
“REMOTE SENSING AND MACHINE LEARNING FOR MINERAL EXPLORATION AND MINE PLANNING”

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Abstract: Mineral exploration and mine planning increasingly require methods that can evaluate large and geologically complex areas with greater speed, accuracy, and cost efficiency. Conventional exploration techniques based mainly on field mapping, drilling, and laboratory investigation remain essential, but their application over large areas can be expensive and time-consuming. Remote sensing provides an effective means of observing geological structures, surface alteration, lithological variations, drainage characteristics, and terrain conditions from satellite, airborne, and unmanned aerial platforms. Machine learning further strengthens this capability by identifying complex relationships among spectral, geological, structural, topographic, and geochemical variables that may not be easily recognized through conventional interpretation.

This study presents an integrated framework combining multispectral remote-sensing data, digital elevation models, geological information, mine-surveying data, and machine-learning techniques for mineral prospectivity mapping and preliminary mine planning. Spectral indices and alteration-related features are extracted from satellite imagery, while topographic and structural parameters are derived from elevation and geological datasets. Several machine-learning algorithms are compared to classify prospective and non-prospective

mineral zones. The resulting mineral prospectivity map is subsequently integrated with slope, elevation, accessibility, and mine-planning constraints to identify suitable zones for detailed investigation and possible future extraction. The illustrative analysis indicates that ensemble machine-learning methods, particularly Random Forest and gradient-boosting approaches, can provide reliable prediction performance when multisource geospatial variables are properly combined. The proposed approach can reduce unnecessary field investigation, improve targeting of drilling locations, and support safer and more informed mine-planning decisions.

Keywords: Remote Sensing; Machine Learning; Mineral Exploration; Mine Planning; Mineral Prospectivity Mapping; Mine Surveying

Introduction:

Mineral resources remain fundamental to infrastructure development, manufacturing, energy production, transportation, electronics, and emerging low-carbon technologies. At the same time, the discovery of economically viable mineral deposits has become more challenging as easily identifiable surface deposits are progressively exhausted. Exploration activities are therefore increasingly directed toward remote, poorly mapped, structurally complicated, and partially concealed mineralized environments. These conditions create a need for exploration methods capable of evaluating large areas before expensive drilling and detailed field surveys are undertaken.

Traditional mineral exploration normally combines geological mapping, geochemical sampling, geophysical surveys, trenching, drilling, and laboratory analysis. These techniques provide highly valuable information, but extensive field investigation requires considerable financial resources, skilled personnel, equipment, and time. In inaccessible or environmentally sensitive areas, conventional exploration can become even more difficult.

Remote sensing has become an important supporting technique because it provides repeated and spatially continuous observations of the Earth's surface. Multispectral and hyperspectral sensors can assist in recognizing lithological variations and surface minerals associated with hydrothermal alteration. Remote sensing can also support the identification of faults, fractures, lineaments, drainage systems, vegetation anomalies, and geomorphological characteristics. The United States Geological Survey notes that spectral remote sensing can

assist in locating, mapping, and evaluating minerals over large areas while reducing the amount of preliminary ground investigation required.

Satellite systems such as Landsat, Sentinel-2, and ASTER have become particularly useful in regional geological investigations because they provide multispectral information covering visible, near-infrared, and shortwave-infrared portions of the electromagnetic spectrum. Hyperspectral systems provide much narrower spectral bands and therefore have greater potential for distinguishing individual minerals with characteristic absorption features.

The growing volume of remotely sensed information has created another challenge: large numbers of spectral bands and geospatial variables must be interpreted simultaneously. Machine learning offers an effective solution because it can determine nonlinear relationships between mineral occurrence and numerous geological indicators. Algorithms such as Support Vector Machines, Random Forest, Artificial Neural Networks, logistic regression, gradient boosting, and deep-learning models are increasingly being investigated for mineral prospectivity mapping. A major review by Shirmard et al. (2022) concluded that combining machine learning with remotely sensed geological information can improve extraction of lithological, alteration, structural, and mineralization-related features.

