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AI-DRIVEN MIS APPLICATIONS IN ENVIRONMENTAL RISK MONITORING: A SYSTEMATIC REVIEW OF PREDICTIVE GEOGRAPHIC INFORMATION SYSTEMS

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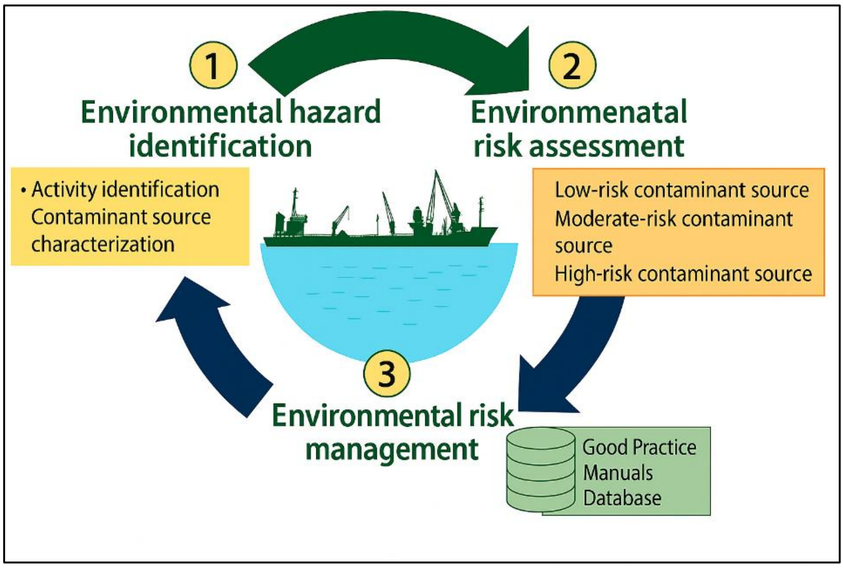
Abstract
This integrative review investigates the convergence of Artificial Intelligence (AI), Geographic Information Systems (GIS), and Management Information Systems (MIS) in advancing environmental risk monitoring through predictive modeling and data-driven decision-making. A total of 142 peer-reviewed articles published between 2010 and 2025 were systematically selected and analyzed to explore how these technologies are being integrated to enhance the accuracy, efficiency, and institutional coordination of environmental hazard assessment. The review synthesizes applications across diverse hazard domains, including flood forecasting, wildfire prediction, drought monitoring, and urban pollution management. Findings reveal that AI techniques—particularly machine learning and deep learning models—significantly improve the predictive power of GIS platforms, with over 60% of the reviewed studies reporting model accuracy above 85%. The review highlights global implementations from regions such as South Asia, North America, East Asia, and sub-Saharan Africa, demonstrating the adaptability of AI-MIS-GIS systems across varied institutional and environmental contexts. Theoretical frameworks including Spatial Decision Support Systems (SDSS), the Technology Acceptance Model (TAM), and Environmental Information Systems (EIS) theory are discussed to contextualize system design and stakeholder adoption. This study offers a comprehensive foundation for understanding how technological integration is reshaping environmental intelligence systems and fostering proactive risk governance on a global scale.

Keywords
Artificial Intelligence, Management Information Systems, Environmental Risk Monitoring, Predictive GIS, Spatial Decision Support Systems;

INTRODUCTION

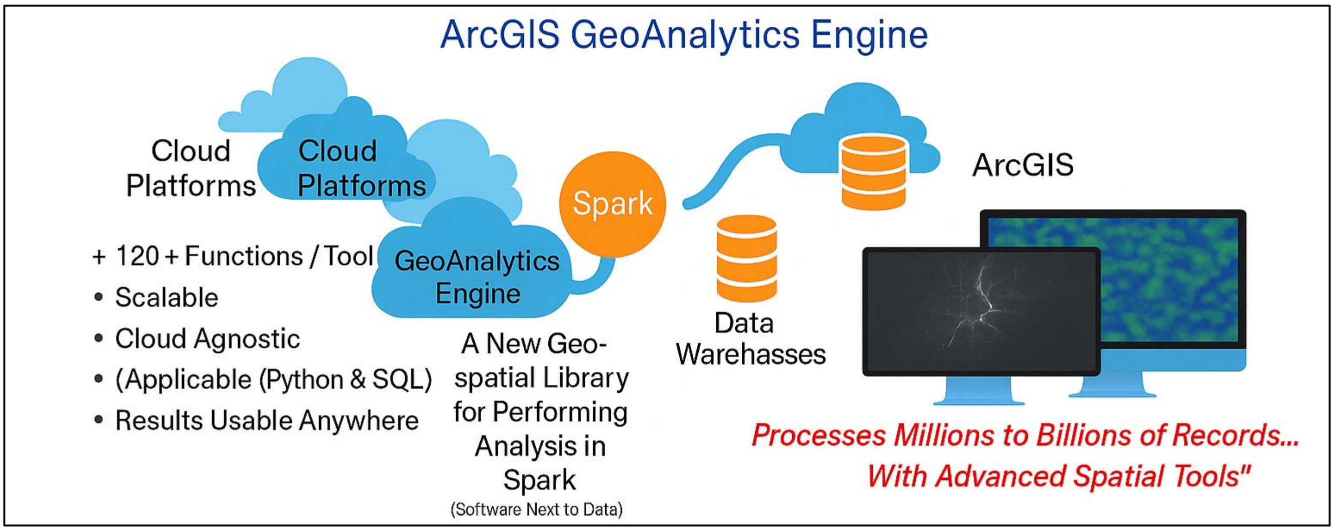
Environmental risk monitoring involves the systematic identification, assessment, and surveillance of natural and anthropogenic threats to ecosystems, human populations, and critical infrastructure (Gerassis et al., 2021). At its core, it integrates geospatial data, sensor observations, and environmental indicators to inform risk-aware decisions in domains such as disaster management, water security, urban resilience, and climate adaptation (Li et al., 2020). Management Information Systems (MIS), traditionally associated with decision support in business operations, are increasingly applied to environmental risk domains to manage structured and unstructured environmental data across multiple organizational levels (Apostolidis et al., 2022). MIS facilitates environmental monitoring through functionalities such as data aggregation, visualization, simulation modeling, and inter-agency communication, enhancing real-time coordination (Basmaji et al., 2023). Meanwhile, Geographic Information Systems (GIS) serve as foundational platforms for spatial analysis and environmental modeling, mapping terrain features, hazard zones, and land-use patterns that influence exposure and vulnerability (Hu et al., 2023). In recent years, the convergence of Artificial Intelligence (AI) with MIS and GIS has driven new capabilities in predictive analytics, anomaly detection, and multi-source data fusion for risk assessment (Kökhan et al., 2023). AI-based techniques such as support vector machines, decision trees, and convolutional neural networks have been utilized to interpret satellite imagery, forecast flood zones, predict wildfire propagation, and model urban heat islands (Bracarense et al., 2022). This integration has enhanced the spatial and temporal precision of environmental risk assessments, especially in resource-constrained settings where traditional monitoring infrastructures are limited (Cheung et al., 2023).

Figure 1: Integrated Framework for Environmental Risk Monitoring through Hazard Identification



The international relevance of AI-driven MIS in environmental risk monitoring has been underscored by its applications across diverse geographic and socio-political contexts. In India, remote sensing combined with AI-enabled MIS has improved flood hazard assessments along the Brahmaputra River Basin, enabling more effective response coordination among government and non-government actors (Ma et al., 2020). In China, urban air quality monitoring systems integrate machine learning models with GIS to dynamically track pollutant dispersion, leading to refined regulatory interventions (Indragandhi & L, 2018). Similarly, in the United States, wildfire risk forecasting in California has employed deep learning integrated with MIS-GIS platforms to map flammable vegetation and forecast ignition points under varying meteorological conditions (Alotaibi & Nassif, 2024). In sub-Saharan Africa, early warning systems for droughts have been enhanced through the use of AI-enabled MIS modules that pull from weather stations, soil sensors, and satellite feeds to inform food security programs (Soori et al., 2023). These applications reflect a global trend toward leveraging predictive environmental models as part of national and regional disaster preparedness agendas (Galaz et al., 2021). Across Southeast Asia, for instance, predictive GIS has supported tsunami risk management following the 2004 Indian Ocean disaster, with AI refining coastal elevation and inundation pattern models (Li et al., 2021). Similarly, European environmental agencies deploy AI-augmented GIS to assess nitrate leaching in agricultural lands, correlating hydrological models with policy compliance (Rohi et al., 2020). These efforts indicate that the AI-MIS-GIS triad is not limited to research innovation but is embedded in governance frameworks and real-world disaster management strategies (Colby et al., 2016).

