https://doi.org/10.31891/2219-9365-2026-86-47
UDK 004.8 : 528.9 : 502.4

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INTELLIGENT GEOGRAPHIC INFORMATION SYSTEMS FOR ENVIRONMENTAL MONITORING: A REVIEW OF CURRENT APPROACHES AND FUTURE DEVELOPMENT PROSPECTS

The paper examines contemporary approaches to the development of intelligent geographic information systems (GIS) for environmental monitoring. It analyzes the transformation of conventional GIS into intelligent systems that integrate artificial intelligence methods, Earth remote sensing, the Internet of Things, and big data technologies. Based on a review of scientific publications, existing approaches are systematized and a generalized classification of intelligent GIS is proposed according to the level of intelligence and technological foundation.

A distinct class of intelligent GIS focused on environmental monitoring is identified, and their main functional types are defined, including systems for monitoring water resources, the atmosphere, biodiversity, environmental risks, and urbanized areas. A generalized architecture of an intelligent GIS is proposed, comprising data acquisition, processing, intelligent analysis, and decision support layers.

Key limitations of current approaches are identified, including challenges in integrating heterogeneous data, low interpretability of artificial intelligence models, limitations in applying large language models to geospatial tasks, and the lack of universal integrated solutions. перспективні напрями розвитку include the development of explainable models, autonomous GIS, integration of knowledge graphs, and real-time data processing.

The scientific novelty of the study lies in the systematization of modern approaches to intelligent GIS, the development of a generalized classification, and the formulation of a concept of intelligent GIS for environmental monitoring as integrated analytical platforms. The practical significance of the results lies in their potential application in the development of advanced environmental monitoring systems and decision support tools.

Keywords: geographic information systems, intelligent GIS, GeoAI, environmental monitoring, artificial intelligence, Internet of Things, big data, Earth remote sensing

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ІНТЕЛЕКТУАЛЬНІ ГЕОІНФОРМАЦІЙНІ СИСТЕМИ ДЛЯ ЕКОЛОГІЧНОГО МОНІТОРИНГУ: ОГЛЯД СУЧАСНИХ ПІДХОДІВ ТА ПЕРСПЕКТИВИ РОЗВИТКУ

У статті досліджено сучасні підходи до розроблення інтелектуальних геоінформаційних систем (ГІС) для екологічного моніторингу. Проаналізовано трансформацію традиційних геоінформаційних систем в інтелектуальні системи, що інтегрують методи штучного інтелекту, дистанційного зондування Землі, Інтернету речей та технології великих даних. На основі аналізу наукових публікацій систематизовано наявні підходи та запропоновано узагальнену класифікацію інтелектуальних ГІС за рівнем інтелектуалізації та технологічною основою.

Виокремлено окремий клас інтелектуальних ГІС, орієнтованих на екологічний моніторинг, та визначено їх основні функціональні типи, зокрема системи моніторингу водних ресурсів, атмосферного повітря, біорізноманіття, екологічних ризиків і урбанізованих територій. Запропоновано узагальнену архітектуру інтелектуальної ГІС, що включає рівні збору даних, їх оброблення, інтелектуального аналізу та підтримки прийняття рішень.

Визначено ключові обмеження сучасних підходів, серед яких складність інтеграції різнорідних даних, низька інтерпретованість моделей штучного інтелекту, обмеження застосування великих мовних моделей у геопросторових завданнях та відсутність універсальних інтегрованих рішень. Перспективними напрямами розвитку є створення пояснюваних моделей, автономних ГІС, інтеграція графів знань та оброблення даних у режимі реального часу.

Наукова новизна дослідження полягає в систематизації сучасних підходів до побудови інтелектуальних ГІС, розробленні узагальненої класифікації та формуванні концепції інтелектуальної ГІС для екологічного моніторингу як інтегрованої аналітичної платформи. Практичне значення отриманих результатів полягає у можливості їх використання під час розроблення перспективних систем екологічного моніторингу та інструментів підтримки прийняття управлінських рішень.

Ключові слова: геоінформаційні системи, інтелектуальні ГІС, GeoAI, екологічний моніторинг, штучний інтелект, Інтернет речей, великі дані, дистанційне зондування Землі.

