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ENHANCING GEOGRAPHIC INFORMATION SYSTEMS WITH SPATIAL DATA MINING

Mirjana Kocaleva Vitanova, Elena Karamazova Gelova, Zoran Zlatev, Aleksandar Krstev

Abstract. This paper explores how Geographic Information Systems (GIS) can be combined with Spatial Data Mining (SDM) to improve the understanding and utilization of large volumes of spatial data. The study begins with defining spatial data and highlighting its significance. It then examines the fundamental concepts of GIS and the methods for managing, analyzing, and modeling spatial data. Furthermore, the research identifies and explains the challenges that arise when integrating GIS with SDM, proposing possible solutions to overcome these issues. This paper provides a detailed insight into the synergy between GIS and SDM tools, aiming to enhance the management and analysis of large spatial data collections.

1. Introduction

We have more location-based information available today than ever before—about individuals we know and global events. Paper maps are no longer necessary, as mobile phones with GPS provide this information in a much faster and clearer way. Location-based services guide us to the nearest restaurants, speed up pizza delivery, and, most importantly, direct emergency services to our homes via the fastest route. The chances of getting lost have significantly decreased, and finding places we want to visit has become easier. With access to Wi-Fi or satellite signals, we can identify ourselves and navigate effortlessly. Adding our location to posts or photos on social media is another way in which, consciously or unconsciously, we contribute to the collection of geographic data [1], [2]. ¹

The phrase "GIS and society" refers to the interaction between technology and society—a two-way relationship where both influence each other. This interaction can be understood as a pull and push dynamic, where technology provides solutions to societal needs. These needs include power, survival, and a high standard of living. Researchers work on a wide range of technological advancements with the hope of meeting these needs. The innovations required are determined by the "technology gate", while the "social gate" decides which advancements are considered acceptable by society. When these gates function properly, technology meets societal needs effectively. However, shortcomings can still emerge, and society must be aware of these risks to prevent any harm that technology might cause [3]. Geographic Information Systems (GIS) effectively address numerous societal needs. Initially, GIS technology was used to create resource

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Keywords: Geographic Information System, Spatial Data Mining, big data.

maps for environmental planning and management, cadastral maps for land use systems, computer-aided design (CAD) drawings, and satellite imagery.

It was developed based on early corporate and scientific computing in the 1960s. Since then, GIS has evolved to include a wide range of applications in both public and private sectors, as well as in collaborative organizations, individual use, and natural resource management. These applications have brought significant benefits, which can be measured using three key metrics: equity (ensuring that benefits are fairly and widely distributed), effectiveness (improving performance), and efficiency (completing tasks faster and with less effort) [4]. GIS is an extremely valuable tool for collecting, storing, processing, and organizing geographic data. With the integration of GIS and Spatial Data Mining (SDM) techniques, large amounts of geographic data can now be processed to reveal valuable patterns and insights. This paper explores the methods, benefits, and applications of using SDM to enhance GIS, drawing from ArcGIS documentation to examine the core concepts of GIS and the management, analysis, and modeling of geographic data.

2. Related work

Papers with similar topics, used for the literature review, are listed below. Chapter [5] provides an overview of GIS concepts, including spatial data structures, information organization, and data modeling. It explores how GIS represents geographical information, processes spatial relationships, and utilizes databases for organizing realworld data. Paper [6] explores the development, capabilities, and applications of GIS, highlighting its role in spatial analysis through georeferencing, distance measures, and overlays. GIS enables the study of spatial dependence, aiding research and planning. While mature in basic functions, further development is needed for seamless integration of spatial statistics and models. Paper [7] explores spatial data mining and geographic knowledge discovery, addressing challenges in analyzing massive, complex spatial datasets. It reviews key tasks like classification, clustering, and geo-visualization, highlighting recent advances in point pattern analysis, space-time prediction, and moving object data. The study underscores spatial data mining's role in geographic information sciences. Next paper [8] presents a data mining framework for geo-spatial and environmental data, integrating pre-processing, clustering, and visual analysis. It introduces new density-based clustering algorithms, a change pattern discovery technique, and post-processing for identifying dynamic spatial patterns. A case study on ozone pollution demonstrates the framework's effectiveness in uncovering valuable insights from geo-spatial air-quality data. Paper [9] explores data mining techniques to enhance remote sensing image classification using GIS data. It introduces two learning granularities—spatial object and pixel—and integrates inductive learning with Bayes classification. A land use study in Beijing using SPOT imagery and GIS data shows that combining these methods improves classification accuracy by 11%, with significant gains for certain classes like gardens and forests. The internship report [10] explores how Belvand Geotechnics leveraged GIS to enhance mining exploration in Cuanza-Sul, Angola. GIS improved decision-making, data integration, and stakeholder engagement

