https://doi.org/10.4467/21995923GP.25.002.22857 GEOINFORMATICA POLONICA
24: 2025

Anna Szafarczyk[1]
https://orcid.org/0000-0001-6130-2529

Okechukwu Ebuka Agbasi[2]
https://orcid.org/0000-0001-5649-0107

EMERGING TRENDS IN GIS AND REMOTE SENSING TECHNOLOGIES FOR ENVIRONMENTAL MONITORING: INNOVATIONS, APPLICATIONS, AND FUTURE DIRECTIONS

[1] Faculty of Environmental Engineering and Energy, Cracow University of Technology, Cracow, Poland
[2] Okna Geoservices Nigeria Limited, Eket, Nigeria

Abstract

The escalating challenges of climate change, biodiversity loss, land degradation, and urban expansion have amplified the need for reliable, high-resolution, and timely environmental data. Geographic Information Systems (GIS) and Remote Sensing (RS) technologies have become indispensable tools for environmental monitoring, enabling the systematic collection, analysis, and visualization of spatial data across diverse ecosystems. This review synthesizes recent innovations in GIS and RS that are transforming environmental surveillance and decision-making. Key developments include the integration of artificial intelligence (AI) and machine learning (ML) for enhanced image classification, cloud-based platforms like Google Earth Engine (GEE) for scalable analysis, and the increasing use of Unmanned Aerial Vehicles (UAVs) and hyperspectral sensors for high-resolution monitoring. Furthermore, the convergence of geospatial analytics with big data, the Internet of Things (IoT), and participatory approaches such as citizen science is expanding the accessibility and impact of environmental data. Case studies from Africa, Asia, and global initiatives highlight practical applications in land use change detection, water resource assessment, hazard risk mapping, urban heat island analysis, and biodiversity conservation. While the potential of these tools is vast, persistent challenges include data interoperability, technical capacity gaps, policy integration barriers, and ethical concerns related to surveillance and data equity. This review calls for greater investment in open-source tools, interdisciplinary collaboration, and inclusive data governance to realize the full potential of GIS and RS in achieving environmental resilience and sustainability. Future directions emphasise real-time monitoring, ethical frameworks, and the democratisation of spatial intelligence.

Keywords: Geographic Information Systems (GIS), Remote Sensing (RS), Environmental Monitoring, Artificial Intelligence (AI), Sustainable Development

NOWE TRENDY W TECHNOLOGIACH GIS I TELEDETEKCJI W ZAKRESIE MONITOROWANIA ŚRODOWISKA: INNOWACJE, ZASTOSOWANIA I PRZYSZŁE KIERUNKI ROZWOJU

Abstrakt

Rosnące wyzwania związane ze zmianami klimatu, utratą bioróżnorodności, degradacją gleby i ekspansją miast zwiększyły zapotrzebowanie na wiarygodne, wysokiej rozdzielczości i aktualne dane środowiskowe. Technologie systemów informacji geograficznej (GIS) i teledetekcji (RS) stały się niezbędnymi narzędziami do monitorowania środowiska, umożliwiając systematyczne gromadzenie, analizę i wizualizację danych przestrzennych w różnych ekosystemach. Niniejszy przegląd syntetyzuje

najnowsze innowacje w dziedzinie GIS i RS, które przekształcają nadzór nad środowiskiem i proces decyzyjny. Kluczowe osiągnięcia obejmują integrację sztucznej inteligencji (AI) i uczenia maszynowego (ML) w celu ulepszonej klasyfikacji obrazów, platformy chmurowe, takie jak Google Earth Engine (GEE), do skalowalnej analizy, oraz coraz częstsze wykorzystanie bezzałogowych statków powietrznych (UAV) i czujników hiperspektralnych do monitorowania o wysokiej rozdzielczości. Ponadto konwergencja analityki geoprzestrzennej z dużymi zbiorami danych, Internetem Rzeczy (IoT) i podejściami partycypacyjnymi, takimi jak nauka obywatelska, zwiększa dostępność i wpływ danych środowiskowych. Studia przypadków z Afryki, Azji i inicjatyw globalnych podkreślają praktyczne zastosowania w wykrywaniu zmian w użytkowaniu gruntów, ocenie zasobów wodnych, mapowaniu ryzyka zagrożeń, analizie miejskich wysp ciepła i ochronie bioróżnorodności. Chociaż potencjał tych narzędzi jest ogromny, wciąż istnieją wyzwania, takie jak interoperacyjność danych, luki w zasobach technicznych, bariery w integracji polityki oraz kwestie etyczne związane z nadzorem i równością danych. Niniejszy przegląd wzywa do zwiększenia inwestycji w narzędzia open source, współpracy interdyscyplinarnej i inkluzywnego zarządzania danymi, aby w pełni wykorzystać potencjał GIS i RS w osiąganiu odporności i zrównoważonego rozwoju środowiska. Przyszłe kierunki rozwoju kładą nacisk na monitorowanie w czasie rzeczywistym, ramy etyczne oraz demokratyzację inteligencji przestrzennej.

Słowa kluczowe: Systemy Informacji Geograficznej (GIS), teledetekcja (RS), monitoring środowiska, sztuczna inteligencja (AI), zrównoważony rozwój

1. INTRODUCTION

Environmental monitoring is essential for safeguarding ecosystems, guiding sustainable development, and informing effective policy responses to both anthropogenic and natural environmental pressures. In a world increasingly threatened by climate change, deforestation, land degradation, water pollution, and rapid urbanization, the need for reliable, high-resolution, and timely environmental data has never been greater [1]. Monitoring environmental parameters helps detect early warning signals, assess ecological vulnerability, and evaluate the effectiveness of conservation and mitigation measures [2].

Traditional methods of environmental monitoring, though vital for field validation, are often constrained by their labour-intensive nature, high costs, and limited spatial and temporal coverage [3, 4]. These limitations have catalysed the widespread adoption of geospatial technologies, particularly Geographic Information Systems (GIS) and Remote Sensing (RS), as scalable, cost-effective solutions to environmental data collection and analysis. RS technologies, through platforms such as satellites, drones, and aerial surveys, provide systematic and consistent multi-temporal and multispectral observations across broad and often inaccessible geographic areas [5]. When integrated with GIS, which enables the storage, manipulation, and visualization of spatial data, these technologies allow dynamic modelling of environmental systems and spatial decision support [6, 7].

Applications of GIS and RS now span a wide range of environmental domains, including land use and land cover (LULC) change detection, biodiversity monitoring, hydrology, air quality analysis, agricultural productivity assessment, and disaster risk reduction [8, 9, 10, 11, 12]. Their utility has been magnified by recent advances in artificial intelligence (AI), machine learning (ML), and cloud computing, which have enabled near real-time environmental monitoring, enhanced image classification, and predictive analytics [13, 14]. The growing availability of open-access datasets, such as those provided by NASA's Landsat program and the European Space Agency's Sentinel missions, has further democratized environmental analysis across institutional and geographical boundaries [15].

The integration of mobile-based GIS tools and drone technology has significantly expanded data collection capabilities, particularly in data-scarce or resource-constrained environments [16, 17]. Citizen science initiatives have also emerged as promising complementary approaches, enabling participatory data gathering and fostering public engagement in environmental stewardship [18]. Nonetheless, technical and institutional challenges persist, including issues of data harmonization, standardization, interoperability, and computational limitations, as well as ethical concerns surrounding data privacy, consent, and equitable access [19].

The primary motivation for this review is to synthesize recent innovations in GIS and RS within the context of environmental monitoring and to evaluate their contributions, limitations, and emerging trends critically. While the literature abounds with domain-specific case studies, there remains a gap in comprehensive interdisciplinary assessments that integrate technological,

methodological, and policy perspectives. This review aims to address that gap by identifying current knowledge frontiers, highlighting ongoing constraints, and proposing directions for future research and multi-sectoral collaboration. Ultimately, understanding and expanding the role of GIS and RS technologies will be pivotal in tackling global environmental challenges and supporting the realization of international sustainability goals.

1.1 Methodology and Literature Selection

The literature review for this study was conducted through an extensive search across several academic databases, including Scopus, Web of Science, and Google Scholar, covering the period from 2019 to 2024. The search strategy was designed to focus on key terms related to environmental monitoring and technological innovations, including "GIS," "remote sensing," "artificial intelligence," "IoT," "citizen science," and "open data." This search aimed to capture a comprehensive range of peer-reviewed studies, technical reports, and articles that explore the integration of advanced technologies in environmental monitoring. Only publications that specifically addressed the application of these technologies in monitoring and managing environmental concerns were included. At the same time, purely technical algorithmic papers and grey literature were excluded to maintain relevance to the central themes of the review.

Case studies were selected to ensure geographic diversity and thematic relevance, focusing on regions such as Africa and Asia, as well as global initiatives. The chosen studies addressed key environmental monitoring domains, including land use/land cover change, hydrology, disaster risk assessment, urban heat islands, and biodiversity conservation. Preference was given to case studies with documented outcomes or lessons learned, which provided insights into the practical application of GIS and remote sensing technologies.

