloud-native GIS and industry SaaS platforms, as well as AI-driven automation, will have significant application potential in GIS service composition. Although model integration technology has a broad application prospect, it also faces some challenges, such as model selection, model interpretation, and model robustness. How to choose the best model or model combination, how to interpret the predictive results of model integration and fusion, and how to enhance the robustness of model integration and fusion are all hot topics in current research.

In the future, with the development of large language model technology, the application prospects of AI-driven automation in the GIS service field are broad. In the future, GIS service Agent tools based on large language models will become an important engine for automated spatial data processing and decision support. These intelligent Agents will have powerful self-learning capabilities. Through deep integration with GIS platforms, they will be able to efficiently analyze and process massive amounts of spatial data and automatically identify complex geographical patterns and trends.

GIS services built on cloud-native GIS and industry-specific SaaS platforms will bring unprecedented flexibility, scalability, and intelligence to various industries. The introduction of cloud-native architecture enables GIS applications to run efficiently in the cloud environment, fully leveraging the elasticity and distributed resources of cloud computing to drive GIS services towards higher levels of automation, intelligence, and real-time performance. GIS services based on cloud-native GIS and industry SaaS will have the ability to self-learn and make decisions. They will be able to automatically generate analysis reports, provide real-time alerts, optimize resource scheduling, and support decision-making, significantly enhancing the intelligent decision-making capabilities of various industries. By integrating with industry-specific SaaS platforms, the unique needs of different industries will be precisely met, and service delivery will become more efficient and convenient. This will provide more efficient, intelligent, and flexible spatial data analysis and decision support across industries, promoting digital transformation and enhancing business competitiveness, truly achieving a leapfrog development from traditional GIS tools to an intelligent service platform for the entire industry.

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