while addressing challenges like data quality and technical requirements. Belvand tackled these with data validation, training, and cloud-based solutions. The report highlights GIS's role in modernizing exploration and suggests future advancements like predictive analytics and machine learning to optimize its potential. SESDI (Semantically Enabled Spatial Data Infrastructures) improves geospatial data retrieval in SDIs by addressing catalog limitations like poor semantics, single-record descriptions, and lack of ranking metrics. It integrates classic information retrieval techniques and introduces ranking metrics for spatial, semantic, temporal, and multidimensional queries [11]. Introductions in Intelligent Railway Geographic Information Systems (IRGIS) are given in [12], which enhance RGIS by using spatial data mining to uncover hidden patterns in railway data. IRGIS supports spatial representation, querying, statistical analysis, and advanced spatiotemporal analysis for improved decision-making in railway planning and management. [13] explores spatial big data mining, highlighting its significance in addressing social, economic, and environmental issues. While spatial big data offers valuable insights, challenges like data overload and pollution hinder its utilization. The study emphasizes knowledge discovery as a key process for transforming spatial big data into actionable intelligence.

3. Ease of use spatial data

A fundamental aspect of the Big Data era is spatial data, which can simply be described as information about a specific area. The vast amount of digital information available today influences our decision-making and perception of the world, both locally and globally. Additionally, it expands the range of questions we can explore. By identifying new markets and strategically placing retail locations, geographic data contributes to increased profitability. In many countries, large-scale infrastructures that support services such as telephone lines, sewage systems, gas networks, electricity, and water supply are increasingly managed through digital geographic databases for service delivery. On a global scale, the rise of spatial data has had a significant impact on political and economic systems. The rapid availability of data over the past decade has led to major breakthroughs, providing deeper insights into human behavior rather than just natural phenomena. Organizations now have access to and analyze a larger volume of data than ever before to better understand their populations. As individuals, our reactions hold greater significance than just our place of residence or economic status, offering deeper insights into our roles within societies and communities [14].

A. Spatial Data and Their Role in the Big Data Era

From sensors, aerial photography, remote satellite images, and other sources, a vast amount of spatial data is collected, exceeding the capacity of the human mind for proper modeling, understanding, analysis, and utilization. As a result, a sophisticated and effective technique is needed to extract knowledge from large spatial databases. The process of extracting knowledge from massive geospatial datasets to identify essential spatial relationships, trends, or patterns that are not explicitly recorded in a spatial

database is called "spatial data mining" (SDM). SDM approaches are an extension of data mining techniques applied to satellite databases related to multiple domains, spatial data, and GIS data. Data related to the physical location of the Earth is known as spatial data. The applications of spatial data mining are numerous and include traffic analysis, NASA's Earth Observation System (EOS), space exploration, resource management, agriculture, geology, and climate change. To generate geospatial data from heterogeneous spatial information, analyze land use changes, and extract spatial association rules from remote sensing databases, it is necessary to mine frequent trajectories in a spatiotemporal database. Extracting geographic rules is known as spatial data mining and has broad applications in real-time systems [15].