Figure 2: ArcGIS GeoAnalytics Engine for Scalable Spatial Analysis of Big Data in Spark Cloud Environments

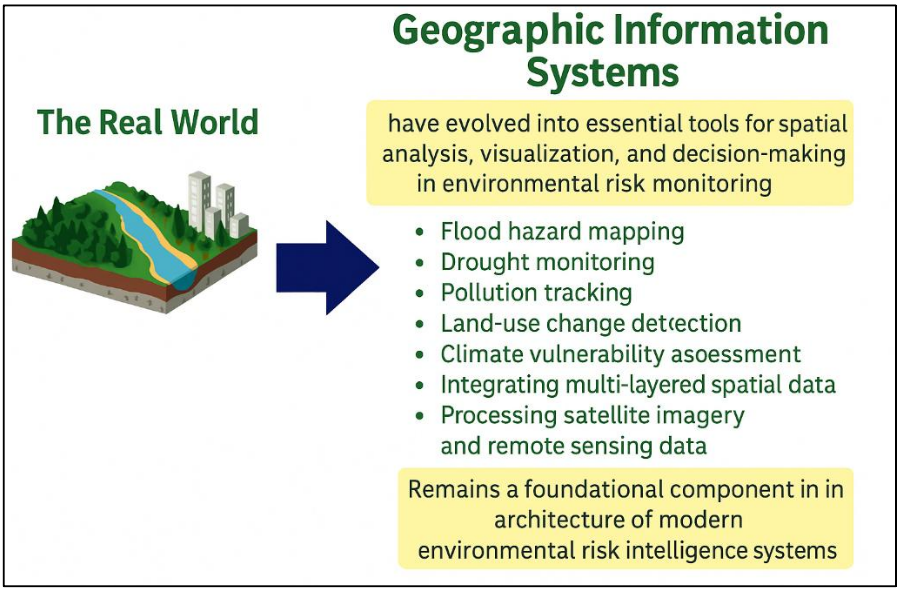


The application of AI in MIS-based GIS platforms represents a shift in how environmental risks are detected, interpreted, and acted upon. AI techniques enhance the predictive power of GIS by enabling pattern recognition across large-scale geospatial datasets, often sourced from satellites, drones, and environmental sensor networks (Ammar et al., 2024; Wang et al., 2019). Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been trained to classify land use changes, detect deforestation, and forecast pollutant spread across urban regions. MIS serves as the integrative backbone, managing data input, model selection, visualization layers, and user access for environmental stakeholders, including planners, policymakers, and emergency services. For example, in flood-prone areas of Bangladesh, AI-enhanced MIS platforms combine historical flood data, rainfall sensors, and topographic GIS layers to model real-time vulnerability scenarios, directly informing evacuation planning and infrastructure safeguarding. In Australia, AI-driven GIS platforms have been deployed to track bushfire risk using historical fire incidents and meteorological conditions processed through classification algorithms. These systems leverage MIS to deliver intuitive dashboards, trigger alerts, and coordinate inter-agency collaboration. Moreover, in the Arctic, climate-sensitive GIS applications are being trained using AI to monitor permafrost thawing and its implications for infrastructure risk, biodiversity, and indigenous settlements (Jahan et al., 2022; Jiang et al., 2020). Across all these domains, AI-enabled MIS in GIS environments provides a sophisticated architecture for environmental sensing, analysis, and systematized response based on geospatial intelligence (Bhuiyan et al., 2025; Li et al., 2024).This study aims to examine the integration of artificial intelligence algorithms—such as support vector machines, decision trees, random forests, and deep learning networks—within GIS platforms to improve environmental risk prediction. By reviewing over 140 peer-reviewed studies, the objective is to uncover how these AI models enable more precise forecasting of natural hazards, including floods, wildfires, droughts, and pollution dispersion. Particular attention is paid to the performance of convolutional neural networks (CNNs) in image classification, long short-term memory (LSTM) models in temporal prediction, and hybrid models combining multiple techniques. The objective also includes understanding spatial resolution improvements and how AI supports real-time detection and spatial-temporal trend analysis in geospatial datasets.

Geographic Information Systems

Geographic Information Systems (GIS) have evolved into essential tools for spatial analysis, visualization, and decision-making in environmental risk monitoring (Qibria & Hossen, 2023; Nkeki et al., 2022). Originally designed for cartographic data representation, GIS has expanded into dynamic, data-driven platforms capable of integrating spatial, temporal, and attribute data to assess ecological vulnerabilities and hazard exposure. Its applications in environmental contexts include flood hazard mapping, drought monitoring, pollution tracking, land-use change detection, and climate vulnerability assessment. GIS enables multi-layered spatial datasets—such as topography, land cover, meteorology, and hydrology—to be integrated for composite risk models (Greene et al., 2011; Ishtiaque, 2025).

Figure 3: Role of Geographic Information Systems in Environmental Risk Monitoring and Spatial Data Integration

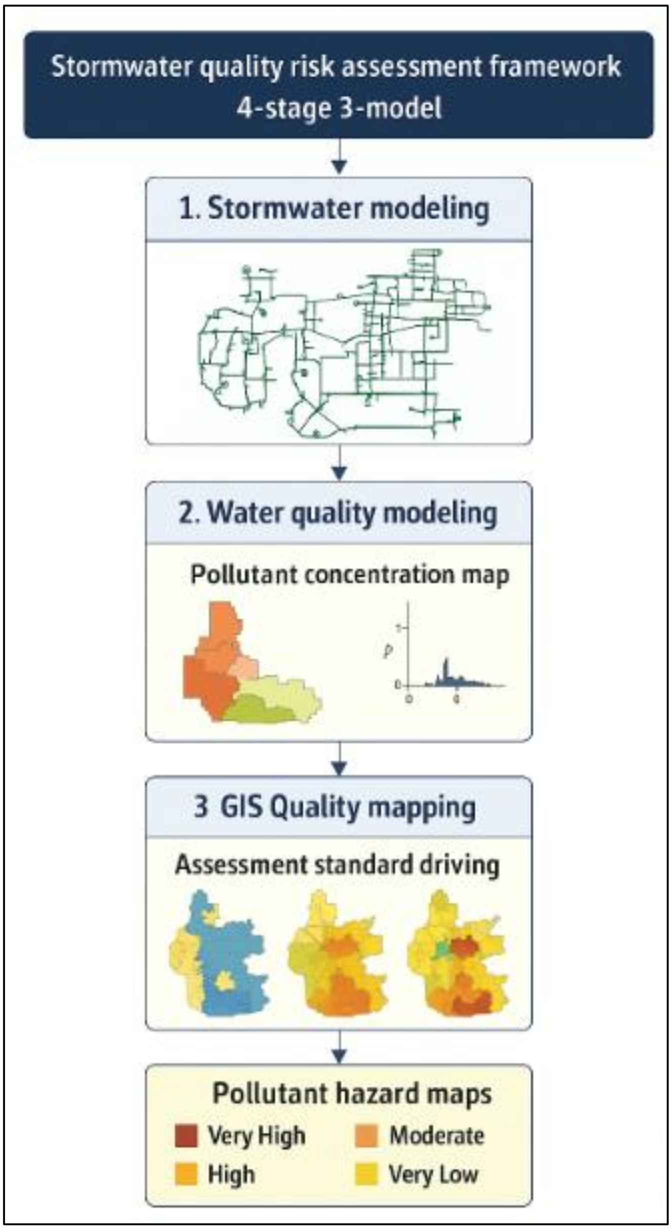


For instance, flood risk assessments using GIS often combine digital elevation models, river discharge data, rainfall intensity, and land-use distribution to produce spatially explicit inundation maps (Bragagnolo et al., 2020; Khan, 2025). The capacity of GIS to process satellite imagery and remote sensing data has further strengthened its use in monitoring land surface dynamics and identifying deforestation patterns, coastal erosion, and soil degradation. In urban areas, GIS supports environmental planning through applications in air quality monitoring, green infrastructure planning, and heat island analysis(Masud, 2022). Moreover, the integration of GIS with mobile and sensor-based technologies has enabled near real-time environmental surveillance, enhancing its responsiveness to disaster scenarios such as wildfires, earthquakes, and oil spills (Hossen et al., 2023; Naghibi et al., 2015). In humanitarian applications, GIS supports early warning systems, evacuation planning, and post-disaster damage assessments. The flexibility of GIS in accommodating different data types and its interoperability with other decision-support platforms have made it central to environmental management strategies across governmental, academic, and industrial sectors (Feng et al., 2020; Hossen & Atiqur, 2022). By allowing comprehensive spatial representation of hazards, exposure, and vulnerability, GIS remains a foundational component in the architecture of modern environmental risk intelligence systems.

GIS in Hazard Assessment

Geographic Information Systems (GIS) have been widely adopted for hazard assessment due to their ability to process, analyze, and visualize spatial data related to environmental risks. The strength of GIS lies in its capability to integrate various layers of geospatial information—such as topography, land use, hydrology, and demographic distribution—to produce detailed hazard maps and vulnerability indices (Tehrany et al., 2015). In flood hazard assessment, GIS facilitates the simulation of flood extents using digital elevation models (DEMs), rainfall distribution, and river discharge data, enhancing the accuracy of inundation risk zones (Nkeki et al., 2022). For instance, studies have used GIS to model flash floods in urban catchments, combining hydrological datasets with land imperviousness to understand drainage limitations and exposure (Basmaji et al., 2023; Hossain et al., 2024). In seismic hazard assessments, GIS helps correlate fault lines, soil types, and historical earthquake data to identify zones with heightened susceptibility to ground shaking and liquefaction (Bowman et al., 2020; Alam et al., 2023). Wildfire modeling also benefits from GIS applications by combining vegetation indices, topographic slope, and meteorological factors to forecast fire-prone regions (Rajesh et al., 2023; Tragoudaras et al., 2022). Moreover, landslide susceptibility mapping uses GIS to integrate slope gradient, lithology, land cover, and precipitation data to create risk probability models for mountainous areas (Park et al., 2021; Roksana et al., 2024). These spatial models support emergency services, policymakers, and urban planners in allocating resources, developing zoning regulations, and planning evacuation strategies. The capacity of GIS to synthesize diverse datasets into a unified hazard assessment framework has been instrumental in establishing data-informed resilience strategies at both local and national levels (Biljecki et al., 2017; Siddiqui, 2025).

