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# An Integrated Gis, Remote Sensing And Ai-Based Framework For Improving Monitoring Methodology Of Protected Natural Areas

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**Abstract.** Effective monitoring of protected natural areas is a critical prerequisite for biodiversity conservation, ecosystem sustainability, and evidence-based environmental management [1,2]. However, many existing monitoring systems remain fragmented, episodic, and weakly integrated with modern geospatial and analytical technologies, which limits their ability to detect spatial–temporal changes and emerging ecological risks in a timely manner [3].

Multisource geospatial data, including satellite imagery and high-resolution aerial observations, are systematically integrated within a GIS environment to assess vegetation dynamics, land cover transformation, and ecosystem stability indicators. Vegetation indices such as NDVI are employed to quantify temporal changes in biomass and ecological condition, while machine learning–based analytical logic supports automated pattern recognition and early identification of environmental threats [4–6].

The practical applicability of the proposed methodology is demonstrated through a case study conducted within a protected natural area under arid environmental conditions. The results indicate that the integrated approach significantly enhances monitoring accuracy, analytical efficiency, and the reliability of management-oriented interpretations compared to conventional monitoring practices. The study contributes to the development of a scalable and adaptable geospatial monitoring framework that supports scientifically grounded decision-making, long-term ecological sustainability, and the digital transformation of protected area management systems.

**Keywords:** GIS-based monitoring; protected natural areas; remote sensing; NDVI; artificial intelligence; environmental management.

**Introduction.** Protected natural areas play a fundamental role in preserving biodiversity, maintaining ecosystem services, and ensuring ecological balance under increasing anthropogenic and climatic pressures [1,2]. Globally, agricultural expansion, urbanization, climate change, and unsustainable exploitation of natural resources have intensified the vulnerability of protected ecosystems, particularly in arid and semi-arid regions [3,7].

Conventional monitoring approaches are often characterized by periodic field observations, limited spatial coverage, and delayed data processing. Such methods frequently fail to capture the dynamic nature of ecological processes and provide insufficient analytical depth for timely decision-making [4]. Moreover, monitoring activities are commonly conducted in isolation from integrated spatial analysis and predictive modeling tools, resulting in fragmented datasets and reduced management effectiveness [5].

This study addresses this methodological gap by proposing an improved monitoring framework for protected natural areas based on the integrated use of GIS, remote sensing data, unmanned aerial observations, and artificial intelligence–driven analysis. The primary objective is to develop a structured, scalable, and scientifically grounded methodology that enhances the accuracy, efficiency, and interpretability of environmental monitoring outcomes, while supporting adaptive ecosystem management [9].

**Materials and Methods**

**Conceptual framework of the monitoring methodology.** The proposed monitoring methodology is designed as an integrated, multi-stage geospatial framework that combines data acquisition, spatial analysis, ecological risk assessment, and decision support within a unified analytical system. The framework emphasizes methodological consistency, spatial completeness, and analytical scalability.

The monitoring process is structured into four interrelated stages:

(1)Data acquisition and preprocessing;

(2)Spatial and ecological analysis;

(3)Ecological risk identification and modeling;

(4)Decision-oriented environmental management.

Each stage builds upon the outputs of the previous one, forming a continuous analytical workflow that supports both descriptive and predictive monitoring objectives. The framework is specifically designed to accommodate heterogeneous data sources and varying environmental conditions, making it applicable to a wide range of protected natural areas.

**Conceptual framework of the monitoring methodology.** The proposed monitoring methodology is based on an integrated geospatial framework that combines data acquisition, spatial analysis, ecological risk assessment, and decision support within a unified analytical system. The framework is designed to ensure methodological consistency, spatial completeness, and analytical scalability.

The monitoring process is structured into four interrelated stages: data acquisition and preprocessing, spatial–ecological analysis, ecological risk identification, and management-oriented decision support. Each stage builds on the outputs of the previous one, forming a continuous workflow that enables both descriptive assessment and predictive interpretation of environmental change.

**Data sources and acquisition.** The monitoring system relies on multisource geospatial data to ensure comprehensive spatial and temporal coverage. Multispectral satellite imagery serves as the primary data source for assessing vegetation condition and land cover dynamics, while high-resolution aerial observations support detailed local-scale analysis [4,11].