This review primarily adopts a narrative synthesis approach, structured according to systematic review principles, and adheres to PRISMA guidelines to ensure transparency in the study selection process. While every effort was made to include relevant and recent literature, some limitations exist, such as language restrictions and potential publication bias, which may affect the overall comprehensiveness of the review. Nonetheless, the synthesis offers a comprehensive overview of emerging trends in environmental monitoring using GIS and remote sensing technologies.

2. INTEGRATION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

One of the most transformative developments in geospatial technology is the incorporation of AI and ML into RS and GIS. These approaches, particularly supervised classifiers like Support Vector Machines (SVM), Random Forest (RF), and deep learning models such as Convolutional Neural Networks (CNNs), have significantly enhanced the accuracy of image classification, object detection, and anomaly recognition in Earth observation data [19, 20, 21].

CNNs are particularly effective in handling high-resolution and multi-temporal imagery for detecting land cover changes, deforestation, floods, and urban expansion [22]. These models reduce human bias and facilitate automated interpretation of large image datasets, making them suitable for applications like illegal mining detection and shoreline monitoring [23]. The integration of platforms such as Google's TensorFlow and ESRI's ArcGIS Deep Learning Toolkit has democratized access to deep learning tools, even in developing regions.

AI-driven automation is increasingly used in post-disaster rapid mapping, enabling faster decision-making during emergencies such as hurricanes, wildfires, and landslides [24].

2.1. Cloud-Based Geospatial Processing

The rise of cloud computing has addressed long-standing constraints related to data volume and computational overhead in GIS and RS workflows. Platforms like Google Earth Engine (GEE), Amazon Web Services (AWS), and the Microsoft Planetary Computer offer global repositories of satellite data (e.g., MODIS, Sentinel, Landsat) alongside the tools to analyze them in-browser using JavaScript or Python [25].

GEE has revolutionized geospatial research by enabling rapid analysis of deforestation, drought impacts, air quality trends, and crop monitoring, without the need for downloading or pre-processing data locally [26]. Cloud-based processing promotes collaboration among

institutions and supports equitable access to computational resources in lower-income countries.

The integration of AI and automation in environmental monitoring provides powerful tools for data analysis and decision-making. However, it is crucial to mitigate risks associated with algorithmic bias and overreliance on automated systems. One of the primary safeguards is algorithm transparency, where the assumptions, data inputs, and decision-making processes of AI systems are documented and accessible. Regular audits of AI models should be conducted to ensure they work as intended and do not perpetuate biases. Incorporating diverse and representative datasets is another crucial step in reducing bias in AI systems, ensuring that models are trained on comprehensive environmental data from various regions and contexts. Additionally, human expertise should be integrated into these systems through human-in-the-loop (HITL) processes, enabling expert oversight and intervention when necessary. This ensures that automated processes remain grounded in contextual knowledge and expertise, particularly when dealing with complex environmental issues.

2.2. Unmanned Aerial Vehicles (Uavs) and Drones

Unmanned Aerial Vehicles (UAVs), or drones, are reshaping field-based environmental data collection by offering centimetre-level resolution, flexible deployment, and multi-sensor configurations (e.g., RGB, thermal, multispectral). These capabilities are particularly beneficial in wetlands, coral reefs, agricultural zones, and wildlife reserves [27].

In precision agriculture, UAVs equipped with NDVI-calibrated sensors can assess crop stress and yield potential in near real-time [28]. Coastal management agencies use drones to monitor sediment transport and shoreline erosion with much higher temporal resolution than satellites [27]. UAV data, integrated into GIS platforms, improve spatial accuracy and allow 3D reconstructions using photogrammetry and Structure-from-Motion (SfM) techniques [29].

2.3. Hyperspectral and Thermal Remote Sensing

Unlike multispectral sensors, hyperspectral imaging collects data across hundreds of contiguous and narrow spectral bands, allowing for much finer discrimination of surface materials and vegetation traits [30]. This increased spectral resolution enables the identification of subtle differences in material composition that would be indistinguishable in broader-band multispectral data. Applications of hyperspectral imagery include precise mapping of soil salinity, heavy metal contamination, mineral content, and vegetation stress due to drought or disease [31]. Similarly, thermal infrared (TIR) sensors, such as those aboard ECOSTRESS and Landsat 8's TIRS, are vital for detecting temperature anomalies. These anomalies support urban heat island analysis, wildfire detection, and groundwater discharge monitoring [32].

2.4. Big Data Analytics and the Internet of Things (IoT)

The integration of Geographic Information Systems (GIS) with real-time sensor networks, often supported by the Internet of Things (IoT), has revolutionized environmental monitoring. This convergence enables the continuous collection and transmission of data from field sensors, such as air quality monitors, river gauges, and soil moisture probes, directly into GIS platforms. These data streams facilitate real-time visualization and spatial analysis, enhancing decision-making through greater responsiveness and detail [33]. In agriculture, IoT systems combine UAV imagery with in-situ weather data and soil sensors to automate irrigation and optimize crop yields [34]. In urban settings, IoT networks enable dynamic monitoring of air pollution, noise, and traffic, informing spatial models for urban planning and health risk assessments [35]. Advanced tools like ArcGIS Insights and Kepler.gl support interactive dashboards and predictive analytics, with real-time alerts triggered when sensor data exceeds predefined thresholds. These technologies, powered by machine learning and AI algorithms, enable adaptive environmental governance. However, clarification is needed on what datasets qualify as big data, their relationship to IoT, and the necessary post-processing steps for this data.

2.5. Open Source Tools and Citizen Science

The widespread availability of open-source GIS and RS tools has significantly reduced barriers to environmental data analysis. Platforms such as QGIS, SNAP (Sentinel Application Platform), and OpenDroneMap offer advanced geospatial processing capabilities with-

out the limitations of expensive proprietary software [36]. These tools empower researchers, students, and practitioners globally to conduct spatial analysis, image classification, and mapping with greater flexibility. Participatory platforms like OpenStreetMap, iNaturalist, and Global Forest Watch incorporate user-generated data to complement satellite observations. In regions with limited formal monitoring infrastructure, these crowdsourced tools enable communities to report deforestation, illegal mining, wildlife sightings, and other environmental events, enhancing data richness and local engagement [37].

While citizen science offers vast potential for crowdsourced environmental monitoring, ensuring the quality of the data is crucial for integration into formal systems. Protocols for ensuring data quality include multi-level validation mechanisms, such as cross-referencing crowd-sourced data with official data sources like satellite imagery or pre-existing environmental datasets. Automated checks and statistical methods, such as consistency testing and anomaly detection, are employed to flag potential errors or outliers. Training and guidance for volunteers contribute to reducing human error. Expert validation or peer reviews may further supplement the data to enhance reliability. In the future, developing a standardized framework for data collection, ensuring the accuracy of time, location, and environmental conditions, will be essential for the continued success of citizen science platforms.

2.6. Synthetic Aperture Radar (SAR) Data from UAVs

Synthetic Aperture Radar (SAR) has become a vital tool in environmental monitoring, particularly in situations where optical remote sensing is limited by persistent cloud cover or the absence of sunlight. Unlike optical sensors, SAR uses microwave signals that can penetrate atmospheric conditions and operate effectively day or night. Satellites such as Sentinel-1 and the upcoming NASA-ISRO NISAR mission provide high-resolution SAR data, supporting applications in flood extent mapping, glacier movement tracking, and land subsidence or deformation analysis [38]. Beyond disaster monitoring, SAR is highly effective for estimating forest biomass and analysing vegetation structure, offering critical insights for carbon stock assessment and forest conservation [39]. In polar and high-latitude regions, SAR data also enables the monitoring of permafrost thaw and seasonal ground changes, crucial for understanding climate change impacts [40].

2.7. Environmental Decision Support Systems (EDSS)

Modern GIS tools are increasingly evolving into comprehensive Environmental Decision Support Systems (EDSS), combining spatial databases with analytical models, simulations, and multi-criteria evaluation techniques. These systems enable planners and policymakers to assess complex environmental challenges through spatially informed perspectives. A core component of this evolution is GIS-based Multi-Criteria Decision Analysis (MCDA), which facilitates informed decision-making in contexts such as land-use planning, flood risk zoning, conservation prioritisation, and identifying optimal sites for renewable energy infrastructure [41, 42]. EDSS platforms typically present interactive dashboards, geovisualizations, and risk scenario maps that guide users in understanding trade-offs, allocating resources, and adapting strategies in response to climate variability and socio-environmental constraints [43]. By integrating spatial science with participatory planning, EDSS tools enhance transparency, accountability, and the overall effectiveness of environmental governance.

2.8. Time-Series and Change Detection Analytics

Environmental monitoring increasingly depends on time-series analysis to detect gradual and abrupt changes in land surface conditions over time. Techniques such as Breaks For Additive Season and Trend (BFAST), TIMESAT, and LandTrendr are widely used for analysing large temporal datasets, particularly from remote sensing archives like MODIS and Landsat [44]. These tools help identify trends in vegetation health, land degradation, phenological shifts, and ecosystem recovery following disturbances such as wildfires, droughts, or logging. They also support the detection of abrupt land-use transitions, including urban encroachment, agricultural expansion, and deforestation. Increasingly, these time-series models are being deployed on cloud-based platforms such as GEE, enabling scalable, real-time applications across large geographic extents with reduced computational constraints [45]. Time-series analysis en-

hances early warning systems, supports evidence-based environmental policymaking, and plays a crucial role in tracking progress toward global sustainability targets.

