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(Review Article)

Artificial Intelligence (AI) and Geographic Information Systems (GIS) Integration for Predictive Water Quality Monitoring in Copper Mining Regions in the USA

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Abstract

Water quality management in US copper mining regions is critical for environmental sustainability and regulatory compliance, addressing persistent challenges such as acid mine drainage, metal contamination, and hydrological cycle alterations across the arid Southwest. This paper reviews the state-of-the-art integration of Geographic Information Systems (GIS) and Artificial Intelligence (AI) collectively referred to as GeoAI as a robust framework for continuous, real-time, and predictive water quality monitoring in this sector. Traditional monitoring methods, often manual and episodic, suffer from substantial time lags and spatial data gaps. GeoAI frameworks overcome these constraints by leveraging remote sensing for spatially extensive data, in-situ sensors for high-frequency measurements, and advanced machine learning models such as Random Forest, LSTM, and XGBoost for forecasting contamination events. The review utilizes examples from major Arizona operations to highlight how this integration provides actionable insights for proactive risk management, compliance validation under Environmental Protection Agency (EPA) and Mine Health and Safety (MSHA) standards, and targeted remediation strategies. Ultimately, adopting integrated GeoAI solutions is essential for advancing environmentally responsible mining practices and protecting critical, scarce water resources.

Keywords: Geographic Information Systems (GIS); Artificial Intelligence (AI); Water Quality Monitoring; Copper Mining

1. Introduction

1.1. The Context of Copper Mining and Water Scarcity in the U.S.

Copper is a vital resource for modern infrastructure and the global energy transition (Podobińska-Staniec et al., 2025), yet its extraction is inherently water-intensive and carries significant environmental risks. In the United States, the majority of copper production is concentrated in the arid and semi-arid regions of the Southwest, notably Arizona, Utah, and New Mexico (Kinkel & Peterson, 1962). This geographic reality creates a fundamental conflict: high water demand in regions defined by severe water scarcity. Global analyses underscore this tension, showing that a significant portion of critical mineral extraction, including copper, occurs in areas already experiencing high to extremely high levels of water stress (Northey et al., 2017). This intensifies local competition for groundwater and surface water, simultaneously magnifying the consequences of any mining-related contamination. Therefore, effective water management is not merely an operational goal but a prerequisite for maintaining a social license to operate and ensuring regional sustainability.

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1.2. Environmental Threats Posed by Copper Mining

The extraction and processing of copper ore pose several distinct and severe threats to surrounding water quality, which often necessitate complex, long-term monitoring and remediation programs (Djanetey et al., 2025).

The most pervasive and enduring threat is Acid Rock Drainage (Mitchell, 2000). Acid Rock Drainage (ARD) is generated when sulfide minerals (such as pyrite) in exposed waste rock and tailings react with oxygen and water, creating sulfuric acid (Simate & Ndlovu, 2021). This acidic effluent then leaches and mobilizes toxic heavy metals including copper, arsenic, lead, and cadmium into surface and groundwater systems. The resulting contaminated plumes can persist for decades or centuries after mining operations cease. Furthermore, copper mining processes often involve large tailings storage facilities (TSFs) and extensive open-pit activities, which contribute to sedimentation and erosion increase (Cacciuttolo et al., 2023; Malama, 2020). The disturbance of large areas of land raises surface runoff and sediment load into natural drainage networks. Contaminant plumes are also a major concern, as leaks, seepage, or catastrophic failures of TSFs or process water impoundments can lead to persistent contamination of aquifers and streams, a problem documented in historical incidents across US copper mines (Gestring, 2019). Hydrological alteration occurs when mine dewatering systems and diversions of natural watercourses fundamentally change local and regional hydrological cycles (Anawar, 2013).