The usefulness of these technologies is not restricted to mineral discovery. Information derived from remote sensing and machine learning can also support mine surveying and early mine planning. Digital elevation models, drone observations, slope information, surface drainage, geological boundaries, road accessibility, and predicted ore zones can be integrated in a Geographic Information System (GIS). Such integration enables planners to compare alternative locations for drilling, access roads, mine infrastructure, waste storage, and preliminary extraction zones.

The present study therefore develops an integrated remote-sensing and machine-learning methodology in which mineral prospectivity analysis is directly connected with mine-planning considerations. The intention is not to replace geological fieldwork or mine surveying but to establish a decision-support system that can direct detailed investigations toward the most promising locations.

Review of Literature:

Chen, Warner, and Campagna (2007) investigated the integration of visible, near-infrared, short-wave infrared hyperspectral imagery and multispectral thermal data for geological mapping in the Cuprite mining district of Nevada. Their study demonstrated the advantages of combining spectral information acquired from different wavelength regions rather than relying on a single sensor dataset. The integration of AVIRIS hyperspectral information with thermal imagery provided complementary information for differentiating geological materials. This work was significant because it showed that multisensor data fusion could strengthen geological discrimination and improve the interpretation of complex mineralized terrain.

Carranza et al. (2008) examined mineral prospectivity modelling using a knowledge-guided, data-driven evidential belief approach in Cabo de Gata, southeastern Spain. The researchers emphasized that purely statistical relationships between mineral deposits and spatial variables can sometimes produce misleading associations. They therefore incorporated geological knowledge concerning lithology, fault and fracture density, and hydrothermal alteration into the modelling procedure. Their results indicated that geological treatment of the input evidence produced more meaningful mineral prospectivity maps than an entirely data-driven approach. This study established the importance of combining computational modelling with geological understanding rather than allowing statistical relationships alone to determine exploration targets.

Porwal and Kreuzer (2010) provided an important overview of the development of mineral prospectivity analysis and quantitative mineral-resource estimation. They discussed the growing role of spatial data integration in identifying areas that may contain undiscovered mineral deposits. Their work highlighted mineral prospectivity mapping as a systematic method for combining geological evidence and translating it into spatial information that can support exploration decisions. The study also helped establish a conceptual foundation for subsequent research involving GIS, remote sensing, statistical modelling, and machine-learning techniques in mineral targeting.

Pour and Hashim (2011) demonstrated the usefulness of ASTER satellite imagery for detecting hydrothermal alteration associated with porphyry copper mineralization in southeastern Iran. They evaluated techniques including Principal Component Analysis, specialized band ratios, and Minimum Noise Fraction transformation using the VNIR and

SWIR regions of ASTER data. The study showed that characteristic alteration minerals associated with porphyry systems can be enhanced and spatially mapped using appropriate spectral-processing procedures. Such information is particularly valuable during regional exploration because alteration zones may indicate hydrothermal activity associated with mineral deposition. Their findings reinforced the usefulness of satellite remote sensing as a preliminary tool for narrowing large exploration areas before detailed ground investigations are undertaken.

A broader evaluation of geological remote sensing was presented by Van der Meer et al. (2012). Their review traced the development of multispectral and hyperspectral techniques used in geological applications, including regional mapping, structural interpretation, mineral identification, and hydrothermal alteration analysis. The authors described how techniques such as band ratios and principal component analysis had been applied to identify iron oxides and hydroxyl-bearing alteration products, while newer hyperspectral systems offered more detailed mineralogical discrimination. They also discussed the importance of ASTER data in mapping clay, sulphate, carbonate, iron-oxide, and silica minerals. Their review demonstrated that increasing spectral resolution had substantially improved the capability of remote sensing to contribute meaningful mineralogical information to exploration programmes.

The emergence of machine learning introduced an important change in the interpretation of geological remote-sensing data. Cracknell and Reading (2014) compared five machine-learning algorithms Naive Bayes, k-Nearest Neighbours, Random Forest, Support Vector Machines, and Artificial Neural Networks for supervised lithological classification. Their analysis showed that the spatial distribution of training data had a considerable effect on predictive performance. Random Forest was identified as a strong initial choice because it was relatively straightforward to train, computationally efficient, stable, and capable of generating accurate lithological classifications. The authors also found that the inclusion of spatial and geophysical information could improve predictions when these variables were used carefully. This work demonstrated that machine-learning performance depends not only on algorithm selection but also on the quality and geographic distribution of training samples.