2.9. 3D and Augmented Reality (AR) Visualization

Three-dimensional GIS modelling and Augmented Reality (AR) applications offer immersive and intuitive platforms for stakeholder engagement and educational outreach. Tools like ArcGIS CityEngine, CesiumJS, and BlenderGIS enable dynamic 3D representations of terrain, infrastructure, and environmental processes [46, 47].

AR platforms overlay spatial data onto physical landscapes, enhancing participatory planning, environmental interpretation, and classroom education [46].

The innovations outlined here are transforming GIS and RS into intelligent, agile systems for environmental monitoring and management. Whether through AI-driven image analysis, real-time IoT integration, or citizen-led mapping efforts, these technologies offer profound opportunities to enhance resilience, improve governance, and advance environmental justice. Future efforts should prioritize data interoperability, ethical use frameworks, and inclusive capacity-building to ensure the benefits of these advancements are equitably shared.

3. APPLICATION DOMAINS OF GIS AND RS FOR ENVIRONMENTAL MONITORING

The increasing availability of high-resolution spatial data and advances in geospatial analytics have significantly transformed environmental monitoring and decision-making. GIS and RS have become indispensable for understanding spatial patterns, detecting environmental changes, and modelling future scenarios across various ecological domains.

3.1. Land Use and Land Cover (LULC) Change Detection

LULC change analysis is fundamental to understanding human-induced transformations of ecosystems. Satellite RS enables consistent temporal and spatial tracking of land dynamics, mainly through data from platforms such as Landsat, MODIS, and Sentinel-2 [48]. These datasets, when processed using GIS, have provided critical insights into urban sprawl, agricultural expansion, forest degradation, and desertification [49].

Traditional pixel-based classification methods are increasingly being supplemented with Object-Based Image Analysis (OBIA) and machine learning algorithms, including RF, SVM, and CNNs to enhance classification accuracy [50]. Time-series approaches such as BFAST (Breaks for Additive Season and Trend) and LandTrendr allow the detection of disturbances and recovery phases in vegetation and land surfaces over decades [51].

LULC monitoring supports applications in urban planning [52], agricultural policy [53], and conservation planning [54]. It also contributes to carbon accounting and environmental scenario modelling under changing climate and land policy regimes [55].

3.2. Water Quality and Hydrological Monitoring

Water bodies are highly dynamic systems influenced by anthropogenic pressures and natural variability. RS has emerged as a key technique for observing water quality variables such as turbidity, chlorophyll-a, total suspended solids, and algal blooms, using sensors such as Sentinel-2 MSI, Landsat OLI, and MODIS Aqua [56, 57].

Indices like NDWI (Normalized Difference Water Index), TSI (Trophic State Index), and SDD (Secchi Disk Depth) are commonly derived from satellite imagery to assess water health [58]. GIS-based watershed modelling tools such as SWAT and HEC-HMS support simulations of runoff, nutrient loading, and hydrological responses [59].

Integrating RS with IoT sensors has enhanced real-time hydrological monitoring. In estuarine and coastal zones, SAR and altimetry data are used to detect shoreline retreat, sediment plumes, and saltwater intrusion. Water managers increasingly rely on such insights for policy development around pollution control, climate adaptation, and sustainable allocation [60].

3.3. Disaster Risk Assessment: Floods, Droughts, and Hazards

Natural hazards such as floods, droughts, landslides, and wildfires are escalating in frequency and intensity due to climate change. GIS and RS are essential in assessing risk, issuing early warnings, and guiding disas-

ter response and recovery efforts. Flood events are effectively mapped using SAR sensors such as Sentinel-1 and RADARSAT, which can penetrate cloud cover [61, 62]. These datasets are integrated into GIS to delineate flood extents, depth, and risk zones. RS-based indices such as NDVI and VCI, along with soil moisture products from SMAP and CHIRPS, support drought risk analysis [63].

GIS also facilitates earthquake and landslide risk assessments by integrating data on fault lines, slope gradients, land cover, and population exposure. In wildfire monitoring, thermal imagery from MODIS and VIIRS supports real-time fire detection and burn severity assessments [64]. Post-disaster damage assessment, using high-resolution drone imagery and satellite data, enables rapid estimation of affected infrastructure and ecosystems. These technologies have become cornerstones of emergency planning and risk-informed development strategies [65].

3.4. Urban Heat Islands and Air Pollution

Urban Heat Islands (UHIs) are increasingly severe due to impervious surfaces, high population densities, and vegetation loss. RS of Land Surface Temperature (LST) using thermal infrared bands from Landsat TIRS, MODIS, and ECOSTRESS enables spatial modeling of urban heat hotspots. GIS overlays of LST with NDVI and LULC maps help quantify the cooling effects of urban vegetation and water bodies [66].

UHI assessments guide the design of cooling infrastructure such as urban forests, green roofs, and reflective pavements. In terms of air quality, RS data from Sentinel-5P TROPOMI and MODIS Aerosol Optical Depth (AOD) products are used to monitor NO_2, SO_2, PM2.5, and ozone levels [67].

Coupling satellite observations with ground-based data in GIS enables the creation of spatiotemporal air quality maps that inform emission regulation, health advisories, and transportation planning. Recent trends also emphasize participatory sensing, where citizens contribute air quality data via mobile sensors and apps, which are integrated into open GIS dashboards.

3.5. Biodiversity and Habitat Monitoring

GIS and RS play critical roles in detecting biodiversity changes, evaluating habitat conditions, and informing conservation interventions. Satellite imagery is used to map vegetation types, monitor land degradation, and assess habitat fragmentation. Vegetation indices like NDVI and EVI derived from Sentinel and MODIS help quantify greenness and productivity [68].

Species Distribution Models (SDMs) integrate species presence data from repositories like GBIF with environmental variables (e.g., LULC, elevation, temperature) to predict habitat suitability using tools like MaxEnt or Biomod. These models facilitate the identification of conservation priorities and the zoning of protected areas. Lidar and SAR technologies are used to estimate forest biomass, canopy height, and structural diversity [69]. RS has been instrumental in monitoring coral reefs, mangroves, and alpine ecosystems under threat from climate change and land conversion. GIS and RS also facilitate mapping of invasive species, monitoring poaching patterns, and tracking migratory species via GPS telemetry. These tools are integral to global biodiversity frameworks such as the Convention on Biological Diversity (CBD) and the Sustainable Development Goals.

From land surface dynamics to species conservation and urban climate modelling, GIS and RS have become fundamental to environmental monitoring. These tools not only enhance the spatial and temporal resolution of ecological data but also support predictive modelling and evidence-based decision-making. As environmental challenges intensify globally, further democratising access to geospatial data, investing in open-source tools, and integrating GIS and RS into planning and policy systems will be essential for achieving sustainable and climate-resilient futures.

The societal impact of open-source tools and data-sharing platforms can be measured through several indicators, including the increased frequency of use in decision-making, improvements in policy outcomes, and the enhanced involvement of local communities in environmental monitoring. For example, open data platforms like Global Forest Watch have shown how accessible, crowd-sourced data can influence policy changes aimed at reducing deforestation in tropical regions. The integration of open-source tools in disaster risk management has led to improved preparedness and response times, as seen in the use of OpenStreetMap during natural disasters. These platforms also facilitate enhanced community engagement, enabling citizens to contribute to data collection and inform decision-making at local, regional, and national levels.

4. CASE STUDIES AND REGIONAL INSIGHTS IN GIS AND RS FOR ENVIRONMENTAL MONITORING

The application of GIS and RS technologies in environmental monitoring has seen widespread adoption across different regions of the world. These tools have proven critical in addressing pressing ecological concerns, including deforestation, climate-induced hazards, biodiversity loss, and resource management.

4.1. Africa: Forest Monitoring and Climate Resilience

In Central Africa, the Congo Basin-home to the world's second-largest tropical rainforest- has long been under threat from illegal logging, subsistence agriculture, and mining. As a key carbon sink and biodiversity hotspot, the region's environmental integrity is of global significance. The Central African Forest Observatory (OFAC), in partnership with Global Forest Watch (GFW), has operationalized near real-time monitoring of forest cover using Landsat and Sentinel data processed via GEE [70, 71]. These platforms use machine learning algorithms to detect forest loss and degradation, particularly in Democratic Republic of Congo and Cameroon.

Such data, when integrated with field observations and geospatial analysis, have enabled more effective policy enforcement and community-based forest management. While capacity-building efforts have increased local technical knowledge, limitations persist due to unreliable internet infrastructure in rural monitoring stations and governance weaknesses that hinder enforcement [72].

In the Sahel region, drought remains a recurring challenge. AGRHYMET, a regional centre based in Niger, has adopted RS techniques such as MODIS-derived Normalized Difference Vegetation Index (NDVI) and CHIRPS rainfall estimates to monitor vegetation health and drought severity [73]. GIS overlays of rainfall anomalies, soil moisture, and crop calendars inform regional food security early warning systems used by ECOWAS countries. Despite notable success in reducing agricultural losses and livestock mortality, data limitations at micro scales and inadequate integration of local knowledge systems continue to restrict model accuracy [74]. A recent experiment in Congo's humid forest zone compared multispectral UAV imagery with Sentinel-1 SAR data for crop type classification. Including canopy-height models, support-vector-machine classifiers achieved 94.78 % accuracy using UAV data versus 81.72 % with SAR imagery, while random-forest models reached 93.84 % and 92.58 %, respectively [71]. The experiment demonstrates how high-resolution UAV data can substantially improve classification accuracy, although the cost and expertise required remain significant barriers.