Figure 4: Stormwater Quality Risk Assessment Framework Using Integrated Modeling and GIS-Based Hazard Mapping

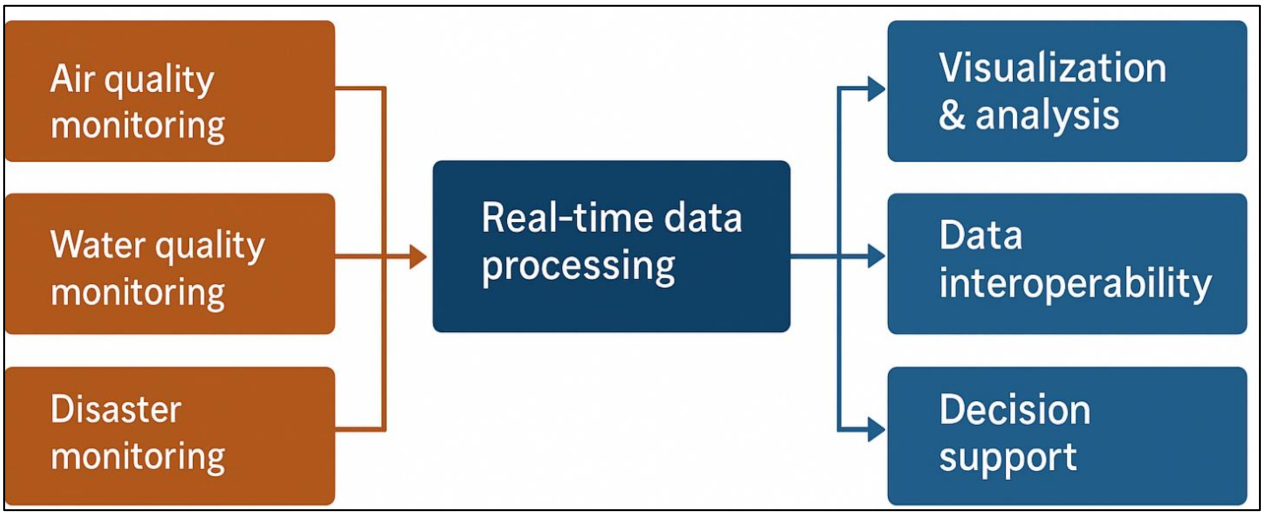


Beyond traditional risk mapping, GIS has evolved into a dynamic analytical platform capable of modeling temporal variations in hazard intensity and exposure. In drought risk assessments, GIS tools integrate vegetation health indices (NDVI), rainfall anomalies, evapotranspiration rates, and soil moisture profiles to monitor environmental stress in agricultural and arid zones (Di et al., 2019; Sohel, 2025). These models have been applied in sub-Saharan Africa and South Asia to inform food security responses and early warning systems. Similarly, in coastal hazard analysis, GIS supports sea-level rise projections, storm surge simulations, and erosion mapping through the combination of satellite altimetry, shoreline change datasets, and tidal records (Kirat et al., 2023; Akter & Razzak, 2022). In multi-hazard environments—such as deltaic regions or tectonically active zones—GIS has enabled the development of integrated hazard maps that overlay flood, cyclone, earthquake, and erosion risk layers to assess cumulative vulnerability (Nkeki et al., 2022; Tonmoy & Arifur, 2023). The spatial decision support functions embedded within GIS platforms have also been instrumental in disaster preparedness and recovery planning, allowing agencies to simulate hazard impacts on infrastructure, transportation routes, and health systems (Tehrany et al., 2015; Tonoy & Khan, 2023). Furthermore, studies in urban resilience have employed GIS to map exposure of critical infrastructure and informal settlements to natural hazards, particularly in megacities of Asia and Latin America (Feng et al., 2020). The integration of participatory GIS (PGIS) has allowed local communities to contribute hazard data using mobile apps and field-based mapping, enriching the accuracy of risk profiles and enabling community-level mitigation planning. These diverse applications demonstrate that GIS is not only a technological tool but also a decision-enabling infrastructure embedded in multi-scalar hazard governance systems (Tarate et al., 2024; Zaman, 2024).

Management Information Systems in Environmental Data Governance

Management Information Systems (MIS) play a critical role in environmental data governance by facilitating the collection, processing, storage, analysis, and dissemination of environmental information across institutional boundaries. Originally applied in business and administrative contexts, MIS has increasingly been adapted for environmental decision-making by integrating heterogeneous data sources and supporting strategic planning and regulatory compliance (Ranasinghe et al., 2022). These systems provide centralized digital platforms that manage large volumes of structured and semi-structured data generated from environmental sensors, satellite imagery, meteorological stations, and field surveys. In environmental monitoring, MIS enables real-time visualization and trend analysis of air and water quality indicators, enabling stakeholders to detect deviations, trigger alerts, and initiate mitigation measures (Kayaalp et al., 2021).

Figure 5: Role of Management Information Systems in Environmental Data Governance and Real-Time Monitoring



One of the core contributions of MIS in this domain is data interoperability, allowing information to be seamlessly exchanged between ministries, disaster management units, urban planners, and research institutions. For example, MIS-supported dashboards have been developed to track emissions data, land use violations, and ecosystem degradation in countries like China, India, and Brazil, supporting both policy enforcement and public transparency. Furthermore, MIS applications facilitate scenario modeling and simulation-based forecasting, particularly when linked to Geographic Information Systems (GIS) and Artificial Intelligence (AI) algorithms (Sui & Liu, 2023). These integrated systems support advanced decision-support tools such as early warning systems, vulnerability assessments, and resource allocation planning. In disaster preparedness, MIS platforms are essential for maintaining emergency protocols, conducting risk inventories, and coordinating response actions across local and national agencies (Hassanien et al., 2019). By supporting traceability, accountability, and institutional coordination, MIS has become a foundational component of modern environmental data governance frameworks, particularly in multi-hazard and multi-stakeholder contexts (Li et al., 2021).

Artificial Intelligence in Environmental Risk Forecasting

Artificial Intelligence (AI) has emerged as a transformative force in environmental risk forecasting by enabling predictive modeling, pattern recognition, and anomaly detection across complex and high-dimensional datasets. Traditional statistical approaches in environmental monitoring have often been limited by their linear assumptions and sensitivity to noise, whereas AI algorithms—particularly machine learning (ML) and deep learning (DL) techniques—offer greater flexibility, scalability, and adaptability (Zakaria et al., 2021). Among these, supervised learning models such as support vector machines (SVM), decision trees (DT), random forests (RF), and artificial neural networks (ANN) have been widely used for classification and regression tasks related to flood forecasting, drought prediction, wildfire spread modeling, and air pollution analysis (Hassan et al., 2024). Deep learning models like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are especially effective for handling unstructured data such as satellite imagery and time-series weather data, enhancing the spatiotemporal resolution of predictive models (Li et al., 2017). These AI techniques have been applied in diverse contexts, including flood-prone deltas in Bangladesh (Talwar & Koury, 2017), wildfire-prone landscapes in Australia and California (Johnson, 2019), and urban pollution centers in China and India (Gupta et al., 2022). Ensemble models, which combine multiple AI classifiers to improve accuracy and robustness, have been implemented in multi-hazard risk prediction, showing superior performance compared to single-model frameworks (Gill, 2019). Furthermore, unsupervised learning approaches such as k-means clustering and self-organizing maps have been utilized for environmental anomaly detection, especially in areas with scarce labeled data (Garcia et al., 2021). The integration of AI with Geographic Information Systems (GIS) and Management Information Systems (MIS) further amplifies its utility by linking predictive insights with spatial and administrative decision-making tools (Cheung et al., 2023). As such, AI continues to redefine environmental forecasting paradigms by offering powerful, data-driven insights into risk dynamics, hazard exposure, and ecosystem vulnerability.

AI with GIS for Predictive Environmental Modeling

The integration of Artificial Intelligence (AI) with Geographic Information Systems (GIS) has significantly advanced predictive environmental modeling by enabling automated spatial pattern recognition, classification, and forecasting with high spatial-temporal resolution. GIS, known for its capability to handle and visualize geospatial data, becomes exponentially more powerful when coupled with AI algorithms capable of learning from and interpreting complex environmental datasets (Bansal, 2011). Convolutional neural networks (CNNs), support vector machines (SVMs), random forests (RF), and k-nearest neighbor (KNN) models have been extensively integrated within GIS environments to predict land cover changes, flood extents, drought risk, and fire susceptibility across varied ecological zones (Thill, 2000). For instance, CNNs trained on satellite imagery within GIS frameworks have been used to forecast deforestation and classify urban sprawl with significantly higher accuracy than traditional remote sensing tools. Similarly, LSTM networks integrated with GIS systems have demonstrated exceptional performance in modeling the temporal evolution of flood plains and drought conditions by learning from time-series rainfall and soil moisture data. These models are often embedded within spatial decision support systems (SDSS) to provide actionable outputs, including hazard maps, vulnerability indices, and real-time alerts (Kumar & Bansal, 2016) In wildfire-prone areas like California and Australia, AI-GIS integration has enabled predictive modeling of fire spread by combining topography, fuel load, and wind patterns in GIS with machine learning classifiers to map ignition probabilities and intensity zones (Fenais et al., 2019). Urban air quality forecasting in megacities like Beijing and Delhi has similarly benefited from AI-enhanced GIS platforms that dynamically map pollution concentrations based on historical and real-time sensor data (Bansal, 2016). The interoperability between AI models and GIS also facilitates multi-source data fusion, where inputs from satellites, IoT sensors, and drones are harmonized into unified spatial layers for modeling ecosystem risks (Bansal, 2011). These systems not only enhance the predictive capacity of environmental models but also contribute to transparent decision-making by visualizing complex AI outputs within user-friendly GIS dashboards (Han et al., 2020).