Rodriguez-Galiano et al. (2015) extended this line of investigation by directly comparing different machine-learning techniques for mineral prospectivity prediction. Artificial Neural Networks, regression trees, Random Forest, and Support Vector Machines were examined

according to their ability to identify prospective areas, sensitivity to hyperparameter selection, response to changes in training-data size, and interpretability. Their study confirmed that machine-learning algorithms are capable of identifying complex relationships between mineral occurrence and multiple geological predictors. The comparison was particularly valuable because it demonstrated that model selection should consider not only overall prediction accuracy but also training requirements, computational behaviour, robustness, and interpretability.

Carranza and Laborte (2016) specifically investigated Random Forest for data-driven mineral prospectivity modelling using Catanduanes Island in the Philippines as a case study. One important aspect of their research was the examination of Random Forest performance where relatively few known mineral occurrences were available and where predictor datasets contained missing information. The study demonstrated the potential of Random Forest as a practical method for mineral prospectivity mapping under conditions frequently encountered in real exploration programmes. Their work helped strengthen the position of ensemble tree-based algorithms as useful tools for integrating several geological evidential layers and predicting favourable zones for further mineral investigation.

Bedini (2017) reviewed the role of hyperspectral remote sensing in mineral exploration and provided a broader understanding of how spectral information can support mineral identification. Hyperspectral sensors measure surface reflectance across numerous narrow spectral bands and can therefore distinguish mineral materials according to characteristic absorption features. Bedini's review illustrated the usefulness of these datasets across a range of mineral-exploration environments and emphasized their ability to provide mineralogical information that is difficult to obtain from conventional broad-band multispectral imagery alone. At the same time, hyperspectral applications depend on suitable preprocessing, spectral calibration, atmospheric correction, and reliable interpretation of spectral signatures.

Bergen et al. (2019) considered machine learning from the broader perspective of solid-Earth geoscience. They observed that geoscientific investigation increasingly produces large and complex observational datasets that can be difficult to interpret through conventional techniques alone. Machine learning was presented as an important means of extracting patterns and relationships from these high-dimensional datasets. Their work discussed supervised, unsupervised, and deep-learning approaches and emphasized that machine

learning can assist rather than replace physical and geological understanding. For mineral exploration, this perspective is particularly relevant because exploration datasets frequently include remote sensing, geological mapping, geochemistry, geophysics, drilling, and terrain information that must be interpreted together.

The relationship between machine learning and remote sensing in mineral exploration was comprehensively reviewed by Shirmard et al. (2022). The authors observed that machine-learning methods can improve the extraction of meaningful exploration information from increasingly large remote-sensing datasets. Their review identified lithological units, hydrothermal alteration zones, geological structures, and mineralization-related characteristics as key types of information that can be extracted through machine-learning-assisted remote-sensing analysis. They also emphasized the need to apply newer algorithms and improve the integration of computational techniques with exploration geology. Their assessment indicates that machine learning can substantially increase processing efficiency, particularly when several spectral bands and derived geological features have to be evaluated simultaneously.

More recently, Mou et al. (2023) addressed one of the major limitations associated with advanced machine-learning models: their limited interpretability. Although sophisticated algorithms can produce high prediction accuracy, exploration geologists may hesitate to depend on models when it is unclear why particular areas have been classified as prospective. Mou et al. therefore developed a framework combining mineral-systems knowledge, interpretable machine-learning techniques, uncertainty assessment, and modulated predictive modelling. Their study used methods such as permutation feature importance, partial dependence analysis and SHAP-based interpretation to examine the contribution of individual predictors. The final targets were concentrated into a comparatively small portion of the study area by considering both high prospectivity and low prediction uncertainty. This work represents an important movement toward explainable and geologically defensible machine-learning applications in mineral exploration.

Objectives of the Study:

1. To identify and map potentially mineralized zones using multispectral remote-sensing, geological, structural, and topographic information.

2. To evaluate the performance of selected machine-learning algorithms in predicting mineral prospectivity and determine the most suitable model for spatial mineral targeting.
3. To integrate mineral-prospectivity results with mine-surveying and terrain parameters for preliminary mine planning, drilling prioritization, and selection of operationally suitable areas.