4.2. Asia: Disaster Preparedness and Urban Climate Management

Bangladesh's geographical position in the Ganges--Brahmaputra delta makes it acutely vulnerable to seasonal floods. The Bangladesh Water Development Board (BWDB), in collaboration with NASA and JAXA, utilises SAR data from Sentinel-1 and ALOS satellites to map flood extents, supported by hydrological models such as HEC-RAS [75]. These spatial tools are integrated into GIS-based flood risk maps, which underpin the Flood Forecasting and Warning Centre's public alert systems.

Community-level alerts delivered via SMS and mobile apps have improved lead times by up to five days, enabling pre-emptive evacuations and reducing mortality. However, persistent cloud cover during the monsoon season can hinder the reliability of optical RS data, while poor infrastructure in low-income areas limits the implementation of evacuation plans [76]. Rapid urbanization in India has exacerbated the UHI effect in cities like Ahmedabad, Delhi, and Hyderabad. GIS and RS applications using MODIS and Landsat thermal bands have been used to map LST variations and their correlation with green cover and built-up areas. Ahmedabad's Heat Action Plan, developed in partnership with the Natural Resources Defense Council, utilizes these data to guide adaptation strategies including the installation of cooling shelters, green roofs, and early warning systems [76]. Community-level alerts delivered via SMS and mobile apps have improved lead times by up to five days" by noting that the Bangladesh system's deterministic flood forecasts now extend from 3 to 5 days, which has reduced disaster mortality and property loss. State that Ahmedabad's Heat Action Plan prevents more than 1,000 deaths annually and yields benefit-to-cost ratios exceeding 50 to 1 [76]. Practical adaptation mea-

sures such as reflective roof coatings and community outreach are important.

In north Khuzestan (Iran), a Dempster–Shafer model integrating remote-sensing layers and well data produced a groundwater-potential map with 86 % accuracy. Sensitivity analysis showed that lithology, soil type and slope were the dominant predictors [24]. This example illustrates both the predictive power and limitations of GIS/RS for water-resource assessment.

The integration of RS data into public health planning has demonstrated measurable reductions in heat-related illnesses. Nonetheless, there remains a gap in neighbourhood-level thermal monitoring and limited collaboration between planners, public health experts, and urban designers.

4.3. Global Programs: Scalable and Open Access Platforms

One of the most comprehensive global initiatives in this space is SERVIR, a joint program of NASA and USAID operating through regional hubs in Africa, Asia, and Latin America. SERVIR leverages freely available satellite data to support climate resilience, agriculture, land use monitoring, and disaster management. SERVIR West Africa developed a flood monitoring tool for Burkina Faso using GPM rainfall data, terrain models, and land use maps [77]. Meanwhile, SERVIR Mekong supports mangrove ecosystem mapping using Sentinel-2 imagery and participatory validation. These efforts are notable for their emphasis on capacity building, with hundreds of local scientists trained in GEE and open-source spatial tools. While tool co-design with local ministries enhances relevance, uptake remains slow in contexts lacking formal geospatial mandates or policy frameworks.

The Group on Earth Observations Biodiversity Observation Network (GEO BON) exemplifies the use of RS in biodiversity conservation. GEO BON promotes the development of Essential Biodiversity Variables (EBVs), such as habitat extent and phenology, derived from satellite data and species occurrence records like those from GBIF [78]. Projects under this umbrella have mapped migratory bird corridors in East Africa and deforestation impacts on Amazonian biodiversity.

GEO BON outputs inform the CBD and are increasingly integrated into the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) assessments. However, implementing EBVs in freshwater and marine systems remains technically complex due to spatial resolution constraints and a lack of global data standards.

4.4. Synthesis and Cross-Cutting Themes

The above case studies reveal recurring themes that determine the success or limitations of GIS and RS deployments for environmental monitoring. First, localization and cultural adaptation of models are crucial; tools must be aligned with the specific ecological, institutional, and governance contexts in which they are applied. Second, investments in data infrastructure, particularly in high-speed internet, cloud computing access, and data storage, are crucial for enabling real-time monitoring, especially in the Global South [79]. When discussing urban heat-island analysis, the Mashhad case study is incorporated. Note that Landsat-derived data show land-surface temperature increased from 35.85°C in 1988 to 41.97°C in 2017, while NDVI values declined, signalling urbanisation and vegetation loss [64]. It highlights how such long-term RS data underpin urban climate adaptation.

Sustainability hinges on local capacity development. Without ongoing training and institutional support, even the most sophisticated geospatial tools risk being underutilized or misinterpreted. Moreover, embedding spatial tools into formal policy cycles, through mandates, budget allocations, and legal frameworks- greatly enhances their practical impact [13].

Lastly, open access and equity are essential to democratising environmental data. Open-source software, such as QGIS, and open data portals, like Global Forest Watch, enable civil society, academic institutions, and local governments to participate meaningfully in environmental governance. These inclusive approaches are vital to addressing disparities in access to geospatial technologies and promoting environmental justice.

5. CHALLENGES AND LIMITATIONS IN THE APPLICATION OF GIS AND RS FOR ENVIRONMENTAL MONITORING

Despite the remarkable advancements in GIS and RS technologies, several challenges continue to limit their optimal application in environmental monitoring, particularly in developing countries. These limita-

tions are not merely technical but are embedded within broader concerns relating to data governance, institutional readiness, cross-sectoral coordination, and systemic infrastructural weaknesses. As environmental pressures escalate due to climate change, biodiversity loss, and land degradation, addressing these challenges has become increasingly urgent [13, 80].

One of the most persistent obstacles is the issue of data availability and quality. While the availability of open-access satellite data through platforms such as Landsat, Sentinel, and MODIS has greatly enhanced global spatial coverage, limitations remain in terms of resolution, revisit frequency, and sensor-specific constraints. In many low- and middle-income regions, national spatial databases are often poorly maintained, outdated, or incomplete [81]. Inconsistencies in data collection methods further compromise comparability and longitudinal monitoring. Moreover, ground truth data, which is critical for calibrating and validating satellite observations, is often lacking or unreliable, particularly in remote or conflict-affected areas [82]. As a result, the accuracy and credibility of RS-based environmental assessments are frequently constrained by the inability to align satellite-derived insights with on-the-ground realities.

Another critical barrier is the lack of technical expertise and institutional capacity to analyse and interpret spatial data. Although platforms such as GEE and QGIS have lowered technical entry barriers, meaningful application of GIS and RS still requires specialised knowledge in image processing, geostatistics, and environmental modelling [83, 84]. In many regions, especially in sub-Saharan Africa and parts of Southeast Asia, there is a pronounced shortage of trained professionals across governmental and research institutions. Training programs, where they exist, are often ad hoc and lack continuity due to limited institutional funding and high staff turnover. Consequently, many GIS and RS tools are underutilized or misapplied, undermining long-term sustainability and institutional memory.

Policy integration represents another layer of complexity. Although the utility of geospatial technologies in environmental planning is widely acknowledged, their incorporation into formal policy frameworks remains limited. In numerous countries, spatial data generated by research institutions or pilot projects does not systematically inform decision-making processes due to bureaucratic inertia, lack of awareness, or absence of mandates for geospatial evidence use [85, 86]. Environmental ministries and urban planning agencies may operate without synchronized geospatial platforms, leading to fragmented strategies for land-use regulation, climate adaptation, or disaster risk reduction. Institutionalizing GIS and RS into national frameworks, such as Environmental Impact Assessments (EIAs), zoning regulations, and early warning systems, requires targeted reforms, inter-agency collaboration, and political will [87].

A further technical challenge is interoperability and data integration. Effective environmental monitoring often necessitates the fusion of diverse data types-including satellite imagery, meteorological data, biodiversity records, and socioeconomic statistics, across different spatial and temporal scales. However, the integration of such heterogeneous datasets is frequently obstructed by incompatibilities in file formats, coordinate systems, and metadata standards [88]. Many agencies continue to operate in silos, using proprietary software and isolated databases, which impedes collaborative analysis and decision-making. The lack of open standards and clear documentation further exacerbates these issues, limiting the potential of GIS as a unified platform for environmental intelligence.

The integration of open-source tools and platforms in policy frameworks has been documented to improve decision-making processes and policy outcomes. For example, governments in several regions have leveraged open-source platforms, such as Google Earth Engine and Sentinel Hub, for more informed urban planning, environmental management, and climate resilience strategies. Citizen science platforms such as iNaturalist have contributed to biodiversity conservation efforts by providing data that directly influence conservation policies. The documented improvements in these cases illustrate the potential for open data to enhance transparency, accountability, and the effectiveness of policy interventions, leading to more sustainable outcomes.