1.3. The Regulatory Imperative and the Need for Predictive Tools

Given the scale of environmental risk, US copper mining operations are subject to rigorous federal and state regulatory frameworks, most notably those mandated by the Clean Water Act and enforced by the United States Environmental Protection Agency (USEPA, 2020). Compliance requires continuous monitoring, meticulous record-keeping, and demonstrating that pollutant discharges meet strict water quality criteria. However, traditional monitoring methods relating to manual sampling and laboratory analysis often suffer from substantial time lags and spatial data gaps, which make timely detection and regulatory compliance challenging (Glasgow et al., 2004).This inadequacy necessitates a technological shift toward predictive and preventative tools where data can be captured and processed autonomously (Djanetey et al., 2025).Ensuring sustainable mining operations requires moving beyond reactive detection toward a framework capable of continuous, real-time monitoring and proactive forecasting of events (Djanetey & Zakaria, 2025)..

1.4. Introducing the GeoAI Solution

This paper assesses the state-of-the-art integration of Geographic Information Systems (GIS) and Artificial Intelligence (AI), collectively termed GeoAI, as the critical solution for managing water quality in the US copper sector. GIS provides the essential spatial foundation, integrating physical infrastructure layers with complex hydrogeological data to map risk and contamination pathways (Ajayakumar, 2024). AI, through advanced machine learning and deep learning models, processes the resulting multi-source data streams to forecast water quality trends with unparalleled speed and accuracy (Zhao et al., 2025). By systematically reviewing the technical components, applications, and regulatory alignment of GeoAI, this paper seeks to provide a comprehensive guide for advancing environmentally responsible mining practices.

2. Limitations of Traditional Monitoring Methods

Traditional water monitoring methods in mining and industrial contexts are severely limited by inherent constraints such as infrequent sampling intervals, spatial data discontinuities, and delayed laboratory analyses (Ruppen, 2022). This hinders the timely detection of contamination events and the accurate characterization of dynamic hydrochemical processes. This process introduces substantial time lags impeding the timely detection of water quality issues. Furthermore, reliance on sparse spatial sampling means that only a fraction of the potentially affected area is monitored, resulting in critical data gaps that can fail to capture localized contamination events (Ciampi et al., 2022). This failure is critical considering the Acid Rock Drainage (ARD) issue, which remains the single most severe long-term environmental threat posed by mining. ARD results from the oxidation of sulfide minerals exposed in waste rock, generating highly acidic water that mobilizes toxic heavy metals like lead, mercury, and copper. Since these episodic measurements do not offer continuous surveillance or predictive analytics, the capacity to anticipate emerging risks associated with ARD mobilization, especially following extreme weather events or sudden process changes, is severely limited. These limitations often result in reactive, rather than proactive, environmental management, allowing pollutants such as acid mine drainage and heavy metals to propagate undetected until they reach ecologically or legally critical thresholds (Mukherjee et al., 2024).

3. The GeoAI Framework: Technology and Trends

The integration of AI and GIS creates a powerful GeoAI framework that addresses the speed, scale, and complexity required for modern environmental monitoring (Vaiyapuri & Julie, 2025).

3.1. GIS for Spatial Data Integration and Hydrogeological Modeling

GIS platforms form the foundation for integrating and visualizing spatial and non-spatial datasets (Pandey & Karnatak, 2024). A comprehensive set of GIS layers is essential for defining the physical environment and monitoring infrastructure. These layers include details on physical infrastructure such as pit boundaries, tailings storage facilities, process water impoundments, and haul roads. They also cover hydrogeology, incorporating drainage networks (surface water pathways), Digital Elevation Models (DEMs), and groundwater monitoring well locations.The GIS spatial database serves as the computational domain for physically-based distributed hydrologic models. GIS facilitates the integration of layers (DEMs, soil, and land cover) with hydrogeological models to simulate complex processes, including evapotranspiration, snowmelt, infiltration, aquifer recharge, groundwater flow, and overland runoff (Pal et al., 2025). This coupling between GIS and simulation models allows operators to predict the fate and transport of contaminants under various operational and climatic scenarios, far exceeding the capability of simple map overlays. These spatial datasets support rigorous water quality risk assessment by facilitating the analysis of runoff patterns, contaminant migration, and groundwater vulnerability (Deng et al., 2021).

