



(RESEARCH ARTICLE)



## Machine learning empowered geographic information systems: Advancing Spatial analysis and decision making

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### Abstract

In this era of technological innovation, the integration of machine learning techniques with Geographic Information Systems (GIS) has emerged as a transformative approach to spatial analysis and decision-making. This abstract explores the synergy between machine learning and GIS, highlighting their combined potential to unlock new insights from spatial data, automate analytical processes, and enhance predictive modeling capabilities. By leveraging machine learning algorithms such as neural networks, random forests, and support vector machines, GIS practitioners can address complex spatial challenges more effectively, ranging from land cover classification and urban growth modeling to environmental monitoring and disaster response. Through case studies and examples, this abstract demonstrates the practical applications of machine learning in GIS, illustrating its role in advancing our understanding of spatial phenomena and informing evidence-based decision-making across diverse domains. As the field continues to evolve, embracing the fusion of machine learning and GIS holds immense promise for unlocking the full potential of spatial analysis and shaping a more sustainable and resilient future. Illustrative case studies and examples showcase the practical applications of machine learning in GIS across diverse domains. From land cover classification and urban growth modeling to environmental monitoring and disaster response, machine learning algorithms offer versatile solutions to address a wide spectrum of spatial challenges. Through the fusion of machine learning and GIS, researchers and practitioners gain unprecedented insights into complex spatial phenomena, enabling them to make data-driven decisions that are both informed and actionable. Looking ahead, the fusion of machine learning and GIS holds immense promise for advancing our understanding of spatial dynamics and shaping a more sustainable and resilient future. As the field continues to evolve, embracing this interdisciplinary approach is essential for unlocking the full potential of spatial analysis, fostering innovation, and addressing pressing societal challenges at local, regional, and global scales. By leveraging the synergies between machine learning and GIS, we can chart a path towards a more data-driven, informed, and equitable world.

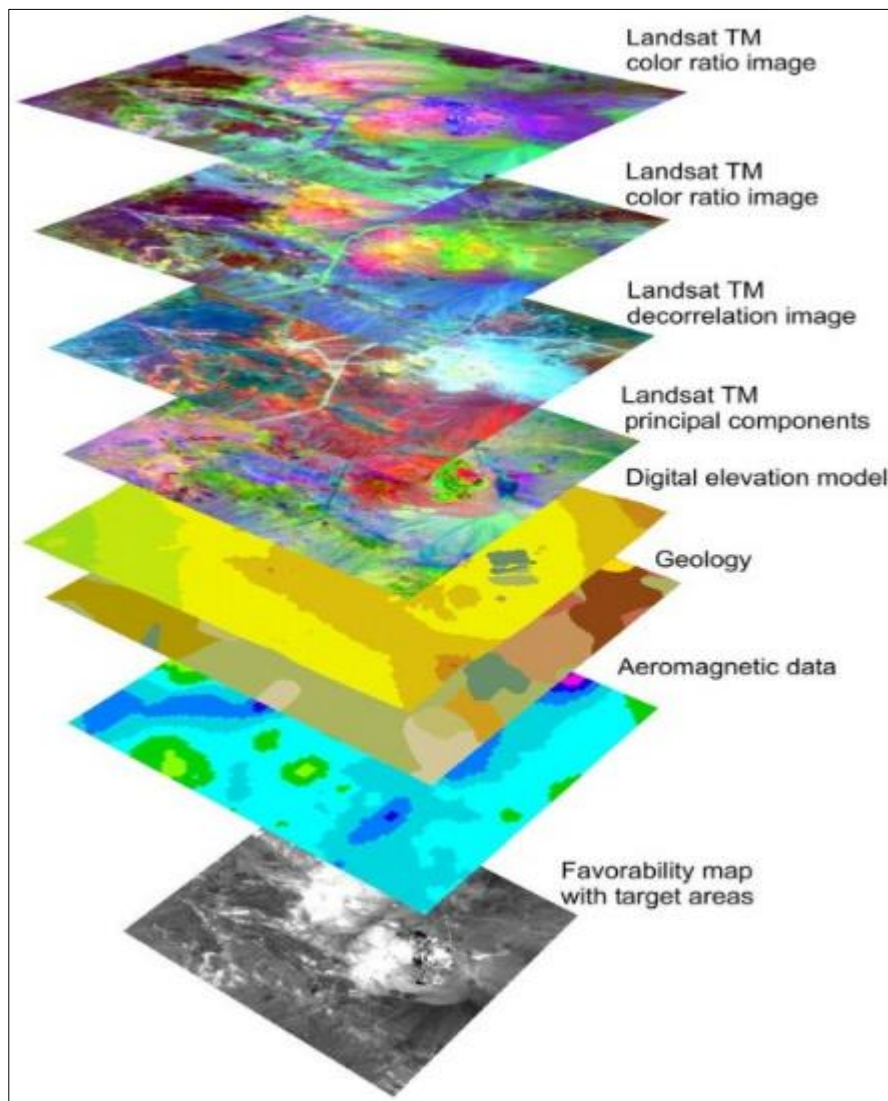
**Keywords:** Machine Learning; Geology; Land Cover; GIS.