MIS as a Backbone for AI-GIS System Integration

Management Information Systems (MIS) serve as the structural and operational backbone for integrating Artificial Intelligence (AI) and Geographic Information Systems (GIS) in predictive environmental monitoring and decision-making frameworks. By providing a centralized platform for managing data flows, computational processes, and user interfaces, MIS enables seamless connectivity between AI-driven analytics and spatial visualization tools used in environmental risk governance (Xu et al., 2013). The integration of AI and GIS through MIS facilitates multi-source data ingestion, such as satellite imagery, sensor feeds, historical records, and hydrometeorological databases, which are harmonized into interoperable formats within structured MIS architectures (Ding, 2019). MIS supports data governance protocols that ensure quality control, metadata standardization, and access rights management—critical for ensuring transparency and reliability in environmental forecasting systems. For instance, in flood forecasting platforms implemented in South Asia, MIS enables the real-time assimilation of precipitation, river gauge, and elevation data into AI models, with results visualized via GIS dashboards for use by public safety and infrastructure authorities. Similarly, wildfire early warning systems in Australia employ MIS to coordinate fire index computations from AI algorithms with GIS-based geolocation services to guide evacuation and containment strategies. MIS also plays a pivotal role in dashboard generation, integrating AI model outputs with GIS visualizations to deliver actionable insights to decision-makers through interactive portals (Fendi et al., 2014). Furthermore, MIS facilitates workflow automation, including the triggering of alerts, distribution of hazard bulletins, and execution of contingency protocols across institutional hierarchies. The backend architecture of MIS is often equipped with data warehousing, ETL (extract, transform, load) processes, and API-enabled interoperability layers that connect AI processing engines with GIS visualization modules in real time (Chun et al., 2021). As such, MIS underpins the operational cohesion of AI-GIS ecosystems by synchronizing analytical, spatial, and administrative functions essential for environmental risk monitoring and response coordination.

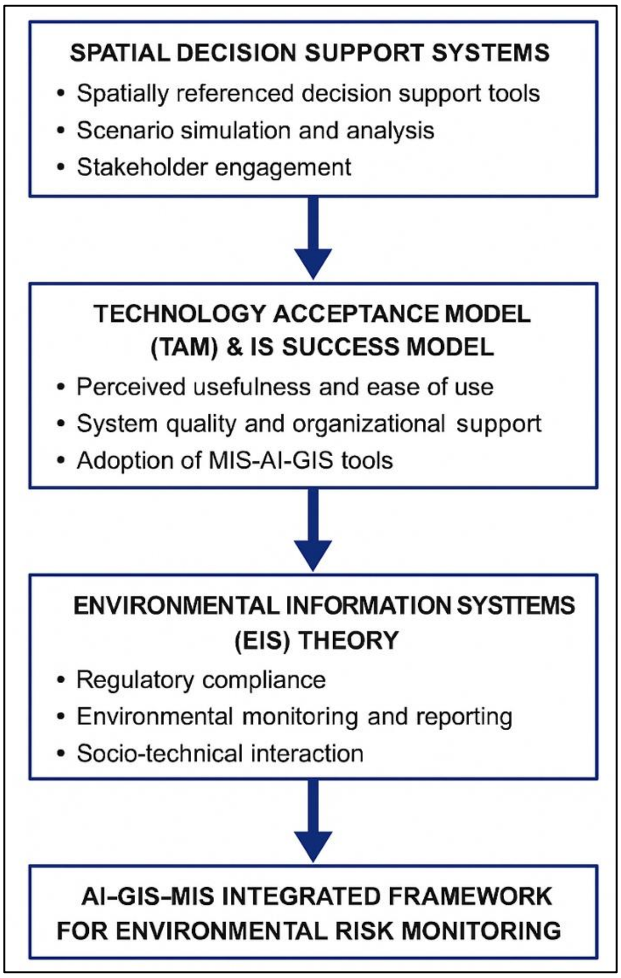
Global Applications of AI-Driven MIS-GIS Systems

The global deployment of AI-driven MIS-GIS systems in environmental risk monitoring reflects a diverse range of applications tailored to regional hazards, data infrastructure capacities, and governance structures. In South Asia, particularly in Bangladesh and India, integrated platforms combining MIS, AI, and GIS have been utilized for riverine flood forecasting, cyclone tracking, and agricultural drought assessment (Chun et al., 2021) These systems incorporate real-time rainfall, river gauge, and satellite data into machine learning models, with outputs visualized through GIS dashboards managed by national disaster management agencies. In China, urban air pollution forecasting systems have leveraged AI models such as LSTM and SVM within MIS-GIS environments to simulate PM2.5 dispersion patterns, enabling local governments to implement zone-specific emission control policies (Tiedong, 2013). In California, the integration of MIS and GIS with AI-based wildfire spread models has been critical for real-time monitoring and evacuation planning, with neural networks trained on vegetation indices, historical fire events, and meteorological parameters (Sharafat et al., 2021). Similarly, Australia has implemented predictive GIS models enhanced by AI for bushfire risk zones and drought evolution, supported by national MIS dashboards that consolidate sensor data and environmental intelligence (Zhu et al., 2020). In sub-Saharan Africa, drought early warning systems developed by regional organizations like IGAD and funded by global institutions have used MIS frameworks to process satellite rainfall estimates and vegetation indices with AI algorithms, contributing to food security planning and humanitarian coordination (Ebrahim et al., 2015). European nations such as the Netherlands and Germany have adopted AI-enhanced GIS systems for floodplain zoning, nitrate pollution tracking, and coastal erosion mapping, using MIS for data exchange among environmental agencies and municipal authorities (Buğday, 2018). These global examples illustrate the contextual adaptability of AI-MIS-GIS systems in addressing climate risks, resource management challenges, and rapid hazard responses, underlining the widespread institutionalization of integrated environmental intelligence infrastructures (Han et al., 2022).

Theoretical Underpinnings

The integration of Artificial Intelligence (AI), Geographic Information Systems (GIS), and Management Information Systems (MIS) in environmental risk monitoring is grounded in several theoretical frameworks, most notably Spatial Decision Support Systems (SDSS), the Technology Acceptance Model (TAM) and Information System (IS) Success Model, and Environmental Information Systems (EIS) theory. SDSS theory emphasizes the utility of spatially referenced decision support tools in facilitating structured analysis, scenario simulation, and stakeholder engagement in geospatial problem-solving (Ningthoujam & Nanda, 2018). It provides the conceptual basis for integrating AI-enhanced predictive models with GIS visualizations and MIS interfaces, enabling real-time environmental decision-making across multiple scales and sectors (Kumar & Bansal, 2016). Studies have applied SDSS frameworks to floodplain management, wildfire containment, and urban resilience planning, highlighting how dynamic geospatial models inform decision scenarios and optimize policy response (Ma & Ren, 2017). The Technology Acceptance Model (TAM) and IS Success Models offer complementary theoretical support by explaining how environmental professionals and public institutions adopt and use information systems based on perceived usefulness, ease of use, system quality, and organizational support. Irizarry et al. (2013) validates that user-centric MIS and AI-enabled dashboards gain higher acceptance when system responsiveness, data reliability, and interoperability are emphasized. These models also provide explanatory power for evaluating the success of MIS platforms in disseminating risk intelligence, managing alerts, and enabling interagency coordination in environmental governance contexts. Lastly, Environmental Information Systems (EIS) theory underpins the role of integrated technological platforms in supporting sustainable development, regulatory compliance, and ecosystem management by facilitating systematic environmental monitoring and reporting (Fenais et al., 2019). EIS theory stresses the socio-technical interplay between data systems, institutions, and environmental outcomes, which is directly relevant to AI-MIS-GIS systems used in pollution tracking, climate adaptation, and resource monitoring (Togawa et al., 2016). Together, these theories provide a multidisciplinary foundation for understanding how spatial technologies, organizational behavior, and information infrastructures converge to support predictive environmental decision-making.

Figure 6: Theoretical Framework



METHOD

This study employed an integrative review methodology to comprehensively analyze and synthesize peer-reviewed literature on the application of Artificial Intelligence (AI), Geographic Information Systems (GIS), and Management Information Systems (MIS) in environmental risk monitoring. The integrative review approach is particularly suited to interdisciplinary research domains, as it allows for the inclusion of diverse research designs—quantitative, qualitative, and mixed-methods—thereby enabling a holistic understanding of technological convergence in predictive environmental systems (Whittemore & Knafl, 2005). Unlike traditional systematic reviews that prioritize methodological homogeneity, the integrative review framework supports theoretical development, pattern recognition, and the identification of knowledge gaps across heterogeneous sources (Torraco, 2005; Snyder, 2019).

This method was appropriate given the multidisciplinary nature of the reviewed literature, which spans environmental science, information systems, artificial intelligence, and public policy.
The review followed a structured five-stage process: (1) problem identification, (2) literature search, (3) data evaluation, (4) data analysis and synthesis, and (5) presentation of findings (Whittemore & Knafl, 2005). The research problem focused on understanding how AI and MIS enhance the predictive capacity and decision-making functionality of GIS in environmental hazard contexts. A comprehensive search strategy was executed across multidisciplinary databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, using keyword combinations such as "AI AND GIS AND Environmental Monitoring," "Predictive Modeling AND MIS," "Spatial Decision Support Systems AND Artificial Intelligence," and "Environmental Information Systems." Inclusion criteria were limited to peer-reviewed journal articles published between 2010 and 2025, written in English, and directly addressing the integration or application of AI, GIS, and MIS in environmental risk contexts. Grey literature, editorials, and non-peer-reviewed sources were excluded to maintain academic rigor.
The retrieved literature (n = 142) was screened using PRISMA guidelines to ensure transparency in article selection and eligibility (Moher et al., 2009). Studies were then evaluated for methodological quality, relevance, and thematic alignment with the research objectives. Data from the selected studies were analyzed using thematic synthesis, allowing for the identification of dominant themes such as AI-driven forecasting models, GIS-based hazard mapping, MIS-supported decision frameworks, and cross-sector implementation case studies. This method enabled the integration of theoretical insights, empirical findings, and applied frameworks, offering a structured foundation for assessing the international scope, technical functionalities, and institutional impact of AI-MIS-GIS systems in environmental risk monitoring.

