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Integration of remote sensing and GIS for mineral exploration and resource estimation in complex geological terrains

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Abstract

The integration of Remote Sensing and Geographic Information Systems (GIS) has transformed mineral exploration by enabling rapid, synoptic, and cost-effective assessment of complex geological terrains. Modern exploration increasingly relies on multispectral, hyperspectral, and radar-based remote sensing techniques to detect surface mineralogical signatures, structural discontinuities, alteration zones, and geomorphological features that traditionally required extensive ground surveys. These technologies provide continuous spatial coverage and the ability to monitor inaccessible or rugged regions, offering a broader perspective on regional geology and mineralization patterns before narrowing down to high-potential targets. Within this broader framework, GIS serves as the analytical backbone for organizing, integrating, and interpreting heterogeneous geoscientific datasets. By combining satellite imagery, geophysical surveys, geochemical samples, digital elevation models, and structural information, GIS enables multi-criteria decision analysis and spatial modeling to prioritize exploration zones. Advanced techniques such as spectral unmixing, lineament extraction, mineral mapping algorithms, and spatial probability modeling further refine the identification of ore-bearing lithologies and hydrothermal alteration systems. These integrations enhance predictive accuracy, reduce exploration risk, and optimize resource allocation. Narrowing the focus to resource estimation, remote sensing-derived datasets increasingly support quantitative assessments by delineating ore boundaries, estimating volumetric extents, and improving the resolution of 3D geological models. Machine learning and geostatistical techniques embedded within GIS platforms allow extrapolation of subsurface characteristics from surface indicators, improving preliminary reserve classification. Furthermore, these integrated workflows facilitate sustainable exploration by reducing environmental footprints and guiding targeted field verification campaigns. Overall, the combined use of remote sensing and GIS presents a powerful, data-driven approach to mineral exploration and resource estimation, providing both a comprehensive regional overview and precise, high-resolution insights necessary for modern mining decision-making.

Keywords: Remote Sensing; GIS; Mineral Exploration; Resource Estimation; Hyperspectral Imaging; Geological Mapping

1. Introduction

1.1. Background: Global Demand for Minerals and Technological Advancements

Global demand for minerals has increased significantly as industrialization, infrastructure expansion, and the transition toward renewable energy accelerate worldwide. Critical minerals such as lithium, cobalt, copper, and rare earth elements have become central to modern technological systems, including electric vehicles, battery storage, telecommunications, and advanced manufacturing [1]. This heightened demand places pressure on governments and mining companies to identify new deposits efficiently while minimizing exploration risks and environmental impact.

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Traditional geological field surveys, though essential, are resource-intensive and limited in their ability to cover vast or inaccessible terrains [2].

Advancements in remote sensing technologies have transformed mineral exploration by enabling rapid, synoptic assessment of large landscapes. Multispectral, hyperspectral, thermal, and radar sensors allow researchers to detect mineralogical signatures, alteration halos, structural disruptions, and geomorphological indicators relevant to ore formation [3]. The increasing spatial and spectral resolution of modern satellite missions such as Sentinel-2, Landsat 8, and commercial hyperspectral systems has improved the precision of lithological mapping and enhanced discrimination of mineral assemblages [4]. These innovations enable exploration teams to identify potential targets before deploying costly field campaigns.

Complementing remote sensing, Geographic Information Systems (GIS) provide robust tools for integrating diverse geoscientific datasets, performing spatial modeling, and supporting multi-criteria analysis [5]. Together, remote sensing and GIS create a comprehensive, scalable workflow for prioritizing exploration zones and supporting informed decision-making. The combined approach is particularly valuable in complex terrains where structural, metamorphic, and erosional processes can obscure mineralization patterns detectable only through advanced spectral and spatial analysis [6]. As demand intensifies, integrated geospatial technologies continue to play an increasingly vital role in supporting efficient, data-driven mineral discovery strategies [7].

1.2. Challenges of Exploration in Complex Geological Terrains

Exploration in complex geological terrains poses substantial scientific and operational difficulties. These regions often include highly deformed metamorphic belts, volcanic arcs, faulted sedimentary basins, or deeply weathered shields where traditional indicators of mineralization may be obscured or altered by geological processes [8]. Structural overprinting, metamorphic re-equilibration, and surface cover such as vegetation or regolith can mask lithological boundaries and hydrothermal signatures, complicating field-based mapping efforts.

Additionally, rugged terrain and limited accessibility hinder systematic surveying, making it challenging to implement ground sampling, geophysical measurements, or trenching programs. In many regions, logistical barriers drive exploration costs upward and restrict the density of field observations. Remote sensing technologies help overcome these constraints but require sophisticated interpretation to distinguish true mineralogical anomalies from environmental or atmospheric noise [3].

Complex terrains also introduce uncertainty into resource estimation. Variations in rock fabric, alteration intensity, and mineral distribution introduce spatial heterogeneity that complicates subsurface modeling [6]. These challenges underscore the need for integrated approaches that merge remotely sensed datasets with spatial analytics to refine geological understanding. Ultimately, addressing these complexities requires methods capable of capturing regional context while supporting precise, localized assessment of mineral potential [9].

Research Aim, Need for Integrated Remote Sensing–GIS Framework, and Contribution

This study aims to evaluate how the integration of remote sensing and GIS can enhance mineral exploration and resource estimation in geologically complex terrains where traditional methods alone may be insufficient [4]. The research addresses the need for a unified framework capable of synthesizing spectral, spatial, structural, and geochemical datasets to improve target identification and minimize uncertainty during early exploration phases [2].

The study contributes by outlining a comprehensive geospatial workflow that leverages multispectral and hyperspectral imagery, digital elevation models, and GIS-based spatial modeling to support efficient mineral prospecting [5]. It demonstrates how integrated datasets can reveal hidden structural controls, detect hydrothermal alteration zones, and refine volumetric estimations necessary for preliminary resource classification [7]. Through a systematic evaluation of tools and processes, the paper offers a structured approach for improving exploration accuracy and reducing operational risk in terrains where geological complexity often obscures mineralization indicators [1].

2. Remote sensing technologies for mineral exploration

2.1. Multispectral and Hyperspectral Imaging: Principles and Mineralogical Signatures

Multispectral and hyperspectral imaging have become indispensable tools for mineral exploration due to their ability to capture diagnostic spectral responses associated with different mineral groups. Multispectral sensors measure reflected sunlight across a limited number of broad spectral bands, enabling the identification of major lithological units and broad alteration features [6]. In contrast, hyperspectral sensors acquire data across hundreds of narrow, contiguous spectral bands, allowing for the detection of subtle absorption features linked to specific minerals such as clays, carbonates, iron oxides, and sulfates [7]. This higher spectral resolution supports precise mineral mapping, particularly in terrains where alteration halos or mineralogical variations are difficult to observe through field-based surveys alone.

The underlying principle of hyperspectral analysis relies on the fact that each mineral exhibits characteristic absorption features associated with electronic transitions or vibrational processes occurring at the molecular level [8]. By analyzing reflectance curves and matching them to known spectral libraries, geoscientists can detect the presence and abundance of minerals that commonly signal hydrothermal systems, such as kaolinite, sericite, alunite, and hematite [9]. These minerals serve as proxies for identifying potential ore-forming environments even when underlying mineralization is not directly visible at the surface.

Advancements in imaging spectroscopy have expanded the utility of remote sensing to geologically complex regions where structural deformation and metamorphism complicate traditional mapping approaches. Hyperspectral imagery enables differentiation between mineral assemblages formed during different geological events, supporting detailed reconstruction of alteration pathways [10]. Additionally, the integration of multispectral and hyperspectral data improves the robustness of classification models by combining broad spatial coverage with detailed spectral fidelity [11]. This dual approach enhances exploratory efficiency, reduces field-mapping uncertainty, and provides a scalable platform for both regional reconnaissance and localized mineral prospecting in diverse geological settings.