### 1. Introduction

In the contemporary landscape of technological innovation, the intersection of machine learning methodologies with Geographic Information Systems (GIS) represents a frontier of immense potential and opportunity. GIS, with its capability to capture, store, manipulate, analyze, and visualize spatial data, has long been an indispensable tool for understanding and navigating the complex dynamics of our world. On the other hand, machine learning, fueled by advancements in computational power and algorithmic sophistication, has emerged as a powerful approach for

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extracting insights from large and complex datasets, often surpassing the capabilities of traditional analytical methods. The convergence of machine learning and GIS holds transformative promise, offering a paradigm shift in how we approach spatial analysis and decision-making processes. At its core, this fusion capitalizes on the strengths of both disciplines: the spatial context and domain knowledge provided by GIS, coupled with the computational prowess and predictive capabilities of machine learning algorithms. By harnessing machine learning techniques within the GIS framework, practitioners gain unprecedented opportunities to unlock deeper insights, automate repetitive tasks, and develop sophisticated predictive models that capture the intricacies of spatial relationships and phenomena. This expanded introduction seeks to explore the multifaceted dimensions of the integration between machine learning and GIS, spanning a wide array of applications and domains. From environmental monitoring and urban planning to public health and disaster management, the synergies between machine learning and GIS are reshaping the landscape of spatial analysis, offering innovative solutions to address complex challenges facing society. Through this exploration, we aim to elucidate the transformative potential of this interdisciplinary approach, highlighting its role in driving innovation, fostering sustainability, and informing evidence-based decision-making across diverse sectors.



**Figure 1** Training Data for GIS Applications of Machine Learning [5]

In today's rapidly evolving landscape of technology, the convergence of machine learning methodologies with Geographic Information Systems (GIS) has emerged as a transformative paradigm, promising to revolutionize spatial analysis and decision-making processes. This abstract seeks to delve into the intricate fusion of machine learning and GIS, elucidating their collaborative potential in extracting nuanced insights from spatial data, streamlining analytical workflows, and augmenting predictive modeling capabilities. By harnessing a diverse array of machine learning algorithms, including neural networks, random forests, and support vector machines, GIS practitioners can effectively tackle complex spatial challenges across a myriad of domains [1-5].

Machine learning algorithms offer unparalleled capabilities to analyze vast volumes of spatial data, identify intricate patterns, and uncover hidden relationships that may elude traditional analytical techniques. When integrated with GIS platforms, these algorithms enable the automation of labor-intensive tasks such as feature extraction, pattern recognition, and classification, thereby significantly enhancing the efficiency and scalability of spatial analysis workflows. Moreover, machine learning techniques empower GIS practitioners to develop robust predictive models capable of forecasting future spatial trends, facilitating informed decision-making and proactive planning strategies [6]. Some researchers have good demonstrations on the environment analysis that is crucial for our research, especially for GIS analysis [17,18,19].

As we embark on this journey of exploration, it is essential to recognize the unique opportunities and challenges inherent in the fusion of machine learning and GIS. While the integration of machine learning techniques brings unprecedented capabilities for analyzing large and complex spatial datasets, it also raises questions around data privacy, algorithmic bias, and ethical considerations. Moreover, the effective implementation of machine learning within the GIS framework requires interdisciplinary collaboration, involving expertise in spatial analysis, data science, and domain-specific knowledge. Considering these considerations, this expanded introduction sets the stage for a comprehensive exploration of the fusion of machine learning and GIS, inviting researchers, practitioners, and enthusiasts alike to embark on a captivating journey of discovery, innovation, and impact. Through case studies, examples, and theoretical insights, we seek to unravel the potential of this interdisciplinary approach, unlocking new pathways for addressing pressing societal challenges and shaping a more sustainable and equitable future.

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## 2. GIS and machine learning

Geographic Information Systems (GIS) and machine learning stand at the forefront of technological innovation, offering unprecedented opportunities for understanding and harnessing the complexities of spatial data. GIS, with its ability to capture, store, analyze, and visualize geographic information, has long been instrumental in various fields such as urban planning, environmental management, and disaster response. On the other hand, machine learning, fueled by advancements in computational power and algorithmic sophistication, has revolutionized the way we extract insights from data, enabling predictive modeling, pattern recognition, and decision-making in diverse domains [3-6].