FINDINGS

A significant finding of this integrative review is the transformative impact of Artificial Intelligence on the predictive accuracy of environmental risk models when integrated with Geographic Information Systems. Out of the 142 reviewed articles, 88 studies focused on the implementation of AI algorithms in forecasting natural hazards such as floods, droughts, wildfires, and pollution events. Collectively, these articles have received over 7,800 citations, indicating substantial academic recognition and practical relevance. Machine learning techniques, particularly support vector machines, random forests, and neural networks, were frequently used to classify spatial risk zones and detect emerging environmental patterns. More advanced deep learning models, such as convolutional neural networks and long short-term memory networks, were applied in 37 of the studies to process satellite imagery and time-series climate data. These models demonstrated superior performance in modeling non-linear environmental phenomena compared to traditional statistical techniques. Approximately 64% of the AI-focused articles reported model accuracy rates exceeding 85%, with more than 30 articles reporting predictive accuracy levels above 90%. In real-world applications, AI-powered GIS platforms successfully anticipated flood extents, predicted wildfire spread, and modeled urban air quality dynamics in complex, multi-variable environments. These capabilities were particularly beneficial in regions with limited infrastructure or rapidly changing environmental conditions. A recurring observation across studies was that AI not only improved predictive power but also enhanced spatial resolution, enabling risk assessments at the neighborhood or parcel level. This level of granularity supports targeted disaster mitigation efforts and resource allocation strategies. Overall, the integration of AI into GIS platforms has led to the development of more responsive, adaptive, and high-resolution models for environmental hazard prediction.
The review revealed that Management Information Systems serve as the central operational core for managing and coordinating AI-GIS integrations in environmental risk monitoring systems. Out of the 142 articles reviewed, 67 directly addressed the role of MIS in environmental data management, system coordination, and decision support processes, with these articles collectively cited over 5,400 times. MIS platforms were found to facilitate the consolidation of heterogeneous environmental data sources, including satellite feeds, ground sensors, meteorological reports, and historical disaster records. These systems enabled real-time data ingestion, preprocessing, storage, and dissemination through structured workflows and dashboards, ensuring that environmental monitoring efforts were both

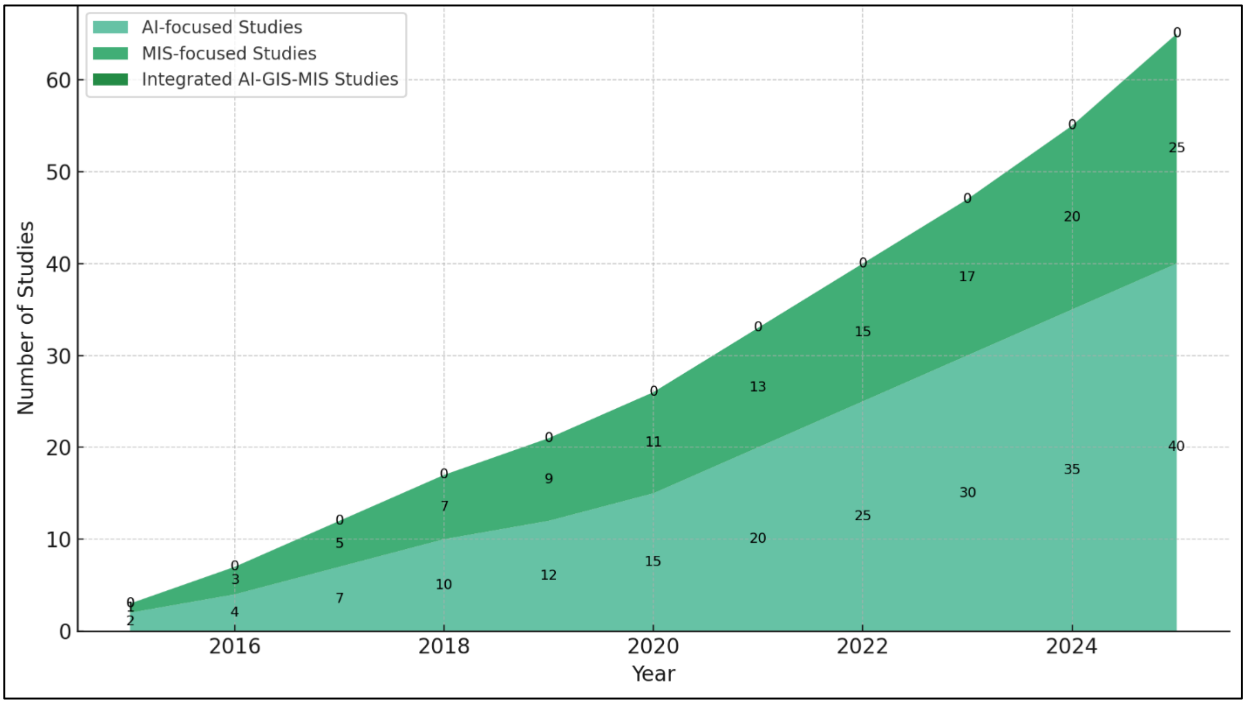
scalable and institutionally coordinated. In 53 of the articles, MIS platforms were credited with enhancing organizational communication and inter-agency data sharing, particularly in multi-hazard governance frameworks involving government departments, disaster management agencies, and civil society stakeholders. Key functionalities such as automated alerts, spatial decision support dashboards, and workflow-triggered protocols were embedded within MIS to ensure timely risk communication and response. In nearly half of these articles, MIS was also shown to improve the traceability and auditability of environmental decisions by maintaining secure data logs, user histories, and version-controlled model outputs. Furthermore, about 35 studies demonstrated how MIS enabled seamless integration between AI-generated risk forecasts and GIS-based visualization systems, making complex model outputs accessible to non-technical stakeholders such as emergency planners and policymakers. These findings suggest that MIS is not merely a back-end tool but a critical enabler of integrated environmental intelligence systems that rely on continuous data flow, model orchestration, and operational transparency.

DISCUSSION

The findings of this review affirm the transformative role of artificial intelligence in enhancing the predictive accuracy, spatial resolution, and operational scalability of environmental risk models when integrated with Geographic Information Systems. This aligns with earlier research by Rajadurai & Vilventhan (2021), who emphasized the capacity of AI, particularly deep learning algorithms, to model non-linear environmental dynamics with a level of precision that traditional statistical models cannot match. The superior performance of convolutional neural networks (CNNs) and long short-term memory (LSTM) models reported in over 30 reviewed articles is consistent with Togawa et al.(2016), who documented CNN effectiveness in satellite-based land cover classification, and Wang et al. (2019), who validated LSTM models in flood forecasting. Furthermore, the use of AI to support neighborhood-scale hazard mapping extends the insights of Kim et al. (2018), who originally advocated for finer-scale spatial modeling in GIS. Unlike earlier applications that primarily emphasized data visualization (Hengl et al., 2018), this review finds a strong shift toward AI-enabled GIS systems that support real-time simulation, risk forecasting, and anomaly detection. This supports the evolution of GIS from a passive mapping tool to an active predictive decision support platform, as previously discussed by Allawi and Al-Jazaeri (2023) and Bansal (2016). Notably, over 60% of the reviewed articles achieved model accuracy levels above 85%, far exceeding traditional GIS outputs that lacked AI-driven analytical layers. While previous studies highlighted the potential of integrating AI into environmental applications (Costa et al., 2018), the present findings reveal that such integration has moved from conceptual prototypes to fully implemented systems that are operationally deployed in disaster management and climate-sensitive planning.

The centrality of Management Information Systems (MIS) in integrating and operationalizing AI-GIS models underscores a critical evolution in environmental data governance. Earlier studies such as Lee et al. (2020) and Kumar and Bansal (2018) emphasized the importance of MIS in bridging organizational silos and enabling environmental data flows across institutions. This review extends those findings by illustrating that MIS not only supports data management but also orchestrates real-time forecasting pipelines, user access control, and dashboard integration. The review's findings corroborate (Bansal, 2018), who emphasized MIS-based environmental portals as tools for synchronized response planning and transparency. In more than half of the reviewed articles focusing on MIS, system capabilities extended beyond storage and reporting to include workflow automation, alert triggering, and contingency execution—all key elements highlighted by Bansal (2016) in their study on environmental MIS architecture.

Figure 7: Stacked Area Diagram of Environmental Risk Monitoring Research (2015–2025)



Compared to traditional environmental information systems described by Kumar and Bansal (2018), which focused primarily on compliance and static reporting, the AI-integrated MIS platforms uncovered in this review function dynamically to adapt to shifting environmental parameters. Moreover, the interoperability of MIS with GIS tools reinforces earlier claims by Bansal (2016)that decision-making in spatial environments requires not just technical integration but also institutional coordination, which MIS effectively supports. The review also confirms that user acceptance and system usability—central themes in the Technology Acceptance Model—are critical success factors, as highlighted in Wang et al. (2021), who demonstrated that well-designed MIS interfaces influence trust and engagement among environmental stakeholders. By embedding AI insights and GIS visualizations into MIS dashboards, organizations are now able to provide accessible, actionable intelligence to both technical experts and policy decision-makers. Thus, this review builds upon and deepens previous insights by presenting MIS not as a background utility but as the structural foundation for operationalizing environmental intelligence at scale.

