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Innovative AI–GIS Frameworks for Wetland Conservation: Technological Advances, Patent Trends, and Future Perspectives

Sangram Tarenia^{1*}, Neeraj Malhotra², Shruti Marhia², Dr. K.V Nagarjuna Reddy³, ⁴Dr. Jatinderpal Singh, ⁵Andhleep

^{1,2,3}Department of Zoology, School of Bioengineering and Biosciences, Lovely Professional

⁴ Associate Professor and Head, Department of Zoology, Baring Union Christian College, Batala 143505, Punjab, India.

⁵ Assistant professor, Department of Zoology, Government College Gurdaspur, Punjab

ABSTRACT:

Background: Wetlands are among the world's most valuable ecosystems, providing biodiversity conservation, carbon sequestration, flood regulation, groundwater recharge, and water purification. However, they are increasingly threatened by urbanization, agricultural expansion, pollution, climate change, and hydrological disturbances. Recent advances in Artificial Intelligence (AI), Geographic Information Systems (GIS), remote sensing, and cloud-based technologies have significantly improved wetland monitoring and conservation. This review critically examines technological innovations, emerging patent trends, and future opportunities for AI–GIS-based wetland conservation. **Methods:** A narrative-systematic review was conducted following PRISMA guidelines. Literature published between 2000 and 2026 was retrieved from Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, IEEE Xplore, Google Scholar, and CrossRef. Patent information was collected from WIPO PATENTSCOPE, Google Patents, Espacenet (EPO), USPTO, and The Lens. Studies were screened using predefined inclusion criteria and synthesized to evaluate technological advances, patent trends, conservation applications, and future research directions.

Results: AI–GIS integration has significantly enhanced wetland mapping, biodiversity monitoring, habitat suitability assessment, hydrological modeling, pollution detection, and climate risk prediction. Machine learning and deep learning combined with satellite imagery, UAVs, and cloud platforms have improved environmental monitoring accuracy. Patent analysis indicates increasing innovation in AI-driven geospatial analytics, digital twins, IoT-based monitoring, and intelligent decision-support systems, although wetland-specific patent development remains limited.

Discussion: AI–GIS technologies are transforming wetland conservation through predictive and data-driven ecosystem management. However, challenges such as limited datasets, algorithmic bias, high computational costs, and inadequate field validation remain. Future research should focus on explainable AI, digital twins, real-time monitoring, and affordable, open-source technologies with greater commercialization potential.

Conclusion: Innovative AI–GIS frameworks offer sustainable solutions for wetland conservation by integrating intelligent monitoring with evidence-based management. Expanding patent activity highlights growing commercial interest, while future

developments should prioritize scalable, cost-effective, and environmentally sustainable technologies to support long-term wetland resilience and conservation.

Graphical Abstract



1. INTRODUCTION

Wetlands are among the world's most productive yet highly threatened ecosystems, providing indispensable ecological, hydrological, climatic, and socio-economic services. They regulate hydrological cycles, improve water quality through natural filtration, sequester significant amounts of carbon, mitigate floods, stabilize shorelines, sustain biodiversity, and support millions of people through fisheries, agriculture, tourism, and other ecosystem services. Despite these benefits, wetlands continue to decline at an alarming rate because of rapid urbanization, agricultural expansion, industrial pollution, invasive species, hydrological modifications, and the accelerating impacts of climate change. These pressures have resulted in habitat fragmentation, biodiversity loss, altered hydrological regimes, declining water quality, and reduced ecosystem resilience, threatening both ecological integrity and human well-being. Traditional field-based monitoring approaches, although ecologically valuable, are often labor-intensive, spatially limited, time-consuming, and insufficient for capturing the complex spatiotemporal dynamics of wetland ecosystems across regional and global scales. Consequently, there is an urgent need for advanced, scalable, and cost-effective monitoring frameworks capable of supporting continuous ecosystem assessment, early threat detection, and evidence-based conservation planning.

Recent advances in Remote Sensing (RS), Geographic Information Systems (GIS), Artificial Intelligence (AI), cloud computing, and unmanned aerial vehicles (UAVs) have transformed environmental monitoring by enabling high-resolution spatial mapping, automated land-use classification, hydrological modelling, biodiversity assessment, pollution detection, habitat suitability analysis, and predictive ecosystem modelling. Machine learning and deep learning algorithms integrated with multi-source geospatial datasets have substantially improved the accuracy of wetland classification and ecological forecasting, while cloud platforms such as Google Earth Engine have facilitated near real-time environmental monitoring at regional and global scales. Nevertheless, existing studies remain largely fragmented, with most investigations focusing on isolated technologies or specific applications rather than providing an integrated perspective that combines remote sensing, GIS, AI, ecological indicators, threat identification, conservation planning, governance, and future technological innovations within a unified framework. Furthermore, limited attention has been given to practical implementation in resource-constrained regions, the integration of stakeholder participation into technology-driven conservation, and the translation of AI-generated outputs into policy-relevant decision support systems. These knowledge gaps highlight the necessity for a comprehensive synthesis that bridges technological advances with ecological conservation and sustainable wetland management.

To address these gaps, this review systematically synthesizes current knowledge on the integration of Remote Sensing, GIS, and Artificial Intelligence for wetland monitoring, threat assessment, and adaptive conservation management using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework. A systematic literature search was performed across major scientific databases, and after applying predefined inclusion and exclusion criteria, 50 peer-

reviewed articles published between 2015 and 2026 were included for qualitative synthesis (**Fig.1**). Unlike previous reviews that primarily emphasize individual technologies, this review presents a comprehensive AI–GIS conservation workflow encompassing data acquisition, geospatial processing, AI-based environmental modelling, wetland condition assessment, threat identification, conservation prioritization, implementation strategies, and adaptive monitoring. Additionally, it discusses emerging technologies including cloud GIS, digital twins, explainable artificial intelligence (XAI), hyperspectral remote sensing, UAV-based monitoring, Internet of Things (IoT) sensors, and future research directions for sustainable wetland management. By integrating ecological science, geospatial intelligence, and policy-oriented conservation strategies into a single framework, this review provides researchers, environmental managers, policymakers, and conservation practitioners with a comprehensive roadmap for developing resilient, data-driven, and evidence-based wetland conservation programmes under changing environmental and climatic conditions.

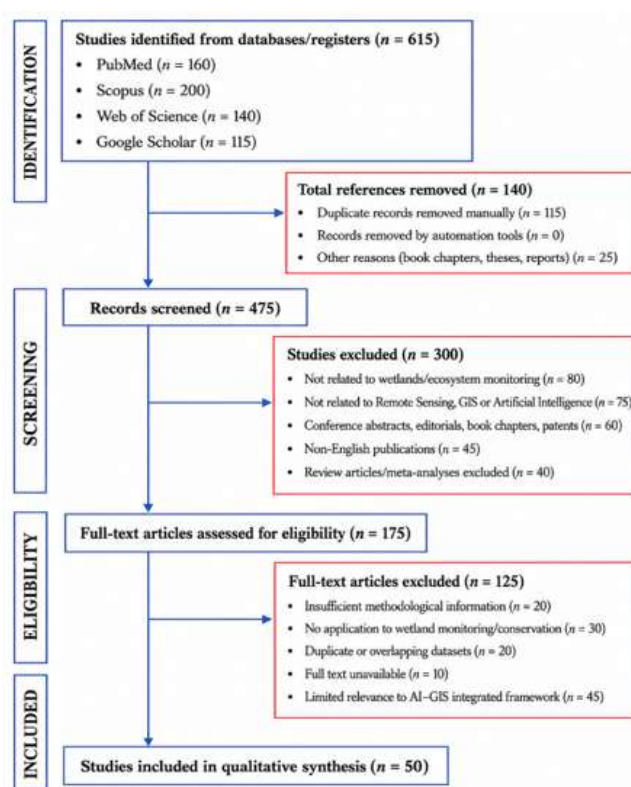


Figure. 1 PRISMA 2020 flow diagram illustrating the systematic literature selection process employed in the present review. Records were identified through comprehensive searches of PubMed, Scopus, Web of Science, and Google Scholar. After the removal of duplicate records and preliminary screening, studies were evaluated according to predefined inclusion and exclusion criteria. Subsequently, full-text articles were assessed for eligibility, and 50 peer-reviewed studies were included in the final qualitative synthesis. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure a transparent, systematic, and reproducible study selection process.

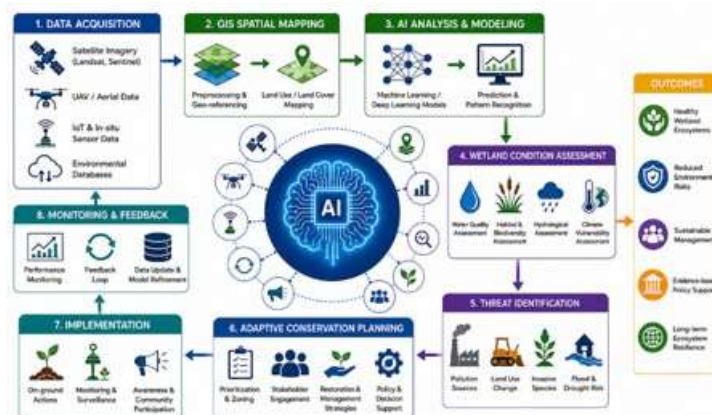


Figure 2. An AI-GIS Based Methodology of Wetland Condition Assessment, Threat Identification, and Adaptive Conservation Management Implementation.

Application of Remote Sensing and GIS in Wetland Protection.

The wetlands require constant, multi-scale observation as the structure, hydrology, and ecology processes of the wetlands are extremely dynamic and susceptible to natural and anthropogenic interruptions. As part of the wider argument concerning the use of technologies in conservation, remote sensing and Geographic Information Systems (GIS) have proven to be the cornerstone of wetland protection considering their ability to deliver spatially explicit, repeatable and long-term environmental observations. These technologies allow scientists and policymakers to determine ecological changes, measure the patterns of degradation and plan evidence-based conservation interventions at local, regional, and global scales (Abdenour et al., 2025; Kingsford et al., 2016).