A recommended model for use is one in which decision-making criteria are created based on nearest neighbors to determine land use. This model enables the identification of spatial databases, determination of relationships between spatial and non-spatial databases, database construction, search optimization, spatial data reorganization, and concise capturing of essential aspects, among others. Interesting findings in related domains are obtained by applying typical data mining techniques to spatial data, such as association rules, classification, clustering, trend identification, and anomaly detection. Spatial data analysis methods include clustering algorithms to identify anomalies and deviations, association discovery to extract topological connections and characteristics of surrounding objects, and their spatial relationships for class identification. Regarding georeferencing, latitude and longitude are unique identifiers for spatial data. GIS (Geographic Information System) is commonly used for storing, retrieving, and editing geographic location data on Earth's surface. In modeling, spatial entities are used to store data in the form of points, lines, areas, networks, and surfaces. Geographic coordinates, in numerical format, are represented through spatial data. These data exhibit autocorrelation and are multidimensional, including location, shape, size, and orientation. Attributes and non-spatial data are independent of geometric factors. Non-spatial data include characteristics such as age, mass, and height. Due to the complexity of geographic operations, optimizing spatial query processing requires significant effort. As a result, retrieving spatial data is considerably more challenging than retrieving non-spatial data. In typical queries for selecting non-spatial data, standard comparison operations such as >, <, =, >=, and \neq are used. For spatial data, geographic coordinates can be used as spatial comparators: east, west, north, south, near, contained within, overlaps, or intersects. An example of a spatial selection query is locating all schools near the city center. Two records in classical joins must share properties that satisfy a predefined relationship. Spatial joints and conventional relational joints are similar in that both connect records based on shared attributes. For example, for points, the nearest relation can be used, while for polygons, the intersection relation would be applied. Some basic spatial queries include:

- Finding intersections in a specific region with regional search.
- Finding objects near a specific object using the nearest neighbor search.

• Finding objects within a predetermined distance from a specific object through scanning.

The three main relations classifying spatial properties are generally distance relations, directional relations, and topological relations. Since topological relations involve nonspatial data, converting non-spatial data into spatial data requires spatial mapping. As shown in Table 1, the development of spatial data enables efficient searching of large spatially based databases using spatial operations. Typically, geographic data mining activities are an extension of data mining tasks, combining spatial data and criteria to create various tasks for identifying classes, determining correlations and common locations between spatial and non-spatial data, creating clustering criteria for anomaly identification, and detecting deviations [16].

B. Data Mining Process: A Step-by-Step Approach

Data mining is a methodological approach for extracting useful information or patterns from vast databases. It involves several sequential steps aimed at transforming raw data into actionable knowledge. Throughout the data mining process, iterations and refinements may occur, where insights from initial analyses inform subsequent steps of preprocessing or data mining. This iterative approach helps enhance the quality and relevance of the acquired knowledge. The process consists of four key steps:

- 1. Data Collection: The first step in the data mining process is identifying, gathering, and organizing the necessary information in preparation for analysis. Any source providing raw data, whether in structured or unstructured format, can be considered a data source, such as data lakes or data warehouses.
- 2. Data Preparation: The primary goal of the second phase is to refine the collected data. To correct any potential inaccuracies, various procedures are involved, such as preprocessing, profiling, and cleaning the data. These stages are critical for maintaining the data's quality before moving on to the mining and analysis processes.
- 3. Data Mining: Once the required level of data preparation is achieved, the data specialist selects the appropriate data mining technique in the third phase. This step involves choosing a suitable set of algorithms for processing the data and using data samples to train these algorithms before applying them to the entire dataset.
- 4. Data Analysis and Interpretation: In this final phase, analytical models are developed for future business decisions based on the findings from the third phase. Additionally, the data science team uses simplified methods, such as data visualizations, to communicate the results to relevant stakeholders. The way the findings are presented facilitates understanding, even for those who are not part of the data science industry.