All datasets were harmonized within a unified coordinate framework. Preprocessing procedures included radiometric correction, atmospheric normalization, and spatial alignment to ensure data comparability and analytical reliability across observation periods.

**Spatial and ecological analysis using GIS and remote sensing.** Spatial analysis was conducted within a GIS environment integrating remote sensing–derived indicators with spatial layers representing land cover structure and environmental constraints. Vegetation dynamics were assessed using NDVI as a quantitative indicator of biomass condition and photosynthetic activity [5,12].

Temporal analysis enabled the identification of seasonal patterns, long-term trends, and anomalous changes associated with environmental stress. Land cover transformation was evaluated through multitemporal comparison, supporting the detection of spatial shifts and ecosystem fragmentation.

**Artificial intelligence based analytical logic.** Artificial intelligence based analytical logic was incorporated to enhance the efficiency and objectivity of data interpretation. Machine learning principles were applied to identify spatial patterns, classify ecological conditions, and detect anomalies within large geospatial datasets.

This component supports the automated identification of high-risk zones and emerging degradation processes, reducing dependence on manual interpretation and improving the consistency and timeliness of monitoring outputs.

**Four-stage monitoring workflow.** The operational workflow consists of four stages: systematic data collection and preprocessing; spatial and ecological analysis; ecological risk identification using integrated GIS and AI-based modeling; and translation of analytical results into decision-support outputs for adaptive environmental management (Figure 1).

This structured workflow ensures that monitoring activities directly inform management strategies and contribute to long-term ecosystem sustainability.

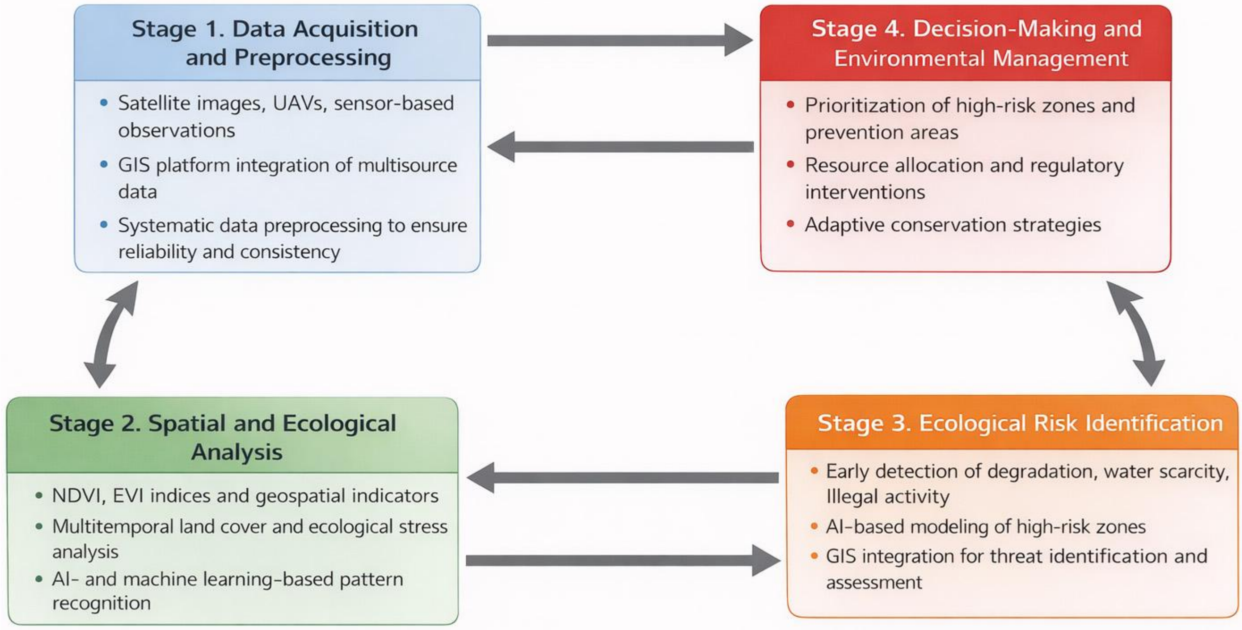


**Figure 1. Mechanism of the improved GIS-based monitoring methodology for protected natural areas**

**Stage 1.** The initial stage of the monitoring process focuses on systematic data acquisition and preprocessing. At this stage, spatial data are collected using satellite imagery, unmanned aerial vehicles, and sensor-based observations to ensure continuous monitoring of protected natural areas. GIS platforms are employed to integrate multisource data, enabling accurate observation of spatial changes in vegetation cover, water resources, and land surface conditions. Data preprocessing procedures ensure the reliability and consistency of information used in subsequent analytical stages.

