

Data-Driven Analytical Techniques in Geographic Information Systems

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To Cite This Chapter

Kılınç, M. (2024). Data-Driven Analytical Techniques in Geographic Information Systems. In M. Haneff Calp & R. Bütüner (Eds.), *Current Studies in Data Science and Analytics* (pp. 1-19). ISRES Publishing.

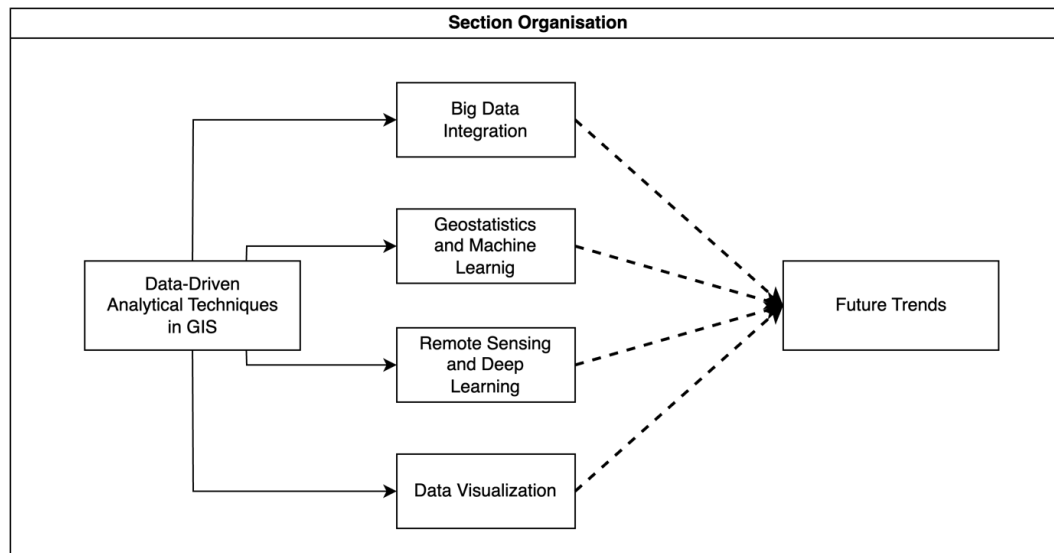
Introduction

Geographic Information Systems (GIS) have become indispensable tools used in different disciplines to analyze and manage spatial data. GIS applications have an important place in many areas such as urban planning, environmental monitoring, transportation, and disaster management. The rapid increase in the amount of spatial data from satellites, sensors, and mobile devices has increased the need for advanced analytical techniques to make sense of these large datasets (Villarroya et al., 2022). In recent years, data-driven approaches have emerged as powerful methods that enhance the capabilities of GIS and have assumed an important role in more accurate predictions, in-depth analyses, and effective decision-making processes (Reichstein et al., 2019). Data-driven analytical techniques analyze spatial data using the power of data science, machine learning, artificial intelligence, and statistical methods. These techniques offer new perspectives that traditional GIS methods may not be able to capture by identifying patterns, trends, and relationships within large datasets. In this context, through the integration of data science with GIS, organizations can explore new dimensions in spatial data analysis, optimize resource allocation, and find solutions to complex spatial problems that could not be solved before (Cao et al., 2024).

Historically, GIS was mostly used for mapping and basic spatial analyses and was developed based on simple geographic techniques with manually collected data (Ahassan & Hossain, 2021). However, with the increase in high-resolution spatial data obtained through satellites, drones, and other remote sensing technologies, GIS has become a more dynamic and complex system. Today, GIS is not limited to the production of static maps but is used in a much wider range of applications such as real-time analysis, predictive modeling, and data visualization. This evolution has accelerated with the merger of GIS and data science. As spatial datasets have increased in both size and complexity, traditional GIS tools have struggled to manage and analyze these large information sources. Data-driven techniques such as machine learning, deep learning, and advanced statistical methods have filled this gap by providing powerful tools to process, analyze, and make sense of large-scale spatial data. These methods enable GIS professionals to gain valuable insights, model future scenarios, and make data-driven decisions (Li, Zhao, et al., 2022). Accordingly, big data plays a central role in modern GIS applications. Big data refers to data sets that are too large or complex to be managed by traditional data processing methods (Piovani & Bonovas, 2022). In the context of GIS, big data comes from various sources such as satellite imagery, sensor networks, mobile devices, social media, and Internet of Things (IoT) devices. These data streams provide extensive information about the physical world, such as land use patterns, weather, transport

flows, and environmental changes. Thus, data-driven analytical techniques enable more comprehensive and accurate analyses using big data. In particular, combining spatial data with other types of data, such as demographic, economic, or environmental information, can help scientists develop models that reflect the complexity of real-world systems. For example, in urban planning, big data can be used to analyze traffic flows, predict congestion hotspots, and optimize public transport routes. In environmental monitoring, big data can be used to monitor deforestation, assess the impact of climate change, and model the spread of pollutants. In this direction, big data also enables real-time analyses in GIS. This is especially critical for disaster management and emergency response applications (Sarker et al., 2020; Shah et al., 2019). By analyzing live data from sensors, drones, and other devices, authorities can monitor evolving situations such as floods or forest fires and make timely decisions to minimize damage. One of the most important developments in data-driven GIS is the integration of machine learning algorithms. Machine learning is a sub-branch of artificial intelligence that enables computers to learn from data and make predictions or decisions without being explicitly programmed (Yue et al., 2020). In GIS, machine learning algorithms are used to detect patterns, classify data, and make predictions based on spatial data. For example, machine learning models can be trained to classify land cover types from satellite imagery, detect urban growth patterns, or predict the probability of natural disasters such as floods or landslides. These models can process large amounts of spatial data and identify complex patterns that are difficult or impossible to detect manually by humans. Furthermore, machine learning can also be used for predictive modeling in GIS; this includes applications such as predicting future land use changes, forecasting population growth or modeling the impact of climate change on ecosystems.