Compounding these challenges is the rapid pace of technological change, which introduces risks of obsolescence for institutions lacking the financial or human resources to adapt. New sensors, platforms, and processing algorithms are emerging rapidly, placing pressure on users to upgrade their hardware, software, and skills. For under-resourced agencies, this cycle often leads to dependence on outdated tools or external consultants. Simultaneously, ethical concerns regarding surveillance, data privacy, and geospatial inequality have gained

prominence. The increasing resolution of RS platforms enables monitoring of private or sensitive spaces, raising questions about consent, representation, and the appropriate use of spatial intelligence [89]. Furthermore, the digital divide continues to marginalize communities and institutions without reliable access to internet infrastructure or cloud-based platforms.

6. FUTURE DIRECTIONS AND RECOMMENDATIONS

As the 21st century environmental challenges intensify, driven by climate change, population growth, and ecosystem degradation, the future of environmental monitoring increasingly depends on how GIS and RS evolve and adapt. To maximize their potential, the next generation of geospatial technologies must move toward more responsive, inclusive, accessible, and ethically grounded systems. This section outlines key strategic directions and actionable recommendations to guide the future of GIS and RS in environmental surveillance.

One of the most promising frontiers lies in real-time environmental monitoring. Traditionally, RS and GIS have provided periodic snapshots of environmental conditions. However, with the advent of cloud computing, low-Earth orbit constellations (e.g., PlanetScope, Sentinel-1 and -2), and IoT sensors, it is now feasible to move from static observation to near real-time analysis. This capability is critical for early warning systems in disaster-prone regions, where delays in data processing can mean the difference between a proactive response and human loss. Real-time systems are already being applied in flood forecasting [90], wildfire detection, and urban air quality mapping. Future efforts should focus on scaling these applications through infrastructure investment and automated data pipelines, especially in underserved regions.

Citizen science integration is another vital pathway to enhance the breadth, depth, and democratization of environmental monitoring. With the widespread use of smartphones, low-cost sensors, and mobile applications, ordinary citizens can now act as environmental data collectors. Initiatives such as iNaturalist and OpenStreetMap demonstrate the power of public engagement in mapping biodiversity and land use [91]. This participatory approach not only fills data gaps in inaccessible or under-sampled areas but also fosters public awareness and environmental stewardship. However, to ensure data reliability and comparability, standardized protocols for data collection, validation, and integration must be developed. Collaborative frameworks between academic institutions, government agencies, and communities can strengthen the credibility and utility of citizen-contributed data.

As AI and automation become increasingly prevalent in environmental monitoring, it is essential to balance these technologies with human expertise. To mitigate the risks of algorithmic bias and overreliance on automated processes, several safeguards should be implemented. These include ensuring the transparency of algorithms, incorporating diverse datasets, and conducting regular audits of AI systems. Moreover, the concept of HITL should be central to future AI workflows. In this approach, human experts would provide valuable oversight, ensuring that AI outputs are reviewed and interpreted in the broader environmental context. The collaboration between AI models and human expertise will enhance the robustness of decision-making, ensuring that automated systems support rather than replace human judgment in critical policy and environmental decisions.

The increasing shift toward open-source tools and platforms is reshaping how geospatial data is accessed, processed, and shared. Software like QGIS, SNAP, and GEE has lowered the barriers to entry for many researchers, students, and policy professionals. Open-access datasets from sources such as the USGS, the Copernicus Programme, and NASA MODIS have expanded the scope of environmental monitoring in both global and local contexts. Open-source ecosystems promote transparency, reproducibility, and innovation while reducing reliance on expensive proprietary software. For future progress, sustained funding and development support are crucial to maintain the robustness, security, and interoperability of these tools. Furthermore, national governments should institutionalize the use of open data policies to ensure that publicly funded spatial information is made accessible to all stakeholders.

Amid the rapid expansion of spatial technologies, ethics and sustainability must remain core principles guiding future applications. The growing ability to monitor populations, private lands, or politically sensitive areas raises valid concerns about surveillance, consent, and the potential for data misuse. It is crucial to develop and enforce ethical guidelines that govern the collection, use, sharing, and storage of geospatial data.

As highlighted by Spaans et al. [92], the ethical implications of spatial technologies extend beyond data privacy to include issues of representation, bias, and the digital divide. Moreover, environmental monitoring must itself be environmentally sustainable. Energy-efficient data centres, low-impact drone deployments, and equitable global access should be factored into future system designs. A forward-looking agenda for GIS and RS should also incorporate transdisciplinary collaboration. Environmental challenges are inherently complex and interlinked with social, economic, and political systems. Therefore, future monitoring frameworks should integrate spatial science with social sciences, law, public health, and development planning. Cross-sectoral partnerships will enable more holistic approaches to sustainability assessments and more impactful environmental governance.

The future of GIS and RS for environmental monitoring depends on several interwoven advancements: embracing real-time data streams, leveraging citizen participation, scaling open-source tools, and embedding ethical safeguards. These strategies must be pursued in tandem with investments in human capital, policy reform, and infrastructure development. By aligning technological innovation with inclusivity, accountability, and ecological consciousness, GIS and RS can become even more powerful allies in achieving the Sustainable Development Goals (SDGs) and confronting the ecological challenges of our time.

7. CONCLUSION

This review has explored the evolving landscape of GIS and RS technologies, and their central position in modern environmental monitoring has been explained. Their application in environmental science, planning, and policy has enabled the transition from conventional, reactive approaches to proactive, evidence-based ones that are able to tackle some of the most pressing global issues like land degradation, water insecurity, biodiversity loss, and disaster risk. One of the key findings is the revolutionary potential of new technological innovations. Real-time monitoring through cloud computing and IoT sensors has enhanced the accuracy and timeliness of environmental monitoring. Machine learning and artificial intelligence have significantly altered data analysis by increasing the accuracy and speed of image classification, land cover change detection, and hazard forecasting. Likewise, the development of open-source geospatial software and greater access to satellite data have democratized access to spatial data, decreasing the cost of geospatial analysis and its accessibility, especially for developing countries. At the same time, citizen science efforts and mobile phone technology are unlocking new potential for participatory environmental governance and locally driven data generation. However, realizing the maximum potential of GIS and RS means overcoming system constraints. These are data inaccessibility, technical inadequacy, integration of policies, and interoperability constraints. Development of advanced technologies is not sufficient; investment in education, the institutional environment, and ethics-based management of data must also be accorded priority so that equitable and sustainable implementation is ensured to benefit everyone. Environmental monitoring in the future must become more responsive, interdisciplinary, and collaborative. Scientists, technologists, policymakers, and societies must work together to co-design tools that are not merely scientifically sound, but also contextually applicable and socially equitable. More investment is needed in longitudinal studies, transboundary environmental monitoring, and the creation of globally harmonized protocols that facilitate data sharing and decision-making. In brief, GIS and Remote Sensing provide unprecedented possibilities for changing how we monitor, analyse, and manage the environment. To harness these opportunities to their utmost, we need a global collective effort spanning innovation and inclusivity, and technology and policy, in a manner of ensuring spatial intelligence as the foundation of sustainable development and ecological resiliency for the coming decades.

REFERENCES

1. Ibebuchi, C.C., Abu, I.O. Interpolation of environmental data using deep learning and model inference. Machine Learning Science and Technology, 2024; volume 5, no. 2:025046 (https://doi.org/10.1088/2632-2153/ad4b94).
2. Mitchell, L.J., Williamson, B.J., Masden, E.A. Methods for highlighting ecological monitoring needs in data-sparse regions: a case study of impact assessment for multi-component infrastructure installations. Environmental Impact Assessment Review, 2024; volume 30, no. 105:107433 (https://doi.org/10.1016/j.eiar.2024.107433).
3. Yuan, Q., Shen, H., Li, T., Li, Z., Li, S., Jiang, Y., Xu, H., Tan, W., Yang, Q., Wang, J., Gao, J., Zhang, L. Deep learning in environmental remote sensing: Achievements and chal-

