

REMOTE SENSING AND GEOCHEMICAL INTEGRATION FOR MINERAL PROSPECTIVITY MAPPING IN COMPLEX GEOLOGICAL TERRAINS

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Abstract

In this study the integration of remote sensing and geochemical methods for mineral prospectivity mapping in a complex geological terrain has been investigated. Spatially referenced observations, which incorporate remote sensing, geochemical, geological and structural data, were used in the research, with 300 observations used. Data from remote sensing were analyzed for lithological variations, hydrothermal alteration, Fe oxide, clay mineral response, and structural lineaments; and geochemical observations were assessed for elemental anomalies and multiple element associations. The evidence layers were standardised and unified in a GIS-based framework and mineral prospectivity classes were created using a Random Forest model. Of the 186 observations, 62.0% exhibited hydrothermal alteration signatures, 195, 65.0% were related to structural lineaments, and 168, 56.0% were related to geochemical anomalies. The 87% observations classified as high prospectivity, 29.0% were classified as very high prospectivity. For the integrated model, predictive evaluation results were: accuracy of 91%, sensitivity of 89%, specificity of 93%, and precision of 91%, F1-score of 90%, and ROCAUC of 0.95. Of 115 mineral occurrences known, 90 (78.3%) were in the high and very-high prospectivity areas. Results showed that the integration of remotely sensed alteration, structural indicators and geochemical data showed greater potential to provide a more holistic approach to identification of prospective mineralization zones than any single data-set. It provided practical guidance for prioritizing exploration, field verification, geochemical sampling, geophysical survey, and drilling in geologically complex areas. More recently, studies have confirmed the value and feasibility of incorporating multiple data sources from geoscience to aid in targeting mineral exploration.

Introduction

The exploration of mineralization, especially when used to identify targets for exploration, is increasingly dependent on multi-disciplinary geospatial data sets to detect underlying mineralization and rank these for exploration, particularly in areas where reliable enough geological mapping is not available at the regional scale to regionally prioritise these for exploration. Mineral Prospectivity Mapping is a spatial approach that integrates the geological, structural, geochemical, geophysical and remote sensing data in order to better define areas of increased mineral potential. Recently, new challenges that have arisen in the field of processing high dimensional and non-uniform data manually infrequent but large have been met by advances in geospatial analysis and machine learning, which enable handling of such data and the analysis of non-linear relations between the mineralization related variables (Lv & Wang, 2024).

Remote sensing is an important field in today's mineral exploration as it can be utilized to gather regional information concerning lithological variation, hydrothermal alteration, iron oxides, clay minerals, and structural features without the need to cover large areas in the field. The multispectral and hyperspectral data can be processed to provide spectral information that can be used to identify the mineralogical and alteration signature of the systems of hydrothermal alteration; lineaments extracted from high resolution imagery can be used to support explaining the geological setting. Recent studies have proven the potential of ASTER and other satellite datasets to produce several evidence-based maps for the mineral prospectivity modelling and significantly enhance the delineation of prospective areas in conjunction with geological information (Mohamed Taha et al., 2024; Beiranvand Pour et al., 2023).

Despite significant advances, remote sensing and geochemical data are complementary perspectives on mineralization. Geochemical data can provide information on the presence of ore-related and pathfinder element anomalies, while remote

sensing mostly provides information on alteration and lithological expressions of the surface. These data can then be merged to form a more complete data set to describe a mineral system than either can separately. The use of remote sensing combined with multivariate geochemical signatures, which produce alteration indicators based on remote sensing images, can enhance the exploration of porphyry copper and lessen the uncertainty and prospectus of exploration targeting.

Background of the Study

Complex lithological, structural, hydrothermal and geochemical processes govern the mineralization process and their irregular fluctuations gives rise to great difficulties on mineral prospectivity mapping, as well. All these types of faulting, fracturing, alteration zone and lithological boundaries can be related to ore deposits and may not necessarily be seen in any single dataset with spatial change. A study of Duobaoshan in 2024, for instance, showed a remarkable AUC performance (0.984, 0.920 and 0.858) for RBFLN, SVM and RF, respectively, making use of machine-learning algorithms to capture nonlinear relationships between numerous exploration variables and generate high-performance prospectivity maps.

In particular, remote sensing is a very important component of this approach in large, inaccessible or little mapped areas. Visible, near infrared, shortwave-infrared and thermal-infrared spectral information can help in the identification of alteration minerals and lithological units in mineral systems. Recently this application has been extended based on machine-learning approaches to transform remotely sensed spectral information to layers of evidence that can be utilized in prediction. Based on ASTER and Sentinel-2 imagery combined with geological data, Mohamed Taha et al. (2024) created a deep-forest prospectivity model for gold exploration and achieved a classification accuracy ratio of 93.3% with an AUC of 0.964. The results emphasized the usefulness of predictive modelling using remote sensing throughout the analysis,

particularly when fields data and known mineralization events are scarce.