2.2. Optical, Thermal, and Radar Sensors in Geological Mapping

Optical remote sensing systems remain essential for geological mapping because they offer high spatial resolution across visible and near-infrared wavelengths, enabling the extraction of lithological boundaries and structural features such as fractures and lineaments [12]. Optical sensors are particularly valuable for mapping surface mineralogy in semi-arid or exposed regions where vegetation cover is minimal, allowing geological units to be distinguished based on reflectivity and colorimetric variations [6]. However, optical data are limited by atmospheric interference and inability to penetrate vegetation or surface cover, motivating the use of complementary sensor types.

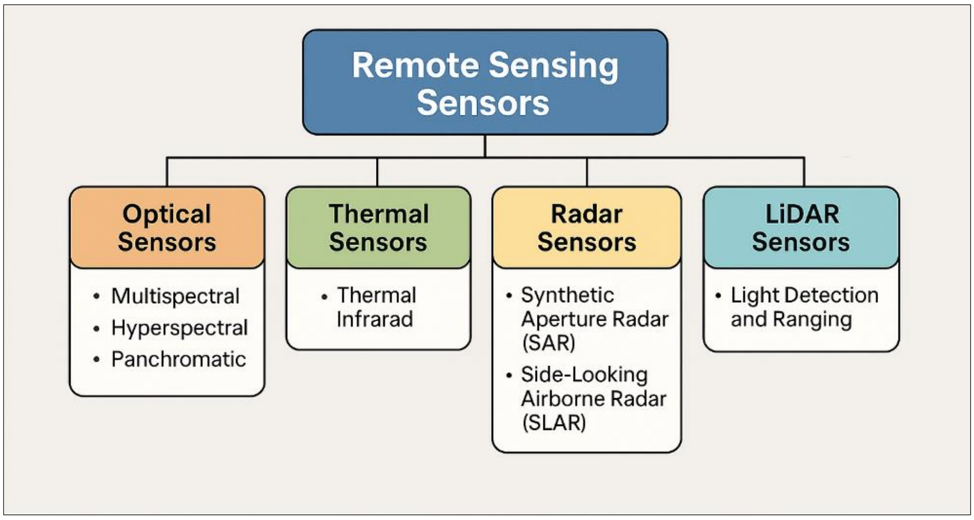

Figure 1 Classification of Remote Sensing Sensors Used in Mineral Exploration

Thermal infrared (TIR) sensors extend the observational capability of remote sensing by detecting emitted radiation associated with surface temperature. Minerals exhibit distinct thermal emissivity characteristics, enabling the differentiation of silicates, carbonates, and sulfates through emissivity spectra [13]. TIR imaging is particularly effective in identifying quartz-rich lithologies and igneous compositions that may not exhibit strong absorption features in shorter wavelengths [10].

Radar systems, including synthetic aperture radar (SAR), provide structural and textural information independent of lighting conditions and cloud cover, making them highly useful in tropical or persistently cloudy regions [14]. Radar backscatter is sensitive to surface roughness, slope, moisture, and dielectric properties, enabling the detection of geological structures such as faults, shear zones, and lithological contacts [15]. These structural insights are crucial for identifying pathways of hydrothermal fluid migration and locating potential mineralized corridors.

Together, optical, thermal, and radar sensors offer a complementary suite of geological mapping tools that overcome individual sensor limitations. Their integration provides a more comprehensive representation of surface conditions and subsurface indicators. This combined perspective is structured more clearly when visualized through *Figure 1*, placed after this subsection, which illustrates the classification of sensors commonly used in mineral exploration [16].

2.3. Spectral Indices, Alteration Zone Detection, and Lithological Discrimination

Spectral indices derived from multispectral and hyperspectral data are essential for identifying mineralogical anomalies associated with hydrothermal alteration and weathering processes. Indices such as the Normalized Difference Vegetation Index (NDVI), Clay Mineral Ratio, and Ferric Iron Index enhance subtle spectral differences that may not be directly observable in raw imagery [17]. These enhancements facilitate rapid detection of alteration zones that commonly accompany ore-forming systems, including argillic, phyllic, and propylitic assemblages [12].

Hydrothermal alteration mapping is especially critical in terrains where mineralization signatures are obscured by complex geological overprinting. By analyzing absorption depths and spectral curvature at key wavelengths, geoscientists can differentiate between mineral groups such as kaolinite–illite series or hematite–goethite pairs, supporting more accurate reconstruction of hydrothermal pathways [9]. This spectral-based approach allows for early targeting of potential mineralized zones before conducting field verification.

Lithological discrimination benefits greatly from spectral transformation techniques, including principal component analysis, minimum noise fraction, and matched filtering algorithms. These tools isolate significant spectral information while reducing noise, enabling more reliable classification of rock types across heterogeneous landscapes [11]. Integration with digital elevation models enhances discriminatory power by correlating lithological boundaries with geomorphological parameters such as slope, curvature, and drainage patterns [14].

By combining spectral indices, alteration mapping, and lithological classification, remote sensing provides a multifaceted analytical framework for identifying mineral-rich environments. This integrated approach is particularly valuable in structurally complex terrains where geological units are spatially fragmented or deeply weathered. Ultimately, the synergy of spectral analysis and spatial modeling improves exploration accuracy while reducing reliance on expensive and logistically challenging ground surveys [6].

3. GIS-based spatial analysis and geological data integration

3.1. GIS as a Decision-Support Framework for Geoscience

Geographic Information Systems (GIS) function as an essential decision-support framework in modern geoscience because they enable the integration, management, and visualization of spatially referenced datasets critical for mineral exploration. Traditional geological assessments often rely on fragmented information from field surveys, geophysical campaigns, and satellite observations, but GIS provides a unified environment where these datasets can be harmonized and analyzed coherently [15]. Through layered mapping, GIS allows geoscientists to overlay diverse datasets such as lithology, structural maps, alteration indices, and geophysical anomalies to identify spatial correlations that may indicate subsurface mineralization [16].

Spatial modeling techniques enhance this capability by incorporating mathematical and statistical tools into exploratory workflows. Functions such as buffer analysis, density mapping, and spatial interpolation help quantify geological relationships and reveal patterns not readily visible in raw datasets [17]. Data harmonization is also central to GIS, ensuring consistency between datasets acquired from different sensors, scales, or coordinate systems. This is particularly important when combining remote sensing imagery with point-based geochemical measurements or line-based structural datasets [18].

GIS also supports temporal tracking of geological processes by managing time-series datasets derived from remote sensing missions. This allows users to detect environmental changes, monitor mining disturbances, and evaluate exploration impacts. The ability to generate 2D and 3D visualizations further strengthens interpretive accuracy by enabling geologists to explore complex terrains in a virtual setting [19]. Ultimately, GIS provides the analytical backbone for mineral exploration, enabling efficient data integration, enhanced interpretability, and robust decision-making in regions characterized by geological complexity [20].

3.2. Integration of Remote Sensing, Geophysical, and Geochemical Datasets

The integration of remote sensing, geophysical, and geochemical datasets within a GIS environment significantly improves mineral exploration outcomes by leveraging the strengths of each discipline. Remote sensing provides regional-scale surface information that identifies lithological units, structural fabrics, and hydrothermal alteration zones detectable through spectral signatures [21]. When merged with geophysical datasets such as magnetic, gravity, and electromagnetic surveys explorers gain insight into subsurface conditions that cannot be inferred directly from surface data alone [17].