**Stage 2.** The second stage involves spatial and ecological analysis based on vegetation indices and geospatial indicators. Indices such as NDVI and EVI are applied to assess vegetation density, growth dynamics, and ecosystem health. This stage enables the identification of spatial patterns related to environmental stress, land degradation, and anthropogenic influence. Artificial intelligence and machine learning algorithms support automated analysis of large datasets, improving the efficiency and objectivity of ecological assessment.

**Stage 3.** At the third stage, potential ecological risks are identified and evaluated using integrated GIS analysis and AI-based modeling. Environmental threats such as land degradation, water scarcity, illegal activities, and ecosystem disturbance are detected at early stages. This stage supports the classification of high-risk zones and provides a scientific basis for preventive and corrective environmental measures.

**Stage 4.** The final stage translates analytical results into decision-oriented outputs for environmental management. High-risk zones and priority areas are identified to support adaptive management strategies, including conservation planning, resource allocation, and regulatory interventions. GIS-based decision-support tools enable efficient visualization and interpretation of monitoring results, facilitating scientifically grounded and timely management decisions.

**Results.** The results demonstrate the methodological effectiveness of combining multisource geospatial data with automated analytical logic for continuous ecosystem monitoring:

**1.** The application of the integrated GIS, remote sensing and AI-based framework enabled a comprehensive assessment of spatial-temporal environmental changes within the protected natural area. The results confirm the methodological effectiveness of combining multisource geospatial data with automated analytical logic for continuous ecosystem monitoring.

**2.** Analysis of NDVI revealed pronounced spatial and temporal variability in vegetation condition. Stable areas exhibited consistently moderate to high index values, while zones affected by water scarcity, soil degradation, and anthropogenic pressure showed persistent declines, indicating increased ecosystem vulnerability.

**3.** Multitemporal analysis identified measurable land cover changes, including fragmentation of natural vegetation and expansion of semi-natural and human-influenced land cover types. GIS-based overlay analysis demonstrated that land use changes frequently coincided with declining vegetation indices.

**4.** The integration of spatial indicators with AI-based analytical logic enabled automated classification of ecological risk zones. High-risk areas were characterized by declining vegetation indices, land cover instability, and unfavorable environmental conditions, and were spatially clustered rather than randomly distributed.

**5.** Automated data processing and AI-based pattern recognition significantly improved monitoring efficiency, reducing analytical time and minimizing subjective interpretation. The resulting spatially explicit outputs support prioritization of conservation measures, resource allocation, and adaptive environmental management strategies.

**Discussion.** The proposed framework represents a significant methodological advancement by integrating GIS, remote sensing, and artificial intelligence into a unified, decision-oriented monitoring system. The observed vegetation dynamics and land cover changes reflect the combined influence of climatic stress and anthropogenic pressure, confirming the value of integrated spatial analysis for identifying ecosystem vulnerability [8,14].

AI-based analytical logic enhances early detection of ecological risk zones by effectively distinguishing systematic degradation patterns from natural variability. Compared with conventional monitoring approaches, the proposed methodology improves spatial coverage, analytical efficiency, and objectivity, while supporting near–real-time environmental assessment.

**Conclusion.** This study presents an improved monitoring methodology for protected natural areas based on the integrated application of GIS, remote sensing, and artificial intelligence. The developed framework enables continuous, spatially explicit, and analytically consistent assessment of environmental change, overcoming the limitations of fragmented conventional monitoring approaches. The results demonstrate that multisource geospatial data integration combined with AI-based analytical logic enhances monitoring accuracy, efficiency, and objectivity, while supporting early identification of ecological risks and decision-oriented environmental management. The modular and scalable structure of the framework allows adaptation to different environmental conditions and data availability scenarios.

Overall, the proposed methodology provides a scientifically grounded and practical tool for ecosystem monitoring, conservation planning, and sustainable management of protected natural areas, and establishes a methodological foundation for future intelligent geospatial monitoring systems.

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