Стаття надійшла до редакції / Received 06.04.2026
Прийнята до друку / Accepted 30.04.2026
Опубліковано / Published 31.05.2026

INTRODUCTION

In recent years, environmental monitoring has evolved from a standalone applied task into one of the key domains for ensuring environmental security, sustainable territorial development, climate change adaptation, and the management of natural and anthropogenic risks. The rapid growth of spatiotemporal data, the proliferation of Earth remote sensing technologies, the development of sensor networks, the Internet of Things, cloud platforms, and artificial intelligence have significantly reshaped the requirements for environmental monitoring systems. Under these conditions, traditional geographic information systems (GIS), primarily focused on data storage, visualization, and basic spatial analysis, no longer fully meet the demands of modern environmental monitoring.

Today, the development of geoinformation technologies is characterized by a transition toward intelligent GIS, where classical spatial analysis tools are combined with machine learning, deep learning, semantic modeling, automated pattern detection, forecasting, and decision support. In the scientific literature, the concept of GeoAI is introduced to describe intelligent GIS, representing a new stage in the evolution of geoinformation science, in which artificial intelligence complements GIS and becomes its analytical core, capable of processing heterogeneous, multimodal data on natural, urbanized, and socio-ecological systems.

The application of such systems is particularly relevant in the field of environmental monitoring. Unlike many other domains, the object of observation here is dynamic, multifactorial, and spatially distributed. The state of surface waters, atmospheric air, soils, landscapes, and biodiversity is determined by the simultaneous influence of natural and anthropogenic factors, requiring integrated analysis of satellite imagery, field measurements, IoT data, statistical indicators, cartographic layers, and even unstructured data sources. Therefore, intelligent GIS are increasingly viewed not merely as auxiliary visualization tools, but as comprehensive systems for environmental analytics, forecasting, and management.

Recent studies indicate that the integration of artificial intelligence with geoinformation technologies already yields tangible results in tasks such as land cover change detection, surface water quality analysis, flood risk assessment, pollution forecasting, disaster management, and environmentally oriented spatial planning. At the same time, the scientific literature lacks a holistic approach to the systematization of intelligent GIS specifically for environmental monitoring: different authors tend to focus either on AI algorithms, sensor infrastructure, or GIS as a platform, while much less attention is paid to their integration within a unified concept of an environmentally oriented intelligent geoinformation system.

It is also important to emphasize that the latest stage of development in this field is associated with the emergence of autonomous and semi-autonomous geoinformation systems, ontology-based knowledge graphs, and the integration of large language models into geospatial analysis. These approaches open fundamentally new possibilities – from automatic generation of queries and analytical scenarios to semantic integration of heterogeneous environmental data and the development of systems capable not only of representing environmental states but also of explaining, forecasting, and recommending management actions. However, the maturity level of these solutions, their accuracy, interpretability, robustness, and suitability for real-world environmental management remain open and debatable issues.

In this context, there is a need for a comprehensive scientific analysis of the current state of intelligent GIS, their classification, the identification of technologies oriented toward environmental monitoring, and the determination of aspects that remain insufficiently explored compared to existing approaches. Such a formulation makes it possible to move from a simple enumeration of technological solutions to a critical understanding of the field, its methodological boundaries, and future development prospects.

Thus, the aim of this study is to generalize and critically analyze modern scientific approaches to the development of intelligent GIS, their classification, the identification of solutions for environmental monitoring, as well as to determine unresolved issues and future directions of this field.

RESEARCH METHODOLOGY

This study is based on a theoretical and analytical research approach aimed at systematizing contemporary scientific knowledge on intelligent GIS for environmental monitoring. The methodological framework combines elements of a systematic literature review and conceptual modeling.

The empirical basis of the study consists of recent peer-reviewed scientific publications devoted to geographic information systems, GeoAI, environmental monitoring, the Internet of Things, and big data technologies. The literature was selected using academic databases such as Scopus, Web of Science, and Google Scholar, with a focus on studies published in recent years that reflect current technological trends and research directions.

The research employs several complementary methods: a literature review and content analysis were conducted to identify key concepts, technological approaches, and application domains of intelligent GIS; a comparative analysis was used to examine differences in existing approaches, particularly in terms of data sources, analytical methods, and system architectures; methods of scientific abstraction and generalization were applied to identify common patterns and relationships across the reviewed studies.