Geophysical methods help delineate buried faults, intrusive bodies, and density contrasts associated with mineralized systems. Their integration with remote sensing-derived structural interpretations enhances the reliability of mapping fluid pathways and mineral deposition zones [18]. Digital Elevation Models (DEMs) further contribute by revealing geomorphological patterns, drainage anomalies, and terrain breaks that may align with subsurface structures [22]. DEM-derived slope, curvature, and watershed metrics often correlate with lithological boundaries and fault systems, assisting in lineament extraction and structural interpretation.

Geochemical datasets including soil, stream-sediment, and rock assays provide ground-truth confirmation of anomalies detected through geophysical and remote sensing techniques. By incorporating these data into GIS, analysts can link surface spectral anomalies with elemental concentrations, increasing confidence in exploration targets [19]. Spatial correlation tools, such as cluster analysis and hotspot mapping, help identify geochemical halos or indicator minerals that support exploration models.

Overlay analysis forms the basis of integrating these heterogeneous datasets by enabling weighted combinations of different evidence layers. This generates exploration potential maps highlighting areas where multiple indicators converge. The placement of Table 1 after this subsection supports clarity by summarizing dataset roles in mineral exploration workflows [23]. The combined use of remote sensing, geophysics, and geochemistry within GIS thus augments interpretive depth, reduces uncertainty, and enhances strategic exploration planning in complex geological environments [24].

3.3. Spatial Multi-Criteria Decision Analysis (SMCDA) and Weighted Overlay Methods

Spatial Multi-Criteria Decision Analysis (SMCDA) provides a structured and quantitative approach for ranking exploration targets by integrating diverse geoscientific indicators within GIS. Unlike traditional qualitative interpretation, SMCDA introduces a systematic method for assigning weights to different evidence layers based on their relevance to mineralization processes [18]. Weighted overlay methods, frequently used in mineral prospectivity mapping, allow multiple datasets such as alteration indices, geophysical anomalies, structural density, and geochemical concentrations to be combined into a composite exploration potential model [16].

The process begins with standardizing input layers to a common scale, ensuring compatibility across variables that may differ in units or measurement techniques. Expert judgment, analytic hierarchy processes, or machine learning–based weighting schemes may be used to assign significance scores to each dataset [20]. The weighted layers are then aggregated to produce a final prospectivity map highlighting zones with the highest exploration likelihood.

SMCDA is particularly advantageous in complex terrains where geological signals are fragmented or ambiguous. By quantifying relative contributions of each factor, the method reduces subjective interpretation and increases transparency in target prioritization [22]. Additionally, sensitivity analysis helps evaluate the influence of weight adjustments, improving model robustness. The integration of remote sensing, geophysical, and geochemical datasets into SMCDA facilitates holistic evaluation of mineral systems by capturing both surface and subsurface indicators [21].

Overall, SMCDA strengthens decision-making by combining scientific rigor with spatial analytics, enabling exploration teams to allocate resources more effectively and identify high-potential targets under uncertainty [19].

Table 1 Primary Geoscientific Datasets and Their Role in Mineral Exploration Models

Dataset Type	Description	Typical Parameters / Data Products	Role in Mineral Exploration Models
Remote Sensing Data (Multispectral and Hyperspectral)	Satellite or airborne spectral imaging used to detect mineralogical signatures and surface alteration patterns.	Spectral reflectance curves, band ratios, vegetation indices, alteration indices (e.g., FDI, LSI).	Identifies alteration zones, maps lithologies, supports early reconnaissance, and provides regional-scale mineral prospectivity signals.
Geophysical Data (Magnetic, Gravity, Radiometric, EM)	Subsurface physical property datasets that reveal structural and lithological variations.	Total magnetic intensity, Bouguer anomaly, K/Th/U radiometrics, resistivity models.	Maps deep structures, identifies faults and intrusions, assists in locating ore-hosting lithologies or conductive/ magnetic anomalies associated with mineralization.
Geochemical Data (Soil, Stream Sediment, Rock Sample Assays)	Surface sampling datasets capturing elemental concentrations and geochemical anomalies.	Major and trace element concentrations, pathfinder elements, anomaly threshold maps.	Reveals geochemical halos, detects mineralizing trends, improves target prioritization when combined with geological layers.
Digital Elevation Models (DEMs)	Terrain-height data derived from LiDAR, photogrammetry, or radar.	Slope, aspect, curvature, topographic roughness metrics.	Assists structural/lineament extraction, drainage analysis, geomorphological interpretation, and supports terrain-correction of other datasets.
Geological Maps (1:50,000 – 1:250,000)	Digitized or scanned national/regional geological mapping datasets.	Lithological boundaries, fault traces, fold axes, stratigraphy, age domains.	Provides foundational geospatial framework, constraints for validation, and training layers for mineral prospectivity modeling.
Drillhole and Borehole Data	Direct subsurface data from drilling campaigns.	Lithology logs, assay values, geotechnical logs, downhole geophysics.	Validates exploration models, calibrates geophysical inversion, supports 3D geological modeling, and provides ore grade continuity data.
Structural and Lineament Data	Derived from RS, DEMs, or field mapping.	Fault orientations, fracture density, lineament networks.	Crucial for understanding mineralizing fluid pathways, targeting structurally controlled mineralization, and evaluating tectonic controls.

3.4. 3D GIS and Subsurface Modeling Enhancements

Advancements in 3D GIS have further expanded the analytical capability of mineral exploration workflows. Three-dimensional geological models integrate drillhole data, geophysical inversions, and structural interpretations to create volumetric representations of ore bodies and host lithologies [24]. These models allow geoscientists to visualize the geometry, depth, and continuity of subsurface units, improving resource estimation accuracy and reducing drilling risk [17].

Subsurface modeling also enhances structural interpretation by enabling the reconstruction of fault networks, intrusive geometries, and stratigraphic variations in areas where surface evidence alone is insufficient. Integration with remote sensing-derived surface features ensures that 3D models remain spatially consistent with observable terrain characteristics [20]. With the GIS foundations established, the next section explores how these integrated datasets are operationalized into mineral exploration workflows, emphasizing predictive modeling, target generation, and uncertainty reduction.

4. Integrated remote sensing–GIS workflow for mineral exploration

4.1. Regional Reconnaissance: Broad-Scale Mapping and Terrain Screening

Regional reconnaissance forms the initial phase of mineral exploration, providing a broad-scale understanding of geological, geomorphological, and structural patterns that may indicate mineralizing systems. Remote sensing is particularly valuable at this stage because it enables synoptic coverage of large and often inaccessible regions, offering an efficient means of identifying lithological domains, major structural trends, and surface alteration signatures [22]. Multispectral and hyperspectral datasets allow explorers to differentiate rock units, classify landforms, and detect spectral anomalies that may reflect hydrothermal activity or weathering processes associated with ore deposits [23].

The use of Digital Elevation Models (DEMs) further enhances terrain screening by revealing slope variations, drainage patterns, and terrain roughness, attributes often correlated with subsurface geological structures [24]. DEM derivatives such as hillshade, aspect, and curvature highlight subtle geomorphic features that may align with fault networks or lithological contacts. When integrated into GIS, these remote sensing layers form a foundational geological framework for regional analysis.

Terrain screening also benefits from machine learning methods capable of analyzing multi-dimensional geoscientific datasets to identify emergent patterns indicative of mineral potential [25]. By combining spatial modeling and spectral analysis, regional reconnaissance narrows broad landscapes into prioritized domains suitable for more detailed structural or alteration mapping. This stage significantly reduces operational uncertainty by ensuring that subsequent exploration efforts focus on areas with the highest geological promise [26].