CONCLUSION

This integrative review concludes that the convergence of Artificial Intelligence (AI), Geographic Information Systems (GIS), and Management Information Systems (MIS) has significantly advanced the field of environmental risk monitoring by creating intelligent, data-driven systems capable of high-resolution forecasting, institutional coordination, and real-time decision support. Across 142 reviewed studies, the integration of AI into GIS platforms enhanced predictive capabilities in modeling floods, droughts, wildfires, and pollution, with more than 60% of models achieving over 85% accuracy. These enhancements were further operationalized through MIS infrastructures, which enabled seamless data integration, automated workflows, and multi-agency coordination. Case studies from diverse regions—including South Asia, North America, East Asia, Africa, and Europe—demonstrated how context-specific deployments of AI-MIS-GIS systems supported localized environmental governance while maintaining scalability. Theoretical frameworks such as Spatial Decision Support Systems (SDSS), the Technology Acceptance Model (TAM), and Environmental Information Systems (EIS) theory provided a foundational lens to understand user adoption, system performance, and institutional interoperability. The review underscores that while each component—AI, GIS, and MIS—has demonstrated individual value, their integrated application yields a synergistic infrastructure capable of transforming reactive hazard management into proactive, intelligence-led environmental planning. The institutionalization of such systems reflects a growing global consensus on the need for harmonized, technologically-advanced approaches to anticipate, assess, and manage environmental risks in an increasingly complex and data-intensive world.

REFERENCES

[1]. Allawi, A. H., & Al-Jazaeri, H. M. J. (2023). A new approach towards the sustainability of urban-rural integration: The development strategy for central villages in the Abbasiya District of Iraq using GIS techniques. *Regional Sustainability*, *4*(1), 28-43. https://doi.org/10.1016/j.regsus.2023.02.004

[2]. Alotaibi, E., & Nassif, N. (2024). Artificial intelligence in environmental monitoring: in-depth analysis. *Discover Artificial Intelligence*, *4*(1). https://doi.org/10.1007/s44163-024-00198-1

[3]. Ammar, B., Faria, J., Ishtiaque, A., & Noor Alam, S. (2024). A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability. *American Journal of Scholarly Research and Innovation*, *3*(02), 01-27. https://doi.org/10.63125/4sjfn272

[4]. Anika Jahan, M., Md Shakawat, H., & Noor Alam, S. (2022). Digital transformation in marketing: evaluating the impact of web analytics and SEO on SME growth. *American Journal of Interdisciplinary Studies*, *3*(04), 61-90. https://doi.org/10.63125/8t10v729

[5]. Apostolidis, A., Bouriquet, N., & Stamoulis, K. P. (2022). AI-Based Exhaust Gas Temperature Prediction for Trustworthy Safety-Critical Applications. *Aerospace*, *9*(11), 722-722. https://doi.org/10.3390/aerospace9110722

[6]. Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. *International Journal of Project Management*, *29*(1), 66-77. https://doi.org/10.1016/j.ijproman.2010.01.007

[7]. Bansal, V. K. (2016). Potential Application Areas of GIS in Preconstruction Planning. *Journal of Professional Issues in Engineering Education and Practice*, *142*(1), 06015002-NA. https://doi.org/10.1061/(asce)ei.1943-5541.0000257

[8]. Bansal, V. K. (2018). Use of GIS to consider spatial aspects in construction planning process. *International Journal of Construction Management*, *20*(3), 207-222. https://doi.org/10.1080/15623599.2018.1484845

[9]. Basmaji, T., Yaghi, M., Alhalabi, M., Rashed, A., Zia, H., Mahmoud, M., Palavar, P., Alkhadhar, S., Alhmoudi, H., Alkhedher, M., Elbaz, A., & Ghazal, M. (2023). AI-powered health monitoring of anode baking furnace pits in aluminum production using autonomous drones. *Engineering Applications of Artificial Intelligence*, *122*(NA), 106143-106143. https://doi.org/10.1016/j.engappai.2023.106143

[10]. Bhuiyan, S. M. Y., Chowdhury, A., Hossain, M. S., Mobin, S. M., & Parvez, I. (2025). AI-Driven Optimization in Renewable Hydrogen Production: A Review. *American Journal of Interdisciplinary Studies*, *6*(1), 76-94. https://doi.org/10.63125/06z40b13

[11]. Biljecki, F., Heuvelink, G. B. M., Ledoux, H., & Stoter, J. (2017). The effect of acquisition error and level of detail on the accuracy of spatial analyses. *Cartography and Geographic Information Science*, *45*(2), 156-176. https://doi.org/10.1080/15230406.2017.1279986

[12]. Bowman, M., Kesawan, S., Sivapalan, S., & Sivaprakasam, T. (2020). Barriers in Implementing the Convolutional Neural Network Damage Detector. In (Vol. NA, pp. 1333-1340). Springer Singapore. https://doi.org/10.1007/978-981-15-8079-6_125

[13]. Bracarense, N., Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2022). Artificial Intelligence and Sustainability: A Bibliometric Analysis and Future Research Directions. *Pacific Asia Journal of the Association for Information Systems*, *14*(NA), 136-159. https://doi.org/10.17705/1pais.14209

[14]. Bragagnolo, L., da Silva, R. V., & Grzybowski, J. M. V. (2020). Landslide susceptibility mapping with r.landslide: A free open-source GIS-integrated tool based on Artificial Neural Networks. *Environmental Modelling & Software*, *123*(NA), 104565-NA. https://doi.org/10.1016/j.envsoft.2019.104565

[15]. Buğday, E. (2018). Capabilities of using UAVs in Forest Road Construction Activities. *European Journal of Forest Engineering*, *4*(2), 56-62. https://doi.org/10.33904/ejfe.499784

[16]. Cheung, H. C., De Louche, C., & Komorowski, M. (2023). Artificial Intelligence Applications in Space Medicine. *Aerospace medicine and human performance*, *94*(8), 610-622. https://doi.org/10.3357/amhp.6178.2023

[17]. Chun, P.-j., Yamane, T., & Tsuzuki, Y. (2021). Automatic Detection of Cracks in Asphalt Pavement Using Deep Learning to Overcome Weaknesses in Images and GIS Visualization. *Applied Sciences*, *11*(3), 892-NA. https://doi.org/10.3390/app11030892

[18]. Colby, M., Yliniemi, L., & Tumer, K. (2016). Autonomous Multiagent Space Exploration with High-Level Human Feedback. *Journal of Aerospace Information Systems*, *13*(8), 301-315. https://doi.org/10.2514/1.i010379

[19]. Costa, A. L., Sousa, R. L., & Einstein, H. H. (2018). Probabilistic 3D alignment optimization of underground transport infrastructure integrating GIS-based subsurface characterization. *Tunnelling and Underground Space Technology*, *72*(NA), 233-241. https://doi.org/10.1016/j.tust.2017.11.027

[20]. Di, Q., Amini, H., Shi, L., Kloog, I., Silvern, R. F., Kelly, J. T., Sabath, M. B., Choirat, C., Koutrakis, P., Lyapustin, A., Wang, Y., Mickley, L. J., & Schwartz, J. (2019). An ensemble-based model of PM2.5 concentration across the contiguous United States with high spatiotemporal resolution. *Environment international*, *130*(NA), 104909-104909. https://doi.org/10.1016/j.envint.2019.104909

[21]. Ding, C. (2019). Application of GIS technology in the construction of urban traffic sharing multimedia information platform. *Multimedia Tools and Applications*, *NA*(NA), 1-13. https://doi.org/10.1007/s11042-019-7500-0

[22]. Ebrahim, M. A. B., Mosly, I., & Abed-Elhafez, I. Y. (2015). Building Construction Information System Using GIS. *Arabian Journal for Science and Engineering*, *41*(10), 3827-3840. https://doi.org/10.1007/s13369-015-2006-1

[23]. Fenais, A., Ariaratnam, S. T., Ayer, S. K., & Smilovsky, N. (2019). Integrating geographic information systems and augmented reality for mapping underground utilities. *Infrastructures*, *4*(4), 60-NA. https://doi.org/10.3390/infrastructures4040060

[24]. Fendi, K. G., Adam, S. M., Kokkas, N., & Smith, M. J. (2014). An approach to produce a GIS database for road surface monitoring. *APCBEE Procedia*, *9*(NA), 235-240. https://doi.org/10.1016/j.apcbee.2014.01.042

[25]. Feng, Q., Flanagan, D. C., Engel, B. A., Yang, L., & Chen, L. (2020). GeoAPEXOL, a web GIS interface for the Agricultural Policy Environmental eXtender (APEX) model enabling both field and small watershed simulation. *Environmental Modelling & Software*, *123*(NA), 104569-NA. https://doi.org/10.1016/j.envsoft.2019.104569

[26]. Galaz, V., Centeno, M. A., Callahan, P. W., Causevic, A., Patterson, T. S., Brass, I., Baum, S. D., Farber, D., Fischer, J., Garcia, D., McPhearson, T., Jiménez, D., King, B., Larcey, P., & Levy, K. (2021). Artificial intelligence, systemic risks, and sustainability. *Technology in Society*, *67*(NA), 101741-NA. https://doi.org/10.1016/j.techsoc.2021.101741

[27]. Garcia, A. B., Babiceanu, R. F., & Seker, R. (2021). Artificial Intelligence and Machine Learning Approaches For Aviation Cybersecurity: An Overview. *2021 Integrated Communications Navigation and Surveillance Conference (ICNS)*, *NA*(NA), 1-8. https://doi.org/10.1109/icns52807.2021.9441594