Based on this analysis, a systematization and classification method was used to develop a generalized framework for intelligent GIS in environmental monitoring. The classification is constructed according to five interrelated criteria: technological foundation, data sources, functional purpose, domain of application, and level of system autonomy. In addition, elements of conceptual modeling were employed to interpret intelligent GIS as integrated analytical platforms that combine data acquisition, processing, analysis, and decision support.

Such a methodological approach makes it possible to move from fragmented descriptions of individual solutions toward a holistic understanding of intelligent GIS and to identify key trends, limitations, and перспективи подальшого розвитку in this field.

RELATED WORKS

In foundational scientific studies addressing the nature of geographic information systems (GIS), they are defined as technologies for the collection, storage, processing, analysis, and visualization of spatial data. Such a functional framework is outlined by the authors in [1], emphasizing that the key value of GIS lies in linking spatial location with attribute data, enabling the identification of spatial patterns. Song and Wu, in turn, in [2], note that the development of GIS has always been closely associated with the overall progress of information technologies and is currently in a phase of integration with large spatiotemporal datasets, cloud environments, mobile computing, the Internet of Things, and artificial intelligence. Lü et al. in [3] extend this perspective by considering geoinformation science as a key component of Earth sciences, environmental management, and smart cities, as well as a field transitioning from the dual model of "nature–human" to a triad of "nature–human–information."

On this basis, the GeoAI paradigm emerges, representing a qualitatively new stage in GIS development. Song et al. in [4] describe GeoAI not merely as the application of machine learning algorithms for mapping, but as a framework for analyzing complex "human–environment" systems. The authors propose classifying GeoAI applications into four major domains: buildings and infrastructure, land-use analysis, natural environment and disasters, and social processes and human activities. Importantly, they also classify the types of data used in GeoAI, including field measurements, spatial databases, large crowdsourced datasets, remote sensing data, photogrammetry, LiDAR, and statistical sources. This makes their work one of the most significant theoretical foundations for identifying classes of intelligent GIS.

A more methodologically oriented perspective on GeoAI is provided by Li and Hsu in [5]. They summarize the application of deep learning, convolutional neural networks, transformers, and computer vision techniques to satellite and UAV imagery, street-level panoramas, and other geospatial data. The authors identify six key characteristics of GeoAI: scalability, automation, high accuracy, sensitivity to subtle changes, robustness to noise, and rapid technological evolution. At the same time, they emphasize that the field still lacks clearly defined theoretical boundaries, and that its methods are often difficult to interpret from the standpoint of classical geographic analysis. Thus, GeoAI is viewed both as a powerful extension of traditional GIS and as a field requiring further conceptual structuring.

A broader scientific perspective is presented in the work of Zhao et al. [6], where artificial intelligence is considered not only as a tool for processing geospatial data but as an instrument for studying Earth systems as a whole. The authors demonstrate that AI is increasingly applied to modeling the atmosphere, hydrology, soils, ecosystems, the cryosphere, and anthropogenic processes. A key conclusion of their study is that AI not only enhances computational efficiency but also transforms the logic of scientific inquiry by enabling the analysis of multilayered, multimodal, and dynamic interactions. However, they also highlight issues related to reliability, reproducibility, interpretability, and computational cost, indicating that the development of intelligent GIS depends not only on algorithmic performance but also on scientific trust.

A separate body of literature focuses on the application of GIS and intelligent methods in urban and infrastructural environments. Elassy et al. [7] examine intelligent transportation systems as one of the most mature examples of integrating spatial data, communication technologies, and control algorithms within smart cities. Patel [8] demonstrates that GIS in transportation is evolving from mapping and routing functions toward the analysis of spatiotemporal patterns, identification of accident-prone areas, and integration with the Internet of Vehicles. Mortaheb and Jankowski [9] reconsider the concept of smart cities through the lens of GeoAI, emphasizing the importance of human-centered integration of urban planning, big data, and geoinformation science. Anwar and Sakti [10] further develop this direction by showing that integrating AI with GIS and environmental science enables urban growth prediction, environmental impact assessment, and the use of overlay analysis, network analysis, hotspot detection, and simulation modeling. Thus, in urban environments, intelligent GIS are increasingly becoming systems for forecasting and decision support rather than merely spatial analysis tools.

Another important direction is the integration of GIS with multilevel spatial models in energy and technical systems. Perwez et al. [13] propose a multimodal hybrid approach for modeling energy consumption in commercial buildings, combining spatial representation with technical parameters and long-term scenarios. Their study shows that the choice of modeling scale significantly affects energy consumption estimates and that neglecting physical and technical factors leads to discrepancies between predicted and actual outcomes.