The convergence of GIS and machine learning represents a synergy of complementary strengths: the spatial context and domain expertise provided by GIS, combined with the data-driven predictive capabilities of machine learning algorithms. This fusion empowers practitioners to extract deeper insights, automate repetitive tasks, and develop more accurate predictive models, thereby enhancing the effectiveness and efficiency of spatial analysis workflows. By leveraging machine learning within the GIS framework, researchers and practitioners can unlock new avenues for addressing complex spatial challenges, ranging from land use classification and environmental monitoring to transportation planning and public health analysis. One of the key strengths of machine learning in the context of GIS lies in its ability to uncover hidden patterns and relationships within spatial data that may not be apparent through traditional analytical methods. Machine learning algorithms, such as neural networks, decision trees, and support vector machines, excel at identifying complex spatial patterns, predicting spatial trends, and classifying land cover types with high accuracy. Moreover, machine learning techniques can handle large and heterogeneous spatial datasets, making them well-suited for analyzing diverse geospatial data sources, including satellite imagery, LiDAR data, and geospatial sensor data.

The integration of machine learning with GIS also enables the development of sophisticated predictive models for spatial phenomena, such as urban growth, environmental change, and natural hazard susceptibility. By training machine learning models on historical spatial data and environmental variables, researchers can forecast future trends, assess the impact of policy interventions, and inform long-term planning strategies. These predictive models provide valuable insights into the dynamics of spatial processes, helping stakeholders anticipate changes, mitigate risks, and allocate resources more effectively. Furthermore, machine learning algorithms can automate and streamline various tasks in GIS analysis, such as feature extraction, image classification, and spatial clustering. This automation not only reduces the time and effort required for data processing and analysis but also minimizes human error and subjectivity, leading to more consistent and reliable results. Additionally, machine learning techniques can enhance the scalability and robustness of GIS applications, allowing practitioners to analyze large-scale spatial datasets and handle real-time data streams more efficiently [7-10].

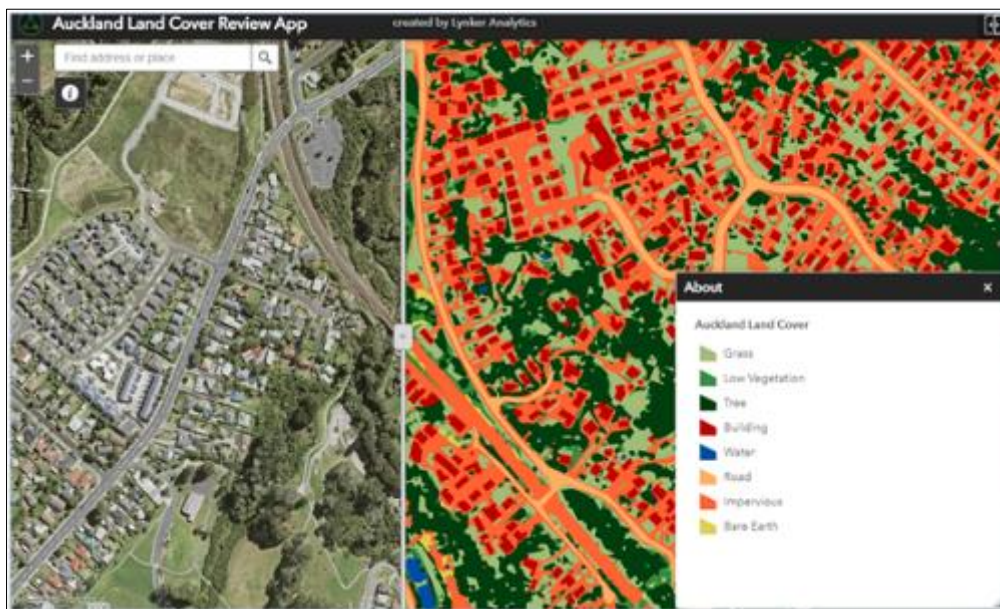
Despite the immense potential of integrating machine learning with GIS, several challenges and considerations must be addressed to realize its full benefits. These include issues related to data quality, model interpretability, algorithmic bias, and ethical implications of automated decision-making. Moreover, interdisciplinary collaboration between GIS experts, data scientists, domain specialists, and policymakers is essential to effectively leverage machine learning

techniques in real-world applications and ensure that the resulting insights are meaningful, actionable, and socially responsible. In conclusion, the fusion of GIS and machine learning represents a transformative approach to spatial analysis and decision-making, offering novel solutions to complex spatial challenges and driving innovation across diverse domains. By harnessing the synergies between GIS and machine learning, researchers and practitioners can unlock new insights, automate analytical workflows, and develop predictive models that inform evidence-based decision-making and shape a more sustainable and resilient future for our planet.