Remote sensing is also important in mapping of wetlands inventory, hydrology, vegetation analysis, and land use-land cover (LULC) change. Existing satellite systems like Landsat and Sentinel are able to offer centuries of history relating to the how wetlands evolve over the decades. Such datasets are especially handy determining such trends as the shrinkage of wetlands, their salinization, erosion, and the loss of vegetation with climate variability and human land (Demarquet et al., 2023; Tian et al., 2015; Wan & Wu, 2022). On the same note, unmanned aerial vehicles (UAVs) can provide high-resolution remote sensing, which can be utilized to map the details of the habitat and monitor biodiversity at its finest, aid in ecological restoration planning, and protect species (Kentsch et al., 2021) [Table 1] discusses the overall use of remote sensing, GIS, and artificial intelligence in the wetlands monitoring and sustainable conservation management.

GIS supplements satellite analysis since it offers a sophisticated spatial analysis capability that converts the uncoded satellite data into practical ecological data. Modelling with the GIS is used in placing wetlands, simulating hydrology flows, mapping ecosystem services, and zoning of habitats. These spatial tools allow conservation agencies to determine the ecologically sensitive areas, calculate the exposure to environmental pressures, and one of the priorities due to spatial decision-making models of the multi-criteria type (Islam et al., 2021; Sarkar et al., 2015; Xie et al., 2015). Additionally, wetland classification regimes using GIS can facilitate large-scale conservation planning in places where field data is low in numbers, hence facilitating the policy making in data-sparse regions.

The capacity to conglomerate continuous cost-effective observation of wetlands is one of the greatest benefits of using remote sensing and GIS. Although field surveys are crucial in the ecological validation, time, and cost constraints coupled with accessibility usually limit field surveys. Geospatial monitoring, in turn, makes it possible to establish consistent time data that enable early warning of ecological disturbances, including pollution outbreak, the spread of invasive species, and alteration of the hydrologic (Gxokwe et al., 2022; Jamali et al., 2020). This is particularly useful in third world countries, to which financial and technical funding to ecological long-term monitoring can be limited. [Table1.] summarizes the wide range of uses of remote sensing, geographic information systems, and the artificial intelligence on wetland surveillance and sustainable conservation management.

Other current studies also reveal relevance of incorporating remote sensing and GIS in new digitalized environment monitoring systems. As an example, with the help of digital twin technology and cloud-based geospatial platforms, it is possible to simulate the ecosystem in real-time and predict the environmental model. Those technologies support adaptive management strategies of wetlands under the influence of changing climatic and land-use conditions through the available scenario-based decision making (Hwang et al., 2025; Lu et al., 2026). Moreover, cloud computing systems like Google Earth Engine have contributed to a much higher access to big data on the environment and geospatial analysis functions so that researchers can perform the analysis of the large areas of wetlands without having to acquire the high-end computing systems on the local level (Jahangeer et al., 2025; L. Yang et al., 2022).

There is also wide application of remote sensing and GIS in monitoring of wetland pollution and water quality assessment. Nutrient loading, heavy metallic contamination, and algal blooms in wetlands can be detected using spectral analysis methods. The applications play a critical role in safeguarding the wetlands against economic effects of industrial discharge and agricultural rundowns, which are some of the top causes of wetland ecosystem degradation in the global context (Anthony, 2023; Fang et al., 2022). Moreover, the spatial models of wetland water quality contribute to sustainable watershed management and assist in instructing the strategies of pollution reduction [Table 1.] summarizes the wide range of uses of remote sensing, geographic information systems, and the artificial intelligence on wetland surveillance and sustainable conservation management.

The other important area of application is in the conservation and habitat suitability of the biodiversity. The GIS habitat modelling with remote sensing vegetation indices enable the researcher to determine areas that are important breeding grounds, migration techniques, and distribution patterns of the species. The methods are favourable to specific conservation interventions, especially on threatened wetland-dependent species like migratory birds and amphibians (Cui et al., 2019; Qu et al., 2022). On the same note, GIS-based landscape connectivity measures are used to determine the ecological corridors needed to sustain the wetland ecosystem in the context of stressors of climate change (Yu et al., 2017).

Notwithstanding such benefits, studies are increasingly highlighting the application of remote sensing and GIS to be incorporated in moderated conservation systems. Lack of ecological sense in over-dependence on complex geospatial modelling renders errors in misclassification and mismanagement decisions. Thus, the field-field ecological survey is still necessary to maintain the accuracy of the data and the ecological (Fois et al., 2021; Kingsford et al., 2016). Participatory GIS methods also contribute to better conservation outcomes by integrating the local ecological knowledge in the process of spatial planning and enhancing the success of stakeholder acceptability and policy implementation (Bakirman et al., 2022) The broad range of applications in relation to the remote sensing, Geographic Information Systems, and artificial intelligence to wetland monitoring, biodiversity protection, governance assimilation, and the encouragement of sustainable operations are briefly summarized in [Table 1.].

Besides, there is moderate and context-specific embrace of remote sensing and GIS technologies, which lead to a decreased data dependency and technical complexity in areas with limited technological network. It is demonstrated that with even moderate-resolution satellite data and straightforward GIS modelling, ecological knowledge will be accurate enough to use effective conservation planning (Orimoloye et al., 2020; Victoria Bukky Ayoola et al., 2024). This Favors the larger conservation viewpoint technology can improve ecological decision-making other than substitute the normal ecological knowledge systems [Table1.] summarizes a general overview of the category into which remote sensing, geographic information systems and artificial intelligence are applied in the thematic areas of wetland monitoring and sustainable management of these important ecosystems.

Considering the past, it is possible to point out that in the future, remote sensing and GIS in wetland protection will be oriented to enhance the accessibility of data and multi-source environmental and create accessible and user-friendly decision-support systems. New achievements in the field of hyperspectral images, AI-driven geospatial modelling, and near real-time environmental detection will enhance even more the possibilities of the conservation of wetlands. Nevertheless, the successful sustainability of implementation will require the creation of a balance between the technological innovation, on the one hand, and ecological knowledge, governance systems and socio-economic realities, on the other hand (A. Ali & Ali, 2026; Sahle & Melaku, 2025).

In general, the tools of remote sensing and GIS will always be necessary to protect wetlands. They form the focus of conservation efforts in the present day due to their capability to give long-term environmental surveillance, spatial analysis and prediction models. Available together with ecological fields expertise, stakeholder participation, and sustainable policy mapping,

such technologies greatly contribute to the efficiency and intensity of wetland conservation efforts in the framework of rising global environmental alteration (Du et al., 2025; Jiang et al., 2024).

Table1. Comprehensive Uses of Remote Sensing, geographic information systems, and artificial intelligence in monitoring wetlands, threats and sustainable conservation management.

Thematic Area	Application Focus	Technological Tools / AI Methods	Key Ecological Indicators	Major Contributions to Wetland Conservation	Limitations / Challenges	Key References
Wetland Inventory and Mapping	Wetland delineation, land-use/land-cover (LULC) classification, vegetation distribution, seasonal wetland dynamics	Landsat, Sentinel-1/2, MODIS, UAVs, Object-Based Image Analysis (OBIA), Random Forest (RF), Support Vector Machine (SVM)	Wetland extent, vegetation cover, shoreline changes, habitat fragmentation	Enables long-term wetland inventory, identifies shrinkage, encroachment, salinization, erosion, and vegetation degradation	Cloud cover, mixed pixels, seasonal variability, limited spatial resolution	Abdenour et al., 2025; Demarquet et al., 2023; Wan & Wu, 2021; Tian et al., 2015; Kentsch et al., 2020
Hydrological Monitoring	Surface water dynamics, water-level fluctuations, floodplain connectivity, hydrological modelling	SAR, Sentinel-1, LiDAR, GIS hydrological models, SWAT, HEC-RAS, Digital Elevation Models (DEM)	Water depth, hydroperiod, inundation frequency, flow velocity	Assesses climate change impacts, water availability, flood prediction, and watershed management	Data scarcity, model uncertainty, limited temporal observations	Xie et al., 2015; Islam et al., 2021
Wetland Degradation and Environmental Change Detection	Habitat degradation, temporal land-cover change, anthropogenic disturbance monitoring	Multi-temporal satellite imagery, Change Detection Algorithms, Time-Series Analysis, Deep Learning	Wetland loss, vegetation decline, fragmentation index, erosion	Early identification of degradation trends and human-induced pressures, supporting restoration planning	Requires long-term datasets and accurate validation	Kingsford et al., 2016; Jamali et al., 2020; Gxokwe et al., 2022
Spatial Decision Support and Conservation Zoning	Ecological sensitivity analysis, protected area prioritization, restoration site selection	GIS-based Multi-Criteria Decision Analysis (MCDA), Analytic Hierarchy Process (AHP), Spatial Modelling	Ecological sensitivity, habitat suitability, conservation priority index	Optimizes conservation planning, zoning, and resource allocation	Subjective weighting of criteria, uncertainty in expert judgement	Sarkar et al., 2015; Nel et al., 2016