Figure 1
Data-Driven Analytical Techniques in GIS Schema



The integration of data-driven techniques with GIS increases the accuracy of spatial analyses, accelerates decision-making processes, and plays an active role in solving wider spatial problems. With these technologies, cities can be planned more efficiently, natural resources can be better protected and the impact of environmental changes can be monitored more accurately. As a result, this evolution in GIS and data science is opening new horizons in the world of spatial analysis and helping to shape the cities, environment, and infrastructure of the future. Accordingly, this research focuses on the basic components and application areas of data-driven analytical techniques in the context of Geographic Information Systems (GIS). In this context, data-driven analytical techniques in the field of GIS are examined, and research on future trends is presented

by making in-depth analyses of big data integration, geo statistics, remote sensing, deep learning, and data visualization (Figure 1). The study also discusses the challenges faced in data-driven GIS analyses and potential future research areas.

Foundations of Data-Driven GIS Analytics

Geographic Information Systems (GIS) are comprehensive tools for analyzing, managing, and visualizing spatial data. GIS plays a critical role in many areas such as urban planning, natural resource management, transport systems, environmental monitoring, and disaster management. Traditional uses of GIS were limited to mapping and basic spatial analyses, but in recent years, with the development of data science and big data analysis, GIS has become more advanced and dynamic. Data-driven analytical techniques have significantly expanded the potential of GIS for spatial data analysis and provided powerful tools for making sense of large data sources. The fundamentals of data-driven GIS analysis involve the combination of disciplines such as data science, statistics, machine learning, and artificial intelligence to analyze spatial datasets. These analytical approaches enable deeper insights, more accurate predictions, and optimized decision-making processes on spatial data. Especially the use of big data sources allows us to understand why data-driven analytical techniques have become so important in GIS.

Fundamentals of GIS and Spatial Data

Geographic Information Systems is an integrated software platform used to collect, manage, analyze, and visualize spatial data (Eccles et al., 2019). Spatial data is a type of data that expresses the location of an object or event and is usually defined by geographic coordinates. These data are used for mapping and spatial analysis. The foundations of GIS are based on vector and raster data types. Vector data are expressed in geometric shapes such as points, lines, and polygons, while raster data are continuous data types consisting of pixels such as satellite images or digital elevation models. Traditional GIS tools were used to process this data and perform basic mapping operations. However, in today's big data era, the huge amount of spatial data from various sources such as satellite imagery, sensors, mobile devices, and social media requires more complex analysis techniques. This is where data science and data-driven analytical techniques come into play.

Data Science and GIS Integration

Data science is an interdisciplinary field that aims to obtain meaningful insights by analyzing large data sets and includes various methods such as statistics, data mining, machine learning, and artificial intelligence. The integration of data science with GIS allows spatial data to be analyzed in a more complex way and to obtain more efficient results. Data-driven GIS analyses focus on discovering patterns, trends, and spatial relationships by processing spatial data collected from large data sources. For example, in urban planning, data science methods can help make more efficient planning decisions by analyzing numerous factors such as traffic flows, population densities, and environmental changes. Similarly, in environmental monitoring applications, more accurate predictions can be made using big data sources to analyze the effects of climate change. Data science, combined with GIS, contributes to solving broader problems by increasing the accuracy of spatial analyses.

The Role of Big Data

Big data refers to data sets that are too large and complex to be managed by traditional methods. Today, GIS is an important tool for analyzing the huge amount of spatial data coming from big data sources. Big data sources are usually collected from sensor networks, satellite imagery, mobile devices, and social media platforms. These data

provide a large knowledge base that can be used for spatial analyses. Data-driven GIS analyses provide the integration of big data and GIS. This integration helps to make better decisions in various application areas, from urban planning to environmental monitoring. For example, satellite imagery, when combined with data from weather sensors, can lead to more accurate and timely decisions in disaster management. Similarly, traffic data from mobile devices can be used to optimize urban transport systems.

Machine Learning and GIS

Machine learning is a technique frequently used in data-driven GIS analyses. Machine learning enables computers to learn from specific datasets and make future predictions or decisions. The combination of GIS and machine learning is highly effective for detecting complex patterns in spatial data and building predictive models. Machine learning is used in various GIS applications such as the classification of satellite imagery, detection of land use changes, and prediction of natural disaster risks. By processing large amounts of spatial data, these algorithms can reveal complex relationships that humans cannot detect manually. In addition, machine learning models can also be used to model future scenarios and make predictions in various fields.

Geostatistics and GIS

Geostatistics is another important method used to perform statistical analyses on spatial data. Geostatistical methods in GIS are used to analyze the distribution of spatial variables in a given region and to understand the relationships between these variables. Geostatistical models, such as kriging, are one of the widely used techniques for predicting and modeling spatial data. Geostatistical methods play an important role, especially in environmental analyses and natural resource management. For example, geostatistics is used to estimate the productivity of agricultural areas or to model the distribution of water resources in a region. Such methods, when combined with GIS, allow for more accurate spatial analyses.