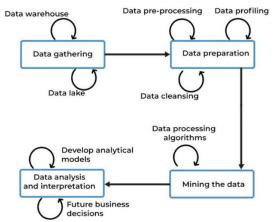


Figure 1 Visual representation of the data mining process [18]

C. Challenges in Spatial Data Mining

Geographic Information System (GIS) data is growing exponentially, evident in the integration of data and massive geographic data mining. Data storage techniques enable the integration and concise storage of information. Big data arises from the rapid growth of data. To process such large datasets, a big data approach was recently developed that utilizes parallel algorithms within Hadoop architecture and MapReduce in a distributed environment. The MRPrePost algorithm, based on Hadoop architecture, was proposed and used in this research for mining vast amounts of data. Using MRPrePost, a hybrid of Dis-Eclat, association rules are used to identify frequently occurring item sets from large spatial data sets. Another challenge arises with datasets differing in scale, where a set of strategies manages internal differences in spatial granularity necessary for data analysis at different scales and resolutions. These discrepancies are harmonized, and significant patterns are extracted through techniques like multi-resolution analysis and spatial aggregation/de-aggregation. Spatial data often originates from diverse sources with varying structures, quality, and formats. The integration and alignment of different spatial datasets can be challenging, leading to inconsistent and questionable analytical results. To ensure data quality and consistency across different sources, preprocessing methods such as transformation, normalization, and cleaning are necessary. Due to the diversity of spatial phenomena and data collection techniques, datasets are prone to uncertainty and noise. Robust strategies for handling noise and uncertainty are essential for reliable analytical results. To minimize the impact of uncertainty on mining results, techniques such as sensitivity analysis, probabilistic methods, and anomaly detection strategies, specifically designed for geographic data, are employed.

4. The process of cartographic visualization of spatial data

The process of translating or converting spatial data from a database into graphical representations is called cartographic visualization. Most of these representations

resemble maps. The use of cartographic methods and techniques is part of the visualization process. Depending on the application, these techniques can be considered a type of grammar that enables the best possible development and design for map usage. The process of visualization can vary significantly depending on the position within the geographic data handling process and the specific goal to be achieved. As mentioned earlier, visualizations can be executed at any stage of spatial data handling procedures. They can be time-consuming or quick to produce, and simple or complex in nature. For example, creating a complete, conventional topographic sheet, an electronic atlas map, a journalistic map, a sketched map, an animation showing the city's development, a three-dimensional image of a structure or mountain, or even a real-time traffic condition display. Additional examples include "quick and simple" representations of part of the database, and maps used for updates or geographic analysis. Visualization can also be used to confirm that the structure of the database or the data collection method is consistent.

5. Core functions of GIS in handling georeferenced data

When working with georeferenced data, the computer system known as GIS (Geographic Information System) offers the following four fundamental functions: Data Collection and Preparation; Data Administration, including Maintenance and Storage; Data Analysis and Processing and Data Visualization. This means that a GIS user can expect support for inputting georeferenced data, analyzing it in various ways, and creating presentations (such as maps and other forms) using the data. This includes options for analyzing georeferenced data, supporting multiple coordinate systems and their transformations, and offering great flexibility in how this information is presented (e.g., colors, symbols, and media used). The use of Geographic Information Systems (GIS), specialized IT systems for handling mapped data, is growing in various organizations, corporations, and members of civil society. They contribute to understanding and analysis of various processes and events. This enables engineers and scientists to explore and study the surface of the world, including hydrologists, ecologists, geologists, and land-use specialists. Large spatial data sets, dynamic models, and state-of-the-art computers facilitate scientific research by providing detailed representations of the environment and processes.

A. Applications of GIS in Urban Management and Data Collection

GIS helps emergency services, urban planners, civil engineers, and social scientists to better manage and understand cities in urban environments. Cadastral maps or plans provide agencies with comprehensive data on land ownership and usage, making planning and management more efficient. With greater accuracy, construction engineers develop new routes and calculate construction costs. GIS is also used by police forces to analyze crime distribution and by healthcare organizations to track disease outbreaks. These findings are valuable for commercial enterprises as well. The automated collection of data in the field of GIS has led to technological advancements in the production of large quantities of geographic data, which represents the surface of the geographical nomenclature of the Earth. Global Positioning Systems (GPS), high-resolution remote