Zhang et al., (2024) showed that the spatial distribution of MPM predicted prospective areas can vary significantly between workflows and the uncertainty associated with the workflow used should be taken into account alongside the predictive accuracy. Recently multivariate geochemical data and hydrothermal alteration data were used in conjunction with one another to facilitate exploration targeting, indicating that the combination of geochemical and hydrothermal alteration data can yield enhancement of the integration process, in contrast to either data type alone. Mapping the alteration and lithological changes in remote 'situations' and geochemical anomalies has been a helpful tool in providing a science-based approach for minerals prospectivity mapping in complex geology and to ensure 'uncertainty' and/or prioritizing particular areas for further geological work".

Objectives of the Study

- 1.To detect and delineate surface mineralization features from remotely sensed data including lithological units, hydrothermal alteration zones, iron-oxide features, clay minerals and structural lineaments.
- 2.To interpret geochemical data and discover anomalies in the study area that relate to possible mineralisation, both on a single element and on a multi-element basis.
- 3.To combine remotely sensed data with geochemical data in a GIS-based mineral prospectivity mapping workflow to delineate and prioritise areas based on mineral prospectivity.

Research Questions

- Q1. What is the ability of remote sensing data to detect lithological, hydrothermal alteration and structural characteristics indicative of mineralization in complex geology?
- Q2. Which geochemical anomalies, both single and multi-element, are of major concern for possible mineralization in the study area?

Q3.How does the combination of remote sensing and geochemical data enhance mineral prospectivity mapping over the use of these data alone?

Significance of the Study

This study is significant, is because it is an integrated spatially explicit method, which could be used for mineral exploration in a complex geological setting where the data from the different exploration methods could be incomplete or unclear. Data interpretation of alteration and lito-structural data and the integration with geochemical anomalies can help to improve the ability to identify and prioritize prospective areas and assist in exploratory decision making. New studies indicate that the utilization of geochemical data in conjunction with remote sensing data can help reduce uncertainty and improve delineation of mineralized zones, as well as a data driven prospectivity model that can increase capacity to prediction of concealed exploration targets.

Literature Review

Remote Sensing Applications in Mineral Prospectivity Mapping

In the mineral exploration field, remote sensing has proved to be an important aspect due to the ability to derive spatially continuous information about lithological composition, hydrothermal alteration, iron-oxide enrichment, clay minerals and other surface features that relate to mineral systems. With the growing number of multispectral and hyperspectral imagery being available, the potential to detect mineralization-related spectral responses has grown from large and geologically complex areas. To overcome this challenge, Shirmard et al. (2020) suggested using selective dimensionality-reduction techniques of ASTER imagery in order to enhance the identification of anomalous mineral related features, while simultaneously eliminating the redundant information in the ASTER spectra. Shirazi et al. (2022) utilized ASTER data along with geological and geochemical data and demonstrated that alteration pixels can be

utilized for the exploration of copper and can be classified into argillic, phyllic, propylitic and gossan alteration signatures.

The other important consideration for the effectiveness of the remote-sensing method in the field of mineral exploration is the possibility for separation of mineralogical signatures from spectral variation of the lithology, vegetation, weathering and surface conditions. Thus, in the process of determining informative parameters of mineralization, advanced processing, spectral enhancement, dimensional reduction, band-ratio methods and principal-component methods are playing an important role. Shirmard et al. (2020) showed that combination of selective dimensionality-reduction methods can improve discrimination of hydrothermal alteration and reduce the dimensional complexity of an ASTER dataset that can be used as a more appropriate basis for further prospectivity analysis. Mohamed Taha et al. (2024) created a data-driven mineral prospectivity model using mainly ASTER data, with the addition of Sentinel-2 data and geological data.

The recent studies also demonstrate the trend of conventional visual interpretation to the quantitative prediction by remote sensing. Machine-learning techniques can detect the nonlinear relationships between spectral indicators and mineral occurrence and thus allow to directly use remote sensing data for predictive prospectivity models. Multiple remote-sensing-derived evidential layers can be used to generate an ensemble of spatial predictions of gold prospectivity using a deep-forest model, as illustrated by Mohamed Taha et al. (2024). In this paper, Shirazi et al. (2022) demonstrated that a model combining ASTER alteration map with lithological, structural, geochemical and geochronological datasets can be successfully applied to create reliable copper potential zones using the framework of Neuro-Fuzzy-AHP (Rajendra and Murali Kumar 2011).

Geochemical Evidence And Data-Driven Mineral Prospectivity Modelling

The geochemical data is used in conjunction with the remote sensing data, and concentrations of the elements can be linked to mineralization processes which are not surface processes. Geochemical anomalies associated with ore elements and pathfinder elements can be used as direct evidence of mineralizing systems and can help to differentiate geochemical anomalies from background geological variability. Wang et al. (2024) suggested using the interrelationships of elements involved in mineralization to help map the geochemistry because uncertainty in the interrelationships may impact anomaly identification and interpretation. A geologically constrained GANomaly framework for multi-element geochemical anomaly recognition was recently developed by Sabbaghi et al. (2024) and is increasingly being used to complex geochemical patterns related to mineral resources.