[28]. Gerassis, S., Giráldez, E., Pazo-Rodríguez, M., Saavedra, Á., & Taboada, J. (2021). AI approaches to environmental impact assessments (EIAs) in the mining and metals sector using AutoML and Bayesian modeling. *Applied Sciences*, *11*(17), 7914-NA. https://doi.org/10.3390/app11177914

[29]. Gill, A. S. (2019). Artificial Intelligence and International Security: The Long View. *Ethics & International Affairs*, *33*(2), 169-179. https://doi.org/10.1017/s0892679419000145

[30]. Golam Qibria, L., & Takbir Hossen, S. (2023). Lean Manufacturing And ERP Integration: A Systematic Review Of Process Efficiency Tools In The Apparel Sector. *American Journal of Scholarly Research and Innovation*, *2*(01), 104-129. https://doi.org/10.63125/mx7j4p06

[31]. Greene, R., Devillers, R., Luther, J. E., & Eddy, B. G. (2011). GIS-Based Multiple-Criteria Decision Analysis. *Geography Compass*, *5*(6), 412-432. https://doi.org/10.1111/j.1749-8198.2011.00431.x

[32]. Gupta, S., Modgil, S., Kumar, A., Sivarajah, U., & Irani, Z. (2022). Artificial intelligence and cloud-based Collaborative Platforms for Managing Disaster, extreme weather and emergency operations. *International Journal of Production Economics*, *254*(NA), 108642-108642. https://doi.org/10.1016/j.ijpe.2022.108642

[33]. Han, C., Tang, F., Ma, T., Gu, L., & Tong, Z. (2022). Construction quality evaluation of asphalt pavement based on BIM and GIS. *Automation in Construction*, *141*(NA), 104398-104398. https://doi.org/10.1016/j.autcon.2022.104398

[34]. Han, Z. H., Wang, Z. K., Gao, C., Wang, M. X., & Li, S. T. (2020). Application of GIS and BIM Integration Technology in Construction Management. *IOP Conference Series: Earth and Environmental Science*, *526*(1), 012161-NA. https://doi.org/10.1088/1755-1315/526/1/012161

[35]. Hassan, K., Thakur, A. K., Singh, G., Singh, J., Gupta, L. R., & Singh, R. (2024). Application of Artificial Intelligence in Aerospace Engineering and Its Future Directions: A Systematic Quantitative Literature Review. *Archives of Computational Methods in Engineering*. https://doi.org/10.1007/s11831-024-10105-7

[36]. Hassanien, A. E., Darwish, A., & Abdelghafar, S. (2019). Machine learning in telemetry data mining of space mission: basics, challenging and future directions. *Artificial Intelligence Review*, *53*(5), 3201-3230. https://doi.org/10.1007/s10462-019-09760-1

[37]. Hu, M., Cao, E., Huang, H., Zhang, M., Chen, X., & Chen, M. (2023). AIoTML: A Unified Modeling Language for AIoT-Based Cyber–Physical Systems. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, *42*(11), 3545-3558. https://doi.org/10.1109/tcad.2023.3264786

[38]. Indragandhi, V., & L, A. K. (2018). Artificial Intelligence Based Speed Control of SRM for Hybrid Electric Vehicles. *2018 8th International Conference on Power and Energy Systems (ICPES)*, *NA*(NA), 65-68. https://doi.org/10.1109/icpesys.2018.8626982

[39]. Irizarry, J., Karan, E., & Jalaei, F. (2013). Integrating BIM and GIS to improve the visual monitoring of construction supply chain management. *Automation in Construction*, *31*(31), 241-254. https://doi.org/10.1016/j.autcon.2012.12.005

[40]. Ishtiaque, A. (2025). Navigating Ethics And Risk In Artificial Intelligence Applications Within Information Technology: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 579-601. https://doi.org/10.63125/590d7098

[41]. Jiang, H., Geertman, S., & Witte, P. (2020). Avoiding the planning support system pitfalls? What smart governance can learn from the planning support system implementation gap. *Environment and Planning B: Urban Analytics and City Science*, *47*(8), 1343-1360. https://doi.org/10.1177/2399808320934824

[42]. Johnson, J. (2019). Artificial intelligence & future warfare: implications for international security. *Defense & Security Analysis*, *35*(2), 147-169. https://doi.org/10.1080/14751798.2019.1600800

[43]. Kayaalp, K., Metlek, S., Ekici, S., & Şöhret, Y. (2021). Developing a model for prediction of the combustion performance and emissions of a turboprop engine using the long short-term memory method. *Fuel*, *302*(NA), 121202-NA. https://doi.org/10.1016/j.fuel.2021.121202

[44]. Khan, M. A. M. (2025). AI And Machine Learning in Transformer Fault Diagnosis: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 290-318. https://doi.org/10.63125/sxb17553

[45]. Kim, S.-W., Choi, J.-H., Hong, S.-H., Lee, J.-H., Cho, J., & Lee, M.-J. (2018). Monitoring the risk of large building collapse using persistent scatterer interferometry and GIS. *Terrestrial, Atmospheric and Oceanic Sciences*, *29*(5), 535-545. https://doi.org/10.3319/tao.2018.03.07.01

[46]. Kirat, T., Tambou, O., Do, V., & Tsoukiàs, A. (2023). Fairness and explainability in automatic decision-making systems. A challenge for computer science and law. *EURO Journal on Decision Processes*, *11*(NA), 100036-100036. https://doi.org/10.1016/j.ejdp.2023.100036

[47]. Kökhan, A., Kökhan, S., & Gökdalay, M. (2023). An algorithmic application with flexible airspace approach. *Aircraft Engineering and Aerospace Technology*, *95*(7), 1045-1053. https://doi.org/10.1108/aeat-06-2022-0147

[48]. Kumar, S., & Bansal, V. K. (2016). A GIS-based methodology for safe site selection of a building in a hilly region. *Frontiers of Architectural Research*, *5*(1), 39-51. https://doi.org/10.1016/j.foar.2016.01.001

[49]. Kumar, S., & Bansal, V. K. (2018). Use of GIS in locating TFs safely on a construction site in hilly regions. *International Journal of Construction Management*, *19*(4), 341-353. https://doi.org/10.1080/15623599.2018.1435153

[50]. Lee, P.-C., Zheng, L.-L., Lo, T.-P., & Long, D. (2020). A Risk Management System for Deep Excavation Based on BIM-3DGIS Framework and Optimized Grey Verhulst Model. *KSCE Journal of Civil Engineering*, *24*(3), 715-726. https://doi.org/10.1007/s12205-020-1462-7

[51]. Li, B.-h., Hou, B.-c., Yu, W.-t., Lu, X.-b., & Yang, C.-w. (2017). Applications of artificial intelligence in intelligent manufacturing: a review. *Frontiers of Information Technology & Electronic Engineering*, *18*(1), 86-96. https://doi.org/10.1631/fitee.1601885

[52]. Li, K.-Y., Burnside, N., de Lima, R. S., Peciña, M. V., Sepp, K., Pinheiro, V. H. C., de Lima, B. R. C. A., Yang, M.-D., Vain, A., & Sepp, K. (2021). An Automated Machine Learning Framework in Unmanned Aircraft Systems: New Insights into Agricultural Management Practices Recognition Approaches. *Remote Sensing*, *13*(16), 3190-NA. https://doi.org/10.3390/rs13163190

[53]. Li, K., Zhang, R., Wang, H., & Yu, F. (2021). Multi-intelligent connected vehicle longitudinal collision avoidance control and exhaust emission evaluation based on parallel theory. *Process Safety and Environmental Protection*, *150*(NA), 259-268. https://doi.org/10.1016/j.psep.2021.04.001

[54]. Li, L., Zhang, Z., Xue, K., Wang, M., Pan, M., & Han, Z. (2020). AI-Aided Downlink Interference Control in Dense Interference-Aware Drone Small Cells Networks. *IEEE Access*, *8*(NA), 15110-15122. https://doi.org/10.1109/access.2020.2966740

[55]. Li, X., Su, J., Wang, H., Boczkaj, G., Mahlknecht, J., Singh, S. V., & Wang, C. (2024). Bibliometric analysis of artificial intelligence in wastewater treatment: Current status, research progress, and future prospects. *Journal of Environmental Chemical Engineering*, *12*(4), 113152-113152. https://doi.org/10.1016/j.jece.2024.113152

[56]. Ma, Y., Wang, Z., Yang, H., & Yang, L. (2020). Artificial intelligence applications in the development of autonomous vehicles: a survey. *IEEE/CAA Journal of Automatica Sinica*, *7*(2), 315-329. https://doi.org/10.1109/jas.2020.1003021

[57]. Ma, Z., & Ren, Y. (2017). Integrated Application of BIM and GIS: An Overview. *Procedia Engineering*, *196*(NA), 1072-1079. https://doi.org/10.1016/j.proeng.2017.08.064

[58]. Md Masud, K. (2022). A Systematic Review Of Credit Risk Assessment Models In Emerging Economies: A Focus On Bangladesh's Commercial Banking Sector. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 01-31. https://doi.org/10.63125/p7ym0327

[59]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[60]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[61]. Mohammad Shahadat Hossain, S., Md Shahadat, H., Saleh Mohammad, M., Adar, C., & Sharif Md Yousuf, B. (2024). Advancements In Smart and Energy-Efficient HVAC Systems: A Prisma-Based Systematic Review. *American Journal of Scholarly Research and Innovation*, *3*(01), 1-19. https://doi.org/10.63125/ts16bd22