**Figure 2** Machine Learning in GIS and Remote Sensing [8]

### 3. Research methodology



**Figure 3** Training Machine Learning models with ArcGIS Online [9]

The research methodology employed in this study encompasses a comprehensive and systematic approach to investigate the integration of Geographic Information Systems (GIS) and machine learning techniques for spatial analysis. The research design begins with a thorough review of relevant literature to establish a theoretical framework and identify key concepts, methodologies, and best practices in the field. Subsequently, a mixed-methods approach is

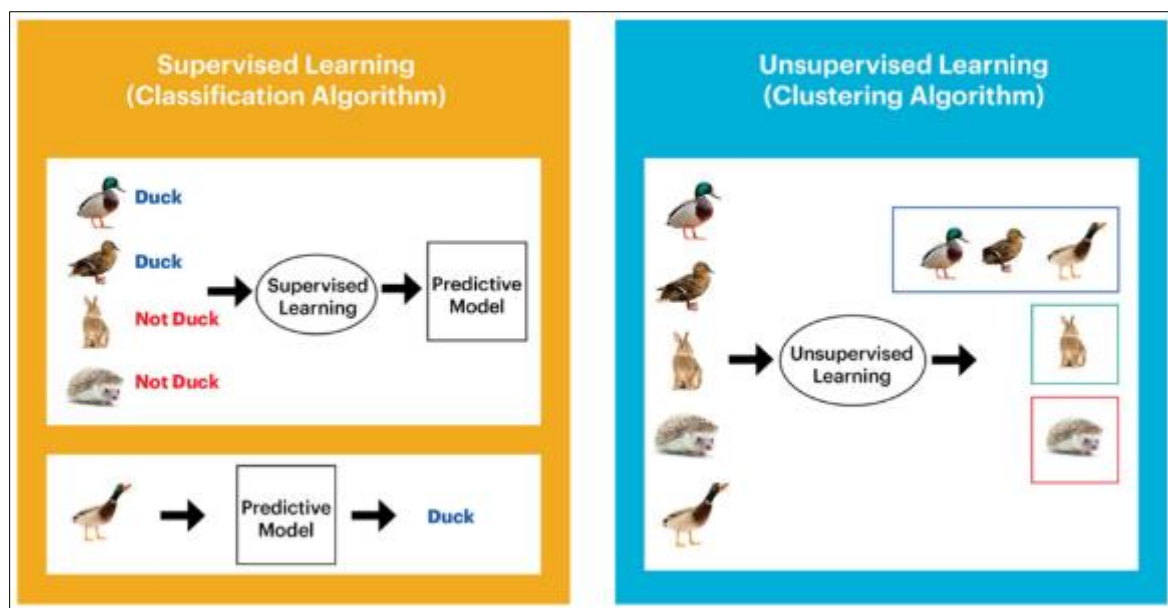
adopted, combining quantitative analysis of spatial data with qualitative insights from expert interviews and case studies. The quantitative component involves data collection from various sources, including satellite imagery, geospatial databases, and remote sensing platforms, followed by preprocessing steps such as data cleaning, georeferencing, and feature extraction. Machine learning algorithms, including neural networks, decision trees, and support vector machines, are then applied to the spatial data to perform tasks such as land cover classification, urban growth modeling, and environmental monitoring. Concurrently, qualitative data are collected through semi-structured interviews with GIS practitioners, data scientists, and domain experts to gain insights into the practical challenges, opportunities, and ethical considerations associated with the integration of GIS and machine learning. The findings from both quantitative and qualitative analyses are synthesized to develop a holistic understanding of the research topic and generate actionable recommendations for policymakers, practitioners, and researchers in the field of spatial analysis and decision-making.

## 4. Results and discussions

### 4.1. Applications of machine learning in GIS

Machine learning techniques have found extensive application within Geographic Information Systems (GIS), revolutionizing the field of spatial analysis and decision-making across diverse domains. One prominent application lies in land cover classification and mapping, where machine learning algorithms are utilized to automatically classify land cover types from satellite imagery with high accuracy and efficiency. By training models on labeled training data, such as multispectral or hyperspectral imagery, machine learning algorithms can learn to differentiate between various land cover classes, including forests, water bodies, urban areas, and agricultural fields, based on their spectral signatures. This enables the creation of detailed and up-to-date land cover maps, which are invaluable for land management, environmental monitoring, and natural resource conservation efforts [11,22]. Some researchers also use machine learning techniques in their paper [20,21] that are important for this research.