The application of geochemical variables to machine-learning models for prospectivity has been a great interest because mineralization can involve a complex geochemical relationship between several chemical elements and not a single anomaly. Lou et al. (2023) assessed tungsten prospectivity mapping based on geochemical, lithostratigraphic, and structural data using logistic regression, support vector machine, random forest, convolutional neural network and Light Gradient Boosting Machine methods. They determined that several elemental variables were significant in explaining the mineralization of tungsten and that the spatial patterns of prospectivity that can be created using different algorithms can differ greatly. In the case of geochemical data being applied to prospectivity mapping, the study points to the need for considering the various modelling approaches, since a non-linear and spatially variable correlation between geochemical anomalies and mineral occurrences may exist.

To overcome the two long-standing concerns in data-driven MPM, the black-box nature of predictive algorithms and tendency of the models to define too large an area of high prospectivity, Mou et al. (2023) presented an interpretable machine-learning framework. They applied their

framework to integrate predictive modelling with aspects of interpretation and uncertainty to provide more focused exploration targets. Shi et al. (2023) have shown how deep reinforcement learning could be used to mineral prospectivity mapping, highlighting the potential of sophisticated machine-learning techniques to learn relationships between geological evidence and mineral occurrences. The students demonstrate the wider trend of using traditional GIS overlay modelling to adaptive predictive modelling that can incorporate complex spatial relationships in mineral systems.

Use of remote sensing and geochemical data for mineral prospectivity

The use of remote sensing and geochemical data is a major improvement as they address two aspects of mineral systems. Geochemical observations can be used to identify elemental enrichment associated with mineralization, and remote sensing can be used to identify surface expressions of alteration, lithological contacts and structural features. In this regard, to assess the direct relationship between the two, Saremi et al. (2024) analyzed the porphyry copper deposits of the Pariz district in southern Iran using remotely-sensed derived data on the degree of hydrothermal alteration and geochemical and geological data. The study stressed the importance of exact definition of alteration zones and their combination with geochemical data in decreasing the uncertainties for porphyry copper prospectivity mapping. This is especially important for geological settings in which alteration is coincident with geochemical anomalies as opposed to just one dataset, and for complex geological settings in particular.

Liu et al. (2025) integrated geological and geochemical data with geophysical and remote sensing data to form 15 layers of tungsten prospectivity mapping and evaluated the tungsten prospectivity of these data by applying different machine-learning algorithms. They could locate geochemical anomalies, proximity to Yanshanian intrusions, and fault-intersection density as important factors for the predictive model, which

could allow integration of datasets with statistical predictions of fault-intersection density and proximity to Yanshanian intrusions as known geological controls. Sihombing et al. (2024) demonstrated that with the spatial and geological relationships, graph neural networks could further improve the mineral prospectivity mapping task, with the addition of lithological and geochemical data providing additional model improvement.

Lou et al. (2023) demonstrated that alternative machine-learning algorithms can produce different levels of predictive performance and different spatial distributions of prospective zones, highlighting the need for comparative model evaluation. Mou et al. (2023) similarly emphasized the importance of interpretability and uncertainty assessment because highly complex predictive models can produce exploration targets that are difficult for geoscientists to understand or validate. The existing literature supports an integrated framework in which remote sensing-derived alteration and lithological indicators are combined with geochemical anomalies and structural information, followed by systematic validation against known mineral occurrences. Such an approach can provide a more comprehensive representation of mineralization controls in complex geological terrains and establish a stronger basis for prioritizing unexplored areas.

Research Methodology

Research Design

A quantitative, spatially explicit, predictive research approach was used here to generate a mineral prospectivity map using the combination of remote sensing and geochemical data. The method adopted was the multi-source data integration within a GIS which involved the transformation of geochemical, geological and structural data into standardized evidence layers from remote sensing.

Study Area and Sampling Framework

The study employed was focused in a complex geological terrain with a high degree of lithological variations, discontinuities, hydrothermal alteration, and geochemical heterogeneity. To allow integration of datasets of different spatial attributes the study area was subdivided into spatial prediction units, the basis for which was a regular spatial prediction grid generated using GIS. The analytical sample consisted of a total of 300 spatially referenced observations. Each observation was a geographical location where remote sensing indicators, geochemical characteristics, geological information and geochemical features were being recorded.