Water Quality and Pollution Assessment	Nutrient loading, eutrophication, heavy metal detection, algal bloom monitoring	Spectral indices (NDWI, MNDWI), Hyperspectral Imaging, Machine Learning Regression Models	Chlorophyll-a, turbidity, suspended solids, dissolved organic matter, nutrient concentration	Enables rapid detection of contamination, pollution hotspots, and watershed management	Requires field calibration and atmospheric correction	Anthony, 2023; Fang et al., 2022; Adebayo et al., 2025
Biodiversity Assessment and Habitat Suitability Modelling	Species distribution, habitat suitability, breeding site identification, migration corridor mapping	GIS habitat models, NDVI, EVI, MaxEnt, Random Forest, Ecological Niche Modelling	Species richness, habitat quality, vegetation health, biodiversity indices	Supports conservation of migratory birds, amphibians, fish, and threatened species	Species occurrence data often limited or biased	Cui et al., 2019; Qu et al., 2022
Landscape Connectivity and Ecological Corridor Analysis	Connectivity assessment, ecological corridor identification, fragmentation analysis	GIS landscape metrics, Graph Theory, Circuit Theory, FRAGSTATS	Connectivity index, fragmentation metrics, corridor integrity	Maintains ecological connectivity, improves species movement and ecosystem resilience	Sensitive to spatial resolution and landscape complexity	Yu et al., 2017
AI-Based Predictive Modelling and Risk Assessment	Wetland change prediction, habitat forecasting, ecological risk assessment, climate vulnerability	Artificial Neural Networks (ANN), CNN, LSTM, Random Forest, XGBoost, Deep Learning	Future wetland extent, degradation probability, climate vulnerability	Improves predictive conservation planning, early warning systems, and adaptive management	Requires large training datasets and computational resources	Jiang et al., 2024; Du et al., 2025; Sahle & Melaku, 2025
Digital Monitoring and Cloud Computing Platforms	Near real-time ecosystem monitoring, large-scale geospatial analysis, scenario simulation	Google Earth Engine (GEE), Digital Twins, Cloud GIS, AI-enabled dashboards	Real-time wetland status, land-use dynamics, ecosystem health	Facilitates rapid analysis, automated monitoring, and adaptive decision-making	Internet dependence, cloud computing costs, technical expertise	Lu et al., 2025; Hwang et al., 2025; Yang et al., 2021; Jahangeer et al., 2025
Participatory GIS and Governance Integration	Community participation, indigenous knowledge integration,	Participatory GIS (PGIS), Mobile GIS, Citizen Science Platforms	Community observations, local ecological knowledge	Enhances stakeholder engagement, policy implementation	Data quality varies depending on community participation	Bakırman et al., 2022; Fois et al., 2021

	environmental governance			n, and socially inclusive conservation		
Cost-Effective Monitoring in Data-Scarce Regions	Wetland monitoring in developing countries using freely available datasets	Landsat, Sentinel, QGIS, OpenStreetMap, Google Earth Engine	Basic land-cover changes, wetland distribution	Provides affordable conservation planning and environmental monitoring	Moderate spatial resolution and limited validation data	(Orimoloye et al., 2020; Victoria Bukky Ayoola et al., 2024)
Climate Change Impact Assessment	Assessment of climate-induced wetland alterations, carbon storage estimation, ecosystem resilience	Climate models, Remote Sensing Time-Series, AI Climate Prediction Models	Surface temperature, evapotranspiration, carbon stocks, inundation patterns	Evaluates climate vulnerability and supports climate adaptation strategies	Uncertainty in climate projections and regional variability	Xie et al., 2015; Lu et al., 2025; Jiang et al., 2024
Future Perspectives	AI-integrated geospatial modelling, hyperspectral imaging, Internet of Things (IoT), Digital Twins, Explainable AI (XAI), Federated Learning	AI-GIS integration, Hyperspectral Sensors, UAV Swarms, Edge AI, IoT Networks	Near real-time ecosystem health, predictive biodiversity monitoring, ecosystem resilience	Enables intelligent, autonomous, and sustainable wetland management through continuous monitoring and decision support	Standardization, interoperability, ethical AI, data privacy, computational requirements	Sahle & Melaku, 2025;(A. Ali & Ali, 2026); Jiang et al., 2024; Du et al., 2025

Research on Artificial Intelligence Applications on Wetlands

It is on this substantial background of remote sensing and GIS in wetlands protection, that artificial intelligence (AI) has emerged as a formidable complement to geospatial technologies, which allows more directly interrogate more complex environmental datasets and facilitate predictive ecological modelling. Since wetlands ecosystems are best classified as highly spatially heterogeneous, with dynamical hydrology it is common to find that traditional forms of analysis cannot help us realise the nonlinear interactions which are allegedly defining of wetlands. Artificial intelligence-powered modelling solutions have a greater chance to examine multi-source environment data, reveal concealed ecological behaviour, and enhance the system of early wetland degradation warnings (Lemenkova, 2024; Zerrouk et al., 2025) as it is depicted in [figure 2].

Machine learning (ML) and deep learning (DL) algorithms are becoming more frequent in classification of wetlands, monitoring of biodiversity, modelling of habitat suitability, and the health of the ecosystem. These algorithms have the capability to analyze large amounts of satellite images and ancillary environmental data to provide extremely precise land cover classifications and accurate wetland boundaries (deliberations). Empirical evidence also shows that AI-based classification is significantly better on wetland vegetation type detection, seasonal water dynamics, and highlights the patterns of micro-habitat distribution as compared with traditional statistical methods of data analysis (Du et al., 2025; Zan et al., 2022). Pattern recognition models and

convolutional neural networks, in their turn, have demonstrated better results in recognizing wetland features through historical maps, as well as multi-temporal satellite images (Stahl & Weimann, 2022). A detailed overview of the corresponding domains of AI application, methodological techniques applicable in them, and their contributions to conservation practise are presented in [Table 2].

The AI can also be useful in predictive environmental modelling where machine learning models are made to predict wetland ecosystem responses to climate change, sea-level rise and land-use transformation. In combination with hydrological simulation models, hybrid machine learning models allow the investigator to forecast future wetland distribution and ecological susceptibility in a variety of climate conditions (Mondal et al., 2025; Raj & Pasfield-Neofitou, 2024). Particularly in climate-sensitive coastal and floodplain wetlands, these predictive tools are useful to conservation in the long-term and risk assessment [see Figure 2.] The following [Table 2.] outlines a systematic overview of the key areas that artificial intelligence can be implemented in the field of wetland conservation and include: classification, predictive modelling, monitoring systems and the assimilation of governance structures.

The other influential impact of AI on the study of wetlands is the biodiversity and ecological health monitoring. Ecological modelling, which uses AI in order to determine species distribution, habitat connectivity, and landscape health assessment, is based on species distribution modelling. Instead, through adding hydrology data, vegetation index, and climate variable, machine learning models can identify hot spots of biodiversity and promote conservation areas (Cui et al., 2019; Qu et al., 2022). Additionally, we can start to use interpretable machine-learning strategies to clarify the ecological factors that can affect the well-being of wetlands to support transparent environmental decision-making (Du et al., 2025).

The availability and scalability of wetland monitoring research have also been increased with cloud-based AI services. Maps created by Google Earth Engine can be used to combine machine-learning processes and satellite data at the global scale, allowing to monitor wetlands on a widespread geographic scale. The cloud-based systems also reduce the barrier to computations and enable real-time monitoring of the environment systems- a crucial feature in the initial detection of wetlands degradation and environmental risks (Jahangeer et al., 2025; L. Yang et al., 2022) as illustrated in [figure 2.] A detailed overview of the AI application domains, analysis tools and contributions to conservation in wetland systems is given in [Table 2].

AI is also progressively being used with the Internet of Things (IoT) and environmental sensor networks to allow real-time monitoring of wetlands in a continuous fashion. These types of integrated systems amass constant water quality, hydrological variability, and ecosystem health indicators data. Real-time surveillance systems can contribute to the urgency of conservation restoration measures and help in the development of adaptive management strategies of wetlands (Ali et al., 2025; Hwang et al., 2025). To add to this, AI-based digital twin ecosystems replicate the ecological wetland processes under different management conditions, which support evidence-based conservation plans (Lu et al., 2026) see [figure 2].

Irrespective of such technological progress, the modern studies emphasize that AI is expected to be used prudently in the context of ecological preservation. Excessive dependence on the sophisticated AI models can establish technical obstacles to local conservation agencies and reduce the ecological interpretability given that the models are viewed as black boxes. In turn, a harmonized AI implementation that values interpretability, ecological validation, and cost-efficiency is advisable in the management of the wetlands sustainably (Maniyar et al., 2025; Pimenow et al., 2025) [Table 2.] provides a summary in a consolidated form of the main areas of AI implementation, toolkit, conservation, and governance which relate to the wetland systems.

Basic AI algorithms like the decision-tree classifier and supervised categorical decision support, are usually appropriate to map the wetlands or monitor the environment in places with limited resources. They require less computation power and provide high accuracy in classification as compared to other models in combination with remote sensing data. These strategies promote the concept of a conservative centre of inclusion that enables the local agencies and inhabitants of the region to have the opportunity to participate directly in the process of monitoring the environment (Islam et al., 2021; Victoria Bukky Ayoola et al., 2024).

A new aspect of AI in the study of wetlands also relates to the socioecological analysis and the modelling of the public opinion. Massive language models and social media analytics are now being used to evaluate the services of cultural ecosystems, community awareness and interest of stakeholders in wetland conservation efforts. These approaches provide the solution between ecological science and the public policy because they involve behavioural data on human beings in the context of

conservation planning (Mouttaki et al., 2022; Zhao et al., 2026)[Table 2.]represents an overall synthesis of the most significant areas where artificial intelligence is used, the tools of analysis being applied, and the aspects of governance that are considered in the process of wetland conservation.

Pollution surveillance and environmental risk assessment in wetlands ecosystems are also based on AI. The pollution models that are based on machine-learning are able to identify the sources of contamination, forecast the pattern of pollutant spreading, and aid the early environmental notifications as shown in [figure 3.]. These abilities are important towards protection of wetlands against pressures of industrial and agricultural pollution (Anthony, 2023; Fang et al., 2022).

However, there are still some weaknesses in AI-based wetland studies. Predictive reliability can be destroyed by model overfitting, dependence on data quality and algorithmic bias. Furthermore, it has high computing requirements, and technical specialisations, and these factors can limit its adoption in the developing world. In that way, further studies ought to be based on the construction of explainable AI, open-source geospatial applications, or low-cost monitoring systems, which will facilitate sustainable and inclusive conservation application (A. Ali & Ali, 2026; Sahle & Melaku, 2025) The overall synthesis of the fields of AI applications, methods of analysis, conservation points and governance in the these systems of wetlands are explained in [Table 2.].

In the future, AI integration in conjunction with remote sensing, GIS, IoT and cloud computing will transform the concept of wetland monitoring and conservation initiatives.[Table 2.] provides an integrative synthesis, listing the fields of use of artificial intelligence in the wetland ecosystem, clarifies the types of analysis followed, assesses the conservation gains achieved, and critically reflects on the governance reflective factors that reference such efforts.. Environmental monitoring is going to be even more enhanced by the emerging technologies, including hyperspectral imaging, real-time ecological modelling, and automated biodiversity monitoring. Nonetheless, the future success of conservation activities realized through the collaboration of AI and ecological field studies, policymaking, and stakeholder involvement will rely on the years to come (Du et al., 2025; Jiang et al., 2024).