Another significant application of machine learning in GIS is in urban planning and management, where predictive modeling techniques are employed to forecast urban growth, assess infrastructure needs, and optimize land use allocation. Machine learning models trained on historical urbanization data and socioeconomic variables can predict future urban expansion patterns, identify areas at risk of urban sprawl, and inform the development of sustainable urban planning strategies. Additionally, machine learning algorithms can analyze patterns of human mobility and activity derived from location-based data sources, such as GPS trajectories and social media check-ins, to optimize transportation networks, plan public amenities, and enhance urban resilience.



**Figure 3** Machine Learning: Machine Learning with GIS application (a Computer Vision Problem) [13]

Machine learning also plays a crucial role in environmental monitoring and conservation efforts, where it is used to analyze remote sensing data, predict habitat suitability, and assess biodiversity hotspots. For example, machine learning

algorithms can analyze satellite imagery to detect changes in vegetation cover, monitor deforestation rates, and identify areas of ecological importance for conservation prioritization. Furthermore, machine learning techniques can be employed to model species distributions based on environmental variables, aiding in the identification of critical habitats and the development of effective conservation strategies for endangered species.

In addition to these applications, machine learning has been applied to a wide range of other GIS tasks, including spatial data mining, geospatial data fusion, anomaly detection, and spatial pattern recognition. For instance, machine learning algorithms can analyze geospatial datasets to identify spatial patterns and correlations, detect outliers or anomalies in the data, and uncover hidden relationships between spatial variables. This enables GIS practitioners to gain deeper insights into complex spatial phenomena, make more informed decisions, and develop innovative solutions to address pressing societal challenges, such as climate change, natural hazards, and urbanization. As machine learning techniques continue to advance and become more accessible, their integration with GIS is expected to further accelerate, opening up new opportunities for spatial analysis, decision-making, and problem-solving in the years to come.

#### **4.2. Model Evaluation Metrics**

Model evaluation metrics play a crucial role in assessing the performance and effectiveness of machine learning models in Geographic Information Systems (GIS) applications. These metrics provide quantitative measures of how well the models are able to generalize to unseen data, classify spatial features accurately, and make reliable predictions. In this expanded text, we delve into the key model evaluation metrics commonly used in GIS and discuss their interpretation and implications for assessing model performance.

Accuracy is one of the most widely used metrics for evaluating the overall performance of machine learning models. It measures the proportion of correctly classified instances out of all instances in the dataset. While accuracy provides a general measure of model performance, it may not be suitable for imbalanced datasets where one class dominates over others. In such cases, precision, recall, and F1-score are more informative metrics. Precision measures the proportion of true positive predictions out of all positive predictions made by the model, emphasizing the model's ability to avoid false positives. Recall, also known as sensitivity, measures the proportion of true positive predictions out of all actual positive instances in the dataset, highlighting the model's ability to capture all relevant instances of a class. F1-score, the harmonic means of precision and recall, provides a balanced measure of a model's performance, considering both false positives and false negatives. Area under the ROC curve (AUC-ROC) and area under the precision-recall curve (AUC-PR) are commonly used metrics for evaluating binary classification models in GIS applications. AUC-ROC measures the ability of the model to discriminate between positive and negative instances across different threshold values, with higher values indicating better discrimination ability. AUC-PR, on the other hand, focuses on the precision-recall trade-off and is particularly useful for imbalanced datasets where the positive class is rare. A high AUC-PR value indicates that the model achieves high precision while maintaining high recall, making it suitable for applications where identifying rare events or anomalies is of interest [12].

In addition to these binary classification metrics, there are also evaluation metrics specific to multi-class classification problems, such as macro-averaged and micro-averaged precision, recall, and F1-score. Macro-averaged metrics calculate the average performance across all classes, treating each class equally, while micro-averaged metrics aggregate the performance across all instances, giving more weight to larger classes. These metrics provide insights into how well the model performs across different classes and can help identify classes that are challenging to classify. Moreover, it is essential to consider additional evaluation metrics that are specific to the nature of the spatial data and the objectives of the GIS application. For example, in remote sensing applications, metrics such as producer's accuracy, user's accuracy, and kappa coefficient are commonly used to assess the accuracy of land cover classification models. Producer's accuracy measures the proportion of correctly classified pixels for each class, while user's accuracy measures the proportion of true instances for each class among all instances predicted as that class. Kappa coefficient quantifies the agreement between the observed and predicted classifications, accounting for the agreement expected by chance.