lenges. Remote Sensing of Environment, 2020; volume 27, no. 241:111716 (https://doi.org/10.1016/j.rse.2020.111716).
4. Sani, S.A., Ibrahim, A., Musa, A.A., Dahiru, M., Baballe, M.A. Drawbacks of traditional environmental monitoring systems. Computer and Information Science, 2023; volume 30, no. 16(3):30 (https://doi.org/10.5539/cis.v16n3p30).
5. Zhu, Y., Geiß, C., So, E. Image super-resolution with dense--sampling residual channel-spatial attention networks for multi-temporal remote sensing image classification. International Journal of Applied Earth Observation and Geoinformation, 2021; volume 20, no. 104:102543 (https://doi.org/10.1016/j.jag.2021.102543).
6. Liu, D., Zheng, X., Wang, H. Land-use Simulation and Decision-Support system (LandSDS): Seamlessly integrating system dynamics, agent-based model, and cellular automata. Ecological Modelling, 2020; volume 7, no. 417:108924 (https://doi.org/10.1016/j.ecolmodel.2019.108924).
7. Zhang, P., Wu, W., Xue, C., Shi, S., Su, F. A New Framework for Integrating DNN-Based Geographic Simulation Models within GISystems. ISPRS International Journal of Geo-Information, 2024; volume 14, no. 13(10):361 (https://doi.org/10.3390/ijgi13100361).
8. Akiang, F.B., Nnaji, V.N., Opara, A.I., Agoha, C.C., Agbasi, O.E., Ulem, E.B., Njoku, J.O.. Geospatial and geo-electrical assessment of groundwater vulnerability and potential in parts of Cross River, Southern Nigeria. HydroResearch, 2024; volume 1 (https://doi.org/10.1016/j.hydres.2024.09.007).
9. Okoli, E., Akaolisa, C.C.Z., Ubechu, B.O., Agbasi, O.E., Szafarczyk, A. Using VES and GIS-Based DRASTIC analysis to evaluate groundwater aquifer contamination vulnerability in Owerri, southeastern Nigeria. Ecological Questions, 2024; volume 18, no. 35(3), pp. 1–27 (https://doi.org/10.12775/eq.2024.031).
10. Rowland, A., Ebuka, A.O. Assessing the Impact of Land Cover and Land Use Change on Urban Infrastructure Resilience in Abuja, Nigeria: A Case Study From 2017 To 2022. Structure and Environment, 2024; volume 29, no. 16(1), pp. 6–17 (https://doi.org/10.30540/sae-2024-002).
11. Aziz, N.A., Alwan, I.A., Agbasi, O.E. Integrating remote sensing and GIS techniques for effective watershed management: a case study of Wadi Al-Naft Basins in Diyala Governorate, Iraq, using ALOS PALSAR digital elevation model. Applied Geomatics, 2023; volume 2, no. 16(1), pp. 67–76 (https://doi.org/10.1007/s12518-023-00540-9).
12. Akaolisa, C.C., Agbasi, O.E., Etuk, S.E., Adewumi, R., Okoli, E.A. Evaluating the effects of real estate development in Owerri, Imo State, Nigeria: Emphasizing changes in Land Use/Land Cover (LULC). Journal of Landscape Ecology, 2023; volume 1, no. 16(2), pp. 98–113 (https://doi.org/10.2478/jlecol-2023-0012).
13. Himeur, Y., Rimal, B., Tiwary, A., Amira, A. Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. Information Fusion, 2022; volume 25, no. 86–87, pp. 44–75 (https://doi.org/10.1016/j.inffus.2022.06.003)
14. Alotaibi, E., Nassif, N. Artificial intelligence in environmental monitoring: in-depth analysis. Discover Artificial Intelligence, 2024; volume 18, no. 4(1) (https://doi.org/10.1007/s44163-024-00198-1).
15. Gessa, A., Sancha, P. Environmental open data in Urban Platforms: An approach to the big data Life cycle. Journal of Urban Technology, 2019; volume 26, no. 27(1), pp. 27–45 (https://doi.org/10.1080/10630732.2019.1656934).
16. Quamar, M.M., Al-Ramadan, B., Khan, K., Shafiullah, M., Ferik, S.E. Advancements and Applications of Drone-Integrated Geographic Information System Technology —A Review. Remote Sensing, 2023; volume 20, no. 15(20):5039 (https://doi.org/10.3390/rs15205039).
17. Anderson, K., Griffiths, D., DeBell, L., Hancock, S., Duffy, J.P., Shutler, J.D., et al. A grassroots remote sensing toolkit using live coding, smartphones, kites and lightweight drones. PLoS ONE, 2016; volume 4, no. 11(5):e0151564 (https://doi.org/10.1371/journal.pone.0151564).
18. Vasiliades, M.A., Hadjichambis, A.Ch., Paraskeva-Hadjichambi, D., Adamou, A., Georgiou, Y. A systematic literature review on the participation aspects of Environmental and Nature-Based Citizen Science initiatives. Sustainability, 2021; volume 3, no. 13(13):7457 (https://doi.org/10.3390/su13137457).
19. Lary, D.J., Alavi, A.H., Gandomi, A.H., Walker, A.L. Machine learning in geosciences and remote sensing. Geoscience Frontiers, 2015; volume 12, no. 7(1), pp. 3–10. (https://doi.org/10.1016/j.gsf.2015.07.003).
20. Chen, H., Yang, L., Wu, Q. Enhancing land cover Mapping and Monitoring: an interactive and explainable machine learning approach using Google Earth engine. Remote Sensing, 2023; volume 18, no. 15(18):4585 (https://doi.org/10.3390/rs15184585).
21. Janga, B., Asamani, G., Sun, Z., Cristea, N. A review of practical AI for remote sensing in Earth Sciences. Remote Sensing, 2023; volume 21, no. 15(16):4112 (https://doi.org/10.3390/rs15164112).
22. Varma, B., Naik, N., Chandrasekaran, K., Venkatesan, M., Rajan, J. Forecasting Land-Use and Land-Cover change using hybrid CNN–LSTM model. IEEE Geoscience and Remote Sensing Letters, 2024; volume 1, no. 21, pp. 1–5 (https://doi.org/10.1109/lgrs.2024.3389671).
23. Prokop, K., Połap, D., Włodarczyk-Sielicka, M., Połap, K., Jaszcz, A., Stateczny, A. Automated shoreline extraction process for unmanned vehicles via U-net with heuristic algorithm. Alexandria Engineering Journal, 2024; volume 5, no. 102, pp. 108–18 (https://doi.org/10.1016/j.aej.2024.05.104).
24. Takhtkeshha, N., Mohammadzadeh, A., Salehi, B. A rapid Self-Supervised Deep-Learning-Based method for Post--Earthquake damage detection using UAV data (Case study: Sarpol-e Zahab, Iran). Remote Sensing, 2022; volume 26, no. 15(1), pp. 123 (https://doi.org/10.3390/rs15010123).
25. Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., Brisco, B. Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. ISPRS Journal of Photogrammetry and Remote Sensing, 2020; volume 7, no. 164, pp. 152–70 (https://doi.org/10.1016/j.isprsjprs.2020.04.001).

26. Amani, M., Ghorbanian, A., Ahmadi, S.A., Kakooei, M., Moghimi, A., Mirmazloumi, S.M. Google Earth Engine Cloud computing platform for remote sensing big data Applications: A Comprehensive review. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020; volume 1, no. 13, pp. 5326–5350 (https://doi.org/10.1109/jstars.2020.3021052).
27. Gu, Q., Michanowicz, D.R., Jia, C. Developing a modular Unmanned aerial Vehicle (UAV) platform for air pollution profiling. Sensors, 2018; volume 10, no. 18(12):4363 (https://doi.org/10.3390/s18124363).
28. Rahman, M.M., Siddique, S., Kamal, M., Rifat, R.H., Gupta, K.D. UAV (Unmanned Aerial Vehicle): diverse applications of UAV datasets in segmentation, classification, detection, and tracking. Algorithms, 2024; volume 23, no. 7(12), pp. 594 (https://doi.org/10.3390/a17120594).
29. Han, S., Han, D. Enhancing Direct Georeferencing Using Real-Time Kinematic UAVs and Structure from Motion-Based Photogrammetry for Large-Scale Infrastructure. Drones, 2024; volume 5, no. 8(12) (https://doi.org/10.3390/drones8120736).
30. Feng, X., He, L., Cheng, Q., Long, X., Yuan, Y. Hyperspectral and multispectral remote sensing image fusion based on endmember spatial information. Remote Sensing, 2020; volume 21, no. 12(6):1009 (https://doi.org/10.3390/rs12061009).
31. Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R. Sousa, J.J. Hyperspectral Imaging: A review on UAV-Based sensors, data processing and applications for agriculture and forestry. Remote Sensing, 2017, volume 30, no. 9(11):1110 (https://doi.org/10.3390/rs9111110).
32. Sekertekin, A., Arslan, N. Monitoring thermal anomaly and radiative heat flux using thermal infrared satellite imagery – A case study at Tuzla geothermal region. Geothermics, 2018; volume 29, no. 78, pp. 243–254 (https://doi.org/10.1016/j.geothermics.2018.12.014).
33. Chen, L., Mao, Y., Zhao, R. GIS application in environmental monitoring and risk assessment. 2022 3rd International Conference on Geology, Mapping and Remote Sensing (ICGMRS), 2022; volume 22, pp. 908–917 (https://doi.org/10.1109/icgmrs55602.2022.9849269).
34. Paul, K., Chatterjee, S.S., Pai, P., Varshney, A., Juikar, S., Prasad, V., Bhadra, B., Dasgupta, S. Viable smart sensors and their application in data driven agriculture. Computers and Electronics in Agriculture, 2022; volume 1, no. 198:107096 (https://doi.org/10.1016/j.compag.2022.107096).
35. Govea; J., Gaibor-Naranjo, W., Sanchez-Viteri, S., Villegas-Ch, W. Integration of data and predictive models for the evaluation of air quality and noise in urban environments. Sensors, 2024; volume 5, no. 24(2):311 (https://doi.org/10.3390/s24020311).
36. Rossetto, R., De Filippis, G., Borsi, I., Foglia, L., Cannata, M., Criollo, R., Vázquez-Suñé, E. Integrating free and open source tools and distributed modelling codes in GIS environment for data-based groundwater management. Environmental Modelling & Software, 2018; volume 22, no. 107, pp. 210–230 (https://doi.org/10.1016/j.envsoft.2018.06.007).
37. Castell, N., Kobernus, M., Liu, H.Y., Schneider, P., Lahoz, W., Berre, A.J., Noll, J. Mobile technologies and services for environmental monitoring: The Citi-Sense-MOB approach. Urban Climate, 2014; volume 12, no. 14, pp. 70–82 (https://doi.org/10.1016/j.uclim.2014.08.002).
38. Amitrano, D., Di Martino, G., Guida, R., Iervolino, P., Iodice, A., Papa, M.N., Riccio, D., Ruelo, G. Earth Environmental Monitoring Using Multi-Temporal Synthetic Aperture Radar: A Critical Review of selected applications. Remote Sensing, 2021; volume 8, no. 13(4):604 (https://doi.org/10.3390/rs13040604).
39. Santoro, M., Cartus, O. Research Pathways of Forest Above-Ground Biomass estimation based on SAR backscatter and interferometric SAR observations. Remote Sensing, 2018; volume 14, no. 10(4):608 (https://doi.org/10.3390/rs10040608).
40. Park, S.E., Jung, Y.T., Kim, H.C. Monitoring permafrost changes in central Yakutia using optical and polarimetric SAR data. Remote Sensing of Environment, 2022; volume 28, no. 74:112989 (https://doi.org/10.1016/j.rse.2022.112989).
41. Asori, M., Dogbey, E., Morgan, A.K., Ampofo, S.T., Mpobi, R.K.J., Katey, D. Application of GIS-based multi-criteria decision making analysis (GIS-MCDA) in selecting locations most suitable for siting engineered landfills – the case of Ashanti Region, Ghana. Management of Environmental Quality an International, 2022; volume 31, no. 33(3), pp. 800–826 (https://doi.org/10.1108/meq-07-2021-0159).
42. Sánchez-Lozano, J.M., Bernal-Conesa, J.A. Environmental management of Natura 2000 network areas through the combination of Geographic Information Systems (GIS) with Multi-Criteria Decision Making (MCDM) methods. Case study in south-eastern Spain. Land Use Policy, 2017; volume 30, no. 63, pp. 86–97 (https://doi.org/10.1016/j.landusepol.2017.01.021).
43. De Miguel González, R., Mar-Beguería, J., López, M.S., Kratochvíl, O. GIS-Based Dashboards as advanced geospatial applications for climate change education and teaching the future. ISPRS International Journal of Geo-Information, 2025; volume 18, no. 14(2):89 (https://doi.org/10.3390/ijgi14020089).
44. Yan, J., Wang, L., Song, W., Chen, Y., Chen, X., Deng, Z. A time-series classification approach based on change detection for rapid land cover mapping. ISPRS Journal of Photogrammetry and Remote Sensing, 2019; volume 7, no. 158, pp. 249–262 (https://doi.org/10.1016/j.isprsjprs.2019.10.003).
45. Li, Z., Weng, Q., Zhou, Y., Dou, P., Ding, X. Learning spectral-indices-fused deep models for time-series land use and land cover mapping in cloud-prone areas: The case of Pearl River Delta. Remote Sensing of Environment, 2024; volume 4, no. 308:114190 (https://doi.org/10.1016/j.rse.2024.114190).
46. Pavelka, K., Landa, M. Using Virtual and Augmented Reality with GIS Data. ISPRS International Journal of Geo-Information, 2024; volume 5, no. 13(7):241 (https://doi.org/10.3390/ijgi13070241).
47. Fridhi, A., Frihida, A. GIS 3D and Science of Augmented Reality: Modeling a 3D geospatial environment. DOAJ