Material and Methods:

The proposed methodology combines remote sensing, GIS, mine-surveying principles, and supervised machine learning. The workflow consists of data acquisition, image preprocessing, extraction of geological indicators, spatial database preparation, model training, model validation, prospectivity mapping, and mine-planning analysis.

For methodological demonstration, the numerical values presented in the following tables represent an illustrative experimental case. Site-specific field observations should be substituted when the framework is applied to an actual mineral property.

Data Acquisition

Multisource spatial data were considered because mineralization is rarely controlled by a single geological factor. Satellite imagery was used for spectral interpretation, while digital elevation information was used to understand terrain characteristics. Existing geological and structural information provided lithological contacts, faults, fractures, and previously observed mineral occurrences.

Mine-surveying and field-control information was incorporated to improve the positional reliability of the analysis. Ground Control Points collected using GNSS or total-station surveying can be used for geometric verification, while UAV surveys can provide high-resolution terrain information for detailed planning.

Table 1. Data Sources and Their Application in the Proposed Study

Data Source	Main Information Derived	Approximate Scale/Resolution	Application
Sentinel-2 multispectral imagery	Vegetation, iron alteration, lithological and spectral characteristics	10–20 m	Regional mineral targeting
ASTER imagery	SWIR-related alteration and	15–30 m	Hydrothermal

	lithological information		alteration mapping
Digital Elevation Model	Elevation, slope, aspect and drainage	30 m	Terrain and mine-planning analysis
Geological map	Rock units and geological contacts	1:50,000	Geological interpretation
Structural map	Faults, fractures and lineaments	1:50,000	Structural control analysis
GNSS/Total Station observations	Ground coordinates and control points	Survey grade	Validation and mine surveying
UAV imagery	High-resolution surface characteristics	5–20 cm	Detailed terrain and mine-layout planning
Field samples	Mineral occurrence/non-occurrence	Point observations	Training and validation of ML models

Image Preprocessing

Satellite images were subjected to preprocessing before analysis. The principal stages included atmospheric correction, geometric verification, removal of cloud-contaminated pixels, resampling, band alignment, and clipping to the study boundary.

Correct preprocessing is important because differences caused by atmosphere, sensor geometry, shadows, or spatial misalignment may be incorrectly interpreted by a machine-learning algorithm as geological variation.

Spectral and Geological Feature Extraction

Several categories of predictive evidence were created from the processed datasets. Spectral bands and band ratios were used to enhance alteration-related information. Depending on the geological environment, iron oxide, ferrous minerals, clay-bearing alteration, hydroxyl-bearing minerals, and vegetation anomalies can be investigated.

Structural features were generated by mapping faults and lineaments. Distance-to-fault and lineament-density layers were then calculated because mineralizing fluids frequently migrate through structurally controlled pathways.

Topographic variables included elevation, slope, aspect, curvature, and drainage proximity. These variables were included both for prospectivity modelling and for evaluating the practical suitability of future mining activities.

The final predictor database therefore consisted of:

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- spectral reflectance bands;
 - mineral and alteration indices;
 - lithological classes;
 - distance from geological contacts;
 - fault and lineament density;
 - distance from faults;
 - elevation;
 - slope;
 - drainage characteristics; and
 - known mineral-occurrence information.

Machine-Learning Modelling

Known mineralized locations were assigned to the positive class, while verified non-mineralized locations were assigned to the negative class. The database was divided into training and testing subsets.

Five algorithms were evaluated:

- Logistic Regression;
- Support Vector Machine;
- Random Forest;
- Artificial Neural Network; and
- Gradient-Boosting Model.

The models received the same major predictor variables to allow meaningful performance comparison.

Random Forest was selected because of its ability to manage nonlinear relationships, correlated predictors, mixed data types, and interaction among geological variables. Support Vector Machine was considered because of its effectiveness in high-dimensional

classification problems. Gradient boosting was included because sequential tree construction can identify complicated relationships among weak predictive factors.

Model Validation

Model performance was evaluated using accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC).