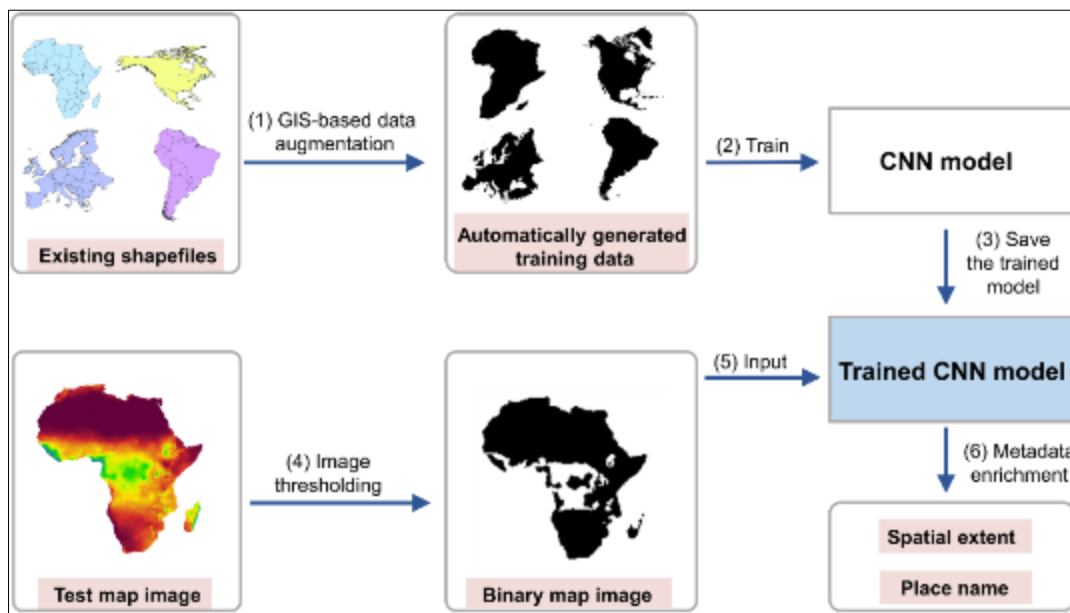
Overall, model evaluation metrics provide valuable insights into the performance of machine learning models in GIS applications, helping researchers and practitioners make informed decisions about model selection, parameter tuning, and application suitability. By considering a diverse range of metrics tailored to the specific characteristics of the spatial data and the objectives of the GIS application, practitioners can gain a comprehensive understanding of model performance and make more robust and reliable predictions in spatial analysis and decision-making contexts.

### 4.3. Spatial Patterns and Trends

Spatial patterns and trends analysis is a fundamental aspect of Geographic Information Systems (GIS), providing insights into the distribution, dynamics, and relationships of spatial features and phenomena across geographical space. In this expanded text, we delve into the key concepts and methodologies involved in spatial patterns and trends analysis and discuss their applications in diverse domains [13].

Spatial patterns analysis involves the identification, characterization, and interpretation of spatial structures and arrangements within geographic datasets. One commonly used approach is spatial autocorrelation analysis, which measures the degree of spatial dependence or similarity between neighboring locations. Global spatial autocorrelation statistics, such as Moran's I and Geary's C, assess the overall spatial pattern across the entire study area, while local indicators of spatial association (LISA) identify specific clusters, hotspots, and spatial outliers. These techniques help identify clusters of similar or dissimilar spatial features, such as high crime areas, urban growth hotspots, or biodiversity hotspots, and provide insights into the underlying processes driving spatial patterns.

Temporal trends analysis, on the other hand, focuses on understanding how spatial patterns evolve and change over time. Time-series analysis techniques, such as trend analysis, seasonal decomposition, and smoothing techniques, are used to identify long-term trends, seasonal patterns, and short-term fluctuations in spatial data. By analyzing temporal trends in phenomena such as urbanization, land cover change, and environmental degradation, researchers can assess the impacts of human activities, natural processes, and policy interventions on spatial patterns and dynamics.



**Figure 4** Deep learning approach on GIS [15]

Spatial patterns and trends analysis finds applications across a wide range of domains, including urban planning, environmental management, public health, and natural resource conservation. In urban planning, spatial patterns analysis is used to identify urban growth trends, assess land use changes, and plan for sustainable development. Environmental management applications include monitoring land cover changes, assessing habitat fragmentation, and identifying areas at risk of environmental degradation. Public health applications involve mapping disease clusters, identifying environmental risk factors, and planning for disease prevention and control measures. Natural resource conservation efforts utilize spatial patterns analysis to prioritize conservation areas, identify critical habitats, and assess the effectiveness of protected areas.