4.2. Lineament Analysis, Structural Mapping, and Tectonic Framework Interpretation

Lineament analysis is a critical component of structural geology because it enables the detection of fractures, faults, shear zones, and lithological boundaries that often control mineralizing fluid pathways. Remote sensing techniques particularly those using optical and radar datasets allow geoscientists to extract linear and curvilinear features associated with tectonic deformation [27]. Radar imagery is highly effective for structural mapping because it is sensitive to surface roughness and dielectric contrasts, supporting lineament identification even in vegetated or cloud-covered regions [28].

Optical datasets complement radar observations by providing high-resolution imagery that captures tonal differences and shadow textures useful for detecting brittle deformation zones. DEM-based derivatives such as shaded relief and slope maps further refine structural interpretations by emphasizing geomorphic discontinuities and ridge–valley alignments [29]. Together, these layers form a structural mosaic that reveals tectonic domains, fault networks, and regional stress orientations.

GIS-based lineament density mapping enhances tectonic framework interpretation by quantifying fracture intensity and identifying structural corridors that may serve as conduits for hydrothermal fluids [22]. These areas often correlate with metallic and non-metallic mineralization, particularly in orogenic, volcanic, or basin-hosted systems. Cross-validation of remote sensing–derived structures with magnetic or gravity lineaments increases interpretive reliability and helps resolve ambiguities arising from surface cover or erosional modification [30].

The importance of structural analysis is emphasized by its placement in the exploration workflow, bridging broad regional reconnaissance and alteration mapping. To illustrate this integration visually, *Figure 2*, inserted after this subsection, presents a schematic of structural lineament mapping derived from combined remote sensing and GIS analysis [24]. This figure reinforces how structural data guide subsequent exploration stages by highlighting deformation zones with high mineralization potential.

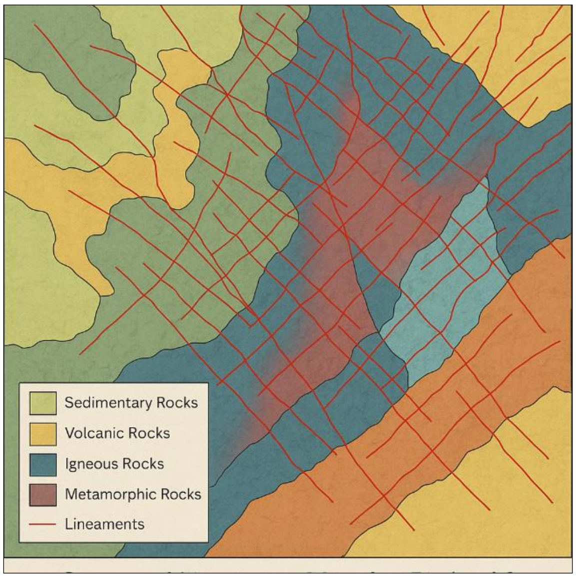

Figure 2 Structural Lineament Mapping Derived from Remote Sensing and GIS Integration

4.3. Hydrothermal Alteration Mapping and Mineral Prospectivity Zonation

Hydrothermal alteration mapping represents a pivotal step in mineral exploration because alteration minerals provide direct or indirect evidence of ore-forming processes. Remote sensing plays a central role in capturing diagnostic spectral signatures associated with clay, sulfate, iron oxide, and carbonate minerals that often mark hydrothermal zones [23]. Hyperspectral analysis enables high-fidelity differentiation of alteration assemblages such as argillic, phyllic, and propylitic zones, allowing geoscientists to reconstruct fluid pathways and locate potential ore centers [26].

GIS-based integration enhances alteration analysis by combining spectral indices with structural layers, geophysical anomalies, and geochemical variables. This synthesis supports the development of mineral prospectivity zonation maps that highlight areas where multiple indicators converge [27]. Weighted overlay and fuzzy logic classifiers are commonly applied to combine alteration intensity with tectonic and lithological evidence, improving the predictive accuracy of prospectivity models.

Multi-temporal analysis further strengthens exploration outcomes by revealing dynamic changes in spectral signatures associated with weathering, vegetation shifts, or anthropogenic disturbance. DEM-derived terrain parameters, when integrated with alteration data, help determine whether spectral anomalies align with topographic highs, depressions, or structural intersections features commonly associated with hydrothermal deposition [29].

By identifying spatial relationships between alteration halos and structural corridors, hydrothermal mapping reduces uncertainty and guides the selection of areas for detailed predictive modeling and drilling. This harmonized approach advances mineral exploration workflows by providing a scientifically grounded basis for prioritizing prospective zones within complex geological terrains [25].

4.4. Deriving Targeted Exploration Zones through Predictive Modeling

Predictive modeling operationalizes the integrated datasets developed through regional reconnaissance, structural mapping, and alteration analysis, enabling the delineation of targeted exploration zones. GIS-based predictive models incorporate spatial statistics, machine learning algorithms, and geological expert knowledge to generate prospectivity surfaces that reflect the relative likelihood of mineral occurrence across a study area [30]. Inputs typically include fault density, alteration intensity, lithological contacts, geophysical gradients, and geochemical anomalies, each weighted according to its relevance to mineralization processes [27].

Machine learning methods such as random forests, support vector machines, and neural networks are increasingly utilized to capture nonlinear relationships between geological variables and known mineral occurrences [22]. These models excel in heterogeneous terrains where traditional linear approaches may fail to resolve complex geological interactions. Validation against known deposits and field evidence ensures predictive robustness.

Composite prospectivity maps generated through predictive modeling highlight exploration targets that satisfy multiple mineralization criteria. These outputs guide drilling campaigns, resource estimation efforts, and field verification programs by reducing spatial uncertainty and focusing on geologically favorable zones [28].

Predictive modeling thus serves as the culmination of integrated geospatial workflows, transforming multi-source datasets into actionable exploration intelligence. By synthesizing structural, spectral, geomorphic, and geochemical indicators, it strengthens the scientific basis for high-confidence targeting while reducing financial and operational risk in mineral exploration [24].

5. Resource estimation using remote sensing–GIS outputs

5.1. Remote Sensing Indicators for Volumetric and Ore Boundary Estimation

Remote sensing provides a powerful foundation for preliminary volumetric assessment and ore boundary delineation by capturing surface mineralogical, geomorphological, and structural signatures that often correlate with subsurface resource distribution [22]. Spectral absorption features detected through multispectral and hyperspectral imaging offer indirect indications of mineral abundance and compositional variation across an ore system [28]. These mineralogical gradients can be spatially analyzed to estimate lateral continuity of alteration halos, enabling preliminary delineation of ore boundaries before drilling begins [29].

Digital Elevation Models (DEMs) further support volumetric estimation by defining morphological patterns associated with lithological contacts, vein systems, or intrusive centers. Slope and curvature derivatives often correlate with lithologic transitions, enabling remote identification of geological boundaries that influence ore geometry [30]. Radar datasets add value by highlighting structural fabrics and penetrative features that may control ore continuity.

Remote sensing also contributes to depth inference by integrating spectral proxies with known geological models. For example, the spatial distribution of iron oxides, clay minerals, or carbonates may serve as surface indicators of hydrothermal processes that extend into the subsurface, forming the basis for extrapolating ore-system geometry [31]. When fused with geophysical or geochemical datasets, these remotely sensed indicators strengthen the preliminary estimation of ore volume and shape.

Although remote sensing alone cannot determine exact subsurface dimensions, its utility lies in guiding drilling campaigns and constraining initial models [18]. By narrowing the spatial search window and identifying geologically coherent boundaries, remote sensing significantly improves the efficiency of volumetric assessment and accelerates the transition to more advanced resource estimation workflows grounded in subsurface data [32].