Summarizing, artificial intelligence is a game changer in wetland research, as it provided a theoretical advantage of environmental modelling, predictive conservation planning and real-time environmental surveillance. Applied to the balanced and ecologically implemented constructs, AI truly enhances wetland protection initiatives tremendously. Management of wetlands in the future can rely on not just technological development but a combination of AI and ecological information, social engagement, and adaptive governance frameworks to provide ecosystem resilience in the long term (Fois et al., 2021; Kingsford et al., 2016).

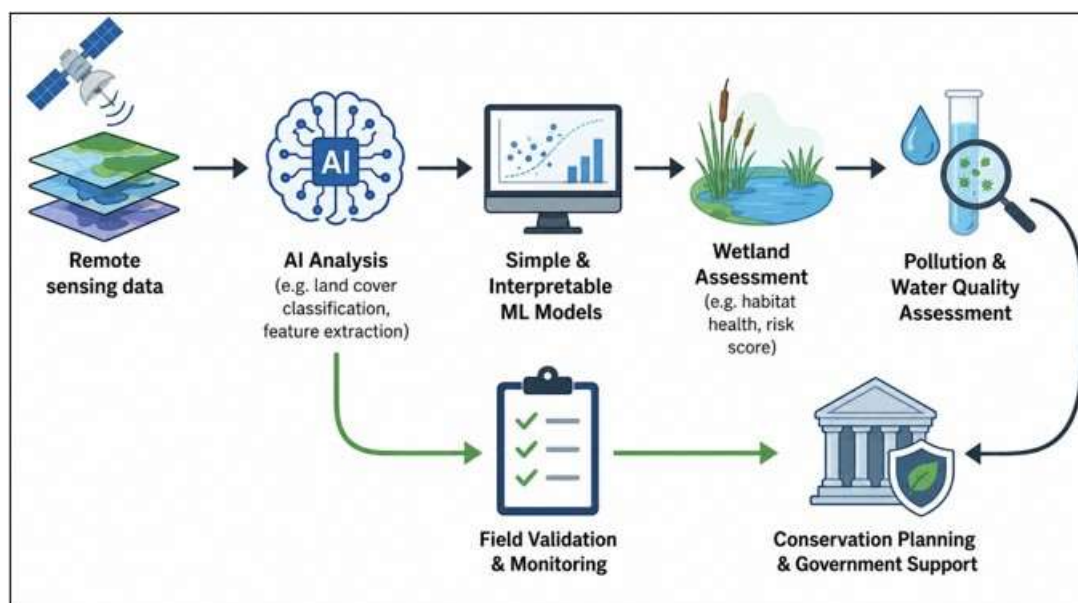


Fig 2. An Integrated Artificial Intelligence-Driven System for the Assessment, Monitoring, and Planning of Wetland Conservation.

Table 2. An Introduction to the Use of Artificial Intelligence in Wetland Conservation: Classification, Predictive Modelling, Smart Monitoring and Integration With governance.

AI Application Domain	Primary Objective in Wetland Conservation	AI Techniques / Computational Tools	Major Ecological Indicators / Outputs	Key Contributions to Wetland Conservation	Current Challenges / Limitations	Representative References
AI-Driven Wetland Classification and Boundary Delineation	Automated wetland mapping, land-use/land-cover (LULC) classification, wetland inventory	Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks (CNN), Random Forest (RF), Support Vector Machine (SVM), Decision Trees	Wetland extent, vegetation cover, shoreline dynamics, habitat boundaries	Improves classification accuracy, automated wetland delineation, rapid inventory generation, change detection	Mixed pixels, seasonal variability, requirement for labelled training datasets	Du et al., 2025; Zan et al., 2022; (Stahl & Weimann, 2022) Victoria Bukky Ayoola et al., 2024
Predictive Ecological and Climate Modelling	Forecast future wetland degradation, climate vulnerability, ecosystem resilience	Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Random Forest Regression, Hybrid AI-Hydrological Models	Climate vulnerability, flood risk, drought frequency, sea-level rise, wetland persistence	Supports climate adaptation, long-term conservation planning, ecological forecasting, restoration prioritization	Model uncertainty, climate projection variability, computational complexity	Mondal et al., 2025; Raj & Pasfield-Neofitou, 2024; Jiang et al., 2024
Hydrological Forecasting and Water Dynamics	Predict hydrological alterations and water availability	AI-SWAT integration, LSTM, Recurrent Neural Networks (RNN), Hydrological AI models	Water level, hydroperiod, inundation extent, groundwater recharge	Improves flood prediction, hydrological restoration, watershed management	Dependence on continuous hydrological observations	Islam et al., 2021; Xie et al., 2015
Biodiversity and Habitat Suitability Modelling	Species distribution prediction, habitat suitability,	Species Distribution Models (MaxEnt), Random Forest, Gradient	Habitat suitability index, species richness, migration corridors,	Enables targeted conservation of threatened species and	Biased occurrence records and insufficient biodiversity databases	Qu et al., 2022; Cui et al., 2019; Du et al., 2025

	ecological connectivity	Boosting, CNN, Ecological Niche Modelling	biodiversity hotspots	ecological corridors		
Pollution Detection and Environmental Risk Assessment	Detect water pollution, nutrient enrichment, ecological contamination	Machine Learning Regression, CNN, Spectral Classification, Pattern Recognition Algorithms	Chlorophyll-a, turbidity, heavy metals, nutrient loading, pollution hotspots	Early contamination detection, ecological risk mapping, watershed-level pollution control	Requires field calibration and sensor standardization	Anthony, 2023; Fang et al., 2022
Wetland Degradation and Change Detection	Monitor habitat degradation and anthropogenic disturbances	Deep Learning, Object Detection, Time-Series AI Analysis, Change Detection Algorithms	Vegetation loss, habitat fragmentation, shoreline erosion, wetland shrinkage	Enables early warning systems and rapid environmental assessment	Long-term datasets required for robust predictions	Kingsford et al., 2016; Jamali et al., 2020; Du et al., 2025
Cloud-Based AI and Large-Scale Environmental Monitoring	Near real-time ecosystem monitoring and large-scale geospatial analytics	Google Earth Engine (GEE), Cloud GIS, AI-enabled Satellite Processing, Distributed Computing	Continuous wetland dynamics, ecosystem productivity, land-cover transitions	Facilitates global monitoring, automated processing, rapid environmental assessment	Internet dependency, cloud computing costs, technical expertise	Yang et al., 2021; Jahangeer et al., 2025
IoT-Integrated Smart Wetland Monitoring	Continuous environmental sensing and automated ecosystem surveillance	AI + IoT Sensor Networks, Edge AI, Wireless Sensor Networks (WSN)	Water quality, pH, dissolved oxygen, temperature, conductivity	Real-time environmental alerts and adaptive ecosystem management	Sensor maintenance, battery life, communication infrastructure	Hwang et al., 2025; Ali et al., 2025
Digital Twin Ecosystems	Virtual simulation of wetland ecosystems for adaptive management	AI-based Digital Twins, Simulation Models, Predictive Analytics	Ecosystem dynamics, restoration scenarios, climate adaptation pathways	Supports scenario analysis, ecosystem forecasting, evidence-based management	High computational requirements and integration complexity	Lu et al., 2025
Decision Support Systems and	Prioritize restoration areas and optimize	AI-assisted GIS Decision Support Systems, Multi-	Ecological sensitivity, restoration priority index,	Supports transparent conservation planning and	Requires multidisciplinary data integration	Sarkar et al., 2015; Jiang et al., 2024

Conservation Prioritization	conservation strategies	Criteria Decision Analysis (MCDA), Explainable AI	conservation effectiveness	policy development		
Socio-Ecological Intelligence and Policy Analytics	Integrate public participation, governance, and environmental policy	Large Language Models (LLMs), Natural Language Processing (NLP), Social Media Analytics	Public perception, stakeholder participation, conservation awareness	Strengthens participatory conservation, policy evaluation, and environmental governance	Data privacy, ethical considerations, misinformation	Zhao et al., 2026; Mouttaki et al., 2022
Explainable and Resource-Efficient Artificial Intelligence	Develop transparent, interpretable, and affordable AI models	Explainable AI (XAI), Decision Trees, Rule-Based Models, Lightweight Machine Learning	Feature importance, uncertainty estimation, interpretable predictions	Enhances model transparency, reproducibility, and adoption in developing regions	Limited ecological XAI frameworks and benchmarking standards	(A. Ali & Ali, 2026; Islam et al., 2021; Sahle & Melaku, 2025; Victoria Bukky Ayoola et al., 2024)
AI-Assisted Restoration Planning	Recommend ecological restoration strategies using predictive analytics	Reinforcement Learning, Optimization Algorithms, AI–GIS Integration	Restoration suitability, ecosystem recovery potential, resilience index	Supports adaptive restoration planning and long-term ecosystem recovery	Requires continuous ecological validation	Jiang et al., 2024; Du et al., 2025
AI Limitations, Ethics, and Governance	Address algorithmic bias, transparency, fairness, and responsible AI adoption	Explainable AI Frameworks, Open-Source Geospatial AI, Responsible AI Principles	Model reliability, uncertainty analysis, governance indicators	Promotes trustworthy, transparent, and policy-compliant AI implementation	Algorithmic bias, overfitting, computational demands, data privacy, interoperability	Pimenow et al., 2024; Maniyar et al., 2025; Fois et al., 2021; Kingsford et al., 2016
Future Directions of AI in Wetland Conservation	Next-generation intelligent environmental monitoring	Foundation Models, Vision Transformers (ViTs), Federated Learning, Edge AI, Digital Twins, Autonomous UAVs, Explainable AI	Real-time biodiversity monitoring, ecosystem intelligence, predictive resilience assessment	Enables autonomous monitoring, scalable conservation, and intelligent environmental decision-support systems	Standardization, interoperability, ethical AI governance, computational sustainability	A. Ali & Ali, 2026; Islam et al., 2021; Sahle & Melaku, 2025; Jiang et al., 2024; Du et al., 2025

The Digital innovation of Artificial Intelligence, remote Sensing and Geographic Information Systems in the conservation of wetlands.