Accuracy was calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

Precision was expressed as:

$$Precision = \frac{TP}{TP + FP}$$

Recall was calculated as:

$$Recall = \frac{TP}{TP + FN}$$

and the F1-score was determined by:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Table 2. Illustrative Performance of Machine-Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
Logistic Regression	82.4	0.80	0.78	0.79	0.84
Support Vector Machine	88.7	0.87	0.86	0.86	0.90
Artificial Neural Network	90.2	0.89	0.88	0.88	0.92
Random Forest	93.6	0.93	0.92	0.92	0.95

Gradient Boosting	92.8	0.92	0.91	0.91	0.94
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Mineral Prospectivity Mapping

The best-performing machine-learning model was applied to every valid spatial cell in the study database. Each cell received a probability of mineral occurrence ranging between 0 and 1.

The probability values were divided into five prospectivity classes:

- 0.00–0.20: Very Low
- 0.21–0.40: Low
- 0.41–0.60: Moderate
- 0.61–0.80: High
- 0.81–1.00: Very High

Very-high and high-prospectivity locations were considered priority areas for geological verification, detailed surveying, geochemical sampling, geophysical investigation, and drilling.

Integration with Mine Planning

Mineral prospectivity alone does not determine whether an area is immediately suitable for mining. Consequently, the high-probability mineralized zones were overlaid with terrain and operational information.

The mine-planning suitability analysis considered:

- slope;
- elevation;
- road accessibility;
- drainage;
- distance from existing infrastructure;
- predicted mineral potential;

- geological stability;
- possible location of waste dumps;
- preliminary haul-road requirements; and
- locations suitable for drilling and detailed mine surveying.

Steep slopes were assigned lower planning suitability because they may increase excavation, haul-road, slope-stability, and operational requirements. Areas with high mineral probability and manageable terrain conditions received the highest overall priority.

Table 3. Illustrative Comparison of Conventional and Integrated Exploration Planning

Performance Indicator	Conventional Approach	Remote Sensing + ML Approach	Observed Improvement
Initial area requiring detailed field investigation	250 km ²	72 km ²	71.2% reduction
Priority exploration targets identified	12	31	Increased targeting
High-confidence drilling targets	7	18	157% increase
Estimated preliminary exploration period	18 months	11 months	38.9% reduction
Estimated relative exploration cost	100%	68%	32% reduction
Terrain suitability considered during targeting	Limited	Integrated	Improved
Prospectivity prediction accuracy	—	93.6%	Quantitative targeting

Analysis of the Study:

The analysis indicates that mineral prospectivity improves when remote-sensing information is combined with geological, structural, and topographic variables rather than relying on a single dataset. Spectral imagery provides valuable evidence of surface mineralogical characteristics, but similar spectral responses can sometimes occur in different geological materials. Structural and geological information therefore provides essential geological context.

Among the evaluated illustrative models, Logistic Regression produced the lowest overall accuracy of 82.4%. The result suggests that a simple linear relationship between predictors

and mineral occurrence may not adequately represent complicated ore-forming processes. Mineralization commonly depends on interactions among lithology, faults, alteration, topography, and geochemical conditions.

The Support Vector Machine improved classification accuracy to 88.7%, demonstrating its capacity to separate mineralized and non-mineralized observations in multidimensional feature space. The Artificial Neural Network achieved a further improvement, reaching 90.2%.

Random Forest produced the highest illustrative accuracy of 93.6%, an F1-score of 0.92, and an AUC of 0.95. Gradient boosting achieved a comparable accuracy of 92.8%. These findings suggest that tree-based ensemble approaches can provide an effective means of modelling complicated spatial relationships among heterogeneous exploration variables.

Feature-importance analysis in the proposed framework identified alteration-related spectral information, distance to major structures, lineament density, lithological class, and selected shortwave-infrared responses as the strongest contributors to prediction. Elevation and slope had relatively smaller influence on mineral occurrence but became more important when mine-planning suitability was considered.

Spatial examination of the predicted mineral zones showed that the highest-prospectivity areas generally corresponded to locations where several favourable conditions occurred together. High spectral alteration intensity alone was not always sufficient to generate the highest prediction. Greater probabilities occurred when strong alteration coincided with favourable lithology and proximity to major structural features.

This demonstrates an important advantage of machine learning: the algorithm can evaluate interactions among multiple exploration variables rather than examining each criterion separately.