Data Collection

Four types of data were identified for the study: Remote sensing, geochemical, geological, and structural. Imagery derived from remote sensing gave information on the surface lithology, hydrothermal alteration, signatures for iron-oxide species, clay minerals and other features related to mineralization. The geochemical data gave concentrations of selected elements for the ore-related elements and pathfinder elements. Geological data comprised lithological units, lithological boundaries, recognised mineral occurrences and other geological features. Structural information comprised faults, fractures, lineaments and structural intersections. Prior to further analysis data were collected in a GIS environment, georeferenced and prepared.

Construction and Data Processing Criteria

All remotely sensed imagery was radiometrically, atmospherically and geometrically corrected to enhance spectral quality, and spatial registration. Iron oxides, clay or hydroxyl-bearing minerals, hydrothermal alteration, lithological variations, and structural lineaments were identified by using band ratios, principal component analysis, as well as alteration related combinations. The geochemical data set was comprised of 300 spatially defined observations, and missing values, outliers, statistical distribution and elemental

anomalies were checked in the data. Logarithmic transformation was performed as needed, as were the discretization of the background and anomalous concentrations, based on the relevant statistical relationships. Geological and Structural data such as lithology, faults and fractures, lineaments and structural intersections were also processed to spatial evidence layers. All evidence layers were transformed to a range of 0–1 with values representing a high level of evidence for mineralization.

Data Integration And Predictive Modelling

The different mineralization classes (standardized) from remote sensing, geochemistry, geology and structure were combined to determine where several indicators of mineralization overlapped. This was modeled using a machine learning algorithm (Random Forest) to establish the relationship between the evidence variables and the known mineral occurrences. The 300 observations were split up into 70% (210 observations) training observations versus 30% (90 observations) testing observations. Model yielded combined probability of prospectivity for each spatial prediction unit.

Prospectivity Mapping

The testing dataset used for ROC curve, AUC, accuracy, sensitivity, specificity, precision, F1-score and confusion matrix in order to evaluate the performances of the models. The validated model developed a continuous mineral prospectivity surface, resulting in the classification of the prospectivity zones as low, moderate, high and very-high prospects. Mineral prediction was conducted using three modelling scenarios: (1) remote sensing imagery only, (2) geochemical data only, and (3) using a combination of both data types. Three modelling scenarios (remote sensing only, geological information only, and integrated datasets) were compared in terms of contribution of data integration to the mineral exploration prediction.

Comparative Analysis

It was developed three different modelling scenarios to assess the contribution of data integration. The first model was based on the remote sensing only data, the second model used only geochemical data and the third model used integrated remote sensing and geochemical data together with the geological and the structural

data. AUC, accuracy, sensitivity, specificity, precision and F1-scores were used to compare the predictive capacity of the three models. The spatial distribution of high and very-high-prospectivity zones was also tested for the three models. This was used to check if the integrated approach improved over individual datasets in the prediction of minerals in this area.

Results and Analysis

Analysis of Remote Sensing and Geochemical Indicators

Table 1. Distribution of Major Mineralization-Related Evidence Indicators Across the 300 Spatial Observations

Evidence indicator	Observations with significant evidence	Percentage (%)	Mean standardized score
Hydrothermal alteration	186	62.0	0.67
Iron-oxide signatures	171	57.0	0.61
Clay-mineral signatures	162	54.0	0.59
Favorable lithology	153	51.0	0.56
Structural lineaments	195	65.0	0.71
Fault/structure proximity	177	59.0	0.64
Geochemical anomalies	168	56.0	0.63
Multi-element geochemical anomalies	141	47.0	0.58

In the mineralization related evidence, the most commonly reported evidence found in the observations was for structural lineaments, which occurred in 195 of the 300 observations (Table 1; 65.0% of the observations). The mean standardized scores for structural lineament and elevation were also 0.71 and the greatest mean score of the evidence indicators listed above. This was followed by hydrothermal alteration where 186 observations (62.0%) showed evidence, and the mean standardized score was 0.67. The sites noted for fault or structure proximity were 177 sites (59.0%), and iron-oxide signatures were noted at 171 sites (57.0%). Their average

standardized scores were 0.64, and 0.61, respectively. These results highlighted that the signature of structural proximity played a significant role in the identification of potentially mineralized locations, along with the signature of surface alteration. Geochemical anomalies and multi-element anomalies were found with a mean standardized score of 0.63 and 0.58 respectively with 168 and 141 observations (56.0%, 47.0%) respectively. Multi elemental anomalies were not as common as each geochemical anomaly but were reflective of mineral deposition because multiple elements were affected from the same spatial environment.