Data Visualisation and GIS

Data visualization is an important component of GIS analyses. Visualization of spatial data allows users to better understand the data and interpret the results of analysis more effectively. Maps, graphs, and 3D models are common tools used in the visualization of spatial data. Data visualization is especially important in decision-making processes. By visualizing the results of spatial analyses, decision-makers can better understand what kind of changes they need to make in a particular area. For example, urban planners can visualize data to map how busy certain roads are to optimize traffic flows. Similarly, disaster management experts can visualize risk zones to analyze the effects of natural disasters.

Big Data Integration and Spatial Data Analysis Techniques

Big data integration has revolutionized spatial data analysis, increasing the efficiency and effectiveness of modern Geographic Information Systems (GIS) (Al-Yadumi et al., 2021; Huang & Wang, 2020; Werner, 2019). GIS is used in many sectors as a powerful tool for the collection, analysis, and visualization of spatial data. GIS, which has a wide range of applications such as urban planning, natural resource management, transport, environmental monitoring, and disaster management, has become capable of solving more complex problems by being supported by big data sources. The increase in data from satellite images, sensor data, social media, and mobile devices has led to the necessity of integrating big data analysis techniques with GIS. In this integration process, various software that provides big data management and analysis (Table 1) are combined with GIS to enable more comprehensive spatial analyses. Platforms such as Apache Hadoop and Apache Spark are prominent in storing and processing large data sets. They are

particularly suitable for processing high-volume data sources such as satellite imagery and sensor data. For example, Apache Spark's distributed processing capabilities enable data sets to be analyzed quickly and monitor traffic density or environmental changes in cities. Without such data processing tools, performing spatial analyses on large datasets would be difficult and time-consuming.

Cloud-based platforms also play an important role in GIS and big data integration. Solutions such as Google BigQuery and Amazon Web Services (AWS) enable large data sets to be quickly stored and analyzed in the cloud environment (Al-Yadumi et al., 2021). For example, studies such as population density and traffic analysis in urban planning projects can be carried out based on data stored in such cloud-based systems. While these platforms accelerate data analysis with SQL-like queries, they also facilitate remote access to data by users. Solutions for the integration of GIS software with big data include platforms such as ESRI ArcGIS and Google Earth Engine. ESRI ArcGIS enables visualization and analysis of large volumes of geographic data by providing strong integration with big data through modules such as GeoAnalytics Server (Mai et al., 2019). Google Earth Engine, on the other hand, focuses on analyzing satellite data and provides a powerful platform for monitoring environmental changes and urban growth analyses. Such platforms not only accelerate data analysis but also enable visual analyses so that decision-makers can gain deeper insights into spatial data. Database extensions such as the open-source GIS platform QGIS and PostGIS have a wide range of uses in big data analyses. QGIS offers flexibility in spatial analyses by integrating with many data sources. PostGIS, on the other hand, allows spatial queries on large data sets, which enables high-performance data processing, especially in areas such as urban data management and environmental monitoring (Janisio-Pawłowska & Pawłowski, 2024). Open-source solutions are often preferred in small and medium-sized projects due to their cost advantage and flexibility. Tools such as GeoMesa and GeoSpark, which work with distributed databases, are ideal for spatial analysis on large datasets. GeoMesa is compatible with distributed databases such as Apache Accumulo, Cassandra, and HBase when performing spatial analysis on large databases. This can be used in areas such as real-time monitoring of sensor data. GeoSpark, on the other hand, runs on Apache Spark, enabling high-speed data processing in areas such as traffic density analysis and disaster area analysis. Such tools are especially advantageous in dynamic environments with continuous data flow (Dritsas et al., 2020).

Real-time analysis and visualization tools are also an important part of big data and GIS integration. Software such as Tableau and MapD (OmniSci) offer powerful solutions for spatial data visualization. For example, Tableau provides a user-friendly interface for urban planning, disaster management, and visualization of environmental changes through big data integration (Bivand, 2022). These tools facilitate the understanding of spatial data through maps, graphs, and interactive visuals. MapD, which offers GPU-accelerated data processing, stands out with its real-time data processing performance in environmental monitoring and traffic density analyses. Advanced analysis techniques such as machine learning and deep learning further advance GIS applications with big data integration. In big data analysis, machine learning techniques provide important contributions in areas such as predicting crime rates in cities or predicting traffic density by creating predictive models. Deep learning is used in projects such as disaster management and environmental change monitoring that require more complex data analyses (Sun & Scanlon, 2019). For example, deep learning models trained on satellite imagery can analyze the spatial distribution of forest fires and provide rapid intervention to the authorities. Such techniques allow for more accurate predictions when working on large data sets. Finally, database solutions such as IBM Db2 Big SQL enable spatial data analysis through SQL-based queries with big data sources.