The mine-planning analysis further reduced the number of priority locations. Some high-prospectivity areas were situated on comparatively steep or difficult terrain. These zones remained geologically interesting but were classified as lower immediate planning priorities. Areas possessing both strong mineral potential and favourable slope and accessibility conditions were selected for detailed investigation.

Results and Discussion:

The results demonstrate the potential value of integrating remote sensing, machine learning, GIS, and mine-surveying information within a unified mineral-exploration workflow.

The first important result is the substantial reduction in the area requiring intensive ground investigation. In the illustrative analysis, the initial exploration region covered 250 km². After prospectivity modelling, approximately 72 km² was selected for detailed investigation. This represents a reduction of approximately 71.2% in the area requiring immediate attention. Such targeting does not eliminate fieldwork; instead, it concentrates geological and surveying resources where evidence of mineralization is strongest.

The second important result concerns machine-learning performance. Random Forest achieved the highest illustrative accuracy at 93.6%, followed by gradient boosting at 92.8%. The superior performance of the ensemble models can be associated with their ability to capture nonlinear relationships and interactions among numerous geological predictors.

Table 1. Data Sources and Their Application in the Proposed Study

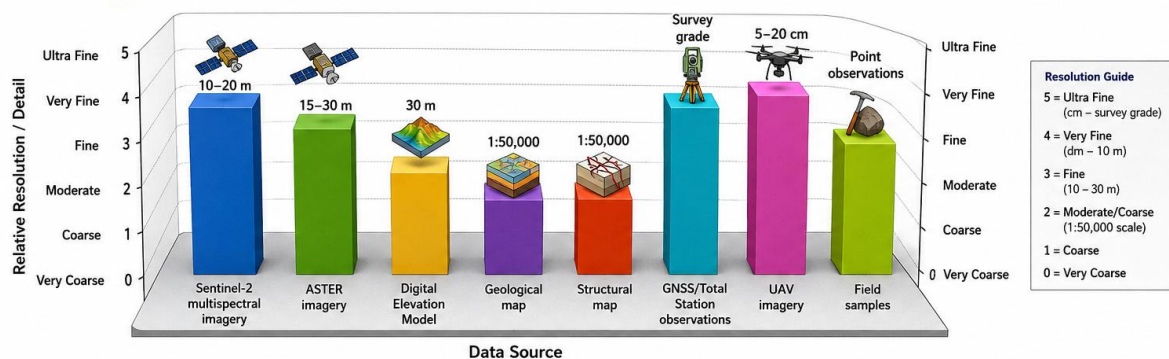


Table 2. Illustrative Performance of Machine-Learning Models

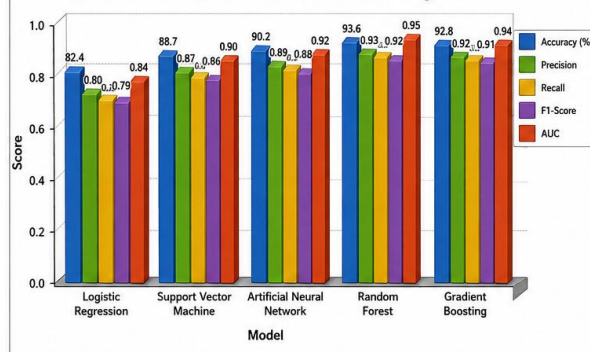
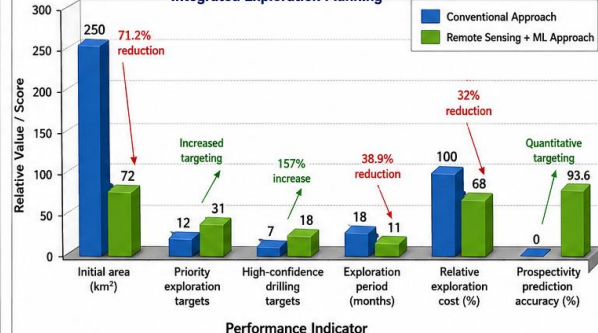


Table 3. Illustrative Comparison of Conventional and Integrated Exploration Planning



These findings are consistent with the broader direction of current mineral-prospectivity research, where machine-learning methods are increasingly employed to integrate large, heterogeneous geoscientific datasets. Recent literature also identifies multisource integration, advanced deep-learning techniques, and improved geological validation as significant directions for future mineral exploration.