A significant body of research is dedicated to environmental monitoring. Chen et al. [14] provide one of the most comprehensive reviews of the use of large-scale remote sensing data for monitoring water environments. They classify methods for water body extraction and water quality assessment, describe types of input imagery and evaluation metrics, and identify key limitations, including data heterogeneity, insufficient spatiotemporal resolution, and reduced model accuracy in complex aquatic environments. They also outline future directions such as cloud computing, new sensor platforms, ensemble methods, and hybrid physical–data-driven models.

Environmental monitoring in a broader sense is systematized by Alotaibi and Nassif [15] and Popescu et al. [16]. These studies demonstrate that AI is widely applied to air and water quality monitoring, biodiversity assessment, soil analysis, climate modeling, and disaster management, while also emphasizing challenges related to data quality, model transparency, and resource constraints.

Sensor-based real-time monitoring systems are discussed by Narayana et al. [17] and Miller et al. [18], who describe architectures based on sensor networks, wireless communication, and IoT platforms, as well as the integration of intelligent agents for pattern detection, forecasting, and automated response.

Another important research direction involves environmental risk management. Studies such as Chan et al. [20] and Neoaz [21] demonstrate the role of GIS in flood vulnerability assessment and disaster management, integrating physical, social, and environmental indicators. These works highlight the increasing role of GIS within decision support systems and environmental information systems.

Recent studies also emphasize the role of knowledge representation and language-based approaches in geoinformation science. Janowicz et al. [27] introduce knowledge graphs for environmental data integration, while Mai et al. [28] and Bhandari et al. [29] explore the application of large language models (LLMs) in geospatial tasks, noting both their potential and limitations in spatial reasoning.

Further developments include autonomous GIS concepts proposed by Li and Ning [31] and Li et al. [32], where large language models serve as reasoning engines capable of automating data acquisition, analysis, and visualization. These approaches represent a transition toward self-operating geospatial systems, though they raise issues of reliability, transparency, and accountability.

Finally, hybrid intelligent models are explored by Tvoroshenko and Gorokhovatskyi [34] and Prabha et al. [35], who demonstrate the effectiveness of combining fuzzy logic, evolutionary methods, and machine learning for analyzing complex spatial systems under uncertainty.

Thus, the analysis of the reviewed studies reveals several stages in the evolution of GIS: from tools for spatial data organization and visualization, to GeoAI-integrated systems, to platforms for environmental monitoring and risk analysis, and ultimately to cognitive, autonomous, and hybrid intelligent systems. However, most studies focus on specific data types, application domains, or modeling approaches. The issue of a comprehensive classification of intelligent GIS specifically for environmental monitoring—considering levels of intelligence, data sources, processing methods, application environments, and management functions—remains insufficiently explored. This gap underscores the relevance of the present study and forms the basis for developing a generalized classification of intelligent GIS.

Based on the analysis of the literature, it can be argued that modern GIS are evolving toward increased levels of intelligence, expansion of data sources, greater complexity of analytical mechanisms, and enhanced decision-support capabilities. At the same time, existing studies lack a unified classification of intelligent GIS specifically suitable for environmental monitoring tasks. Some authors focus on data types, others on algorithms, and still others on application domains or levels of system autonomy.

A Generalized Classification of Intelligent GIS for Environmental Monitoring

In this regard, it is appropriate to propose a generalized classification of intelligent GIS for environmental monitoring based on five interrelated criteria: technological foundation, data sources, functional purpose, domain of monitoring, and level of autonomy. Such an approach enables a transition from fragmented descriptions of individual solutions to a systematic understanding of intelligent GIS as a class of analytical systems.

The first classification criterion is the technological foundation of the system, i.e., the class of methods forming its analytical core (Fig. 1).