Table 1
Big Data Software Integrated into Geographic Information Systems and Features

Software / Tool	Scope	Features	Use Cases
Apache Hadoop	Big data storage and processing	Data storage with HDFS (Hadoop Distributed File System), data processing with MapReduce	Satellite data processing, sensor data storage, urban data analysis
Apache Spark	Big data analytics and processing	Distributed data processing, stream analytics, GIS data analysis with PySpark and Scala support	Real-time analytics, environmental monitoring, disaster management
Google BigQuery	Big data analysis and management	SQL-like queries for big data analysis, high-speed data processing	Urban planning, traffic density analysis, environmental data analysis
ESRI ArcGIS	GIS platform	Geographic data integration, data visualization, big data modules (GeoAnalytics Server)	Satellite imagery, urban planning, environmental monitoring, disaster management
Google Earth Engine	Satellite and environmental data analytics	Processing large satellite data, ready-to-use datasets for environmental analysis	Deforestation, water resources monitoring, urban growth analysis
Amazon Web Services (AWS) S3	Cloud data storage and big data management	Storage and processing of large datasets, API support for GIS software integration	Satellite data storage, real-time urban data processing
Azure Synapse Analytics	Big data integration and analytics	Distributed data processing, machine learning models for GIS data analysis	Environmental change monitoring, urban infrastructure analysis, disaster management
QGIS	Open-source GIS platform	Integration with big data modules, data extraction from various big data sources	Urban planning, environmental change analysis, geographic distribution modeling
PostGIS	Database extension for geographic data	Spatial queries on large datasets, data storage, high-performance geographic data processing	Urban data management, environmental monitoring, geographic data storage
GeoMesa	Spatial analysis for big data	Spatial analysis in distributed databases (compatible with Apache Accumulo, Cassandra, and HBase)	Sensor data analysis, real-time monitoring, disaster management
GeoSpark (Apache Sedona)	Spatial analysis on large datasets	Spatial data processing on Apache Spark, parallel GIS data analysis	Traffic density analysis, urban planning, disaster area analysis
Hortonworks Data Platform	Big data integration	GIS data processing on the Hadoop ecosystem, real-time analytics	Satellite imagery, sensor data, urban infrastructure
Tableau	Data visualization	Big data integration with spatial data visualization, map-based data analysis	Urban planning, disaster management, visualization of environmental changes
MapD (OmniSci)	GPU-accelerated big data analytics and GIS	Real-time spatial data processing and visualization, high-speed data querying	Environmental monitoring, disaster management, traffic density analysis
IBM Db2 Big SQL	Structured and unstructured big data analysis	SQL-based spatial data analysis on Hadoop and other data sources	Urban infrastructure analysis, environmental data integration, GIS analysis on big data

IBM Db2 Big SQL, which can be integrated with Hadoop and other big data sources, is used in projects such as urban infrastructure analysis and environmental data integration. Such solutions add value to GIS applications from a big data perspective by providing flexibility in analyzing both structured and unstructured data.

In conclusion, big data integration and spatial data analysis techniques are important developments that expand the potential of GIS and offer solutions to the complex spatial problems of the modern world. The increase in big data sources has made it necessary to go beyond traditional GIS methods and get support from fields such as data science, machine learning, and deep learning. Integration of these techniques with GIS enables more accurate analyses, faster decision-making processes, and solving wider spatial problems. In the future, deeper integration of big data and GIS will enable more complex analyses and more effective decisions in many areas from urban planning to environmental monitoring. Big data-driven GIS will help shape the cities, environment, and infrastructure of the future, contributing to the sustainable development of modern societies.

Geostatistics and Machine Learning in GIS

Geographical Information Systems (GIS) is a powerful tool that enables analyzing spatial data in many fields and drawing meaningful conclusions from these data. In order to use the power of GIS more effectively, different methods and techniques are utilized. Among these methods, geostatistics and machine learning techniques, which have a wide range of applications in data science, stand out. While geostatistics tries to understand spatial patterns and variability by analyzing the relationships between spatial data, machine learning provides the ability to learn data patterns and predict future events or situations. The harmonious use of both methods in GIS makes it possible to reach faster and more accurate solutions to complex spatial problems.

Geostatistical methods often examine the spatial distributions of data, allowing us to make predictions in missing or unsampled regions. These methods utilize statistical models to explore the trends and spatial dependencies of a given area. Geostatistical methods, which are frequently used in the analysis of environmental variables and management of natural resources, enable detailed analyses in many areas from environmental pollution to water quality (Hasan et al., 2021). The table below summarises the main geostatistical methods used in the context of GIS and the areas in which these methods are prominent (Table 2). When the table is examined in detail, Kriging, one of the geostatistics methods, can generate predictions for non-sampled locations by analyzing the spatial dependence between data points. This method is especially effective in applications such as determining the distribution of air pollution throughout the city and creating water quality maps (Miao & Wang, 2024). Thiessen Polygons creates regions specific to each data point and enables analyses based on the distance between these points. It is frequently used in precipitation measurements and population density analyses. IDW (Inverse Distance Weighting) determines the spatial distribution of environmental variables by giving more weight to data points closer to the location to be predicted; it is a preferred method for creating temperature maps and analyzing terrain features. Semivariogram analyses spatial dependence over distance, while Spline Interpolation is used to create a continuous surface from data points and is useful in analyses such as elevation maps (Li, Baorong, et al., 2022).

Spatial Autocorrelation analyses the distribution of similar values using Moran's I, thus contributing to the identification of spatial patterns such as water pollution or vegetation cover. Finally, Trend Surface Analysis allows us to understand large-scale spatial trends and is used to analyze issues such as land slope or temperature variations (Love et al., 2022).