3.2. Remote Sensing and Sensor Networks

Remote sensing plays a critical role in large-scale environmental surveillance by providing time-series observations of key indicators (Chen et al., 2022). Data from platforms such as Sentinel-2, Landsat 9 and MODIS are used to detect and monitor several essential environmental factors. These factors include subtle alterations in hydrological regimes and land-cover conditions , as well as surface water dynamics, vegetation health, and sedimentation zones (Caballero et al., 2022; Chaves et al., 2020). These remote sensing methods, when fused with real-time in-situ measurements from sensor stations, enable the spatio-temporal analysis of water quality trends across the entire mining landscape(Smentek et al., 2025).

3.3. AI and Advanced Predictive Modeling

During analysis, advanced machine learning techniques are employed to model and predict Water Quality Indices (WQI) and assess contamination risks. While traditional and standard models have been used, the latest research emphasizes the superiority of deep learning models for high-frequency, time-series water quality data. Two major models that demonstrate this capability are Long Short-Term Memory (LSTM) Networks and Extreme Gradient Boosting (XGBoost)(Waheed & Xu, 2025: Amuah et al., 2025)). LSTMs are specialized Recurrent Neural Networks (RNNs) that are highly effective at capturing complex temporal dependencies and non-linear patterns inherent in continuous sensor data. This makes them ideal for anticipating contamination trends and future water quality events based on historical flow and chemical readings (El-Shafeiy et al., 2023). XGBoost is an advanced ensemble method that has demonstrated exceptional predictive accuracy and robustness in both classification and regression tasks related to WQI prediction, frequently outperforming many traditional models (Zounemat-Kermani & Kheimi, 2025). These GeoAI models are trained using a combination of historical and current datasets, alongside spatial variables such as elevation, rainfall, land use, and proximity to contamination sources (Gonzales-Inca et al., 2022). Rigorous validation against withheld field measurements is necessary to ensure the predictive reliability of these models.

4. Real-World Monitoring Context: Arizona Copper Operations

The necessity of GeoAI is best demonstrated by the scale and complexity of active open-pit copper mines in the American Southwest, notably the Morenci Mine in Greenlee County and the Pinto Valley Mine (Capstone Copper) in the Globe-Miami district. These are two of the largest copper producers in North America, and their operations present massive, long-term environmental challenges that overwhelm traditional monitoring capabilities.

The Morenci Mine, covering over 61,000 acres, involves massive open pits and extensive tailings storage facilities (TSFs) (Mining Technology, 2023). The sheer physical footprint generates monumental volumes of waste rock and exposes vast areas of sulfide minerals, amplifying the long-term risk of Acid Rock Drainage (ARD). GeoAI is indispensable here because it provides the only viable means of surveillance across this immense area. Satellite-based remote sensing tracks ground deformation and water levels in the TSFs, while Geo-referenced sensor networks in monitoring wells provide localized, high-frequency chemical data that feeds the predictive models. This fusion of wide-area monitoring and pinpoint chemical analysis allows operators to identify incipient contaminant plumes before they reach community water sources.

The Arizona climate, characterized by long arid periods punctuated by intense, erosive monsoon rains, creates volatile surface runoff conditions that can rapidly mobilize contaminants. GeoAI systems address this by integrating Digital Elevation Models (DEMs) and real-time precipitation data. GIS models accurately simulate runoff pathways across the disturbed landscape, instantly updating based on weather radar to predict where and when highly contaminated water will reach drainage networks. Furthermore, GeoAI assists in tracking plume migration; by combining predicted flow with sensor data, LSTM models forecast the trajectory and concentration of metal-laden seepage plumes originating from TSFs and waste dumps. This enables the proactive deployment of containment or treatment measures. Without this GeoAI capability, operators would be reacting to laboratory results days after the event, potentially leading to health, safety and regulatory violations.