The growth of environmental pressures facing wetland ecosystems highlights a need to observe and manage integrated frameworks enhancing the combined application of various technological and ecological structures. Remote sensing, GIS, and artificial intelligence substantiate the possibility of large-scale environmental observation, spatial analysis and decision support, and complex data processing and predictions of ecology respectively. Therefore, AI, GIS, and remote sensing have been combined synergistically, and it creates a complex of technological features that can support sustainable wetlands protection in the constantly changing environment (Abdenour et al., 2025; Jiang et al., 2024). The integrated technology framework that is going to be implemented in place to mitigate the key wetland stressors is presented in [Figure 3.].

Combined geospatial-ai models allow a real-time evaluation of combined-some-source climate data, including satellite data, UAV data, climate data, hydrological data as well as field ecological data. The result of this convergence is more accurate wetland classification and hydrological modelling and ecosystem health assessments because of the combination between spatial mapping and predictive analytics. The multi-scale operational structure of these geospatial–AI solutions is summarized in [Table 3.]. Empirical research indicates that optimally matching machine learning algorithms with obtained environmental variables by using remote sensing leads to a significant increase in the accuracy of wetland mapping and allows a longitudinal monitoring of the ecosystem (Rapinel et al., 2023; Zerrouk et al., 2025).

Among the most salient benefits of such integration lies the fact that it allows monitoring of multi scales of wetlands. The fields that are supported by remote sensing include regional and global wetland mapping, GIS offers spatial analysis of the landscape, and AI forms the basis of local-scale predictive modelling and pattern recognition. Together, these technologies enable conservation planners to monitor wetland changes between the landscape and the microhabitat scale, which will lead to improved ecological knowledge and to an intensified degree of conservation planning (Demarquet et al., 2023; Du et al., 2025). The multi-scale monitoring is specifically instrumental in identifying an initial process of ecosystem degradation and developing preventive restoration measures. The concept of this integrated multi-scale monitoring is presented in [Figure 3.].

Combined AI-GIS-remote sensors are also being utilized in vulnerability modelling and evaluation of the impact caused by climate change. The long-term satellite data can be interrogated by machine learning models to predict how wetlands will respond to increase in sea-level, changes in temperature, and changes in precipitation. Such predictive models are used to make informed wetland conservation planning resilient to climate changes and influx conservation sites in response to hypothetical future climatic changes (Mondal et al., 2025; Raj & Pasfield-Neofitou, 2024). [Table 3.] summarizes the broader multi-scale geospatial-AI applications that can be used to enhance adaptive ware-escalation managerial operations.

The other critical use of combined paradigms is in the assessment of the ecosystem services and preservation of the biodiversity. Using the combination of spatial habitat mapping and AI-based species distribution modelling, researchers can use this to identify biodiversity hotspots, migratory pathways, and important ecological connectivity areas. This combined strategy helps to implement the right interventions aimed at conserving wetlands and maintain the performance of ecological resilience in fragmented wetland environments (Cui et al., 2019; Qu et al., 2022). In addition, wetland ecosystem service valuation is based on integrated geospatial modelling which includes the potential of carbon sequestration, the ability to purify water, and flood control capabilities (Fois et al., 2021; Kingsford et al., 2016)). [Figure 3.] represents the interrelationship between the elements of biodiversity and ecosystem service assessment internalized inbuilt in the integrated monitoring system.

Real-time monitoring of the environment and management adaptive ecosystems are also being transformed due to the convergence of AI, GIS and remote sensing. Cloud-based solutions and artificially intelligent monitoring systems allow to monitor the wetland hydrology, water quality and plant dynamics in real time. Such real-time surveillance systems help in early detection of environmental disturbances including pollution incidences, invasive species reproduction and hydrological changes (Yang et al., 2021; Hwang et al., 2025). Moreover, wetland ecological responses can also be simulated within a digital twin ecosystem to wetlands under diverse management and climatic conditions and, thus, will enable evidence-based conservation decision-making (Lu et al., 2025). [Table 3.] provides the general overview of multi-scale geospatial-AI solutions to adaptive monitoring and stewardship of wetland ecosystems.

Combined frameworks provide additional strength to policy-based conservation planning, as well as, stakeholder engagement. Combining the idea of participatory geographical information systems with environmental modelling by artificial intelligence empowers conservation and management in general by incorporating human-centered ecological information with scientific sources. This strategy is especially significant in areas where conservation of wetlands depends on the involvement of communities and the ecological knowledge of the local people (Bakirman et al., 2022; Zhao et al., 2026). Also underpinning

national and international conservation initiatives using integrated technological platforms are, Ramsar wetland monitoring and sustainable development planning (Goyal et al., 2025). As theorized in the built-in monitoring structure [Figure 3.]

Irrespective of these benefits, integration of technological systems should be done with care in order to protect ecological relevance and sustainability in the long-term. Findings suggest a potential loss in interpretability as well as increasing the level of technological dependence with an overdependence on highly sophisticated AI-based systems particularly in resource-limited conservation systems. In response to this fact, balanced integration approaches which combine advanced modelling with the classical ecological field validation are suggested as a feature to achieve sustainable conservation (Maniyar et al., 2025; Pimenow et al., 2025). The numerous thematic elements, technological functionality, and conservation donations that are explored in this section are tabulated in [Table3.]

In the context of the cost-effective conservation planning, moderate and context-sensitive integration also make it easier. Research exhibits that integrating moderate-resolution of remote sensing datasets, GIS analysis, and simple machine learning models could provide significant ecological information at relatively low-technical infrastructure requirement of the conservation agency in the (Orimoloye et al., 2020; Victoria Bukky Ayoola et al., 2024). This support with a larger sustainability lens reiterates that conservation technologies must be used in enhancement of ecological decision making without creating technological obstacles towards implementation.

Innovative studies also bring to light the perspectives of the potential of incorporated AI-GIS-remote sensing systems to monitor pollution and evaluate environmental risks. Such systems point out areas of contamination, anticipate the route of transportation of pollutants and locate zones of ecological risk. These applications would prove important in the protection of the wetlands against the pressures of industrial effluents, agricultural effluents, and urban pressures (Anthony, 2023; Fang et al., 2022). The above-mentioned elements related to the pollution monitoring and environmental risk evaluation are implemented in the under-holy, integrated AI-GIS monitoring model as outlined in [Figure 3.]. In this part, the synthesised thematic factors, technical features, and environmental input which has been discussed are tabulistically grouped in [Table 3.].

In the future, the direction of research may narrow down the errors in interoperability of data, fine-tune the explainable aid, and build a user-friendly decision-support system that can be implemented all over the world by conservation agencies. Integrated wetland conservation frameworks will be more strengthened in the future by hyperspectral remote sensing and automated biodiversity surveillance, and cloud-based geospatial analytics (A. Ali & Ali, 2026; Sahle & Melaku, 2025). Based on the integrated monitoring architecture shown in the [Figure 3.].

In sum, AI along with GIS and remote sensing are the path to the next stage of sustainable wetland protection. Integrated technological systems can be used to provide the overall analysis of the ecosystem and adaptive conservation across space and time by combining spatial mapping, predictive modelling and real time monitoring of the environment. However, the success of conservation in the long run depends on the balance between technological innovation and ecological expertise, social-economic and participatory governance. Optimized in this kind of balanced structures, the system of integrated AI-GIS-remote sensing can be significantly useful in global wetland conservation in the face of the era of rapid environmental change (Du et al., 2025; Jiang et al., 2024).

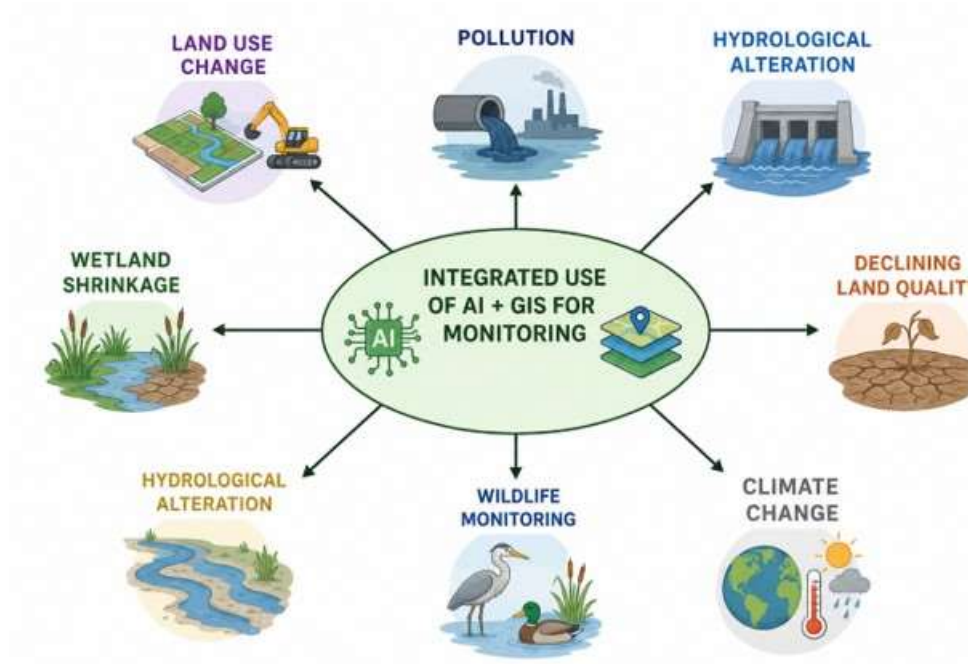


Fig 3. An Integrated Artificial Intelligence (AI) and Geographic Information Systems (GIS) Framework for Monitoring Wetland Degradation and Related Environmental Stressors.

Table 3. Multi-Scale Geospatial-AI Solutions to Adaptive Wetlands Monitoring and Management.