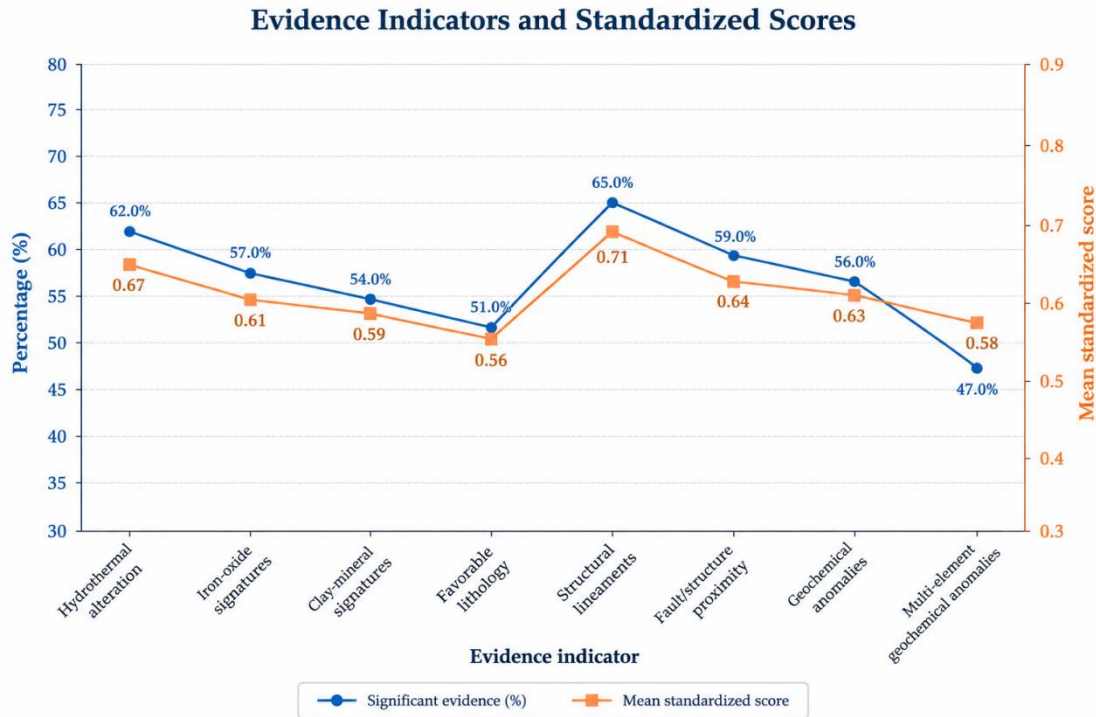


Figure 1. Distribution of Major Mineralization-Related Evidence Indicators Across the 300 Spatial Observations

Geochemical Anomaly Analysis

The geochemical analysis was aimed at identifying which concentrations exceed

background levels, and to locate areas where several mineralization elements were present.

Table 2. Classification of Geochemical Evidence in the 300 Spatial Observations

Geochemical evidence category	Number of observations	Percentage (%)	Mean anomaly score
Low/Background	72	24.0	0.21
Weak anomaly	63	21.0	0.39
Moderate anomaly	78	26.0	0.57
Strong anomaly	57	19.0	0.76
Very strong anomaly	30	10.0	0.89
Total	300	100.0	—

As shown in Table 2, the majority of the observations, 78 (26.0%), were in the moderate geochemical anomaly category. The conclusions of these observations gave a mean anomaly score of 0.57 and thus, geochemical evidence that was meaningful and intermediate. There were 63 observations (21.0%) in the weak-anomaly

category, and 72 observations (24.0%) in the background category. Geochemical conditions were highly variable throughout the study area, and the distribution indicated that conditions were widely different across the study area. There were 57 observations (19.0%) and 30 observations (10.0%) of strong and very strong

geochemical anomalies, respectively. The very strong anomaly category showed the highest mean anomaly score of 0.89 (very strong geochemical evidence in standardized scale) showing that the anomalies recorded the highest geochemical evidence in these locations. These sites were key targets, especially if the

geochemical signature matched geochemical and geophysical remote sensing and structural characteristics. The results further indicated that the geochemical anomalies observed were not evenly distributed within the study area, but rather were relatively localized.