5.2. GIS-Based Geostatistical Modeling and Reserve Classification

GIS-based geostatistical modeling enhances mineral resource estimation by integrating spatial analysis techniques with predictive statistical frameworks that quantify ore distribution and grade variability. Ordinary kriging, indicator kriging, inverse distance weighting, and co-kriging remain widely applied approaches for interpolating grade values across an ore body using drillhole or sampling data [33]. These geostatistical methods rely on spatial autocorrelation principles captured through variogram modeling, enabling analysts to assess continuity, anisotropy, and spatial heterogeneity within mineral deposits.

GIS provides the computational environment necessary to manage and visualize the input datasets such as drillhole coordinates, assay data, geological boundaries, and structural features allowing seamless incorporation into geostatistical estimators [28]. Spatial interpolation outputs are then transformed into block models representing estimated grades and tonnages, forming the basis for resource classification.Reserve classification frameworks such as measured, indicated, and inferred categories depend heavily on the statistical confidence of interpolation models as well as data density and geological understanding [34]. GIS facilitates uncertainty mapping, cross-validation analysis, and error quantification, supporting transparent classification aligned with reporting standards. Integration with geochemical and remote sensing–derived anomaly maps further strengthens model reliability by embedding geological context into the statistical outputs.

Table 2 Geostatistical Approaches Commonly Applied in Mineral Resource Estimation

Geostatistical Method	Core Principle	Key Input Requirements	Strengths	Limitations / Considerations
Ordinary Kriging (OK)	Uses spatial autocorrelation to estimate grades at unsampled locations assuming a constant but unknown mean.	Variograms, drillhole grades, spatial coordinates.	Produces unbiased estimates with minimum variance; widely accepted in reporting codes (JORC, NI 43-101).	Sensitive to variogram modeling; may smooth out local grade variations.
Simple Kriging (SK)	Similar to OK but assumes a known global mean for the entire deposit.	Global mean, variograms, spatial data.	Effective where global average grade is well constrained; numerically stable.	Less flexible in heterogeneous deposits; may underestimate local variability.
Indicator Kriging (IK)	Converts grade data into binary indicators to model probability of exceeding a threshold cut-off.	Indicator thresholds, indicator variograms.	Useful for highly skewed or non-normal grade distributions; helps delineate ore/waste boundaries.	May oversimplify continuous grade distributions; threshold selection is subjective.
Co-Kriging (CK)	Uses secondary correlated variables (e.g., geophysics, geochemistry) to enhance grade prediction.	Primary + secondary datasets, cross-variograms.	Improves estimates where secondary data is abundant; reduces uncertainty.	Requires strong correlation between datasets; complex modeling.
Sequential Gaussian Simulation (SGS)	Generates multiple equiprobable realizations to quantify spatial uncertainty.	Normal-score transformed data, variograms.	Captures grade variability realistically; useful for risk analysis and mine planning.	Computationally intensive; requires careful distribution transformation.
Multiple Indicator Simulation (MIS)	Simulates grade values using multiple indicator thresholds to model non-Gaussian distributions.	Indicator variograms, threshold classes.	Handles complex, multimodal grade distributions; suitable for heterogeneous ore bodies.	Interpretation of multiple realizations can be challenging.
Inverse Distance Weighting (IDW)	Grades are interpolated using distance-based weighting without spatial autocorrelation modeling.	Drillhole grades, coordinates.	Simple, transparent, fast; good for preliminary resource models.	Not geostatistically rigorous; does not consider spatial structure or uncertainty.

After this subsection, Table 2 is included to summarize common geostatistical approaches used in resource estimation and their optimal application scenarios, providing readers with a clear comparative reference [35]. Ultimately, GIS-based geostatistical modeling transforms raw sampling data into structured resource estimates that underpin feasibility studies, economic evaluations, and mine planning decisions [36].

5.3. Integrating 3D Geological Models with Surface-Derived Data for Enhanced Accuracy

Integrating 3D geological models with surface-derived datasets significantly improves the precision and interpretive robustness of mineral resource estimation. Surface datasets such as remote sensing imagery, DEM derivatives, structural lineament maps, and geochemical indices provide essential constraints on lithological boundaries, alteration patterns, and structural geometries observable at the terrain surface [29]. When incorporated into 3D modeling software, these constraints ensure that subsurface interpretations remain consistent with regional geological context and observable field evidence.

3D models typically incorporate drillhole logs, geophysical inversions, and stratigraphic interpretations to produce volumetric representations of ore bodies. By integrating remote sensing–derived structural and spectral indicators, modelers can refine the geometry of ore lenses, identify zones of geological complexity, and adjust model parameters to reflect known surface processes [30]. This fusion of datasets is particularly effective in terrains where structural overprinting or weathering obscures subsurface relationships.

Machine learning algorithms and automated modeling tools enhance integration by correlating surface signatures with subsurface attributes through multivariate analysis. These methods reduce interpretive subjectivity while improving the reproducibility of geological models [32]. Additionally, 3D visualization enables exploration teams to evaluate mineral continuity, depth variability, and ore-body morphology with improved clarity.

Ultimately, the integration of surface-derived datasets with 3D geological models produces more geologically coherent resource estimates. This synergy strengthens confidence in volumetric assessments, supports accurate classification of reserves, and reduces financial uncertainty in project development [26]. By bridging the gap between surface observation and subsurface representation, integrated 3D modeling has become an indispensable component of modern mineral exploration workflows [31].

6. Case studies in complex geological terrains

6.1. Application in Metamorphic Belts (Example: Eastern Africa or Canadian Shield)

Metamorphic belts such as the Eastern African Orogen and the Canadian Shield present complex geological environments where remote sensing and GIS have proven particularly effective for mineral exploration. These regions are characterized by high-grade metamorphic rocks, polyphase deformation, and extensive structural overprinting that obscure lithological boundaries and mask mineralization indicators observable at the surface [37]. Remote sensing techniques especially hyperspectral imaging enable the detection of mineralogical variations linked to metamorphic facies transitions, shear zones, and alteration halos associated with gold and base-metal deposits, even when outcrops are limited [38].

Integration with GIS enhances this capability by enabling spatial correlation of spectral anomalies with structural elements such as fold hinges, shear corridors, and greenstone belts. Lineament density mapping helps identify zones of increased brittle deformation that often localize mineralizing fluids in metamorphic terrains [39]. DEM derivatives provide additional interpretive depth by highlighting geomorphological patterns that coincide with buried structures or lithological boundaries.

When combined with geophysical datasets such as aeromagnetic or gravity surveys remote sensing inputs support the delineation of granitoid intrusions, banded iron formations, and deformation zones that host mineralization in the Canadian Shield and Eastern African domains [40]. These integrated workflows allow for precise targeting of prospective zones, reducing exploration uncertainty in terranes where geological complexity poses significant interpretive challenges [41].

6.2. Application in Volcanic and Hydrothermal Terrains (Example: Andes or Papua New Guinea)

Volcanic and hydrothermal terrains such as the Andes and Papua New Guinea are among the world’s most prolific mineral belts, hosting porphyry copper, epithermal gold, and massive sulfide deposits. These regions feature intense magmatism, hydrothermal alteration, and structural disruption, creating mineralogical and spectral signatures ideally suited for remote sensing analysis [42]. Multispectral and hyperspectral sensors detect alteration minerals such as alunite, kaolinite, jarosite, and chlorite that form zoned patterns around hydrothermal centers, enabling early-stage identification of mineralized systems [43].

GIS-based integration reinforces this by correlating spectral alteration zones with volcanic edifices, intrusive centers, and regional fault systems. Lineament extraction reveals structural conduits that control hydrothermal flow and ore deposition, particularly in Andean porphyry systems where mineralization is structurally focused [44]. DEM-derived morphotectonic analysis provides additional insight by mapping volcanic collapse structures, dome complexes, and erosional remnants that align with known mineralized centers.