Thematic Component	Integrated Technological Function	Major Ecological Indicators / Outputs	Key Contributions to Wetland Conservation	Current Challenges / Research Gaps	Representative References
Integrated Geospatial-AI Framework	Integration of Remote Sensing (RS), GIS, Machine Learning (ML), Deep Learning (DL), and cloud-based analytics	Wetland extent, ecosystem integrity, land-use dynamics, ecological health	Enables large-scale environmental monitoring, ecosystem modelling, predictive conservation planning, and spatial decision-making	Integration of heterogeneous datasets, interoperability, model interpretability	Abdenour et al., 2025; Jiang et al., 2024
Multi-Source Data Integration	Fusion of satellite imagery, UAV observations, LiDAR, IoT sensors, climatic variables, hydrological datasets, and field ecological surveys	Vegetation indices (NDVI, EVI), water quality, hydroperiod, biodiversity metrics	Improves wetland classification accuracy, hydrological modelling, ecosystem health assessment, and habitat characterization	Data harmonization, temporal inconsistencies, sensor calibration	Rapinel et al., 2023; Zerrouk et al., 2024

Multi-Scale Environmental Monitoring	Local UAV monitoring integrated with regional/global satellite observations and GIS spatial analysis	Habitat fragmentation, shoreline dynamics, vegetation change, landscape connectivity	Detects degradation from microhabitat to landscape scales, supporting restoration prioritization	Limited temporal resolution, validation across spatial scales	Demarquet et al., 2022; Du et al., 2025
Climate Change Vulnerability Modelling	AI-assisted climate prediction integrated with long-term satellite and meteorological datasets	Temperature anomalies, sea-level rise, flood frequency, drought severity, carbon dynamics	Predicts future ecosystem vulnerability, supports climate adaptation and resilience planning	Uncertainty in climate projections and regional model transferability	Mondal et al., 2025; Raj & Pasfield-Neofitou, 2024
Hydrological Dynamics Assessment	GIS hydrological models, SAR-based inundation mapping, Digital Elevation Models (DEM), AI forecasting	Surface water extent, hydroperiod, groundwater recharge, floodplain connectivity	Improves water resource management, flood forecasting, and ecological flow assessment	Complex hydrological interactions, limited field validation	Islam et al., 2021; Xie et al., 2015
Biodiversity and Ecosystem Services Assessment	GIS habitat suitability models integrated with AI species distribution modelling (MaxEnt, Random Forest)	Species richness, migration corridors, habitat suitability, ecosystem services, carbon sequestration	Identifies biodiversity hotspots, ecological corridors, conservation priority zones, and ecosystem service values	Species occurrence bias and limited biodiversity datasets	Qu et al., 2022; Cui et al., 2019; Kingsford et al., 2016; Fois et al., 2021
Pollution and Environmental Risk Monitoring	AI-assisted spectral analysis, hyperspectral imaging, water quality modelling, contamination risk prediction	Nutrient loading, chlorophyll-a, turbidity, heavy metals, pollution hotspots	Enables early detection of contamination, eutrophication, and ecological risk zones for timely intervention	Need for field calibration and standardized validation	Anthony, 2023; Fang et al., 2022
Landscape Connectivity and Ecological Corridor Analysis	GIS landscape metrics, graph theory, connectivity modelling	Habitat fragmentation, ecological corridors, landscape resilience	Supports restoration planning, wildlife movement, and maintenance of ecosystem connectivity	Spatial uncertainty and scale dependency	Yu et al., 2017; Nel et al., 2016
Real-Time Environmental	Cloud GIS, Google Earth Engine (GEE),	Near real-time ecosystem health,	Facilitates continuous monitoring,	High computational demand,	Yang et al., 2021; Hwang et al.,

Monitoring and Digital Twins	Digital Twins, AI-enabled dashboards, IoT monitoring	environmental alerts, ecosystem simulation	scenario analysis, adaptive ecosystem management, and disaster preparedness	infrastructure dependency	2025; Lu et al., 2025
Participatory GIS and Policy-Based Planning	Participatory GIS (PGIS), citizen science platforms, AI-assisted ecological modelling	Community observations, indigenous ecological knowledge, governance indicators	Enhances stakeholder participation, Ramsar compliance, policy implementation, and socially inclusive conservation	Data quality variability and institutional coordination	Bakırman et al., 2022; Zhao et al., 2026; Goyal et al., 2025
Adaptive Conservation Planning	AI-based prioritization integrated with GIS decision-support systems and ecological restoration models	Restoration priority maps, ecological sensitivity, conservation effectiveness	Supports adaptive management, restoration strategies, zoning, and long-term ecosystem sustainability	Dynamic policy integration and socioeconomic considerations	Sarkar et al., 2015; Jiang et al., 2024
Sustainable and Balanced Technology Integration	Integration of AI predictions with ecological field validation and expert interpretation	Model reliability, ecological accuracy, decision confidence	Reduces overreliance on automation, improves transparency and practical applicability	Limited explainability of AI models and field data availability	Pimenow et al., 2024; Maniyar et al., 2025
Cost-Effective Conservation Planning	Open-source GIS (QGIS), freely available RS datasets (Landsat, Sentinel), lightweight AI algorithms	Baseline wetland inventory, habitat mapping, land-cover dynamics	Supports conservation in resource-limited regions with reduced operational costs	Moderate spatial resolution and limited computational resources	(Orimoloye et al., 2020; Victoria Bukky Ayoola et al., 2024)
Explainable AI (XAI) and Decision Support	Explainable AI, interpretable machine learning, AI-assisted ecological decision systems	Feature importance, transparent predictions, uncertainty estimation	Improves trustworthiness, reproducibility, and policy acceptance of AI-generated decisions	Lack of standardized ecological XAI frameworks	(A. Ali & Ali, 2026; Sahle & Melaku, 2025)
Future Research Directions	Hyperspectral remote sensing, UAV swarms, federated learning, edge AI, digital	Real-time biodiversity monitoring, autonomous ecosystem assessment,	Enables autonomous monitoring, scalable global conservation networks, and	Standardization, interoperability, ethical AI, data privacy, computational sustainability	A. Ali & Ali, 2026; Sahle & Melaku, 2025; Jiang et al., 2024; Du et al., 2025

	twins, cloud-native geospatial AI	predictive ecological intelligence	next-generation environmental decision-support systems		
Overall Integrated Conservation Framework	Integration of spatial mapping, predictive AI analytics, ecological modelling, digital monitoring, stakeholder engagement, and adaptive governance	Ecosystem resilience, biodiversity conservation, climate adaptation, conservation effectiveness	Provides a holistic, evidence-based framework for sustainable wetland management from data acquisition to policy implementation	Requires multidisciplinary collaboration, standardized workflows, and continuous validation	Jiang et al., 2024; Du et al., 2025; Abdenour et al., 2025

Drivers of Wetland Degradation

Regardless of the modern world, it is not said that substantial improvements to technologies of monitoring and conservation of wetlands have been enough to stop the disastrous trend of their degradation that is being observed globalized. The discussion on combination of technological solutions to sustainable conservation highlights the need to have a clear understanding of the underlying forces contributing to the falling wetlands. A combination of the pressures of anthropogenic influence and environmental changes brought by climate affects wetland degradation, as a whole, disrupted hydrology, biodiversity structure, nutrient cycling, as well as the ecosystem services provision. These drivers must be properly understood to design effective conservation measures that can be implemented based on the AI, GIS, and remote sensing (Abdenour et al., 2025; Kingsford et al., 2016).

One of the most powerful drivers of the wetlands degradation is rapid urbanization. The urban growth also defines urban expansion that causes the transformation of the wetlands land and infrastructural drainage, as well as increased surface runoff and the expansion of surface runoff, which is also enriched with pollutants and sediments. Expansive urban footprints are known to sever wetlands capitals, reduce ecological connectivity, and alter natural hydrological regime, which leads to biological extinction and a poor capacity to withstand ecosystem changes

(Liu et al., 2024; Orimoloye et al., 2020). Moreover, precautionary heat island effect and shifted pattern of precipitation and runoffs contribute even more to ecological stress especially in rapidly growing areas.

The other significant factor is the intensification in agriculture. Activities involving the development of arable land usually involve draining of wetlands, underground water sourcing, and reworking of natural waterways. High fertilizer and pesticide input result in nutrient loading and eutrophication which cause algal proliferation and hypoxia, which severely affect the aquatic biodiversity (Fang et al., 2022; Jamali et al., 2020). In addition, agricultural effluent deposits heavy metal and other toxic substances into wetland soils and waters, precipitating permanent ecological destruction (Anthony, 2023).

Wetlands put through hydrological change caused by dams and irrigation schemes as well as water diversion projects have a significant impact on the functioning of wetlands. Changes in the flow regimes alter the sediment deposition, vegetation cover and the habitat of the wetland-dependent species. Hydrological change also undermines wetland water storage, decreases the flood-reducing properties and increases vulnerability to extreme weather (Duan et al., 2024; W. Yang et al., 2016). Over exploitation of wetlands due to the extraction of water to irrigate and supply industries to industries in a number of river basin systems has led to the partial or total drying of wetlands.

The other big threat relating to the sustainability of wetlands is industrial pollution. The release of industrial facilities releases the heavy metals, chemical poisoning and organic pollutants into the water body, undermining the water quality and disrupting the food chains. The long-term pollutants which are deposited in the sediments are bioactive across decades, with a resultant

chronic ecological stress, leading to loss of biodiversity (Anthony, 2023; Fang et al., 2022). The aspect of the industrial development being close to the wetland enhances the probability of unintentional chemical releases and long-term pollution.

The gravitating effect of climate change is increasingly becoming one of the drivers of change in the world. Increased temperatures, shifting rain patterns, a rise in sea levels, and the increased frequency of extreme weather conditions change the wetland hydrology and ecosystem processes. The erosion causing the sea level increase can endanger coastal wetlands, specifically via saltwater intrusion, mangrove loss and (Mondal et al., 2025; Raj & Pasfield-Neofitou, 2024). The longer periods of droughts and unpredictable rainfalls also influence inland wetlands affecting the balance of water and biodiversity structures.

The changes in land-use and land cover are, intrinsically, interconnected to urbanization as well as agricultural expansion. Wetlands are converted to industrial estates, residential estates or agricultural lands, lessening the wetland area and interfering with the ecological mechanisms. The patterns of wetlands loss in the world due to land use transformations show that global trends are consistent despite very fast global changes in rapidly growing economies (Demarquet et al., 2023; Islam et al., 2021). Such conversion leads to fragmentation that disables species moving pathways and increases the susceptibility of the ecosystem.

Invasive species introduction is a new force of wetland degradation. Introduced plants and animals may alter nutrient circulation, outcompete natives and cause food web imbalances. Intrusive aquatic plants, e.g., can obstruct the movement of water and reduce oxygen supplies, have a negative impact on fish and amphibian species (Cui et al., 2019; Fois et al., 2021). The climate change and global trade have led to the introduction of these species in the remote wetland ecosystems.