Table 2
Geostatistical Methods for Spatial Data Analysis in GIS

Method	Description	Application Areas
Kriging	An interpolation technique for spatially estimating data points in geographic datasets	Air pollution distribution, water quality analysis, soil properties
Thiessen Polygons	Mapping and defining unique regions for each data point	Rainfall measurement data, population density analysis, service area determination
IDW (Inverse Distance Weighting)	Distributes values from points to surrounding areas, giving weights based on distance	Temperature maps, land properties, pollutant distribution
Semivariogram	Examines spatial variability and determines spatial relationships between data points	Soil moisture analysis, spatial analysis of climate variables
Spline Interpolation	Used to create a continuous surface from data points	Surface modeling, elevation maps, detailed terrain analysis
Spatial Autocorrelation (Moran's I)	Analyzes how data is distributed spatially and identifies similarities	Water pollution analysis, vegetation distribution, urban density analysis
Trend Surface Analysis	Used to understand trends within a specific area	Terrain slope and elevation analysis, temperature and rainfall trends

Table 3
Machine Learning Techniques for GIS Applications

Machine Learning Method	Description	Application Areas
Support Vector Machines (SVM)	Used for classification and regression analysis; finds the optimal hyperplane to separate data	Land classification, natural disaster risk analysis
Decision Trees	Classifies data by branching based on specific decision rules	Environmental risk analysis, water resources assessment
Random Forests	A model formed by combining multiple decision trees, commonly used for classification and regression	Land cover classification, deforestation analysis, urban development analysis
K-Nearest Neighbors (KNN)	Classifies data based on similarity between neighboring points; non-parametric method	Land type classification, population density analysis
Artificial Neural Networks (ANN)	Performs prediction and classification on complex datasets; consists of layers and learns from data	Air pollution prediction, environmental change monitoring, disaster risk assessment
Deep Learning	Advanced analysis and prediction on large datasets, especially in image analysis	Satellite image analysis, forest fire detection, traffic density prediction
Semi-Supervised Learning	Learning process with limited labeled data, useful for data constraints	Spatial data classification, urban data analysis
Clustering (K-Means)	Groups data into meaningful clusters by assigning each data point to the nearest cluster	Population density, natural resource distribution, land use analysis

Machine learning methods offer great advantages in terms of speed and accuracy in GIS analyses. These methods, which automate processes such as classification, prediction, and pattern recognition, especially on large datasets, provide valuable information in environments with complex and dynamic data. The table above summarises the main machine learning techniques commonly used for GIS and their application areas (Table 3).

Support Vector Machines (SVM) is a powerful method in classification and regression analyses and can find the most appropriate hyperplane to classify data into classes. This method provides effective results in land classification and natural disaster risk analyses (Yousefi et al., 2020). Decision Trees branch and classify data by applying certain decision rules at each node; they are widely used in environmental risk analyses and water resource assessment (Rodríguez et al., 2021; Sánchez-Ortiz et al., 2021). Random Forests provides a model that improves accuracy by combining multiple decision trees and is successful in land cover classification, deforestation analysis, and urban development analysis. K-nearest neighbor (KNN) classifies according to the similarity of neighboring points; it is especially preferred in land type classification and population density analysis (Ge et al., 2020). Artificial Neural Networks (ANN) perform prediction and classification on complex datasets and are widely used in areas such as air pollution prediction, environmental change monitoring, and disaster risk assessment. Deep Learning, on the other hand, has the capacity to perform advanced analyses on large datasets and plays an important role in satellite image analysis, forest fire detection, and traffic density prediction (Adegun et al., 2023). While Assisted Learning is used in areas such as data classification and urban data analysis by working with under-labeled data, Clustering (K-Means) groups data into meaningful clusters and is a preferred technique for population density, natural resource distribution, and land use analysis.

GIS offers a wide range of analyses and predictions by using both geostatistics and machine learning techniques in spatial data analysis. Geostatistics provides an important tool in addressing environmental and social issues by modeling spatial relationships between data. Machine learning, on the other hand, brings flexibility to GIS by extracting meaning from large data sets and automatic learning processes. When these two methods come together, versatile analysis opportunities are provided for users to make more accurate and reliable decisions. The impact of GIS is expanding in many areas from urban planning to natural resource management and disaster monitoring. Faster processing of data and detailed analyses create a strong infrastructure for early detection and management of environmental problems. Thus, complex spatial data gain meaning and strategic decision-making processes are based on more solid ground. These techniques, which increase the power of GIS, also contribute to the creation of more sustainable and smart cities in the future.

Remote Sensing and Deep Learning for Spatial Data

Remote sensing and deep learning are two powerful analysis tools that are becoming increasingly critical in modern Geographic Information Systems (GIS). With the development of technology, huge datasets can be collected to help us understand and observe our environment. Remote sensing provides high-resolution data from large areas with techniques such as satellite imagery, LiDAR, and thermal imaging, and is used in a wide range of fields from tracking environmental events to urban planning. Deep learning methods come into play in the analysis of these data; they can quickly and accurately perform operations such as extracting meaningful information from large data sets, pattern recognition, classification, and prediction. While remote sensing techniques increase the effectiveness of GIS projects by continuously collecting data from the environment, deep learning algorithms enable more advanced analyses by making use of these data (Zhang et al., 2022). The combination of the two approaches provides great benefits in a wide range of applications such as environmental monitoring, planning of urban areas, and natural disaster management.

Remote sensing techniques provide a wide data source in the process of collecting environmental and spatial data. The main advantage of these techniques is the ability to analyze different features by collecting information from large geographical areas. Satellite imagery allows continuous observation of large areas, while aerial photography allows more detailed data to be collected. LiDAR technology is used to create high-resolution 3D maps of the land surface using laser beams. Multispectral and hyperspectral imaging techniques allow the identification of features such as vegetation, water resources, and mineral distribution in a given area (Buckley et al., 2013). Thermal imaging is used in analyses such as the urban heat island effect by monitoring temperature changes, while radar remote sensing offers the advantage of obtaining images regardless of weather conditions. The following table summarises the remote sensing techniques commonly used in GIS applications and their application areas (Table 4).