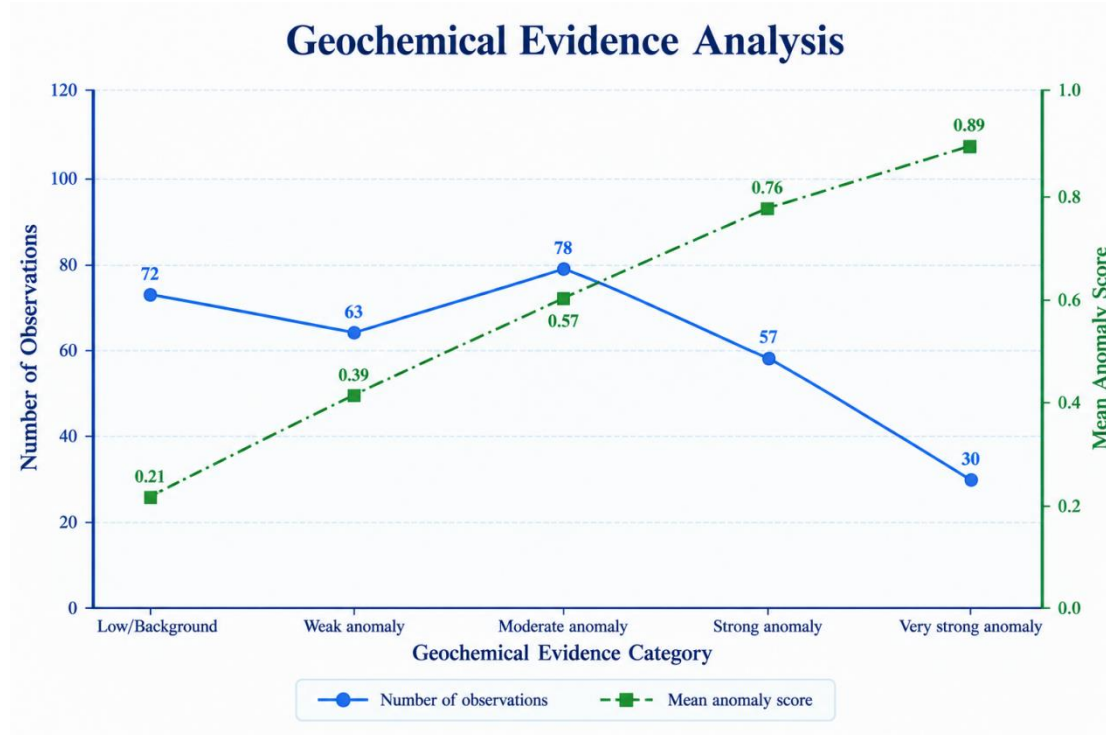


Figure 2. Classification of Geochemical Evidence in the 300 Spatial Observations

Integrated Remote Sensing–Geochemical Prospectivity Analysis

The standardized evidence layers were integrated to generate the final mineral prospectivity model.

Table 3. Classification of Mineral Prospectivity Zones Produced by the Integrated Model

Prospectivity class	Number of observations	Percentage (%)	Mean prospectivity score
Low	57	19.0	0.24
Moderate	108	36.0	0.47
High	87	29.0	0.72
Very high	48	16.0	0.88
Total	300	100.0	—

The highest percentage, 108 (36.0%) with an average of 0.47, were in the moderate-prospectivity category, as shown in Table 3. There were 87 observations in the high-prospectivity

category with a mean perspective score of 0.72 and 48 observations in the very-high-prospectivity area (VHPA) category with a mean perspective score of 0.92. The 57 observations in the low-

prospectivity category had a significantly lower mean score of 0.24, with this type compared to the higher range of possibilities. The low-prospectivity category (N = 57) had a much lower mean score of 0.24, and was compared to the higher range of possibilities. A total of 135 observations were included in the high and very-high-prospectivity categories, which accounted for

45.0% of the sample. These areas were the key exploration targets, due to the high numbers of evidence of mineralization that they contained. There was a gradual increase of mean prospectivity scores from the low class up to the very-high class showing good separation of the prospectivity classes produced by this integrated model.