A strong impact is also left by socio- economic pressures. The development increases the demand of land, water and resource mining thereby resulting to the exploitation of the wetlands. Lack of policy and good governance structures in most places and the lack of awareness to people increases degradation (A. Ali & Ali, 2026; Sahle & Melaku, 2025). Economic dependence on wetlands resources e.g. fisheries, agriculture and fuelwood harvesting can lead to avoidable exploitation in case they are not put within check.

This loss of ecological knowledge and the low participation of the stakeholders in the conservation planning further weaken the wetland stewardship. Unless conservation strategies and approaches are based on local knowledge of their environment and community, they tend to fail because they lack support locally and their implementation is ineffective (Bakırman et al., 2022; Zhao et al., 2026). Long term sustainability therefore cannot be achieved without integrated conservation models that combine technological monitoring and participatory governance in the conservation process.

Wetland degradation can be implicitly triggered by technological constraints and lack of data. In the areas that lack effective monitoring of the environment degradation can go unnoticed until the damaging effects on the eco-system occur. This fact can be combined to highlight the fact that integrated AI-GIS-remote sensing monitoring systems are urgently needed to detect it early and plan (Rapinel et al., 2023; L. Yang et al., 2022).

The synergistic effect of local actions of several degradation drivers often causes cumulative ecological effects. To make an example, a combination of climate change and land reclamation and pollution can accelerate the withdrawal of the wetlands. These types of cumulative pressures emphasize the need to have complex conservation frameworks to observe various environmental stressors together at the same time (Du et al., 2025; Jiang et al., 2024).

Overall, degradation of wetlands is a product of a sophisticated combination of environmental, technological, socio-economic, and policy related aspects. identify urbanization, intensification of agriculture, hydrological changes, contamination, climate changes, invasive species and governance issues as all adding to the global disappearance of wetlands. The drivers are significant to understand in coming up with integrated conservation initiatives that have AI, GIS, and remote sensors as their backbone. Sustainable management of wetlands will rely on how these drivers are addressed with the framework of the coordinated technological observation, ecological restoration, high policy enforcement, and community-based conservation (Abdenour et al., 2025; Kingsford et al., 2016).

Management and Government issues in the contemporary organizational settings.

Expanding the background knowledge about wetland degradation drivers and astonishing technological potential of artificial intelligence, geographic information systems, and remote sensing integration, one will realize that the governance and management frameworks are one of the most influential factors in the success of the wetland conservation. In cases where modern monitoring technologies are easily accessible, the performance of conservation activities may be crippled by flawed governance, incoherent institutional duties, inadequate implementation of policies, and poor co-ordination of stakeholders. The inherent complexity of wetland management commission is enhanced not only by the fact that wetlands are located at the intersection of the ecological system and socio-economic reliance, but also by the multi-level regulatory frameworks (Abdenour et al., 2025; Kingsford et al., 2016).

Institutional fragmentation is one of the critical issues of governance. The management of wetlands is often controlled by various agencies that have their mandates on water resources, forestry, biodiversity conservation, agriculture, and urban development among others. Such a multi-agency management structure usually leads to overlapping of mandates, non-consistency in policy execution as well as inadequate coordination among agencies. This fragmentation compromises the effectiveness of the management, slows down conservation responses, and becomes particularly harmful in the case of the environmental crises (A. Ali & Ali, 2026; Jiang et al., 2024). In most of the regions, despite the presence of policy designation of wetland conservation, these policies are still not well incorporated in the national land-use plans thus enabling the constant wetland conversion and degradation.

The other important cause of wetlands loss is policy enforcement constraints. Despite many nations having implemented laws as well as international conservation agreements on wetlands such as the Ramsar Convention policies, implementation is often poor because of limited monitoring abilities, budget constraints and administrative limitations. Without effective enforcement tools, the illegal encroachment of wetlands, pollution leakage, and the unregulated extraction of resources proceed showing no changes (Abdenour et al., 2025; Kingsford et al., 2016). This is particularly evident in fast growing areas where the priorities of growing economies often override the priorities of environmental protection in policy formulation and implementation.

Yet another significant problem to governance is balancing conservation goals and socio-economic development requirements. Wetlands often form the basis of local livelihoods in terms of fisheries, agriculture, tourism and harvesting of resources. When rigid conservation rules, which do not consider local socio-economic realities are established, there is a probability of resistance by the communities. Based on this, the most sustainable models of wetland governance combine the ecological conservation with livelihood insecurity and economic sustainability (Fois et al., 2021; Sahle & Melaku, 2025). Inclusion of communities in the governance models of wetlands is becoming a key requirement in the effectiveness of its conservation over the long term.

In most wetland management programmes, engagement of stakeholders is lopsided. This significant lack of involvement of the local communities, indigenous people, and the local government in general normally results in conservation plans that are ecologically sound, yet socially infeasible. The participatory governance systems improve handing of compliance, contribution of conservation education, and sustainable resource-use approaches (Bakirman et al., 2022; Zhao et al., 2026). It is possible to note that the inclusion of traditional ecological knowledge may considerably enhance the planning of wetland restoration and ecologic monitoring.

Access to information, and technological control are other emerging issues in the management of the wetlands. Though the currently existing technologies in AI, GIS, or remote sensing provide a strong monitoring effect, disparities in access to technological background generate areas of inequality between developed and developing. Numerous agencies on the local level do not have the technical knowledge, computing capacity and monetary assets to operate sophisticated geospatial observation structures (Maniyar et al., 2025; Pimenow et al., 2025). Such a technological inequality is liable to create reliance on outside agencies or global organizations and thus limit local conservation independence.

The other governance problem is that there are no uniform wetland monitoring systems in different regions. The global wetlands conservation data has been increasingly distorted due to divergent systems of wetland classification, indicators of monitoring and reporting systems. International cooperation in the protection of wetlands could be improved with the help of standardized monitoring, which should be supported by the idea of AI-driven data harmonizing (Rapinel et al., 2023; L. Yang et al., 2022). In the absence of standardised datasets, cross-country comparison of the status of wetlands is still an issue.

Among the management barriers that still exist are financial constraints. Wetland conservation is a common competitor with the infrastructure development, agriculture and industrial investment in terms of funding allocations. The sustainable

monitoring programmes in wetlands require a long-term financial commitment, which is usually not available in the developing economies (G. Ali et al., 2025; Victoria Bukky Ayoola et al., 2024). More practical solutions to low-resource areas are presented by conservation strategies that raise limited GIS, remote sensing surveillance, and a specific AI model.

Wetland management is another type of approach that is complicated by climate governance. Wetlands have been very important in climate regulation in terms of sequestration and buffering of climate. However, the policies to address climate adaptation and mitigation are often established without considering the wetlands conservation policies. Wetlands cannot be governed in isolation because integrated climate-wetland governance approaches are the only way to ensure the highest level of ecosystem resilience can be achieved (Mondal et al., 2025; Raj & Pasfield-Neofitou, 2024).

Another governance challenge is in transboundary management of wetlands. Most of the wetlands are across borders, thus international coordination is needed in order to achieve conservation. Conflicts between policy priority, economic benefits, and consistency of coastal resources make transboundary wetland safeguarding activities difficult (Jiang et al., 2024). Multilateral shipping structures enabled by mutual geospatial observations can achieve greater border conservation results.

The new issues of technological governance and ethics have appeared in the context of wetland monitoring with AI. The ownership of data, the openness of the algorithms, and making of the decisions should be tackled when implementing automated environmental and surveillance regimes. The automated decision system may cause inappropriate conservation practices in an event of over-reliance and the lack of ecological interpretation (Maniyar et al., 2025; Sahle & Melaku, 2025).

Wetland conservation is one of the areas in which adaptive models of governance are being advocated. Adaptive governance stresses on dynamic policies models, constant ecological surveillance, integration of stakeholder feedback and dynamic administration approaches. Adaptive governance can be supported with AI and GIS technologies that would enable real-time monitoring of the environment and making predictions about environmental risks (Hwang et al., 2025; Lu et al., 2026).

The other significant management issue is the inclusion of wetland conservation into larger landscape and watershed-wide planning. Wetlands are also very sensitive to the upstream hydrological criteria and land-use patterns. Watershed-wide protection of wetlands without planning at the watershed level tends to be ineffective in ensuring the long-term health of the upkeep of the ecosystem (Duan et al., 2024; W. Yang et al., 2016). River basin as well as landscape-level conservation models are therefore needed. The proper governance of wetlands still requires institutional capacity building. Geospatial technologies, ecological surveillance, and data interpretation training programmes of the local agencies would significantly enhance conservation results. The capacity-building programmes also promote the sustainability of monitoring programmes over the long term (Christofi et al., 2025; Espinel et al., 2024).

To summarize, challenges of governance and management are one of the greatest obstacles to proper wetland conservation. Fragility of the institutions, poor implementation of policies, socio-economic tensions, restricted involvement of stakeholders, financial resources and inequality in technology are all barriers to conservation effectiveness. These governance issues require a combination of policy systems, participatory management strategies, uniformity in the methods of monitoring, and equitable technological resources. In the end, the sustainable conservation of the wetlands will be premised on the integration of the governance structures into the ecological science frameworks, innovations in technology, and community-based environmental (Abdenour et al., 2025; A. Ali & Ali, 2026; Kingsford et al., 2016).

Restoration and Preservation Methodologies.

Using the discussion on system of governance and management issues, the practical implementation scheme of wetland sustainability is put in place using wetland restoration and conservation programmes. A successful wetland restoration initiative requires an interdisciplinary intervention and application of ecological science, technological tracking devices, policy decisions, and the involvement of stakeholders. Although success of conservation policies depends on the structure of governance, the restoration strategies implement processes that provide the operational mechanisms that will turn around the degradation and reconstruct the lost ecological resilience. Modern wetland protection depends more on the synthesis of traditional ecology restoration operations with geospatial analytics and the monitoring of a wetland based on artificial intelligence to facilitate adaptive management (Abdenour et al., 2025; Kingsford et al., 2016).