Geophysical data including magnetics and induced polarization further refine exploration models by imaging subsurface alteration caps, sulfide zones, and intrusive bodies. When integrated with remote sensing in GIS, these datasets produce mineral prospectivity maps that highlight overlapping zones of structural, geochemical, and spectral significance. To visually reinforce this integration, Figure 3, placed after this subsection, illustrates an example of mineral potential mapping in a complex geological setting using remote sensing and GIS [45].

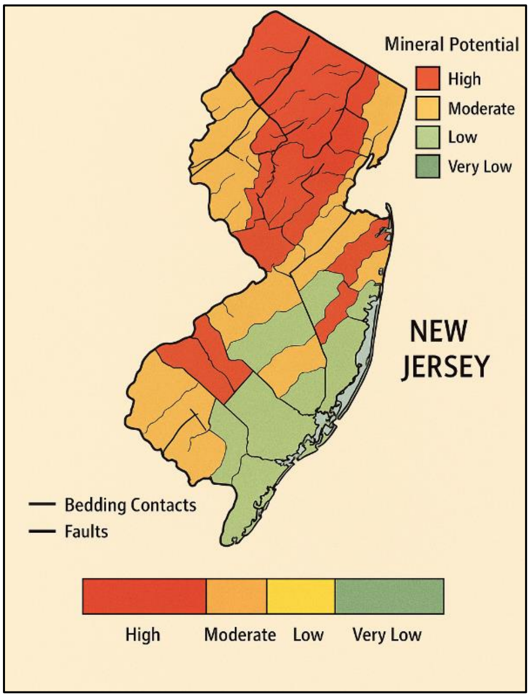

Figure 3 Example of Mineral Potential Mapping in a Complex Geological Setting [3]

6.3. Lessons Learned and Cross-Case Synthesis

The case studies demonstrate that the combined use of remote sensing and GIS provides substantial advantages across geological environments, but they also highlight context-specific considerations that influence exploration outcomes [36]. In metamorphic belts, where surface exposure is often limited and deformation intense, structural mapping and geophysical integration are critical for resolving lithological complexity and identifying buried mineralization pathways [38]. In contrast, volcanic and hydrothermal terrains benefit most from spectral analysis of alteration halos and DEM-supported morphotectonic interpretation, which reveal hydrothermal centers and mineralization zoning patterns [42].

A common lesson across both environments is the value of multi-source data integration. Remote sensing offers rapid, regional coverage; geophysics supplies subsurface constraints; geochemistry provides ground truth; and GIS offers the analytical framework for synthesizing these inputs [41]. Machine learning and predictive modeling further enhance exploration accuracy by identifying nonlinear relationships between datasets that traditional methods may overlook [44].

7. Technical and operational challenges

7.1. Spectral Mixing, Atmospheric Interference, and Sensor Limitations

Remote sensing applications in mineral exploration are constrained by several spectral and atmospheric limitations that affect data reliability and interpretive accuracy. Spectral mixing occurs when multiple surface materials contribute to a single pixel's reflectance signal, a challenge particularly prevalent in heterogeneous terrains where vegetation, soils, and weathered rocks overlap spatially [42]. This reduces the fidelity of mineralogical mapping and complicates the detection of narrow hydrothermal alteration zones. Atmospheric interference including aerosol scattering, water vapor absorption, and variable illumination further distorts recorded spectra, requiring complex correction algorithms that may introduce additional uncertainty [43]. Sensor-specific limitations also influence data quality; for instance, multispectral sensors lack sufficient spectral resolution for discriminating compositionally similar minerals, while hyperspectral systems may suffer from low signal-to-noise ratios over dark or shadowed surfaces [44]. Additionally, radar systems, though valuable for structural mapping, are sensitive to surface moisture and roughness variations, which can obscure geological signatures [45]. These inherent limitations highlight the importance of integrating multiple datasets and applying robust preprocessing techniques to mitigate spectral and atmospheric distortions in mineral exploration workflows [46].

7.2. Data Quality Issues, Spatial Gaps, and Inconsistent Geological Coverage

Data quality and coverage inconsistencies pose additional challenges that influence the effectiveness of remote sensing–GIS integration in exploration projects. Variability in spatial resolution across datasets such as combining coarse-resolution global DEMs with high-resolution commercial imagery can produce misalignment and reduce interpretive coherence [47]. Spatial gaps caused by cloud cover, sensor malfunction, or limited revisit frequency further constrain continuous monitoring, especially in tropical regions where persistent cloudiness reduces optical data availability [48]. Heterogeneous geological coverage is also common, with some regions lacking sufficient geophysical or geochemical datasets to complement remote sensing observations [49]. In structurally complex areas, limited field validation exacerbates uncertainty, making it difficult to differentiate genuine geological anomalies from sensor artifacts or environmental noise. Metadata inconsistencies, varying acquisition times, and differing coordinate systems introduce additional harmonization requirements during GIS integration. These limitations underscore the necessity of rigorous preprocessing, multi-sensor data fusion, and methodological cross-validation to ensure reliable outputs in mineral exploration and resource estimation [50].

8. Future directions and innovation pathways

8.1. Machine Learning, Deep Learning, and Automated Lithological Classification

Recent advances in machine learning and deep learning have significantly improved automated lithological classification by enabling algorithms to detect non-linear patterns in complex geoscientific datasets. Convolutional neural networks (CNNs) are particularly effective for processing multispectral and hyperspectral imagery, extracting mineralogical features that may be difficult to distinguish using traditional spectral methods [45]. Support vector machines and random forests also enhance classification accuracy by integrating spectral, structural, and geomorphological variables [46]. Deep learning–based spectral unmixing reduces the effects of pixel-level mixing in heterogeneous terrains [47]. These techniques collectively streamline exploration workflows by providing rapid, repeatable, and scalable lithological mapping capabilities [48].

8.2. Cloud-Based Geospatial Analytics and Real-Time Mineral Mapping

Cloud-based geospatial platforms have transformed mineral exploration by enabling large-scale processing of remote sensing data and real-time mineral mapping. Platforms such as Google Earth Engine and cloud-hosted GIS solutions facilitate rapid analysis of multi-temporal datasets, overcoming computational constraints associated with desktop systems [49]. These environments also support automated workflows, integrating machine learning models for on-demand alteration detection, lineament extraction, and lithological classification [50]. Real-time data ingestion from satellites with high revisit frequencies enhances the monitoring of dynamic geological environments, while distributed computing accelerates predictive modeling [51]. This shift toward cloud-native geospatial analytics strengthens decision-making and expands the scalability of mineral exploration operations [55].

9. Conclusion

The integration of remote sensing and GIS has fundamentally reshaped mineral exploration by enabling geoscientists to analyze vast, complex terrains with unprecedented precision and efficiency. Remote sensing provides comprehensive spectral, structural, and geomorphological insights, capturing mineralogical signatures and geological patterns that are often inaccessible or obscured at the surface. When combined with the spatial analytical power of GIS, these datasets become part of a cohesive decision-support framework capable of revealing relationships, predicting mineralization zones, and guiding targeted exploration with far greater accuracy than traditional methods alone.

This synergistic approach enhances every stage of exploration, from regional reconnaissance and structural analysis to alteration mapping, predictive modeling, and preliminary resource estimation. By integrating surface observations with subsurface models, it reduces uncertainty, narrows exploration targets, and optimizes resource allocation. Importantly, these technologies also support more environmentally conscious and sustainable mineral development. Remote sensing minimizes the need for intrusive field activities, while GIS enables scenario analysis and careful planning to reduce ecological impacts.

Ultimately, the combined use of remote sensing and GIS not only improves the scientific rigor of mineral exploration but also aligns the sector with modern sustainability imperatives, providing a transformative pathway toward responsible and efficient resource discovery in complex geological settings.