sensors, location-based services, surveys, and other interdisciplinary sources provide GIS data. These heterogeneous components are interconnected and provide geo-referenced spatial databases, offering spatial information about location, relationships with other features, and descriptions of non-spatial (attribute) properties. A spatially organized database offers detailed information on who, what, and where. GIS has become increasingly important in data mining and knowledge management analysis. When combined with GIS and satellite imagery, spatial data mining techniques are used in various studies to extract relevant facts related to applications across different fields, such as traffic hazards, railway analysis, agricultural land evaluation, fire analysis, changes in forest cover, forestry, and more. This approach enables the identification of patterns and trends that can inform decisions and strategies in these areas, leveraging spatial data for a more comprehensive understanding of environmental and societal processes.



Figure 2 GIS components [14]

B. Challenges in GIS

Due to the variety of formats, representation methods, and sources of data in GIS databases that contain spatial information, analyzing these databases can be quite challenging. The following are some of the issues GIS faces when extracting geographic data from geodatabases:

- The necessity of specialized knowledge to integrate and interpret both spatial and non-spatial data effectively.
- Diverse file formats, making the selection and representation of data for retrieval from geodatabases complex.
- Understanding information presented as images.
- Selection and transformation of non-spatial features into spatial ones.
- False precision that conceals the sources of error.
- Overuse of data that is not relevant to the research objectives or decision-making processes.
- These challenges highlight the complexities involved in working with GIS data, emphasizing the need for advanced techniques, expert knowledge, and proper management of spatial and non-spatial data to ensure effective analysis and decision-making.

6. Data visualization in arcGIS

ArcGIS is a Geographic Information System (GIS) tool developed by the Environmental Systems Research Institute (Esri). It helps improve GIS and Spatial Data Management (SDM) through its advanced visualization technology. ArcGIS provides resources and functionalities for generating, organizing, analyzing, and sharing maps and geographic data.

The symbols, colors, and layout of geographic data influence how a map reader interprets the intended message and how the map should be understood. ArcGIS Pro allows users to modify the way vector or raster features are displayed on a map. Symbology is used to make features visible and customizable, helping create visually appealing and relevant maps. Avoiding the use of a single symbol is important, as it only shows where features are located but does not provide additional important information about them. Layers can be symbolized in various ways, including [17, 18]:

- When symbolizing based on names, codes, or descriptions, unique value symbology works well for categorical (qualitative) data. For example, a map displaying 50 states where each state is assigned a different color based on its name.
- Graduated color symbology is used for numerical (quantitative) data with attributes indicating numerical values, such as population. Features are grouped into classes based on data values, and each class is assigned a color. A common approach is to use a gradient from a lighter shade (representing lower values) to a darker shade (representing higher values). Different classification methods can be used, and each method represents the same data differently by dividing the values in distinct ways.
- Point data can be represented using graduated symbols, which rely on quantitative attributes. The symbol size corresponds to data value ranges, with larger symbols indicating higher values and smaller symbols indicating lower values.
- When working with large datasets, displaying individual points may lead to cluttered and difficult-to-read maps. Heat maps aggregate data points into a simplified and more understandable visual representation. By symbolizing features based on density, heat maps can be used to visualize data concentration effectively.

A. 3D Data Visualization

While working in 3D can enhance data visualization and analysis by providing a unique perspective, mapping in ArcGIS for Desktop is often performed in 2D. However, since the world itself is three-dimensional, representing data in 3D offers deeper insights into terrain and the spatial relationships between real-world objects.

Using 3D GIS allows for a better understanding of geographic data and its interactions. For example, locating the underground epicenter of an earthquake or analyzing a mine's structure are spatial challenges that can only be addressed using 3D solutions. Since viewing the environment in three dimensions makes it easier to express concepts and illustrate relationships, 3D data improves communication when displayed on a map.

