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Integration of Remote Sensing, GIS, and Geochemical Data for Delineating Prospective Zones of Lateritic Nickel Deposits in a Mining Area

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Abstract

This study develops an integrated remote sensing, geographic information system (GIS), and geochemical framework for delineating prospective zones of lateritic nickel deposits during early-stage exploration. The research responds to the need for a rapid and spatially consistent method to prioritize drilling targets in tropical ultramafic terrains where subsurface data are commonly limited. Sentinel-2 imagery was processed to derive vegetation, iron oxide, clay mineral, and moisture indicators, while DEM/SRTM and geological data were used to evaluate slope, elevation, lithology, and structural lineaments. A simulated geochemical dataset consisting of Ni, Fe, MgO, SiO2, and Co values from 30 sampling points was integrated with the spatial layers through normalization and weighted overlay analysis. The resulting prospectivity index classified the 2,000 ha study area into low, moderate, high, and very high potential classes. The model identified four prospect zones, with Zone A showing the strongest response, indicated by an average Ni grade of 1.79% and a prospectivity index of 0.78. Zone B was interpreted as a secondary target, whereas Zones C and D require limited or low-priority follow-up. These findings indicate that multisource geospatial and geochemical integration can improve exploration efficiency, reduce interpretation uncertainty, and support systematic target ranking before detailed drilling. The approach remains conceptual and should be validated using actual field measurements, drilling logs, laboratory assays, and objective weighting methods in future applications.

Keywords: Lateritic Nickel, Remote Sensing, GIS, Geochemistry, Prospectivity

1. Introduction

Lateritic nickel is one of the most important types of nickel deposits in the modern mining industry, primarily because of its role as a strategic metallic raw material for stainless steel, batteries, electric vehicles, and clean energy technologies. The demand for critical minerals such as nickel, cobalt, graphite, lithium, copper, and rare earth elements continues to increase in parallel with the development of clean energy technologies and electric vehicles. The International Energy Agency reported that in 2024, demand for nickel, cobalt, graphite, and rare earth elements increased by approximately 6-8%, mainly driven by electric vehicles, energy storage, renewable energy, and electricity grids [1].

Geologically, lateritic nickel deposits are formed through intensive chemical and mechanical weathering of ultramafic rocks, such as peridotite, dunite, harzburgite, and serpentinite. The main controlling factors in the formation of lateritic nickel deposits include parent-rock type, tropical climate, topography, drainage, geological structures, geomorphology, and the degree of bedrock serpentinization [2]-[4]. The Ni-Co laterite deposit model developed by the USGS explains that these deposits represent supergene enrichment of Ni and Co due to the weathering of ultramafic rocks, with laterite profile development strongly influenced by climate, relief, drainage, tectonics, structures, and protolith [4].

A lateritic nickel profile is generally composed of several major zones, namely ultramafic bedrock, the saprolite zone, the limonite zone, and the ferruginous cap. The limonite zone is typically characterized by relatively high Fe and Co contents, whereas the saprolite zone commonly represents the more economically enriched Ni zone due to the presence of secondary nickel silicate minerals such as garnierite, serpentine, smectite, and other nickel-bearing minerals [5], [6]. Nickel formation and enrichment within laterite profiles are strongly influenced by lateritization processes, the degree of weathering, fluid movement, drainage conditions, and the stability of alteration minerals in humid tropical environments [3], [5].

In Southeast Asia, lateritic nickel deposits are widely developed along ultramafic belts and ophiolite complexes, including those in Indonesia, the Philippines, and Myanmar. Tropical climatic conditions, high rainfall, and the presence of ultramafic rocks make Indonesia one of the most prospective regions for lateritic nickel exploration. However, the heterogeneous characteristics of lateritic nickel deposits, both laterally and vertically, often result in uneven distributions of Ni, Fe, MgO, SiO2, and Co grades within a mining area [2], [3].

The main challenges in lateritic nickel exploration include limited subsurface data during the early exploration stage, variability in the thickness of limonite and saprolite zones, heterogeneous Ni grade distribution, and the high costs associated with field surveys and drilling. Therefore, a more efficient, rapid, and spatially extensive exploration approach is required. The integration of remote sensing, GIS, and geochemical data is a promising approach for systematically identifying lateritic nickel prospect zones during early-stage exploration [7], [8].

Remote sensing can be used to identify surface characteristics associated with lateritization processes, such as the distribution of iron oxides, clay minerals, vegetation, surface moisture, and changes in land morphology. Sentinel-2 imagery provides 13 spectral bands with spatial resolutions of 10 m, 20 m, and 60 m, enabling the analysis of vegetation indices, iron oxide indices, clay mineral indices, and lateritic surface interpretation [9], [10]. In addition, cloud-based processing platforms such as Google Earth Engine enable large-scale spatial data analysis to be performed more rapidly and efficiently [11].