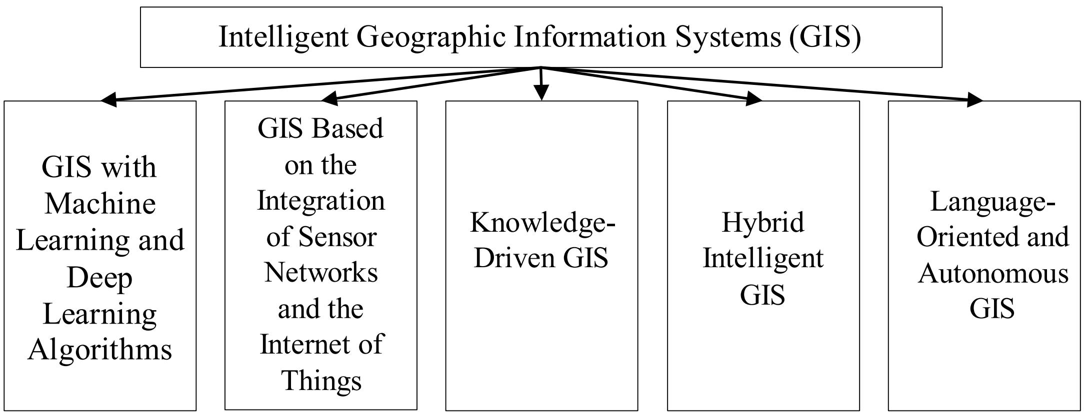

Fig. 1. Classification of Intelligent GIS Based on Technological Foundations
Source: developed by the author based on [1–35]

The first group includes GIS based on machine learning and deep learning algorithms. This class constitutes the core of the GeoAI paradigm, where spatial data are combined with methods for classification, segmentation, change detection, forecasting, and pattern recognition. Such systems are particularly effective for processing satellite, UAV, and visual data, as well as for automated mapping and assessment of land, water bodies, and urban areas.

The second group consists of intelligent GIS based on the integration of sensor networks and the Internet of Things. In these systems, the geoinformation environment is combined with continuous streams of field and real-time measurements, enabling real-time monitoring. These solutions are especially important for monitoring water parameters, atmospheric air quality, soils, and microclimatic conditions.

The third group includes knowledge-driven GIS that utilize knowledge graphs, semantic enrichment, and tools for integrating heterogeneous data. Their distinguishing feature is the ability to operate not only with observational datasets but also with relationships, context, and semantic connections between environmental objects, events, territories, and indicators.

The fourth group comprises hybrid intelligent GIS, which combine deterministic, stochastic, fuzzy, and data-driven approaches. These systems are particularly suitable under conditions of incomplete data, high uncertainty, and complex multifactor dynamics of the monitored environment.

The fifth group includes language-oriented and autonomous GIS, where large language models or generative models are used for query generation, geoprocessing planning, result analysis, and the production of cartographic or textual outputs. This is the most recent direction, still not fully mature, but already indicating a transition toward systems capable of constructing complete analytical workflows.

The second important classification criterion is the type of data sources used by the system, as data characteristics largely determine both system architecture and analytical methods (Fig. 2).

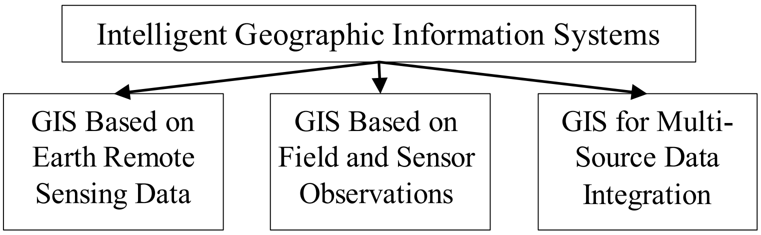

Fig. 2. Classification of Intelligent GIS by Data Sources

Source: developed by the author based on [1–35]

The first category includes systems based on Earth remote sensing data, such as satellite imagery, aerial photography, photogrammetric materials, and LiDAR data. These systems are widely used for monitoring land cover, water bodies, land degradation, urban areas, and natural hazards.

The second category consists of systems based on field and sensor observations, where key roles are played by sensors, automated stations, mobile devices, weather stations, and other continuous measurement tools. These systems provide long-term temporal coverage but are often spatially localized.

The third category includes systems integrating multi-source data, combining satellite observations, statistical datasets, crowdsourced data, field measurements, archival records, and real-time data. This type is characteristic of modern intelligent GIS, enabling multidimensional environmental analysis while introducing challenges related to data heterogeneity, format incompatibility, temporal scales, and accuracy levels.

From the perspective of functional purpose, intelligent GIS for environmental monitoring can be divided into five classes (Fig. 3).