Table 4
Remote Sensing Techniques in GIS

Technique	Description	GIS Applications
Satellite Imagery	High-resolution images captured from satellites for various spatial analyses	Land use classification, urban growth analysis, environmental monitoring
Aerial Photography	Images taken from aircraft to capture detailed spatial data	Topographic mapping, disaster assessment, infrastructure planning
LiDAR (Light Detection and Ranging)	Uses laser pulses to measure distances and create high-resolution 3D maps of the Earth's surface	Terrain modeling, forestry analysis, flood risk assessment
Multispectral Imaging	Captures images across multiple wavelengths to identify material characteristics	Vegetation analysis, water body detection, mineral exploration
Thermal Imaging	Uses infrared sensors to detect temperature variations in the environment	Urban heat island analysis, forest fire detection, industrial monitoring
Radar Remote Sensing	Uses radar waves to capture images, allowing for analysis regardless of weather conditions	Land deformation monitoring, soil moisture analysis, oceanographic studies
Hyperspectral Imaging	Captures a broad spectrum of light to distinguish materials based on their spectral signatures	Agricultural assessment, mineral identification, environmental monitoring

Satellite imagery makes it possible to monitor large areas quickly and with high resolution. Satellite images, which are preferred for land use classification and urban growth analyses, are also important for environmental monitoring studies. Aerial photography allows obtaining more detailed spatial data and is used in studies that require detailed analysis such as disaster assessment and infrastructure planning. LiDAR maps the land surface in high resolution with laser pulses. This technique is very effective in forest analyses, terrain modeling, and flood risk assessment. Multispectral imaging enables versatile analyses such as vegetation analysis, detection of water resources, and mineral exploration. Thermal imaging analyses environmental problems such as the heat island effect in urban areas and the detection of forest fires by measuring temperature changes. Radar remote sensing collects data regardless of weather conditions and finds applications in different fields such as land deformation monitoring and ocean research. Hyperspectral imaging offers the advantage of separating materials according to their spectral signatures in studies such as agricultural evaluation and mineral detection (Shukla & Kot, 2016).

Deep learning techniques play an important role in the process of analyzing and learning large data sets. It provides fast and accurate results by automating complex processes such as pattern recognition, classification, and prediction, especially in GIS data. Deep learning performs tasks such as detecting buildings, creating road maps, and classifying vegetation by performing detailed analyses on satellite and aerial images. In the table below, the main deep learning techniques used in GIS applications and the usage areas of these techniques are given (Table 5).

Table 5
Deep Learning Techniques in GIS

Technique	Description	GIS Applications
Convolutional Neural Networks (CNN)	Deep learning techniques specialized in image analysis and feature extraction	Land cover classification, urban structure detection, deforestation monitoring
Recurrent Neural Networks (RNN)	Processes sequential data, useful for time series spatial data analysis	Weather prediction, traffic flow analysis, temporal change detection
Generative Adversarial Networks (GAN)	Used for generating synthetic data and enhancing image quality	Satellite image enhancement, filling missing data, land use simulation
Autoencoders	Unsupervised learning method used for dimensionality reduction and feature extraction	Noise reduction in remote sensing data, anomaly detection in spatial datasets
Transfer Learning	Leveraging pre-trained models for similar tasks to reduce training time and improve accuracy	Rapid deployment for land cover classification, disaster assessment
Semantic Segmentation	Pixel-level image classification for detailed object detection	Building and road detection, vegetation mapping, land use analysis
Object Detection	Identifies specific objects within an image, used for counting and tracking	Tree counting, vehicle detection, wildlife monitoring

Convolutional Neural Networks (CNN) perform particularly well in image analysis and are used in areas such as land cover classification and urban structure detection. Recurrent Neural Networks (RNN) are a suitable technique for analyzing time series data and are preferred in weather forecasting or traffic flow analyses. Generative Adversarial Networks (GAN) are used to improve image quality and generate synthetic data. It is an ideal technique for processes such as satellite image enhancement and missing data filling (Zaytar & El Amrani, 2021). Autoencoders are used as an unsupervised learning method to reduce the dimensionality of data and feature extraction; it is useful for noise reduction in remote sensing data and anomaly detection in spatial data sets. Transfer learning reduces training time and improves accuracy by using pre-trained models on similar tasks, enabling rapid land cover classification and disaster assessment (Alem & Kumar, 2022). Semantic segmentation provides detailed object detection by classifying each pixel in the image and is used in detailed analyses such as building and road detection. Object detection, on the other hand, identifies specific objects in the image and is useful in counting and tracking operations; it is especially effective in tasks such as tree counting, vehicle detection, and wildlife monitoring.

In general terms, the combination of remote sensing and deep learning techniques provides in-depth analyses and fast solutions in GIS projects. These methods support

decision-making in critical areas such as environmental monitoring, urban planning, and disaster management by making sense of big data sources. With the developing technology, the efficiency and accuracy provided by these techniques contribute to the creation of more sustainable and smart cities. While remote sensing enables the collection of spatial data covering a wide area, deep learning enables making predictions for the future by making sense of these data. In this direction, the combination of these two methods in GIS applications has the potential to enable better management of modern cities and environmental systems.