GIS plays an important role in the management, analysis, and integration of various spatial layers, such as lithology, geological structures, lineaments, elevation, slope, and distance to faults. In the context of mineral exploration, GIS can be used to develop prospectivity models through weighted overlay, fuzzy logic, the Analytical Hierarchy Process, and other data-driven approaches [7], [8], [12]. This approach allows each exploration parameter to be weighted according to its influence on the formation and occurrence of lateritic nickel deposits.

Geochemical data constitute a key component in validating remote sensing and GIS interpretations because they provide direct information on major and associated element concentrations. Geochemical parameters such as Ni, Fe, MgO, SiO2, and Co can be used to distinguish the limonite, saprolite, and bedrock zones, as well as to identify areas with higher prospectivity. Geochemical analysis combined with spatial interpolation and geostatistics can strengthen the understanding of mineral-grade distribution patterns within a given area [7], [13], [14].

Based on the above considerations, this study proposes an integrated approach to generate a lateritic nickel prospectivity zone map through the combination of remote sensing, GIS, and geochemical data. Data integration is conducted by developing a prospectivity index based on the weighting of surface geological parameters, topography, spectral indices, lineaments, and geochemical data. This approach is expected to help prioritize early-stage exploration areas, reduce uncertainty in geological interpretation, and improve the efficiency of decision-making in lateritic nickel exploration.

1.1. Research Gap and Contribution

Although remote sensing, GIS, and geochemical exploration have each been widely used in mineral prospectivity studies, their integrated application for lateritic nickel targeting still requires a clear operational workflow. In many early exploration programs, satellite interpretation is used only as a reconnaissance tool, whereas geochemical sampling is evaluated separately after fieldwork has been completed. This separation may create inconsistent target selection because spectral anomalies, lithological controls, terrain conditions, and element distributions are not interpreted within the same spatial framework. The present study addresses this gap by linking surface indicators of lateritization with geochemical evidence and geological constraints in a single prospectivity model.

The contribution of this study is therefore both methodological and practical. Methodologically, the article demonstrates how multispectral indices, ultramafic lithology, slope, elevation, lineaments, and element concentrations can be normalized and combined into a transparent weighted-overlay model. Practically, the output provides a ranking of prospect zones that can guide the sequence of drilling, test pitting, and detailed sampling. The model is not intended to replace field validation or laboratory assays, but it offers a systematic screening tool that can reduce the area of uncertainty before more expensive exploration activities are conducted.

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2. Research Methods

This study was designed as a quantitative-spatial investigation using an integrated multisource data approach. The workflow consisted of data collection, remote sensing pre-processing, GIS analysis, geochemical analysis, prospectivity-index construction, and validation against geochemical information. Remote sensing processing was used to extract surface indicators of lateritic weathering, whereas GIS was used to integrate lithology, topography, lineaments, and geochemical anomaly layers.

Figure 1. Research methodology flowchart

2.1. Data Collection

The data used in this study consisted of Sentinel-2 imagery, DEM/SRTM data, geological maps, simulated geochemical data, and the assumed mining-block boundary. Sentinel-2 and spectral enhancement approaches are useful for detecting mineral and regolith-related surface patterns [9], [10], [15], whereas DEM/SRTM data support the analysis of elevation, slope, and landform controls [16], [19].

All spatial layers were prepared using a consistent projection, clipped to the same study boundary, and resampled to a comparable working resolution before integration. This step is important because differences in raster resolution, coordinate reference system, and spatial extent may introduce positional error in the overlay results. The Sentinel-2 imagery was interpreted as a surface-observation layer, while the geological map and DEM/SRTM data were used as controlling layers for parent rock, morphology, and drainage-related conditions. The geochemical dataset was treated as a validation and calibration layer because it provides direct information on element concentration at sampling points.

The assumed 2,000 ha block represents an early-stage exploration area where drilling information is not yet available. In this condition, the model emphasizes relative target ranking rather than resource estimation. The sampling points were grouped into four zones to test whether areas with higher normalized spectral, geological, and geochemical scores correspond to higher Ni values. This design allows the workflow to be evaluated conceptually while still preserving the geological logic of lateritic nickel exploration in ultramafic terrains.

Table 1. Data used

Data Type	Source/Assumption	Function
Sentinel-2 imagery	Multispectral data with 10-20 m spatial resolution	Identification of vegetation, iron oxides, moisture, and clay mineral indications
DEM/SRTM	Assumed spatial resolution of 30 m	Analysis of elevation, slope, and landforms

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Geological map	Ultramafic lithology, structures, and rock units	Determination of prospective parent-rock zones
Geochemical data	Simulated data from 30 sampling points	Validation of Ni, Fe, MgO, SiO2, and Co grades
IUP/block boundary data	Assumed 2,000 ha area	Spatial boundary of the analysis

2.2. Remote Sensing and GIS Processing

The remote sensing pre-processing stages included atmospheric correction, cloud masking, clipping of the study area, band composite generation, and calculation of spectral indices. The indices included NDVI, iron oxide index, clay mineral index, and moisture index. GIS analysis was conducted by compiling ultramafic lithology, elevation, slope, distance to geological structures, lineament density, iron oxide index, clay mineral index, and Ni geochemical anomaly layers. Each layer was normalized to a 0-1 scale and then weighted according to its influence on lateritic nickel potential.