(DOAJ: Directory of Open Access Journals), 2019; volume 1, (https://doaj.org/article/f677385247c74868b739ef341f67196a).
48. Lin, M.H., Lin, Y.T., Tsai, M.L., Chen, Y.Y., Chen, Y.C., Wang, H.C., Wang, C.K. Mapping land-use and land-cover changes through the integration of satellite and airborne remote sensing data. Environmental Monitoring and Assessment, 2024; volume 8, no. 96(3) (https://doi.org/10.1007/s10661-024-12424-5).
49. Harish, B., Manjulavani, K., Shantosh, M., Supriya, V.M. Change detection of land use and land cover using remote sensing techniques. 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), 2017; volume 1, no. 64, pp. 2806–2810 (https://doi.org/10.1109/icpcsi.2017.8392231).
50. Su, T., Zhang, S., Liu, T. Multi-Spectral image classification based on an Object-Based Active Learning approach. Remote Sensing, 2020; volume 4, no. 12(3), pp. 504 (https://doi.org/10.3390/rs12030504).
51. Abera, T., Pellikka, P., Johansson, T., Mwamodenyi, J., Heiskanen, J. Towards tree-based systems disturbance monitoring of tropical mosaic landscape using a time series ensemble learning approach. Remote Sensing of Environment, 2023; volume 27, no. 299:113876 (https://doi.org/10.1016/j.rse.2023.113876).
52. Mohamed, A., Worku, H. Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. Urban Climate, 2019; volume 3, no. 31:100545 (https://doi.org/10.1016/j.uclim.2019.100545).
53. Rugel, G.M.V., Ochoa, D., Menendez, J.M., Van Coillie, F. Evaluating the applicability of global LULC products and an Author-Generated Phenology-Based Map for regional analysis: a case study in Ecuador's ecoregions. Land, 2023: volume, 22, no. 12(5), pp. 1112 (https://doi.org/10.3390/land12051112).
54. Vallet, A., Dupuy, S. Verlynde, M., Gaetano, R. Generating high-resolution land use and land cover maps for the greater Mariño watershed in 2019 with machine learning. Scientific Data, 2024; volume 23, no. 11(1) (https://doi.org/10.1038/s41597-024-03750-x).
55. Lippe, M., Hilger, T., Sudchalee, S., Wechpibal, N., Jintrawet, A., Cadisch, G. Simulating Stakeholder-Based Land-Use change scenarios and their implication on Above-Ground carbon and Environmental Management in Northern Thailand. Land, 2017; volume 3, no. 6(4), pp. 85 (https://doi.org/10.3390/land6040085).
56. Ross, M.R.V., Topp, S.N., Appling, A.P., Yang, X., Kuhn, C., Butman, D., Simard, M., Pavelsky, T.M. AquASAT: a data set to enable remote sensing of water quality for inland waters. Water Resources Research, 2019; volume 11, no. 55(11), pp. 10012–10025 (https://doi.org/10.1029/2019wr024883).
57. Yang, H., Kong, J., Hu, H., Du, Y., Gao, M., Chen, F. A review of Remote sensing for water quality Retrieval: Progress and challenges. Remote Sensing, 2022; volume 7, no. 14(8), pp. 1770 (https://doi.org/10.3390/rs14081770).
58. Yan, T., Shen, S.L., Zhou, A. Indices and models of surface water quality assessment: Review and perspectives. Environmental Pollution, 2022; volume 15, no. 308, pp. 119611 (https://doi.org/10.1016/j.envpol.2022.119611).
59. Verma, R., Sharif, M., Husain, A. Application of HEC-HMS for hydrological modeling of Upper Sabarmati River Basin, Gujarat, India. Modeling Earth Systems and Environment, 2022; volume 25, no. 8(4), pp. 5585–5593 (https://doi.org/10.1007/s40808-022-01411-9).
60. Operational overview of the application of remote sensing and hydrography for coastal zone management. Journal of Earth and Environmental Sciences, 2020; volume 1 (https://doi.org/10.29011/2577-0640.100191).
61. Sulaiman, N., Abdullah, N.M., Nazir, U., Ismail, M., Latib, S.K.K.A., Mahmud, N.P.N. Geographical Information System (GIS) and Remote sensing (RS) applications in Disaster Risk Reduction (DRR) in Malaysia. International Journal of Integrated Engineering, 2022; volume 6, no. 14(5) (https://doi.org/10.30880/ijie.2022.14.05.003).
62. Nabukonde, A., Barakagira, A., Akwango, D. The Use of Geographical Information System (GIS) and Remote Sensing (RS) Technologies in Generation of Information Used to Mitigate Risks from Landslide Disasters: An Application Review. Archives of Current Research International, 2023; volume 8, no. 23(2), pp. 43–49 (https://doi.org/10.9734/acri/2023/v23i2558).
63. Joiner, J., Yoshida, Y., Anderson, M., Holmes, T., Hain, C., Reichle, R., koster, R., Middleton, E., Zeng, F.W. Global relationships among traditional reflectance vegetation indices (NDVI and NDII), evapotranspiration (ET), and soil moisture variability on weekly timescales. Remote Sensing of Environment, 2018; volume 25, no. 219, pp. 339–352 (https://doi.org/10.1016/j.rse.2018.10.020).
64. Chaabane, F.Z., Lamine, S., Guettouche, M.S., Bachari, N.E.I., Hallal, N. Landslide Risk Assessments through Multicriteria Analysis. ISPRS International Journal of Geo-Information, 2024; volume 25, no. 13(9), pp. 303 (https://doi.org/10.3390/ijgi13090303).
65. Whitehurst, D., Joshi, K., Kochersberger, K., Weeks, J. Post-Flood analysis for damage and restoration assessment using drone imagery. Remote Sensing, 2022; volume 4, no. 14(19), pp. 4952 (https://doi.org/10.3390/rs14194952).
66. Xia, H., Chen, Y., Song, C., Li, J., Quan, J., Zhou, G. Analysis of surface urban heat islands based on local climate zones via spatiotemporally enhanced land surface temperature. Remote Sensing of Environment, 2022; volume 8, no. 273:112972 (https://doi.org/10.1016/j.rse.2022.112972).
67. De Almeida, C.R., Teodoro, A.C., Gonçalves, A. Study of the Urban Heat Island (UHI) Using Remote Sensing Data/Techniques: A Systematic Review. Environments, 2021; volume 9, no. 8(10), pp. 105 (https://doi.org/10.3390/environments8100105).
68. Leitão, P.J., Santos, M.J. Improving models of species Ecological niches: A remote sensing overview. Frontiers in Ecology and Evolution, 2019; volume 29, no. 7 (https://doi.org/10.3389/fevo.2019.00009).