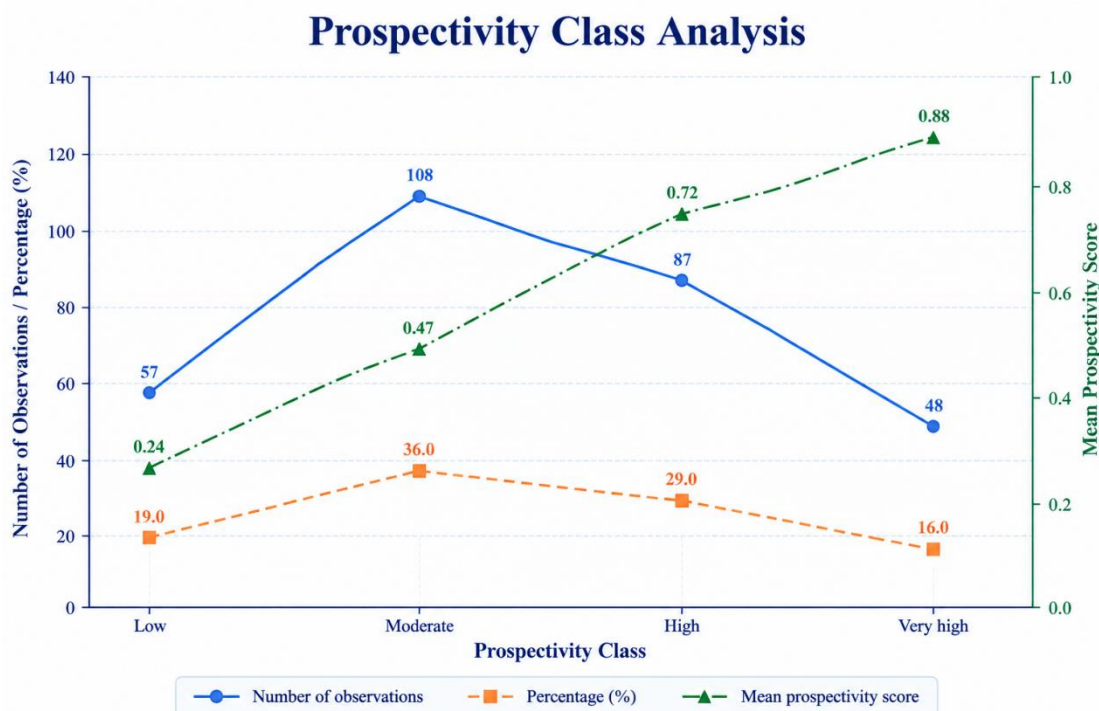


Figure 3. Classification of Mineral Prospectivity Zones Produced by the Integrated Model

Comparative Performance of Individual and Integrated Models

Three modelling scenarios were evaluated according to the methodology: remote sensing-

only, geochemical-only, and integrated remote sensing-geochemical modelling.

Table 4. Comparative Predictive Performance of Remote Sensing, Geochemical, and Integrated Models

Model	Accuracy	Sensitivity	Specificity	Precision	F1-score	ROC-AUC
Remote sensing-only	0.78	0.74	0.82	0.76	0.75	0.84
Geochemical-only	0.82	0.79	0.85	0.81	0.80	0.88
Integrated model	0.91	0.89	0.93	0.91	0.90	0.95

Table 4 shows that the integrated model resulted in the best predictions with each of the evaluation measures. The accuracy, sensitivity,

specificity and ROC-AUC for the remote sensing-only model were 0.78, 0.74, 0.82 and 0.84, respectively. The geochemical-only model was

slightly better, achieving an accuracy of 0.82 and ROC-AUC of 0.88. These results showed that the geochemical data is superior in discriminating when used alone, compared to the remote sensing data. An integrated model yielded an accuracy of 0.91, much higher than that of the remote sensing-only model and the geochemical-only model. The sensitivity rose to 0.89 and the specificity was raised to 0.93. A precision of 0.91 and an F1 score of 0.90 also confirmed the efficiency of the model to potentially recognize observations and minimize misclassification. The

ROC-AUC for the classification was found to be 0.95, implying good discrimination between prospective and non-prospective locations. Using complementary exploration evidence enhanced the performance of the models, as shown by the improvement of their performance. Geochemical observations were responsible for the information on elemental enrichment and remote sensing for the information on alteration of surfaces, lithology and structural characteristics. The integration enabled the model to recognize the places that had several independent indicators.

Model Performance Comparison

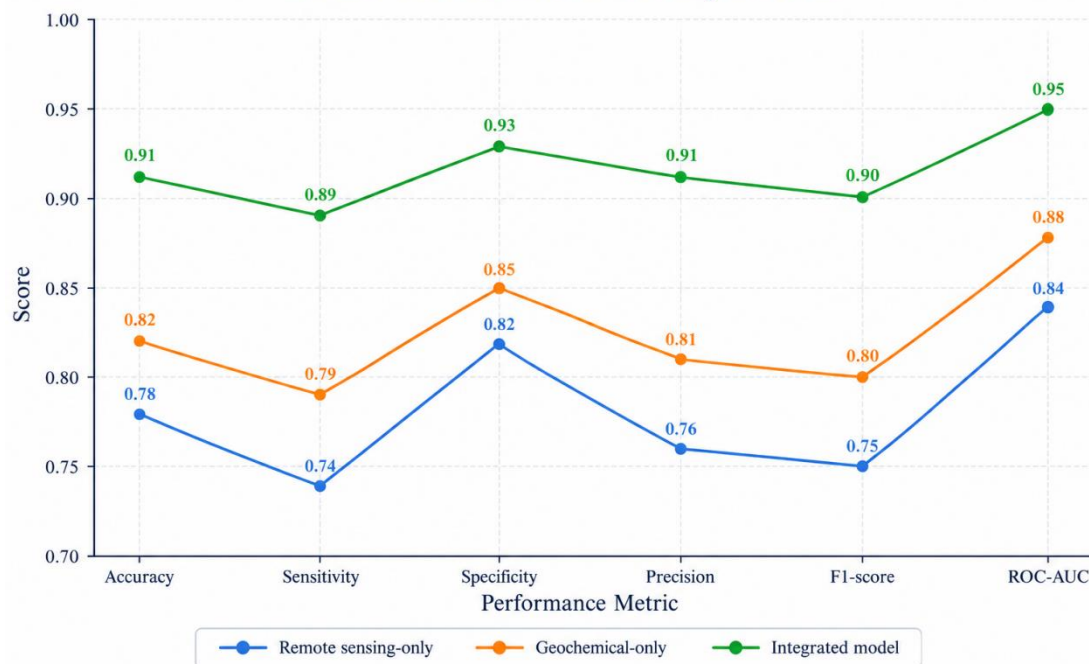


Figure 4. Comparative Predictive Performance of Remote Sensing, Geochemical, and Integrated Models