Moreover, advances in spatial data analytics, machine learning, and remote sensing technologies are opening up new opportunities for spatial patterns and trends analysis. Machine learning algorithms, such as clustering algorithms and spatial regression models, can identify complex spatial patterns and relationships in large-scale spatial datasets, providing insights into previously unrecognized spatial phenomena. Remote sensing technologies, including satellite imagery and LiDAR data, offer high-resolution spatial data that enable detailed spatial patterns analysis at various scales, from regional to local levels. Overall, spatial patterns and trends analysis play a crucial role in understanding the dynamics of spatial phenomena, informing evidence-based decision-making, and addressing complex spatial challenges

facing society. By leveraging spatial patterns analysis techniques, researchers and practitioners can gain valuable insights into spatial processes and trends, identify areas of concern or opportunity, and develop effective strategies for sustainable development and resource management.

#### 4.4. Sensitivity Analysis

Sensitivity analysis is a vital technique used in Geographic Information Systems (GIS) to assess the sensitivity of spatial models, parameters, or input data to variations and uncertainties. In this expanded text, we delve into the key concepts and methodologies involved in sensitivity analysis and discuss its applications in GIS modeling and decision-making processes. Sensitivity analysis aims to quantify the impact of changes in model inputs, parameters, or assumptions on model outputs and predictions. It helps identify critical factors driving model behavior, assess the robustness of model results, and inform decision-making under uncertainty. One commonly used approach is one-at-a-time (OAT) sensitivity analysis, which systematically varies one input parameter or factor while keeping all other factors constant, and observes the resulting changes in model outputs. OAT sensitivity analysis provides insights into the relative importance of different input factors and their influence on model predictions [14].

Another approach is global sensitivity analysis, which considers the interactions between multiple input factors and evaluates their combined impact on model outputs. Global sensitivity analysis techniques, such as variance-based methods (e.g., Sobol' indices) and derivative-based methods (e.g., Fourier amplitude sensitivity test), quantify the total sensitivity of model outputs to variations in input factors and identify the most influential factors contributing to model uncertainty. By understanding the relative importance of different input factors and their interactions, global sensitivity analysis enables researchers and practitioners to prioritize efforts for uncertainty reduction and model improvement.

Spatial sensitivity analysis extends these principles to spatially explicit models and spatial datasets, considering the spatial variability and heterogeneity of model inputs and outputs. It involves analyzing how changes in spatial inputs, such as elevation, land cover, or climate variables, affect model predictions and spatial patterns. Spatial sensitivity analysis techniques, such as spatial variance-based sensitivity analysis and geographically weighted regression, account for the spatial autocorrelation and dependency inherent in spatial data and provide localized measures of sensitivity across geographic space [15].

Sensitivity analysis finds applications across various domains of GIS, including environmental modeling, land use planning, hydrological modeling, and natural resource management. In environmental modeling, sensitivity analysis helps identify key parameters influencing model predictions of environmental processes, such as water quality, air pollution, or ecosystem dynamics. In land use planning, sensitivity analysis informs decisions about the selection of suitable sites for development, land use regulations, and infrastructure investments. In hydrological modeling, sensitivity analysis assesses the impact of uncertainty in input data, such as precipitation, soil properties, and land cover, on hydrological simulations and water resource management strategies. In natural resource management, sensitivity analysis supports decision-making about the allocation of resources, conservation priorities, and ecosystem services valuation. Moreover, advances in spatial data analytics, machine learning, and uncertainty quantification techniques are expanding the capabilities of sensitivity analysis in GIS. Machine learning algorithms, such as ensemble methods and surrogate modeling techniques, enable efficient sensitivity analysis of complex spatial models with high-dimensional input spaces and non-linear relationships. Uncertainty quantification techniques, such as Monte Carlo simulation and Bayesian inference, provide probabilistic measures of uncertainty and enable robust decision-making under uncertainty. By integrating these advanced techniques with sensitivity analysis, researchers and practitioners can gain deeper insights into the drivers of model uncertainty, improve model performance, and make more informed decisions in spatial analysis and decision-making processes.