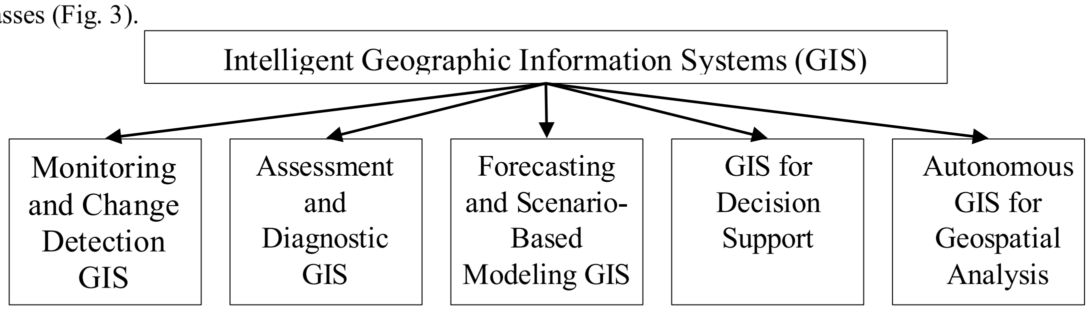

Fig. 3. Classification of Intelligent GIS by Functional Purpose

Source: developed by the author based on [1–35]

The first class includes systems for observation and change detection, aimed at identifying spatiotemporal changes in environmental conditions such as water bodies, land cover, air pollution, vegetation, and temperature anomalies.

The second class consists of systems for environmental assessment and diagnostics, which determine levels of degradation, vulnerability, pollution, or risk. Examples include systems for water quality assessment, flood vulnerability analysis, soil contamination evaluation, and urban environmental load assessment.

ISSN 2219-9365

The third class includes systems for forecasting and scenario modeling, focused on predicting future changes such as pollution spread, land subsidence, urban growth, energy consumption, flooding, or ecosystem degradation.

The fourth class comprises decision support systems, where analytical results are directly translated into recommendations, action plans, or management scenarios. These include systems for environmental management, renewable energy planning, disaster response, and territorial development strategies.

The fifth class includes autonomous geospatial analysis systems, which represent a transition from decision support to independent analytical reasoning. In such systems, the intelligent module not only performs computations but also designs analytical workflows, selects data, and produces final conclusions.

Considering the domain of monitoring, five main groups of intelligent GIS can be identified (Fig. 4).

The first group includes water monitoring systems, covering boundary detection, water quality assessment, level monitoring, hydrological analysis, and water risk evaluation.

The second group consists of atmospheric and climate monitoring systems, dealing with temperature, humidity, air composition, pollution particles, weather conditions, and climate anomalies.

The third group includes systems for monitoring land, vegetation, and agroecosystems, integrating GIS with soil fertility assessment, crop monitoring, pest analysis, drought detection, irrigation management, and precision agriculture.

The fourth group comprises systems for risk and disaster monitoring, focusing on floods, landslides, subsidence, industrial accidents, fires, and other hazardous processes.

The fifth group includes urban environment monitoring systems, where environmental aspects are integrated with infrastructure analysis, transportation systems, urban flows, quality of life, and spatial organization, which is particularly relevant for smart city concepts.

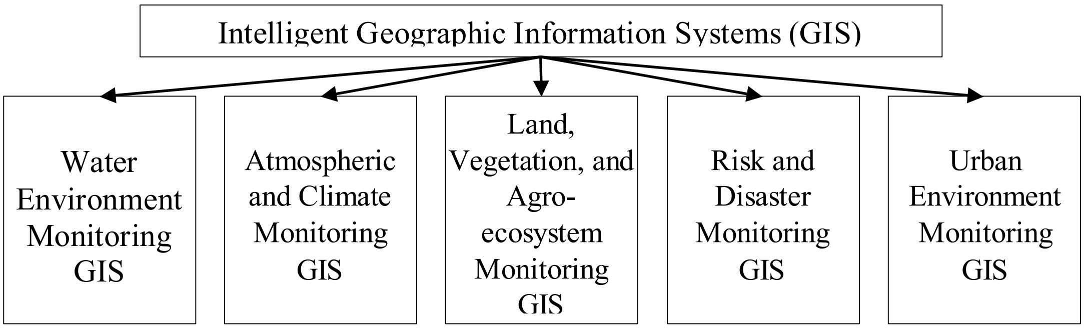

Fig. 4. Classification of Intelligent Geographic Information Systems by Application Domain of Monitoring
Source: developed by the author based on [1–35]

The most recent classification criterion is the level of autonomy. Based on contemporary studies, four groups of intelligent GIS can be distinguished (Fig. 5).