The primary driver for the adoption of GeoAI in the US copper sector is the stringent enforcement of federal environmental laws. The most relevant of these is the Clean Water Act (CWA), which dictates wastewater discharge limits via the National Pollutant Discharge Elimination System (NPDES) permits. GeoAI is vital to achieving the following:

Proactive Compliance Forecasting: GeoAI transforms compliance from a retrospective reporting requirement into a proactive management tool.2 XGBoost and LSTM models are trained on historical discharge data, meteorological forecasts, and sensor readings to predict whether future effluent will exceed NPDES limits days in advance. This crucial lead time allows mine management to make critical operational decisions, such as halting or reducing process water discharge, diverting contaminated runoff to on-site treatment facilities, or adjusting chemical dosing in treatment plants. By anticipating non-compliance events, GeoAI ensures compliance and sustainability.

Auditing and Transparency: The integration of GeoAI significantly enhances transparency and regulatory confidence. GIS provides a single platform to aggregate and visualize data from multiple, non-traditional sources (e.g., satellite-detected vegetation stress, ground-based inclinometers, and well logs). Regulators can use this spatially validated data to verify compliance reports by cross-referencing self-reported discharge data with independent remote sensing observations (Erue et al., 2024). It also helps to prioritize inspections, focusing limited regulatory resources on areas where GeoAI models predict the highest risk of TSF instability or contaminant mobilization. Furthermore, public-facing GeoAI dashboards support corporate social responsibility by allowing local communities and stakeholders to monitor key water quality parameters, rebuilding trust and enhancing the miner's social license to operate.

5. Recommendations and Future Directions

The integration of GeoAI into mining operations provides a clear path for sustainable practice. The first critical step is to implement automated, high-frequency water monitoring. This involves the deployment of real-time sensor networks throughout mining sites, which must then integrate their outputs with AI-driven anomaly detection to issue immediate alerts for any pollutant threshold exceedance. Alongside monitoring, facilities should adopt closed-loop water recycling systems. These systems are designed to capture, treat, and reuse process water internally, which minimizes freshwater withdrawals and decreases the volume of effluent discharge, aligning with sustainable mine water management. A major focus must be to strengthen tailings water containment. This requires employing advanced seepage, drone, and remote sensing inspections alongside physical controls, such as lined dams or dry stacking, to reduce the risk of structural instability and protect local water resources. Simultaneously, operations need to improve Acid Mine Drainage controls by utilizing chemical neutralization and passive treatment systems, like constructed wetlands, to prevent acid generation. Continuous water quality sensors are essential here to improve the evaluation of treatment efficacy. Finally, mines should promote transparency and community engagement by making water quality data publicly accessible via online dashboards and regular environmental reports to foster trust and encourage collaborative stewardship of impacted water resources.

6. Conclusion

The integration of Artificial Intelligence (AI) and Geographic Information Systems (GIS), collectively referred to as GeoAI, represents a transformative advancement in water quality monitoring across copper mining regions of the United States. This paper underscores that conventional monitoring practices often characterized by periodic sampling and delayed analysis are insufficient for addressing the spatial heterogeneity and temporal variability of contamination processes such as acid mine drainage and metal leaching. By contrast, GeoAI frameworks enable real-time, predictive environmental intelligence through the fusion of remote sensing data, in-situ sensor networks, and advanced machine learning algorithms, including Random Forest, Long Short-Term Memory (LSTM), and XGBoost models.

The adoption of these integrated approaches enhances both the temporal responsiveness and spatial resolution of water quality assessments, facilitating early detection of pollution events and enabling proactive mitigation before regulatory thresholds are exceeded. Case examples from major Arizona operations, illustrate how GeoAI applications can inform targeted remediation, optimize operational decisions, and ensure compliance with Environmental Protection Agency (EPA) and Mine Safety and Health Administration (MSHA) standards.

Looking forward, the institutionalization of GeoAI within environmental governance frameworks will be pivotal to ensuring the sustainability of copper mining in arid and water-stressed regions. Broader implementation should focus on the standardization of GeoAI methodologies, the expansion of high-frequency monitoring networks, and the integration of open-access data platforms to promote transparency and public trust. GeoAI offers a pathway toward predictive, data-driven, and environmentally responsible mining practices.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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