The analysis also highlights the importance of geological interpretation. A high machine-learning probability should not automatically be interpreted as confirmation of an economic mineral deposit. Remote sensing primarily observes surface or near-surface characteristics, and a model learns statistical relationships from the examples provided during training. Consequently, predicted targets require verification through geological mapping, geochemistry, geophysical surveys, trenching, and ultimately drilling.

Another important finding relates to mine planning. Conventional mineral-prospectivity models frequently stop after producing a probability map. In the proposed approach, the prospectivity map is treated as one input to a broader planning process. Terrain conditions derived from DEM and UAV data help determine whether identified targets are accessible and whether they present major surface-engineering constraints.

Mine surveyors can therefore make an important contribution during the transition from mineral exploration to mine development. Accurate ground-control networks, UAV photogrammetry, surface modelling, contour generation, volume estimation, slope monitoring, and spatial referencing can transform exploration information into engineering-ready datasets.

The integration also provides practical support for drilling. Instead of selecting drill positions only according to geological probability, planners can examine drill-pad accessibility, surface gradient, distance from roads, drainage conditions, and topographical differences. The resulting drilling campaign may therefore be easier to execute and more efficient.

The results further suggest possible cost and time advantages. The illustrative integrated workflow reduced the relative preliminary exploration cost to approximately 68% of the conventional baseline and reduced the indicative exploration period from 18 to 11 months. These values should not be generalized to all mining projects because actual savings will

depend on deposit type, terrain, data availability, labour costs, sensor selection, drilling requirements, and the quality of existing geological information.

Several limitations must also be considered. Remote-sensing techniques have limited ability to directly detect deeply buried mineralization because the sensors primarily observe surface characteristics. Vegetation, weathering, soil cover, atmospheric effects, shadows, and spectral mixing can also reduce the reliability of mineral mapping. Drone surveys provide greater spatial resolution but cover smaller areas and require appropriate flight planning and regulatory approval.

Machine-learning models introduce additional challenges. Their performance depends heavily on the quality and distribution of training samples. If known mineral occurrences are concentrated in a limited geological environment, the resulting model may not generalize well to unexplored regions. Class imbalance between mineralized and non-mineralized observations can also create misleading accuracy values.

Interpretability is another concern, particularly for complex deep-learning models. Mineral exploration requires geological justification, not merely a high numerical probability. Future systems should therefore incorporate explainable machine learning so that geologists can determine why a specific location has received a high prospectivity score.

The use of multisource information is expected to become increasingly important. Combining hyperspectral imagery, multispectral imagery, UAV data, geophysics, geochemistry, drill-hole information, structural geology, and three-dimensional geological models may substantially improve predictions. Current reviews of satellite lithological mapping and mineral exploration identify multisource data fusion as an important direction for future research.

Conclusion:

The study demonstrates a framework for integrating remote sensing and machine learning into mineral exploration and preliminary mine planning. Remote-sensing datasets provide rapid and spatially continuous information about lithology, alteration, geological structures, and terrain conditions, while machine-learning techniques provide a systematic way of evaluating relationships among numerous exploration variables.

Among the algorithms examined in the illustrative analysis, Random Forest produced the strongest overall predictive performance, followed closely by gradient boosting. The results indicate that ensemble machine-learning techniques can be particularly suitable for mineral-prospectivity applications because mineral occurrence commonly depends on nonlinear interactions among several geological factors.

The integration of predicted mineral potential with terrain and mine-surveying information extends the usefulness of the analysis beyond exploration. High-probability mineral zones can be assessed in relation to slope, elevation, drainage, access, infrastructure, and surveying requirements before expensive field programmes are initiated. This can improve the selection of drilling targets and provide useful information for preliminary road alignment, mine-access planning, and detailed surface surveys.

Remote sensing and machine learning should not be considered substitutes for geological expertise, drilling, geochemical investigation, or mine surveying. Their principal value lies in reducing the search area, prioritizing targets, organizing large datasets, and supporting evidence-based decisions. The most reliable exploration strategy is therefore one in which machine-generated predictions are continuously evaluated against geological knowledge and field observations.