References

[1] Srivastava PK, Bhattacharya AK. Groundwater assessment through an integrated approach using remote sensing, GIS and resistivity techniques: a case study from a hard rock terrain. International Journal of Remote Sensing. 2006 Oct 1;27(20):4599-620.

[2] Oni D. Hospitality industry resilience strengthened through U.S. government partnerships supporting tourism infrastructure, workforce training, and emergency preparedness. World Journal of Advanced Research and Reviews. 2025;27(3):1388–1403. doi:https://doi.org/10.30574/wjarr.2025.27.3.3286

[3] Mekonnen SZ, Woldai T, Carranza EJ. Geological and mineral potential mapping by geoscience data integration. International Institute for Geo-Information Science and Earth Observation. 2008 Apr.

[4] Solarin A, Chukwunweike J. Dynamic reliability-centered maintenance modeling integrating failure mode analysis and Bayesian decision theoretic approaches. International Journal of Science and Research Archive. 2023 Mar;8(1):136. doi:10.30574/ijsra.2023.8.1.0136.

[5] Avtar R, Sahu N, Aggarwal AK, Chakraborty S, Kharrazi A, Yunus AP, Dou J, Kurniawan TA. Exploring renewable energy resources using remote sensing and GIS—A review. Resources. 2019 Aug 19;8(3):149.

[6] Chibueze, T. Access to credit and financial inclusion of MSMEs in sub-Saharan Africa: Challenges and opportunities. International Journal of Financial Management and Economics,(2025). 8(2), 12. https://doi.org/10.33545/26179210.2025.v8.i2.609

[7] John BI. Integration of intelligent scheduling optimization systems improving production flow, minimizing delays, and maximizing throughput across large-scale industrial operations. Global Journal of Engineering and Technology Advances. 2020;5(3):156–169. Available from: https://doi.org/10.30574/gjeta.2020.5.3.0118

[8] Chibueze T, Orivri O, Egunjobi M. Digital banking and MSME performance in Nigeria. International Journal of Research in Finance and Management (IJRFM). 2025;8(2):405-416. doi:10.33545/26175754.2025.v8.i2e.568

[9] Temiloluwa Evelyn Olatunbosun, and Cindy Chinonyerem Iheanetu. 2025. “Data-Driven Insights into Maternal and Child Health Inequalities in the U.S”. Current Journal of Applied Science and Technology 44 (8):98–110. https://doi.org/10.9734/cjast/2025/v44i84593.

[10] Prince Enyiorji. AGENTIC AI ECOSYSTEMS INTEGRATING GOVERNANCE CONTROLS, PROGRAM MANAGEMENT STRUCTURES, AND ADAPTIVE PERSONALIZATION TO BALANCE CONSUMER AUTONOMY, TRANSPARENCY, AND FINANCIAL SYSTEM ACCOUNTABILITY. International Journal Of Engineering Technology Research and Management (IJETRM). 2024Dec21;08(12):579–95.

[11] John BI. Strategic Oversight of AI-Enabled Manufacturing Transformation: Advancing Process Automation, Quality Assurance, System Reliability, and Enterprise-Wide Operational Performance Excellence. International Journal of Research Publication and Reviews. 2024 Dec;5(12):6182-6194. ISSN: 2582-7421.

[12] Bamidele Igbagbosanmi John. CROSS-FUNCTIONAL ENGINEERING LEADERSHIP COORDINATING MULTIDISCIPLINARY TEAMS TO ACHIEVE SYNCHRONIZED EXECUTION, TECHNICAL ALIGNMENT, AND CONSISTENT OPERATIONAL IMPROVEMENT IN MANUFACTURING. International Journal Of Engineering Technology Research and Management (IJETRM). 2022Dec21;06(12):161–77.

[13] Enyiorji P. Designing a self-optimizing cloud-native autonomous finance system for SMEs using multi-agent reinforcement learning. International Journal of Financial Management and Economics. 2025;8(1):596–605. doi:10.33545/26179210.2025.v8.i1.660.

[14] Otoko J. Economic impact of cleanroom investments: strengthening US advanced manufacturing, job growth, and technological leadership in global markets. Int J Res Publ Rev. 2025;6(2):1289-304.

[15] Derera R. Machine learning-driven credit risk models versus traditional ratio analysis in predicting covenant breaches across private loan portfolios. International Journal of Computer Applications Technology and Research. 2016;5(12):808-820. doi:10.7753/IJCATR0512.1010.

[16] Obinna Nweke. STRATEGIC DATA UTILIZATION FOR MINORITY-OWNED BUSINESSES: ENHANCING MARKET PENETRATION, CUSTOMER INSIGHTS, AND REVENUE GROWTH. International Journal of Engineering Technology Research and Management (IJETRM). 2025Mar29;09(03).

[17] Ebere Juliet Onyeka. (2025). AI-Driven Financial Risk Mitigation in Energy Investments: Enhancing Capital Allocation and Portfolio Optimisation. New Advances in Business, Management and Economics Vol. 8, 67–79. https://doi.org/10.9734/bpi/nabme/v8/5643

[18] Tetteh C, Crispus OA. Training Truth: Algorithmic Bias, Black Feminist Epistemologies, and Corrective AI for Historical Archives. International Journal of Research Publication and Reviews. 2024;5(1):6157-6168. Available from: https://ijrpr.com/uploads/V6ISSUE11/IJRPR22308.pdf

[19] P. N. Ezra, L. O. Agbo, C. A. Okonta and J. C. Nzekwe. On Optimal Product-mix for Profit Optimization of Sharks Bakery Company. Asian Res. J. Math. [Internet]. 2023 Feb. 1 [cited 2025 Nov. 14];19(2):1–8. Available from: https://journalarjom.com/index.php/ARJOM/article/view/639

[20] Ogunyemi FM. Developing robust accounting models for quantifying scope 3 emissions and climate-related liabilities in energy-intensive corporate value chains. International Journal of Financial Management and Economics. 2019;2(2):97–105. doi:10.33545/26179210.2019.v2.i2.658

[21] Nweke O, Adelusi O. Utilizing AI-driven forecasting, optimization, and data insights to strengthen corporate strategic planning. International Journal of Research Publication and Reviews. 2025;6(3):4260-4271. doi: https://doi.org/10.55248/gengpi.6.0325.1209

[22] Ibitoye J. Zero-Trust cloud security architectures with AI-orchestrated policy enforcement for U.S. critical sectors. International Journal of Science and Engineering Applications. 2023 Dec;12(12):88-100. doi:10.7753/IJSEA1212.1019.

[23] Tetteh C. Invisible Commerce: Using AI to Map African Women's Trade Networks and Mutual Aid Economies (1870s to 1950s). World Journal of Advanced Research and Reviews. 2023;18(02):1475-1488. doi: 10.30574/wjarr.2023.18.2.0861.

[24] Emi-Johnson O, Fasanya O, Adeniyi A. Predictive crop protection using machine learning: A scalable framework for U.S. agriculture. International Journal of Science and Research Archive. 2024;12(02):3065-3083. doi:10.30574/ijsra.2024.12.2.1536.

[25] Harris JR, Wilkinson L, Grunsky EC. Effective use and interpretation of lithogeochemical data in regional mineral exploration programs: application of Geographic Information Systems (GIS) technology. Ore Geology Reviews. 2000 Jun 1;16(3-4):107-43.