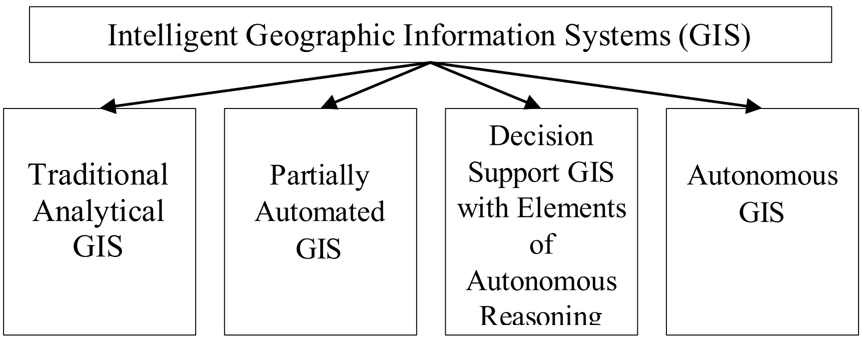

Fig. 5. Classification of Intelligent GIS by Level of Autonomy
Source: developed by the author based on [1–35]

The first group includes traditional analytical GIS, where all key operations are performed by the user, and the system serves primarily as a tool for data processing and visualization.

The second group includes partially automated intelligent GIS, where algorithms for classification, segmentation, forecasting, and anomaly detection are embedded in workflows, but problem formulation and interpretation remain the responsibility of the user.

The third group consists of decision support systems with elements of autonomous reasoning, capable not only of computation but also of generating recommendations, identifying patterns, warning about risks, and integrating diverse data types.

The fourth group includes fully autonomous GIS, where language or generative models act as the core of system control, enabling automatic generation of geoprocessing workflows, data retrieval, analysis, and reporting.

This classification by autonomy most clearly reflects the future trajectory of intelligent GIS development.

Thus, the proposed classification demonstrates that intelligent GIS for environmental monitoring should be considered as a multidimensional class of systems, where not only algorithms but also data types, application domains, management functions, and levels of autonomy are essential. This approach enables a shift from isolated technical solutions toward a generalized model of intelligent GIS as integrated platforms for environmental monitoring, analysis, forecasting, and decision support.

CONCLUSIONS

This study provides a comprehensive analysis of contemporary approaches to the development of intelligent geographic information systems (GIS) for environmental monitoring. Based on a systematic review of scientific literature, the evolution of GIS has been examined, highlighting their transformation from data management and visualization tools into integrated analytical platforms that incorporate artificial intelligence, remote sensing, the Internet of Things, and big data technologies.

The main scientific contribution of this work lies in the development of a generalized classification of intelligent GIS for environmental monitoring. Unlike existing approaches, which typically focus on individual aspects such as data types, algorithms, or application domains, the proposed classification integrates five key dimensions: technological foundation, data sources, functional purpose, monitoring domain, and level of autonomy. This multidimensional approach enables a more holistic understanding of intelligent GIS as complex analytical systems.

The study also identifies a distinct class of intelligent GIS oriented specifically toward environmental monitoring and systematizes their main functional types, including systems for monitoring water resources, atmospheric conditions, land and agroecosystems, environmental risks, and urban environments. In addition, a conceptual view of intelligent GIS as integrated platforms for monitoring, analysis, forecasting, and decision support is substantiated.

At the same time, several key limitations of current approaches have been identified. These include challenges in integrating heterogeneous data sources, limited interpretability of artificial intelligence models, insufficient maturity of language-model-based geospatial systems, and the lack of universal integrated solutions suitable for real-world environmental management tasks. These issues indicate that further development of intelligent GIS requires not only technological advancements but also methodological refinement and improved system transparency.

The перспективи подальших досліджень are associated with the development of explainable artificial intelligence models, the advancement of autonomous GIS, the integration of knowledge graphs for semantic data processing, and the implementation of real-time data analysis. Special attention should also be given to improving interoperability between systems, ensuring data quality, and enhancing the practical applicability of intelligent GIS in environmental governance.

Overall, the results of this study can be used as a theoretical and methodological basis for the development of next-generation environmental monitoring systems and decision support tools, contributing to more effective management of environmental processes and sustainable development.

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