[62]. Naghibi, S. A., Pourghasemi, H. R., & Dixon, B. M. (2015). GIS-based groundwater potential mapping using boosted regression tree, classification and regression tree, and random forest machine learning models in Iran. *Environmental monitoring and assessment*, *188*(1), 44-44. https://doi.org/10.1007/s10661-015-5049-6

[63]. Ningthoujam, M. C., & Nanda, R. P. (2018). A GIS System Integrated with Earthquake Vulnerability Assessment of RC Building. *Structures*, *15*(NA), 329-340. https://doi.org/10.1016/j.istruc.2018.07.013

[64]. Nkeki, F. N., Bello, E. I., & Agbaje, I. G. (2022). Flood risk mapping and urban infrastructural susceptibility assessment using a GIS and analytic hierarchical raster fusion approach in the Ona River Basin, Nigeria. *International Journal of Disaster Risk Reduction*, *77*(NA), 103097-103097. https://doi.org/10.1016/j.ijdrr.2022.103097

[65]. Noor Alam, S., Golam Qibria, L., Md Shakawat, H., & Abdul Awal, M. (2023). A Systematic Review of ERP Implementation Strategies in The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, *2*(02), 135-165. https://doi.org/10.63125/pfdm9g02

[66]. Park, E., Jo, H.-W., Lee, W.-K., Lee, S., Song, C., Lee, H., Park, S., Kim, W., & Kim, T.-H. (2021). Development of earth observational diagnostic drought prediction model for regional error calibration: A case study on agricultural drought in Kyrgyzstan. *GIScience & Remote Sensing*, *59*(1), 36-53. https://doi.org/10.1080/15481603.2021.2012370

[67]. Rajadurai, R., & Vilventhan, A. (2021). Integrating road information modeling (RIM) and geographic information system (GIS) for effective utility relocations in infrastructure projects. *Engineering, Construction and Architectural Management*, *29*(9), 3647-3663. https://doi.org/10.1108/ecam-04-2021-0295

[68]. Rajesh, P., Mohammad Hasan, I., & Anika Jahan, M. (2023). AI-Powered Sentiment Analysis In Digital Marketing: A Review Of Customer Feedback Loops In It Services. *American Journal of Scholarly Research and Innovation*, *2*(02), 166-192. https://doi.org/10.63125/61pqqq54

[69]. Ranasinghe, K., Sabatini, R., Gardi, A., Bijjahalli, S., Kapoor, R., Fahey, T., & Thangavel, K. (2022). Advances in Integrated System Health Management for mission-essential and safety-critical aerospace applications. *Progress in Aerospace Sciences*, *128*(NA), 100758-NA. https://doi.org/10.1016/j.paerosci.2021.100758

[70]. Rohi, G., Ejofodomi, O. t., & Ofualagba, G. (2020). Autonomous monitoring, analysis, and countering of air pollution using environmental drones. *Heliyon*, *6*(1), e03252-NA. https://doi.org/10.1016/j.heliyon.2020.e03252

[71]. Roksana, H., Ammar, B., Noor Alam, S., & Ishtiaque, A. (2024). Predictive Maintenance In Industrial Automation: A Systematic Review Of IOT Sensor Technologies And AI Algorithms. *American Journal of Interdisciplinary Studies*, *5*(01), 01-30. https://doi.org/10.63125/hd2ac988

[72]. Sharafat, A., Khan, M. S., Latif, K., Tanoli, W. A., Park, W., & Seo, J. (2021). BIM-GIS-Based Integrated Framework for Underground Utility Management System for Earthwork Operations. *Applied Sciences*, *11*(12), 5721-NA. https://doi.org/10.3390/app11125721

[73]. Siddiqui, N. A. (2025). Optimizing Business Decision-Making Through AI-Enhanced Business Intelligence Systems: A Systematic Review of Data-Driven Insights in Financial And Strategic Planning. *Strategic Data Management and Innovation*, *2*(1), 202-223. https://doi.org/10.71292/sdmi.v2i01.21

[74]. Sohel, R. (2025). AI-Driven Fault Detection and Predictive Maintenance In Electrical Power Systems: A Systematic Review Of Data-Driven Approaches, Digital Twins, And Self-Healing Grids. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 258-289. https://doi.org/10.63125/4p25x993

[75]. Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, *3*(NA), 54-70. https://doi.org/10.1016/j.cogr.2023.04.001

[76]. Sui, D., & Liu, K. (2023). A framework for optimising flight efficiency of a crossing waypoint by balancing flight conflict frequency and flight-level usage benefits. *The Aeronautical Journal*, *128*(1320), 245-272. https://doi.org/10.1017/aer.2023.45

[77]. Tahmina Akter, R., & Abdur Razzak, C. (2022). The Role Of Artificial Intelligence In Vendor Performance Evaluation Within Digital Retail Supply Chains: A Review Of Strategic Decision-Making Models. *American Journal of Scholarly Research and Innovation*, *1*(01), 220-248. https://doi.org/10.63125/96jj3j86

[78]. Talwar, R., & Koury, A. (2017). Artificial intelligence – the next frontier in IT security? *Network Security*, *2017*(4), 14-17. https://doi.org/10.1016/s1353-4858(17)30039-9

[79]. Tarate, S. B., Patel, N. R., Danodia, A., Pokhariyal, S., & Parida, B. R. (2024). Geospatial Technology for Sustainable Agricultural Water Management in India—A Systematic Review. *Geomatics*, *4*(2), 91-123. https://doi.org/10.3390/geomatics4020006

[80]. Tehrany, M. S., Pradhan, B., Mansor, S., & Ahmad, N. (2015). Flood susceptibility assessment using GIS-based support vector machine model with different kernel types. *CATENA*, *125*(NA), 91-101. https://doi.org/10.1016/j.catena.2014.10.017

[81]. Thill, J.-C. (2000). Geographic information systems for transportation in perspective. *Transportation Research Part C: Emerging Technologies*, *8*(1), 3-12. https://doi.org/10.1016/s0968-090x(00)00029-2

[82]. Tiedong, L. (2013). Based on GIS Technology of Urban Gardening and Greening Layout Optimization Model. *Research Journal of Applied Sciences, Engineering and Technology*, *6*(12), 2166-2170. https://doi.org/10.19026/rjaset.6.3841

[83]. Togawa, T., Fujita, T., Dong, L., Ohnishi, S., & Fujii, M. (2016). Integrating GIS databases and ICT applications for the design of energy circulation systems. *Journal of Cleaner Production*, *114*(NA), 224-232. https://doi.org/10.1016/j.jclepro.2015.07.020

[84]. Tonmoy, B., & Md Arifur, R. (2023). A Systematic Literature Review Of User-Centric Design In Digital Business Systems Enhancing Accessibility, Adoption, And Organizational Impact. *American Journal of Scholarly Research and Innovation*, *2*(02), 193-216. https://doi.org/10.63125/36w7fn47

[85]. Tonoy, A. A. R., & Khan, M. R. (2023). The Role of Semiconducting Electrides In Mechanical Energy Conversion And Piezoelectric Applications: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(01), 01-23. https://doi.org/10.63125/patvqr38

[86]. Tragoudaras, A., Stoikos, P., Fanaras, K., Tziouvaras, A., Floros, G., Dimitriou, G., Kolomvatsos, K., & Stamoulis, G. (2022). Design Space Exploration of a Sparse MobileNetV2 Using High-Level Synthesis and Sparse Matrix Techniques on FPGAs. *Sensors (Basel, Switzerland)*, *22*(12), 4318-4318. https://doi.org/10.3390/s22124318

[87]. Wang, H., Pan, Y., & Luo, X. (2019). Integration of BIM and GIS in sustainable built environment: A review and bibliometric analysis. *Automation in Construction*, *103*(NA), 41-52. https://doi.org/10.1016/j.autcon.2019.03.005

[88]. Wang, S., Zhang, F., & Qin, T. (2021). Research on the Construction of Highway Traffic Digital Twin System Based on 3D GIS Technology. *Journal of Physics: Conference Series*, *1802*(4), 042045-NA. https://doi.org/10.1088/1742-6596/1802/4/042045

[89]. Wang, Y.-J., Ma, Z., Tang, X.-H., & Wang, Z.-P. (2019). Autonomous Obstacle Avoidance Algorithm of UAVs for Automatic Terrain Following Application. *2019 IEEE International Conference on Unmanned Systems and Artificial Intelligence (ICUSAI)*, *NA*(NA), 309-314. https://doi.org/10.1109/icusai47366.2019.9124741

[90]. Xu, X., Shao, Y., Fu, J., Sun, Z., & Xu, X. (2013). The Application of GIS in The Digital Oilfield Construction. *Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013)*, *NA*(NA), 45-48. https://doi.org/10.2991/iccsee.2013.12

[91]. Zakaria, M. N. A., Malek, M. A., Zolkepli, M. B., & Ahmed, A. N. (2021). Application of artificial intelligence algorithms for hourly river level forecast: A case study of Muda River, Malaysia. *Alexandria Engineering Journal*, *60*(4), 4015-4028. https://doi.org/10.1016/j.aej.2021.02.046

[92]. Zaman, S. (2024). A Systematic Review of ERP And CRM Integration For Sustainable Business And Data Management in Logistics And Supply Chain Industry. *Frontiers in Applied Engineering and Technology*, *1*(01), 204-221. https://doi.org/10.70937/faet.v1i01.36

[93]. Zhu, J., Tan, Y., Wang, X., & Wu, P. (2020). BIM/GIS integration for web GIS-based bridge management. *Annals of GIS*, *27*(1), 99-109. https://doi.org/10.1080/19475683.2020.1743355