B. Benefits of 3D GIS

Visualizing GIS data in three dimensions significantly enhances our understanding of spatial relationships in the real world, making data more engaging and decision-making more effective. It can also highlight potential effects of variables such as elevation and slopes on our data. Several data sources can be used for 3D GIS management, including:

- ✓2D GIS data
- ✓ Various 3D file formats
- ✓ Interactive editing tools
- ✓ Geodatabase 3D objects

Some GIS challenges require 3D representation, such as:

- Determining visibility from a specific location
- Analyzing the intersection of groundwater well with underground structures

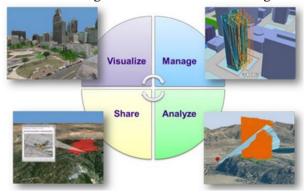


Figure 3 Presentation of the four basic functions of Geographic Information Systems (GIS) in the context of 3D data representation [17]

3D data visualization and analysis are widely used across various sectors, including:

- Urban and Regional Planning Environmental assessments, event planning, disaster management, and visual impact analysis.
- Civil Engineering Processing LiDAR elevation data, telecommunications, terrain modeling, and analysis.
- Defense Tactical planning, mission briefing, situational awareness, and reconnaissance.
- Facility Management Navigation (distribution and routing), space planning, security planning, and disaster management.
- Education Visualization of scientific data.
- Safety and Disaster Management Planning for security, disaster response, and tactical operations.
- Water Resources Floodplain mapping and visualization of underground water bodies.
- 3D Topographic Mapping National-scale mapping for terrain representation.
- Land Management Inventory and landscape modeling.

7. Conclusion

To enhance the understanding of spatial data, this thesis explores the relationship between Geographic Information Systems (GIS) and Spatial Data Mining (SDM). It

emphasizes the critical importance of integrating GIS with SDM methodologies by examining how GIS organizes, interprets, and simulates spatial data. The thesis outlines practical approaches for managing and analyzing spatial data, which are crucial for informed decision-making in various fields, including urban planning, environmental management, and disaster response, with examples from ArcGIS documentation. The integration of GIS and SDM faces several challenges, including data heterogeneity, the scalability of algorithms for large spatial datasets, and the complexity of spatial pattern analysis. Overcoming these obstacles requires continuous improvements in algorithm design, computational efficiency, and interdisciplinary collaboration among GIS experts, data scientists, and domain specialists. Using interactive maps, charts, and 3D visualizations, GIS enhances transparency and facilitates data-driven decision-making. Future advancements should focus on expanding the analytical capabilities of GIS by integrating it with artificial intelligence and machine learning. Additionally, improving the usability of SDM tools and establishing standardized methodologies for spatial data mining will make advanced spatial analysis more accessible. By leveraging the combined potential of GIS and SDM, organizations can optimize resource allocation, improve spatial planning strategies, and mitigate risks associated with spatial phenomena.

Looking ahead, the goal is to develop more efficient spatial data mining algorithms that can process large-scale geospatial datasets in real time. Enhancing automation in GIS-SDM integration through AI-driven techniques will further improve predictive modeling and decision-making. Another key objective is to establish open-source frameworks for spatial data mining, enabling greater accessibility and collaboration across industries. Additionally, increasing the adoption of cloud-based GIS solutions will ensure scalability and adaptability for diverse applications. Lastly, fostering interdisciplinary research between geospatial science, data analytics, and policymaking will support the development of innovative solutions for sustainable urban development, environmental monitoring, and disaster resilience.

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Mirjana Kocaleva Vitanova Goce Delcev University Faculty of computer science, Krste Misirkov 10A Stip, North Macedonia

E-mail address: mirjana.kocaleva@ugd.edu.mk

Elena Karamazova Gelova Goce Delcev University Faculty of computer science, Krste Misirkov 10A Stip, North Macedonia

E-mail address: elena.gelova@ugd.edu.mk

Zoran Zlatev Goce Delcev University Faculty of computer science, Krste Misirkov 10A Stip, North Macedonia

E-mail address: zoran.zlatev@ugd.edu.mk

Aleksandar Krstev Goce Delcev University Faculty of computer science, Krste Misirkov 10A Stip, North Macedonia

E-mail address: aleksandar.krstev@ugd.edu.mk