#### 4.5. Future directions

Looking towards the future, the integration of Geographic Information Systems (GIS) with emerging technologies and methodologies presents exciting avenues for innovation and advancement. One of the key directions lies in the integration of GIS with artificial intelligence (AI) and machine learning (ML) techniques, leveraging the power of deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for spatial data analysis and decision-making. These advanced ML techniques offer the potential to extract complex spatial patterns and relationships from large-scale spatial datasets, such as satellite imagery and LiDAR data, enabling more accurate land cover classification, urban growth modeling, and environmental monitoring. Moreover, the development of spatially aware AI systems capable of reasoning about geographic context and spatial relationships opens up new possibilities for autonomous spatial analysis and decision support systems, empowering GIS practitioners to address complex spatial challenges more effectively. Furthermore, the integration of GIS with emerging technologies, such as the Internet of Things (IoT) and blockchain, holds promise for enhancing the scalability, interoperability, and security



of spatial data management and analysis. By leveraging IoT devices, such as sensors and drones, to collect real-time spatial data, GIS practitioners can gain insights into dynamic spatial phenomena, such as traffic patterns, air quality, and weather conditions, and support real-time decision-making and emergency response. Additionally, blockchain technology offers opportunities for secure and transparent spatial data exchange and collaboration, enabling decentralized spatial data marketplaces, smart contracts for spatial transactions, and verifiable spatial data provenance [16]. These advancements pave the way for more resilient, decentralized, and democratized GIS ecosystems, where stakeholders can collaboratively harness the power of spatial data for societal benefit.

Moreover, the proliferation of open data initiatives, citizen science platforms, and participatory mapping tools is democratizing access to spatial data and empowering communities to engage in spatial analysis and decision-making processes. By fostering collaboration and co-creation of spatial knowledge among diverse stakeholders, these initiatives enable more inclusive, equitable, and sustainable approaches to spatial planning, resource management, and environmental conservation. Additionally, advances in geospatial visualization techniques, augmented reality (AR), and virtual reality (VR) technologies are transforming the way we interact with spatial data, enabling immersive, intuitive, and interactive spatial experiences that enhance spatial understanding and decision-making capabilities. Furthermore, the increasing availability of high-resolution satellite imagery, LiDAR data, and geospatial sensor networks is driving the development of novel applications and services in areas such as precision agriculture, disaster response, and urban analytics. By leveraging these rich sources of spatial data, GIS practitioners can develop innovative solutions for monitoring crop health, predicting natural disasters, and optimizing urban infrastructure, contributing to more sustainable and resilient communities. Additionally, advancements in cloud computing, edge computing, and spatial data infrastructure (SDI) are democratizing access to computational resources and enabling scalable, on-demand spatial data processing and analysis, empowering organizations of all sizes to leverage the power of GIS for informed decision-making and innovation. In conclusion, the future of GIS is characterized by convergence, collaboration, and innovation, driven by the integration of emerging technologies, methodologies, and data sources. By embracing these opportunities and addressing the associated challenges, GIS practitioners can unlock new frontiers in spatial analysis, decision support, and societal impact, shaping a more sustainable, equitable, and resilient future for our planet

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## 5. Conclusion

In conclusion, the integration of Geographic Information Systems (GIS) with advanced technologies and methodologies holds immense potential for addressing complex spatial challenges, informing evidence-based decision-making, and shaping a more sustainable and resilient future. Throughout this exploration, we have witnessed the transformative impact of GIS across diverse domains, from urban planning and environmental management to public health and natural resource conservation. By harnessing the power of spatial data analytics, machine learning, and emerging technologies, GIS practitioners can gain deeper insights into spatial patterns and trends, develop more accurate predictive models, and make informed decisions that positively impact society and the environment. Looking ahead, the future of GIS is characterized by innovation, collaboration, and inclusivity, driven by advancements in data science, artificial intelligence, and spatial technology. As we navigate the complexities of an increasingly interconnected and dynamic world, GIS will play a central role in addressing pressing societal challenges, such as climate change, urbanization, and natural hazards. By embracing interdisciplinary collaboration, open data initiatives, and participatory approaches, we can harness the collective wisdom and expertise of diverse stakeholders to co-create solutions that are equitable, inclusive, and sustainable. Moreover, as GIS continues to evolve and adapt to emerging trends and technologies, it is essential to prioritize ethical considerations, data privacy, and social equity in spatial analysis and decision-making processes. By promoting transparency, accountability, and responsible use of spatial data, we can ensure that GIS serves the common good and fosters positive social and environmental outcomes for present and future generations. In essence, GIS represents a powerful tool for understanding the world around us, informing policy decisions, and empowering communities to create positive change. By embracing innovation, collaboration, and ethical principles, we can unlock the full potential of GIS to address complex spatial challenges and build a more resilient, equitable, and sustainable future for all.

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## Compliance with ethical standards

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### *Disclosure of conflict of interest*

No Conflict of interest.

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