Spatial Data Visualization and Interpretation

Spatial data visualization and interpretation is an important component of data analysis in Geographic Information Systems (GIS). Visualization of spatial data supports users' decision-making processes by facilitating the understanding of complex geographic information. Visualization enables faster and more effective interpretation of data by representing multidimensional data with graphs, maps, and various visual tools. This contributes to the understanding of not only location-based information but also patterns, relationships, and variability in the analysis of spatial data. In this context, data visualization in GIS has a wide range of applications from urban planning to natural resource management, from environmental monitoring to crisis and disaster management (Nasr-Azadani et al., 2023).

Data visualization tools and libraries enable GIS analysts to present spatial data in dynamic and interactive formats. For example, ArcGIS and QGIS are powerful GIS software widely used for spatial analysis and visualization. These platforms help urban planners analyze infrastructure development projects, environmental scientists monitor ecosystem changes, and public institutions to plan post-disaster recovery processes (Pavelka & Landa, 2024). The detailed analysis and mapping tools provided by ArcGIS allow users to view and analyze data in layers. For example, ArcGIS is often preferred for identifying natural disaster risk zones or monitoring urban expansion. QGIS, on the other hand, is a popular choice especially for research and academic studies due to its open-source nature and provides flexibility in spatial data analysis and mapping processes.

Table 6

Tools and Libraries for Spatial Data Visualization and Interpretation

Tool/ Library	Description	Areas of Use
ArcGIS	An advanced GIS platform for spatial analysis and data visualization	Mapping, geographic analysis, data visualization
QGIS	An open source GIS software; offers spatial data management and analysis capabilities	Map creation, data integration, analysis
Tableau	Data visualization and analysis platform; supports visualization of spatial data	Spatial data analysis, map-based data visualization
D3.js	JavaScript library for creating web-based data visualizations	Dynamic map visualizations, interactive data visualization
Leaflet	A lightweight JavaScript library for creating web-based interactive maps	Web mapping, interactive map creation
Mapbox	A web-based mapping platform with extensive map editing and visualization capabilities	Map creation, geographic data visualization, location-based analysis

Google Earth Engine	A cloud-based platform for analysis and visualization on large spatial datasets	Satellite imagery analysis, environmental change monitoring, spatial analysis
Matplotlib (Python)	PA Python-based data visualization library; can visualize GIS data in 2D	Graph drawing, data analysis, basic map visualization
GeoPandas (Python)	Python-based library for analyzing and visualizing geographic data	Geographic data processing, map analysis, spatial data visualization
Kepler.gl	A powerful tool for interactively visualizing large data sets	Geographic data visualization, urban planning, logistics analysis

Tableau, another important tool for data visualization, allows visualizing various data types, including spatial data. Tableau helps users explore spatial relationships within data by creating interactive maps. For example, spatial analyses of different data, such as population density, traffic flow, or health data, can be quickly and clearly visualized using Tableau (Taylor et al., 2021). These visualizations enable decision-makers to promptly understand the data and make strategic decisions with the visualized information. JavaScript libraries such as D3.js and Leaflet, which are used for web-based data visualization, enable GIS data to be shared with wider audiences. While D3.js is used to create dynamic and customizable visualizations, Leaflet is ideal for developing interactive maps thanks to its lightweight structure and user-friendly interface. For example, a Leaflet can be used to visualize air pollution rates in a city, allowing users to see the pollution density on a map. Such web-based visualizations enable a wide range of users to access spatial analyses and present data more effectively (Table 6).

Figure 2
Mapbox Usage Example



Platforms such as Mapbox offer flexibility in spatial data visualization, enabling the creation of high-resolution maps and the addition of customized data layers. For example, a logistics company can use Mapbox to visualize delivery routes (Figure 2) and reduce costs through route optimization.

Cloud-based solutions such as Google Earth Engine are used to analyze large spatial datasets. Google Earth Engine, which allows analyses of satellite images and environmental data, is particularly effective in monitoring and analyzing environmental changes. For example, a researcher who wants to analyse the deforestation process in Amazon forests can observe long-term changes by using the data sets provided by Google Earth Engine. In the Python ecosystem, libraries such as Matplotlib and GeoPandas are frequently preferred tools by data scientists and GIS experts for data analysis (Fleischmann et al., 2022). Matplotlib offers the user flexibility in creating 2D graphics and maps and is an ideal tool for simple maps. GeoPandas, on the other hand, is a powerful library for processing and visualizing geographic data and has a wide range of applications, especially in spatial data analysis. For example, an analyst who wants to examine the distribution of green space in a city can easily map different types of green space and their spatial relationships with GeoPandas. In addition, Kepler.gl, which is used for big data visualization, stands out as a powerful tool for presenting geographic data in an interactive and dynamic way (Zuo et al., 2022). Kepler.gl helps urban planners to analyze traffic density or logistics distribution networks. For example, an administrator who wants to monitor the traffic flow in a city can use Kepler.gl to visualize heavy traffic zones and make strategic decisions for necessary adjustments.

These tools and libraries enable spatial data to be presented in a more understandable and effective way. Visualization in GIS projects contributes directly to decision-making processes by making analysis results accessible and interpretable by a wider range of users. Visualization techniques allow the simplification of complex data structures and facilitate a better understanding of spatial patterns. The visual richness provided by these tools contributes to the more effective use of spatial analyses in a wide range of fields from academic research to industrial applications.