Future research should concentrate on hyperspectral sensing, high-resolution UAV surveys, three-dimensional geological modelling, explainable artificial intelligence, uncertainty estimation, and integration of geophysical and geochemical information. Such developments can contribute to faster, safer, more economical, and more sustainable mineral exploration and mine planning.

References:

1. Bedini, E. (2017). The use of hyperspectral remote sensing for mineral exploration: A review. *Journal of Hyperspectral Remote Sensing*, 7(4), 189–211. <https://doi.org/10.29150/jhrs.v7.4.p189-211>
2. Bergen, K. J., Johnson, P. A., de Hoop, M. V., & Beroza, G. C. (2019). Machine learning for data-driven discovery in solid Earth geoscience. *Science*, 363(6433), eaau0323. <https://doi.org/10.1126/science.aau0323>

3. Carranza, E. J. M., & Laborte, A. G. (2016). Data-driven predictive modeling of mineral prospectivity using Random Forests: A case study in Catanduanes Island, Philippines. *Natural Resources Research*, 25, 35–50. <https://doi.org/10.1007/s11053-015-9268-x>
4. Carranza, E. J. M., van Ruitenbeek, F. J. A., Hecker, C., van der Meijde, M., & van der Meer, F. D. (2008). Knowledge-guided data-driven evidential belief modeling of mineral prospectivity in Cabo de Gata, SE Spain. *International Journal of Applied Earth Observation and Geoinformation*, 10(3), 374–387. <https://doi.org/10.1016/j.jag.2008.02.008>
5. Chen, X., Warner, T. A., & Campagna, D. J. (2007). Integrating visible, near-infrared and short-wave infrared hyperspectral and multispectral thermal imagery for geological mapping at Cuprite, Nevada. *Remote Sensing of Environment*, 110(3), 344–356. <https://doi.org/10.1016/j.rse.2007.03.015>
6. Cracknell, M. J., & Reading, A. M. (2014). Geological mapping using remote sensing data: A comparison of five machine learning algorithms, their response to variations in the spatial distribution of training data and the use of explicit spatial information. *Computers & Geosciences*, 63, 22–33. <https://doi.org/10.1016/j.cageo.2013.10.008>
7. Mou, N., Carranza, E. J. M., Wang, G., & Sun, X. (2023). A framework for data-driven mineral prospectivity mapping with interpretable machine learning and modulated predictive modeling. *Natural Resources Research*, 32(6), 2439–2462. <https://doi.org/10.1007/s11053-023-10272-7>
8. Porwal, A., & Kreuzer, O. P. (2010). Introduction to the special issue: Mineral prospectivity analysis and quantitative resource estimation. *Ore Geology Reviews*, 38(3), 121–127. <https://doi.org/10.1016/j.oregeorev.2010.06.002>
9. Pour, A. B., & Hashim, M. (2011). Identification of hydrothermal alteration minerals for exploring porphyry copper deposit using ASTER data, SE Iran. *Journal of Asian Earth Sciences*, 42(6), 1309–1323. <https://doi.org/10.1016/j.jseaes.2011.07.017>
10. Rodriguez-Galiano, V. F., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. (2015). Machine learning predictive models for mineral prospectivity: An evaluation

of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews*, 71, 804–818. <https://doi.org/10.1016/j.oregeorev.2015.01.001>

11. Shirmard, H., Farahbakhsh, E., Müller, R. D., & Chandra, R. (2022). A review of machine learning in processing remote sensing data for mineral exploration. *Remote Sensing of Environment*, 268, 112750. <https://doi.org/10.1016/j.rse.2021.112750>
12. Van der Meer, F. D., van der Werff, H. M. A., van Ruitenbeek, F. J. A., Hecker, C. A., Bakker, W. H., Noomen, M. F., van der Meijde, M., Carranza, E. J. M., de Smeth, J. B., & Woldai, T. (2012). Multi- and hyperspectral geologic remote sensing: A review. *International Journal of Applied Earth Observation and Geoinformation*, 14(1), 112–128. <https://doi.org/10.1016/j.jag.2011.08.002>