[26] Chinedu J. Nzekwe, Seongtae Kim, Sayed A. Mostafa, Interaction Selection and Prediction Performance in High-Dimensional Data: A Comparative Study of Statistical and Tree-Based Methods, J. data sci. 22(2024), no. 2, 259-279, DOI 10.6339/24-JDS1127

[27] Otoko J. Microelectronics cleanroom design: precision fabrication for semiconductor innovation, AI, and national security in the U.S. tech sector. Int Res J Mod Eng Technol Sci. 2025;7(2)

[28] Tetteh C. Reading against the Colonial Archive: Using AI to Recover the Hidden Economic Contributions of Market Women in Ghana (1890–1957) and African American Washerwomen in the U.S. South (1865–1920). International Journal of Research Publication and Reviews. 2024;5(12):6153-6168. Available from: https://ijrpr.com/uploads/V5ISSUE12/IJRPR36944.pdf

[29] Eldosouky AM, El-Wahed MA, Attia M, Saada SA, Abbas MA. Advanced integrated strategy for structural and mineralogical exploration of inaccessible regions employing remote sensing and multiscale analysis of aeromagnetic data. Scientific Reports. 2025 Aug 25;15(1):31205.

[30] Onyechi VN. Managing large-scale capital projects in oil and gas: Cross-functional engineering leadership, cost performance and execution excellence. Global Journal of Engineering and Technology Advances. 2024;21(3):210-223. doi:10.30574/gjeta.2024.21.3.0233

[31] Shupe SM, Akhavi MS. Integration of remotely sensed and GIS data for mineral exploration: Halifax Pluton area, Nova Scotia, Canada. Geocarto International. 1989 Sep 1;4(3):49-54.

[32] Tetteh C. Voices of Continuity: Creating an AI-Enhanced Digital Oral Archive of Ghanaian Queen Mothers and African American Church Mothers as Custodians of Community Power. International Journal of Science and Research Archive. 2025;15(02):1923-1940. doi: https://doi.org/10.30574/ijsra.2025.15.2.1643

[33] Rajan Girija R, Mayappan S. Mapping of mineral resources and lithological units: A review of remote sensing techniques. International Journal of Image and Data Fusion. 2019 Apr 3;10(2):79-106.

[34] Ayodeji I. Okeyode, Victor N. Onyechi, and Olanrewaju M. Okuyelu. 2023. “High Performance Aqueous Fluids in Deepwater Operation”. Journal of Geography, Environment and Earth Science International 27 (12):64–75. https://doi.org/10.9734/jgeesi/2023/v27i12737.

[35] Confidence N. Oguebu and Chinedu Jude Nzekwe. Database resilience in the era of persistent threats: Integrating breach forensics, anomaly detection, and predictive models. International Journal of Research Publication and Reviews. 2024;5(12):2184–2206. doi:10.55248/gengpi.5.1224.3528. Available from: https://doi.org/10.55248/gengpi.5.1224.3528

[36] Alarifi SS, Abdelkareem M, Abdalla F, Abdelsadek IS, Gahlan H, Al-Saleh AM, Alotaibi M. Fusion of multispectral remote-sensing data through GIS-based overlay method for revealing potential areas of hydrothermal mineral resources. Minerals. 2022 Dec 9;12(12):1577.

[37] Nweke Obinna, Adelusi Oluwatosin. Utilizing AI Driven Forecasting, Optimization, and Data Insights to Strengthen Corporate Strategic Planning. International Journal of Research Publication and Reviews. 2025 Mar;6(3):4260-4271. doi: 10.55248/gengpi.6.0325.1209.

[38] Omogiate PM. Designing automated audit mechanisms to evaluate compliance of generative AI platforms with federal authorship and ownership disclosure requirements. International Journal of Science and Research Archive. 2023;10(2):1536–1549. doi:10.30574/ijsra.2023.10.2.1099.

[39] Tetteh C. Recovering Lost Lives: Machine Learning to Surface African Women in Trans-Atlantic Slave Records. International Journal of Science and Research Archive. 2022;7(02):899-911. doi: 10.30574/ijsra.2022.7.2.0314. Available from: https://doi.org/10.30574/ijsra.2022.7.2.0314

[40] Chinedu Jude Nzekwe and Christopher J. Ozurumba. Advanced modelling techniques for anomaly detection: A proactive approach to database breach mitigation. International Journal of Science and Research Archive. 2024;13(02):2893–2909. doi:10.30574/ijsra.2024.13.2.2511. Available from: https://doi.org/10.30574/ijsra.2024.13.2.2511

[41] Ayankoya MB, Omotoso SS, Ogunlana AA. Data Driven Financial Optimization for Small and Medium Enterprises (SMEs): A Framework to Improve Efficiency and Resilience in U.S. Local Economies. International Journal of Management and Organizational Research. 2025 Jul;4(4):90–97. https://doi.org/10.54660/IJMOR.2025.4.4.90-97

[42] Emi-Johnson O G, Nkrumah K J (April 17, 2025) Predicting 30-Day Hospital Readmission in Patients With Diabetes Using Machine Learning on Electronic Health Record Data. Cureus 17(4): e82437. DOI 10.7759/cureus.82437

[43] Chinedu Jude Nzekwe and Christopher J. Ozurumba. Integrated strategies for database protection: Leveraging anomaly detection and predictive modelling to prevent data breaches. World Journal of Advanced Research and Reviews. 2024;24(03):1451–1466. doi:10.30574/wjarr.2024.24.3.3843. Available from: https://doi.org/10.30574/wjarr.2024.24.3.3843

[44] Sabins FF. Remote sensing for mineral exploration. Ore geology reviews. 1999 Sep 1;14(3-4):157-83.

[45] Emi-Johnson O, Fasanya O, Adeniyi A. Explainable AI for pesticide decision-making: Enhancing trust in data-driven crop protection models. International Journal of Computer Applications Technology and Research. 2025;14(01):147-161. doi:10.7753/IJCATR1401.1013.

[46] Obinna Nweke. STRATEGIC DATA UTILIZATION FOR MINORITY-OWNED BUSINESSES: ENHANCING MARKET PENETRATION, CUSTOMER INSIGHTS, AND REVENUE GROWTH. International Journal of Engineering Technology Research and Management (IJETRM). 2025Mar29;09(03).

[47] Adeyanju BE, Loto AO, Bello M, Adebisi T. Food Safety and Hygienic Practices Among Street Food Vendors in Ife East Local Government Area, Osun State, Nigeria. International Journal of Research and Scientific Innovation (IJRSI). 2025 Mar;12(15):468. doi: 10.51244/IJRSI.2025.121500042P.

[48] John BI. Data-driven resource optimization approaches enhancing capacity planning, labor utilization, material efficiency and continuous improvement across manufacturing project lifecycles. GSC Advanced Research and Reviews. 2023;17(3):220–236. doi: https://doi.org/10.30574/gscarr.2023.17.3.0467

[49] Abdelkareem M, Al-Arifi N. Synergy of remote sensing data for exploring hydrothermal mineral resources using GIS-based fuzzy logic approach. Remote Sensing. 2021 Nov 9;13(22):4492.

[50] Omali TU. Utilization of remote sensing and GIS in geology and mining. Int. J. Sci. Res. in Multidisciplinary Studies. 2021 Apr;7(4).

[51] Tagwai MG, Jimoh OA, Shehu SA, Zabidi H. Application of GIS and remote sensing in mineral exploration: current and future perspectives. World Journal of Engineering. 2024 Apr 26;21(3):487-502.

[52] Mostafa, S.A.; Smith, K.; Nelson, K.; Elbayoumi, T.; Nzekwe, C. A Learning Strategy Intervention to Promote Self-Regulation, Growth Mindset, and Performance in Introductory Mathematics Courses. Eur. J. Investig. Health Psychol. Educ. 2025, 15, 198. https://doi.org/10.3390/ejihpe15100198

[53] Rajesh HM. Application of remote sensing and GIS in mineral resource mapping-An overview. Journal of mineralogical and Petrological Sciences. 2004;99(3):83-103.