Challenges and Future Trends in Data-Driven GIS

Data-driven Geographic Information Systems (GIS) have become an important tool for collecting, analyzing, and interpreting spatial data, empowered by technologies such as big data analytics, artificial intelligence, and IoT. However, the development and implementation of data-driven GIS solutions involve many challenges. Various factors ranging from data quality to computational costs can affect the use and accuracy of these systems. At the same time, the predicted trends for the future development of GIS promise the emergence of smarter and more powerful systems. In this context, it is important to conduct a review of the challenges and future trends facing data-driven GIS solutions.

Challenges in Data-Driven GIS

Data-driven GIS requires a robust infrastructure to process and analyze large amounts of spatial data. However, the increase in the amount of this data and the increasing complexity of the data pose some significant challenges to GIS solutions. These challenges include data quality and accuracy, data integration and harmonization, data security and privacy, high computational costs, and data processing infrastructure.

Data Quality and Accuracy: The accuracy of data in GIS solutions directly affects the reliability of the results obtained. Data from different sources may sometimes be inconsistent or outdated. For example, incompatibilities between different data sources, such as satellite imagery or sensor data, can cause deterioration in data quality. Furthermore, some data may be incomplete or inaccurate, which can compromise the accuracy of GIS analyses. Therefore, it is important to develop automated error detection and data cleaning processes to improve data quality.

Data Integration and Harmonisation: In data-driven GIS solutions, integrating and

harmonizing data from different sources poses a major challenge. Various data types such as satellite images, GPS data, social media data, and sensor data from IoT devices need to be analyzed together. However, collecting these data in different formats and at different time intervals complicates the integration process. This situation requires harmonization of data in order to make accurate analyses in GIS solutions.

Data Security and Privacy: GIS projects are responsible for protecting data security and privacy, especially in studies involving large amounts of user data. Data containing location information of users, such as GPS data, raises privacy issues. Especially by combining data collected from security cameras in cities and social media platforms, there may be the potential to interfere with the private lives of individuals. Therefore, advanced encryption methods and data anonymization techniques should be used to ensure data security and privacy.

High Computational Costs: One of the most important challenges of data-driven GIS solutions is that big data processing requires high computational power and cost. Especially processing and analyzing large volumes of spatial data in real-time requires powerful hardware and advanced software. This increases the cost of GIS projects and makes it difficult for smaller-scale projects to access these technologies. While cloud computing solutions have the potential to reduce some of these high costs, cloud computing costs may also increase in the long term.

Data Processing Infrastructure and Performance: The data processing infrastructure required for GIS projects varies depending on the size of the data and the depth of the analysis. Especially in spatial analyses in big cities or time-critical projects such as monitoring natural disasters, fast and efficient data processing infrastructure is required. If a high-performance computing infrastructure is not established or is inadequate, data processing time may be prolonged and the accuracy of analyses may be adversely affected. Therefore, it is very important to use powerful and scalable data processing infrastructures in GIS projects.

Future Trends in Data-Driven GIS

The future of data-driven GIS has great potential with developing technologies. Innovations in areas such as artificial intelligence, machine learning, IoT, and cloud computing are making GIS solutions smarter, faster, and more effective. Future trends in data-driven GIS include smart city solutions, augmented reality (AR)-based mapping, real-time data analytics, more powerful AI-powered models, and cloud-based GIS solutions.

Smart City Solutions: Data-driven GIS solutions are critical for smart cities. Many aspects of city life such as traffic management, energy distribution, waste management, and security can be monitored and optimized with GIS. GIS solutions for smart cities contribute to making cities more sustainable and efficient. For example, thanks to real-time data from sensors, traffic density can be analyzed and transport routes can be managed more efficiently.

Augmented Reality (AR) and GIS: Augmented reality technology, when combined with GIS, can offer more interactive mapping and data presentation. Augmented reality-supported GIS solutions enable users to visualize environmental data more effectively. For example, it becomes possible to observe the status of infrastructure projects in a city or changes in natural disaster areas in real-time. This technology facilitates the use of GIS data in the field and provides users with a richer experience.

Real-Time Data Analytics: In the future, data-oriented GIS solutions are expected to become more effective with real-time data analytics. Thanks to IoT devices, satellite

systems, and sensor networks, real-time data can be collected continuously. These data can be quickly analyzed in GIS systems and provide instant information to decision-makers. Especially in areas that require instant intervention such as natural disaster management, urban traffic control, and environmental monitoring, real-time data analytics provide a great advantage.

Artificial Intelligence Supported GIS Models: Artificial intelligence and machine learning allow for more in-depth analysis of GIS data. In the future, AI-supported GIS solutions will be more widely used in areas such as predicting environmental risks, monitoring urban development, and modeling the effects of natural disasters. These models support decision-making processes and increase the effectiveness of GIS by producing faster and more accurate results. GIS systems integrated with artificial intelligence make significant contributions to data-driven decision-making processes by performing better in big data analyses.

Cloud-Based GIS Solutions: Cloud computing plays an important role in the future of data-driven GIS solutions. In projects with intensive big data processing, cloud-based GIS solutions facilitate data storage, processing, and analysis processes. Thanks to cloud technology, GIS projects can be supported with a cost-effective and flexible infrastructure. This enables small-scale businesses and local governments to access data-driven GIS solutions at lower costs.

The future of data-driven GIS enables the emergence of more advanced, intelligent, and user-friendly systems with technological innovations. GIS solutions powered by new technologies such as artificial intelligence and machine learning play an important role in solving environmental and social problems. New approaches such as augmented reality, real-time data analytics, and cloud-based solutions expand the usage areas of GIS and make it applicable in more sectors. These developments contribute to the adoption of data-driven GIS solutions by more institutions and organizations.

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