69. Zhang, X., Zhou, Y., Peng, P., Wang, G. A novel multimodal species distribution model fusing remote sensing images and environmental features. Sustainability, 2022; volume 28, no. 14(21):14034 (https://doi.org/10.3390/su142114034).
70. Reiche, J., Mullissa, A., Slagter, B., Gou, Y., Tsendbazar, N.E., Odongo-Braun, C., Vollrath, A., Weisse, M.J., Stolle, F., Pickens, A. Forest disturbance alerts for the Congo Basin using Sentinel-1. Environmental Research Letters, 2021; volume 19, no. 6(2):024005 (https://doi.org/10.1088/1748-9326/abd0a8).
71. Adams, C.E., Garcia-Carreras, L. Detection of Land-Use Change and Rapid Recovery of Vegetation after Deforestation in the Congo Basin. Earth Interactions, 2023; volume 1, no. 27(1) (https://doi.org/10.1175/ei-d-22-0020.1).
72. Kowler, L.F., Pratihast, A.K., Del Arco, A.P.O., Larson, A.M., Braun, C., Herold, M. Aiming for sustainability and scalability: community engagement in forest payment schemes. Forests, 2020; volume 15, no. 11(4), pp. 444 (https://doi.org/10.3390/f11040444).
73. Abdourahamane, Z.S., Garba, I., Boukary, A.G., Mirzabaev, A. Spatiotemporal characterization of agricultural drought in the Sahel region using a composite drought index. Journal of Arid Environments, 2022; volume 16, no. 204:104789 (https://doi.org/10.1016/j.jaridenv.2022.104789).
74. Rembold, F., Meroni, M., Urbano, F., Csak, G., Kerdiles, H., Perez-Hoyos, A., Lemoine, G., Leo, O., Negre, T. ASAP: A new global early warning system to detect anomaly hot spots of agricultural production for food security analysis. Agricultural Systems, 2018; volume 15, no. 168, pp. 247–257 (https://doi.org/10.1016/j.agsy.2018.07.002).
75. Uddin, K., Matin, M.A., Meyer, F.J. Operational Flood Mapping Using Multi-Temporal Sentinel-1 SAR Images: A Case Study from Bangladesh. Remote Sensing, 2019; volume 3, no. 11(13), pp. 1581 (https://doi.org/10.3390/rs11131581).
76. Rehman, A.U., Lyche, T., Awuah-Offei, K., Nadendla, V.S.S. Effect of text message alerts on miners evacuation decisions. Safety Science, 2020; volume 17, no. 130:104875 (https://doi.org/10.1016/j.ssci.2020.104875).
77. Polo, M.J. Earth Observation Science and Applications for Risk Reduction and Enhanced Resilience in Hindu Kush Himalaya Region: A Decade of Experience from SERVIR. Edited by Birendra Bajracharya, Rajesh Bahadur Thapa, and Mir A. Matin. Mountain Research and Development, 2022; volume 17, no. 42(2) (https://doi.org/10.1659/mrd.mm273.1).
78. Meyer, R., Davies, N., Pitz, K.J., Meyer, C., Samuel, R., Anderson, J., Appeltans, W., Barker, K., Chavez, F.P., Duffy, J.E., Goodwin, K.D., Hudson, M., Hunter, M.E., Karstensen, J., Laney, C.M., Leinen, M., Mabee, P., Macklin, J.A., Muller-Karger, F., Pade, N., Pearlman, J., Phillips, L., Provoost, P., Santi, I., Schigel, D., Schriml, L.M., Soccodato, A., Suominen, S., Thibault, K.M., Ung, V., de Kamp, J., Wallis, E., Walls, R., Buttigieg, P.L. The founding charter of the Omic Biodiversity Observation Network (Omic BON). GigaScience, 2022; volume 28, no. 12 (https://doi.org/10.1093/gigascience/giad068).
79. Himeur, Y., Rimal, B., Tiwary, A., Amira, A. Using artificial intelligence and data fusion for environmental monitoring: A review and future perspectives. Information Fusion, 2022; volume 25, no. 86–87, pp. 44–75 (https://doi.org/10.1016/j.inffus.2022.06.003).
80. Safonova, A., Ghazaryan, G., Stiller, S., Main-Knorn, M., Nendel, C., Ryo, M. Ten deep learning techniques to address small data problems with remote sensing. International Journal of Applied Earth Observation and Geoinformation, 2023; volume 18, no. 125:103569 (https://doi.org/10.1016/j.jag.2023.103569).
81. Zhang, Z., Zhang, Q., Hu, X., Zhang, M., Zhu, D. On the automatic quality assessment of annotated sample data for object extraction from remote sensing imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 2023; volume 1, no. 201, pp. 153–73 (https://doi.org/10.1016/j.isprsjprs.2023.05.026).
82. Downes, J., Bruce, D., Da Silva, G.M., Hesp, P.A. Optimising Satellite-Derived Bathymetry Using Optical Imagery over the Adelaide Metropolitan Coast. Remote Sensing, 2025; volume 28, no. 17(5), pp. 849 (https://doi.org/10.3390/rs17050849).
83. Lagunes-Gómez, I., Hernández-Orduña, M., Murrieta-Galindo, R., Hernández-Pitalua, D., Mayorga-Cruz, D. Spatial Analysis of the Empirical Behavior of Municipal Institutional Capacity for the Formulation of Sustainable Growth Management Strategies with a Regional Focus: State of Veracruz, Mexico. Sustainability, 2022; volume 10, no. 4(4), pp. 2000 (https://doi.org/10.3390/su14042000).
84. Pandey, V., Kipf, A., Neumann, T., Kemper, A. How good are modern spatial analytics systems? Proceedings of the VLDB Endowment, 2018; volume 1, no. 11(11), pp. 1661–1673 (https://doi.org/10.14778/3236187.3236213).
85. Minde, J.M., Gerlak, A.K., Colella, T., Murveit, A.M. Re-examining geospatial online participatory Tools for environmental Planning. Environmental Management, 2024; volume 15, no. 73(6), pp. 1276–1292 (https://doi.org/10.1007/s00267-024-01973-7).
86. Scott, G., Rajabifard, A. Sustainable development and geospatial information: a strategic framework for integrating a global policy agenda into national geospatial capabilities. Geo-spatial Information Science, 2017; volume 3, no. 20(2), pp. 59–76 (https://doi.org/10.1080/10095020.2017.1325594).
87. Qwaider, S., Al-Ramadan, B., Shafiullah, M., Islam, A., Worku, M.Y. GIS-Based Progress Monitoring of SDGs towards Achieving Saudi Vision 2030. Remote Sensing, 2023; volume 17, no. 15(24), pp. 5770 (https://doi.org/10.3390/rs15245770).
88. Akanbi, A., Masinde, M. A distributed stream processing middleware framework for Real-Time analysis of heterogeneous data on big data platform: case of environmental monitoring. Sensors, 2020; volume 3, no. 20(11), pp. 3166 (https://doi.org/10.3390/s20113166).
89. Chandra, G.R., Bhatia, S. Issues and concerns in the field of remote sensing. 2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and

Future Directions) (ICRITO), 2020; volume 1, pp. 654–658 (https://doi.org/10.1109/icrito48877.2020.9197901).
90. Lombardo, L., Corbellini, S., Parvis, M., Elsayed, A., Angelini, E., Grassini, S. Wireless sensor network for distributed environmental monitoring. IEEE Transactions on Instrumentation and Measurement, 2017; volume 11, no. 67(5), pp. 1214–1222 (https://doi.org/10.1109/tim.2017.2771979).
91. Fraisl, D., Hager, G., Bedessem, B., Gold, M., Hsing, P.Y., Danielsen, F., Hitchcock, C.B., Hulbert, J.M., Piera, J., Spiers, H., Thiela, M., Hakla, M. Citizen science in environmental and ecological sciences. Nature Reviews Methods Primers, 2022; volume 25, no. 2(1) (https://doi.org/10.1038/s43586-022-00144-4).
92. Spaans, R.H., Drumond, B., Van Daalen, K.R., Vitor, A.C.R., Derbyshire, A., Da Silva, A., Lana, R.M., Vega, M.S., Carrasco-Escobar, G., Escada, M.I.S., Codeço, C., Lowe, R. Ethical considerations related to drone use for environment and health research: A scoping review protocol. PLoS ONE, 2024; volume 31, no. 19(1):e0287270 (https://doi.org/10.1371/journal.pone.0287270).