Hydrological restoration is among the recovery plans that form the basis. Since the ecological health of wetlands is largely dependent on the natural water flow regimes, restoration of natural hydrological connectivity can be the first step towards the recovery of wetlands. This includes the reconnection of floodplains, eradication of artificial drainage systems, reinstatement of

groundwater recharge facilities, and reinstatement of seasonal fluctuations of water. The hydrological restoration promotes the sediment transport and nutrient cycling as well as habitat appropriateness to the aquatic and semi-aquatic organisms (Duan et al., 2024; W. Yang et al., 2016). With the aid of GIS and remote sensing, hydrological modeling allows restoration planners to simulate the water flow conditions and optimization of restoration design.

Another important element in the conservation strategies of wetlands is vegetation restoration. Reintroduction of native vegetation helps stabilize soil, enhance performance of water filtration and regain biodiversity structure. Remote sensing is permissible in terms of monitoring vegetation recovery and patterns of distributing species long-term after restoration measures (Carrasco Baquero et al., 2025; Demarquet et al., 2023). Mangrove and coastal wetland ecosystems are some of the environments in which vegetation restoration is especially crucial because of its role in stabilizing the shoreline and meeting climate change requirements (Mondal et al., 2025; Sun et al., 2025).

The water quality management, and the forms of pollution control are the key restoration strategies. The use of constructed wetlands and bioengineered wetland treatment systems is increasingly being used to improve the water quality and alleviate the nutrient loading. The systems help to remove natural pollutants naturally by using microbial systems, plants and sediment filtration (Abdulsalam et al., 2025; Fang et al., 2022). The pollution management expressed through GIS-based pollution mapping and AI-based water quality prediction models can further enhance the effectiveness of pollution management by identifying the hotspots of contamination.

Landscape or scale conservation planning has proved to be an essential approach to the sustainability of wetlands in the long run. The condition of wetlands is a lot reliant on watershed hydrology and the immediate land utilisation pattern. Integrated watershed management solutions consider the effects of land-use change upstream, agro conduction, and city increase on the wetland ecosystems (Orimoloye et al., 2020; Van Deventer et al., 2016). The geospatial technologies can be used to analyse the landscape connectivity and ecological corridors planning to preserve the species migration patterns.

AI applications are actively implemented to improve efficiency in the monitoring and planning of restoration. Machine learning models are used in wetland classification, habitat suitability modeling and ecosystem health assessment. Pattern recognition through AI identifies parameters of wetlands impairment at an early stage, which allows the proactive undertaking of the restoration operations (Lemenkova, 2024; Zerrouk et al., 2025). The interpretable machine learning models are also used to estimate the ecological drivers of the wetland health and forecast restoration success probabilities (Du et al., 2025).

That is the potential new approach to restoration called the digital twin. Digital wetland twins are simulations of real-time ecosystem processes that utilizes built environmental information and enables the restoration managers to trial intervention scenarios before those images are implemented in the field (Lu et al., 2026). Correspondingly, the continuous evaluation of biodiversity and health status of the ecosystem is possible with the help of real-time monitoring systems which combine GIS, AI, and environmental DNA (eDNA) analysis (Hwang et al., 2025).

Conservation strategies Community-based conservation strategies are essential to a successful endeavour in restoration. The involvement of local communities in the planning of restorations contributes to a better conservation acceptance, higher efficiency in the monitoring process, and the encouragement of sustainable management of the resource utilization processes. Currently, transparency and conservation accountability are improved through the tool of participatory GIS and community monitoring programs (Bakirman et al., 2022; Zhao et al., 2026). Making indigenous ecological knowledge a part of the restoration can dramatically upgrade protection in culturally sensitive wetland landscapes.

It is also significant to conservation strategies that are backed by policy. There is a need to strengthen the protection laws of wetlands, enhance enforcement systems, and the inclusion of wetland conservation as a national climatic and land-use policy in order to achieve long-term sustainability (A. Ali & Ali, 2026; Sahle & Melaku, 2025). Cooperation systems across borders are also crucial in the preservation of transboundary wetlands ecosystems.

More emphasis is being laid on cost effective conservation strategies especially at developing locations. The solutions to conservation are realized through the moderate technology integration using simplified AI models, open-access remote sensing data, and straightforward GIS tools that are affordable but do not affect the quality of the ecological monitoring (Maniyar et al., 2025; Victoria Bukky Ayoola et al., 2024). Through this method, there will be technological inclusivity and conservation implementation in resource-constrained settings.

Nature-based solutions (NbS) are becoming increasingly known as a valid wetland conservation technique across the world. Wetlands in themselves are natural climate adaptation systems, which include the reduction of the risks of floods, water quality, and the carbon storage. The inclusion of wetland restoration as a climate mitigation policy will help in strengthening ecosystems and meet the objectives of sustainable development (Fois et al., 2021; Jiang et al., 2024).

Restoration strategies should have monitoring and evaluation frameworks. The harmless use of satellite data archives, the use of UAV maps and AI-assisted ecological assessment can guarantee the success of restoration and assist with adaptive management planning (Kentsch et al., 2021; Rapinel et al., 2023). This is done through constant monitoring, which detects new threats in time and enables quick measures to be achieved through conservation efforts.

As another crucial method of restoration, invasive species management should be mentioned. Ecosystem restoration and habitat recovery are effective in controlling invasive species to restore the native biodiversity and ecosystems stability (Cui et al., 2019; Fois et al., 2021). A remote sensing and AI-based classification helps in controlling invasive species more effectively by detecting the enemy at an earlier stage.

Combined multi-technology restoration models are the future of wetland and conservation. The integration of AI, GIS, remote sensing, hydrological modeling, and ecological field surveillance would allow a comprehensive assessment of the wetland ecosystem and provide the restoration plan (Jahangeer et al., 2025; L. Yang et al., 2022). This sort of combined strategies contributes to precision of conservation and sustainable management of wetlands.

To sum up, the restoration and conservation of wetlands should be consistent with a combination of ecological, technological, and management methods. The basic elements of sustainable wetland conservation are hydrological rehabilitation, vegetation rehabilitation, pollution, community involvement, and policy. Such technologies as AI based ecological modeling, digital twins and real time monitoring systems contribute to the efficiency of restoration even further. However, to achieve success in long-term conservation, technological innovation should be perfectly balanced with ecological knowledge, stakeholder involvement, and environmental governance based on the (Abdenour et al., 2025; Kingsford et al., 2016).

CONCLUSION AND FUTURE PROSPECTIVE

Wetlands are among the most ecologically valuable ecosystems on Earth, yet they continue to experience unprecedented degradation due to rapid urbanization, land-use change, industrial pollution, hydrological alterations, invasive species, and climate change. The present review demonstrates that the integration of RS, Geographic Information Systems (GIS), and AI has fundamentally transformed wetland monitoring and conservation by enabling high-resolution mapping, automated land-use classification, predictive ecological modelling, biodiversity assessment, pollution detection, and real-time environmental surveillance. Compared with conventional field-based approaches, AI-enabled geospatial technologies provide faster, more accurate, and scalable solutions for detecting environmental changes, identifying ecological threats, and supporting adaptive conservation planning. Collectively, these technologies facilitate evidence-based decision-making and improve the effectiveness of restoration strategies at local, regional, and global scales.

Future research should prioritize the development of next-generation intelligent wetland monitoring systems that combine hyperspectral remote sensing, LiDAR, synthetic aperture radar (SAR), unmanned aerial vehicles (UAVs), Internet of Things (IoT) sensor networks, environmental DNA (eDNA), cloud-native geospatial platforms, Digital Twins, and Explainable Artificial Intelligence (XAI). Emerging approaches such as Vision Transformers (ViTs), foundation models, multimodal AI, federated learning, edge AI, reinforcement learning, and autonomous monitoring systems are expected to substantially improve predictive accuracy, ecological interpretation, and real-time environmental decision-making. Equally important is the integration of socio-economic datasets, citizen science, participatory GIS, and policy-oriented decision-support systems to strengthen ecosystem governance and community-based conservation. Standardized benchmarking datasets, open-source AI frameworks, and internationally harmonized monitoring protocols should also be established to enhance reproducibility, interoperability, and global collaboration.

Overall, this review provides a comprehensive synthesis of contemporary AI–GIS applications in wetland conservation while presenting an integrated technological framework that bridges environmental monitoring, ecological assessment, predictive analytics, and adaptive management. By identifying current research gaps, emerging technologies, and future opportunities, this work offers a practical roadmap for researchers, conservation practitioners, policymakers, and environmental managers. The continued convergence of artificial intelligence, geospatial science, ecological knowledge, and sustainable governance has the

potential to transform wetland conservation from a reactive management approach into a predictive, intelligent, and resilient ecosystem management paradigm capable of addressing future environmental challenges and supporting global biodiversity and climate sustainability goals.

List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DEM	Digital Elevation Model
DL	Deep Learning
eDNA	Environmental DNA
EPO	European Patent Office
EVI	Enhanced Vegetation Index
FRAGSTATS	Fragmentation Statistics Software
GEE	Google Earth Engine
GIS	Geographic Information System
GPS	Global Positioning System
IoT	Internet of Things
LIDAR (LiDAR)	Light Detection and Ranging
LLM	Large Language Model
LSTM	Long Short-Term Memory
LULC	Land Use/Land Cover
MCDA	Multi-Criteria Decision Analysis
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MNDWI	Modified Normalized Difference Water Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NLP	Natural Language Processing
OBIA	Object-Based Image Analysis
PGIS	Participatory Geographic Information System
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QGIS	Quantum Geographic Information System
RF	Random Forest
RNN	Recurrent Neural Network
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SDGs	Sustainable Development Goals
SDM	Species Distribution Model
SVM	Support Vector Machine
SWAT	Soil and Water Assessment Tool
UAV	Unmanned Aerial Vehicle
USPTO	United States Patent and Trademark Office
ViT	Vision Transformer
WIPO	World Intellectual Property Organization
WSN	Wireless Sensor Network
XAI	Explainable Artificial Intelligence

XGBoost	Extreme Gradient Boosting
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DECLARATION OF USE OF AI

The authors declare that no generative AI tools were used in the preparation, writing, analysis, or interpretation of this manuscript. Grammarly was used solely for grammar checking and to improve the readability of the text. In addition, the trial version of BioRender was used exclusively to create the schematic illustrations included in the manuscript. The authors reviewed and approved all content and take full responsibility for the accuracy and integrity of the manuscript.

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