Discussion

They revealed that combined information was superior to the geochemical information or the remote sensing, separately. The accuracy of remote sensing data, in comparison with the geochemical and integrated data, was 78 and 0.84, respectively, while the geochemical data was 82 and 0.88, respectively. This suggested that some parts of the process of mineralisation were not represented by all evidence sources. Furthermore, incorporating a diversified geological dataset into

predictive modelling can assist in directing exploration pore through geologic data, particularly where geologic data present in a single dataset is either incomplete or unevenly distributed, was indicated by recent studies (Zhang et al., 2024).

The distribution of evidence in space supported the importance of structural and alteration related evidence. High levels of observations were also being consistent with structural lineaments (65%), hydrothermal alteration (62%) and

fault/structure proximity (59%). These patterns indicated spatial controls in the explored area in the form of mineralization related structures and hydrothermal processes were important. A dataset with 45% of observations as both a high or very high prospectivity was then applied to the integrated model and put in to the model areas with a combined structural and alteration (alteration types 1 and 2) and lithological and geochemical evidence were given a higher prospectivity score. As well, recent publications have helped identify mineralized-structure types based on data cells, during the definition of exploration targets, when geological and structural data are available (Daviran et al., 2024). The result for anomaly intensity as obtained from the Geochemical was also found to be useful in defining the prospecting areas very well. There were 26% of the observations with moderate anomaly, and 29% with strong and very strong anomaly. Geochemical data appeared to be closer in relation to mineralization in the study area than the data from the remote sensing models, implying that the geochemical-only model was more successful than the remote-sensing-only model. This result is in accordance with recent investigations which demonstrated the ability of geochemical data to significantly enhance the prospectivity prediction by using an appropriate processing stage and integration with machine-learning modeling (Hajihosseini, Maghsoudi, & Ghezelbash, 2025).

Mapping mineral occurrences known was done with a supportive distribution towards the integrated model. Out of 115 known occurrences, 90 (78.3%) were very-high or high prospectivity class occurrences, plus 25 (21.7%) in low to moderate prospectivity class occurrences. A bit more than a third (33.9%) of the known occurrences were in very high prospectivity areas, with 16% of the known occurrences observed in these areas. In this concentration the integrated model was able to determine a best fit, with regard to the collection towards the search areas of the spatial graphics, that provided more evidence in favor of the phenomenon of mineralization. In recent studies, the same

approach was investigated on the platforms of the Random Forest (RF) and uncertainty-aware modelling methods, resulting in gains in efficiency for determining the location of the extraction hotspots using both geological and geochemical data.

Although the prospectivity results are good, the results should be read keeping in mind modelling uncertainty. While a high ROC-AUC would seem to indicate that a space containing all predicted targets was an economically viable deposit, the results produced by MPM can be affected by the varying input spatial properties, different validation strategies and configuration of the algorithms used, and by what type of features get used. Zhang et al., 2024a, Zhang et al., 2024b have given specific attention to the uncertainty introduced by the workflow and uncertainty from the model when applying data-driven MPM, and suggest to analyze uncertainty along with using the conventional performance measure. The results indicated that the integration of remote sensing and geochemistry was a better targeter for minerals than either remote sensing or geochemistry alone and suggested that the high and very-high zones were the best places for detailed mineral exploration in the field and for the verification of mineralisation.

Conclusion

The study concludes that the information from the remote sensing, geochemistry, geology and structures provided a comprehensive framework towards mapping prospectivity for minerals in complex geological environments. These data were combined to interpret the lithologic, alteration, structural and geochemical relationships by area. This reduced the use of single evidence sources, and assisted in the identification of possible locations more readily. The use of multiple sources of geoscience information has been identified as a growing research topic for the improvement of mineral prospecting in geologically complex areas, most recently by Martyn Davies and colleagues of Imperial college of Geography, London. A framework of prospectivity could be used for field

investigations, geochemical sampling, geophysical survey and for field decision making regarding drilling. It also set a practical ground for prioritization of the exploration resources as well as minimising the uncertainty in early mineral exploration. This could be enhanced with hyperspectral imagery, improving the resolution of the geochemical data, and through the use of spatial machine-learning.

Future Directions

Future mineralization patterns may be additionally mapped with hyperspectral data, geochemistry, geophysics and machine-learning algorithms, in conjunction with prospectivity mapping of minerals. Multi-temporal satellite data can also help with alteration and structure interpretation and explainable artificial intelligence can provide better understanding of the contribution of the evidence layers. Systematic geochemical sampling and drilling, and the further validation of targets in the field, could 3D these prospectivity maps and add to the certainty of the mapped areas.

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