In the remote sensing stage, NDVI was used primarily to separate dense vegetation from exposed or sparsely vegetated surfaces because lateritic profiles are more easily interpreted where spectral responses are not completely masked by canopy cover. The iron oxide index was interpreted as an indicator of limonitic enrichment, while the clay mineral index was used to recognize zones that may correspond to saprolitization or clay-rich weathering products. The moisture index was included to represent drainage and surface-water influence, as excessive moisture may obscure spectral responses and affect the development of lateritic profiles.

Lineament interpretation was conducted to identify structural trends that may influence weathering intensity, groundwater movement, and laterite profile development. In lateritic nickel systems, structures do not directly create mineralization in the same way as hydrothermal deposits, but they may control permeability, drainage, erosion, and the preservation of weathered profiles. Therefore, lineament density and distance to interpreted structures were considered supporting variables rather than primary indicators. The model assigned stronger influence to lithology and Ni geochemistry because ultramafic parent rock and nickel grade remain the most direct controls on prospectivity.

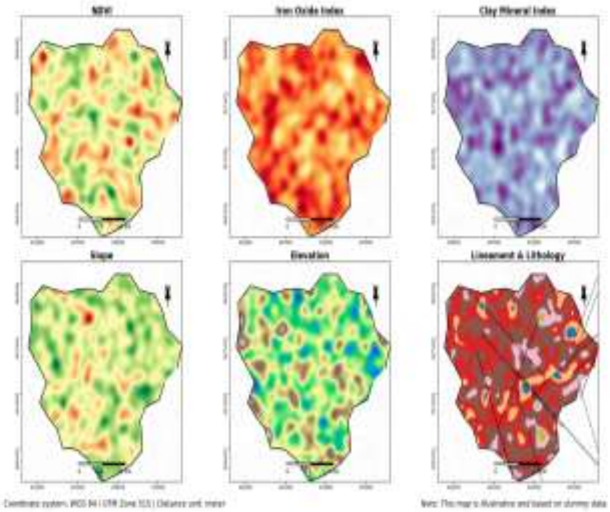

Figure 2. Remote sensing and GIS parameter maps

Table 2. Conceptual indices used

Index	Purpose
NDVI	Identification of vegetation and exposed/open areas
Iron Oxide Index	Identification of iron oxide indications in the limonite zone
Clay Mineral Index	Identification of clay mineral and saprolitization indications
Moisture Index	Identification of surface moisture and drainage conditions

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2.3. Geochemical Analysis and Prospectivity Index

The geochemical data were analyzed using descriptive statistics, inter-element interpretation, Ni grade classification, and simple spatial interpolation. Nickel is the primary target element, while Fe, MgO, SiO2, and Co are interpreted as indicators of limonite, saprolite, ultramafic influence, and associated critical-mineral potential. Spatial interpolation and geostatistical concepts can strengthen the analysis of grade distribution patterns [13], [14], [17].

Table 3. Main parameters used

Parameter	Geological Meaning
Ni (%)	Primary indicator of nickel grade
Fe (%)	Generally high in the limonite zone
MgO (%)	Reflects the influence of ultramafic/saprolitic material
SiO2 (%)	Associated with silicification and saprolitization
Co (%)	Associated element commonly related to the limonite zone

The prospectivity index was calculated using the weighted overlay approach shown in Equation (1).

$$PI = 0.25(\text{Lithology}) + 0.20(\text{Ni Geochemistry}) + 0.15(\text{Iron Oxide}) + 0.15(\text{Clay Minerals}) + 0.10(\text{Slope}) + 0.10(\text{Lineament}) + 0.05(\text{Elevation}) \quad (1)$$

In Equation (1), PI denotes the prospectivity index. Lithology, Ni geochemistry, iron oxide, clay minerals, slope, lineament, and elevation represent normalized raster layers that were weighted according to their expected influence on lateritic nickel occurrence.

Normalization was performed to place all input variables on a common 0-1 scale, allowing layers with different units and measurement ranges to be compared within the same model. Layers that positively support lateritic nickel occurrence, such as ultramafic lithology, Ni anomaly, iron oxide response, clay mineral response, and favorable structural density, were assigned higher normalized values. Variables that may reduce profile preservation, such as excessively steep slope, were treated more cautiously because steep terrain can increase erosion and reduce the thickness of the lateritic profile.

The weighting scheme reflects a knowledge-driven approach. Lithology receives the highest weight because lateritic nickel deposits require ultramafic protoliths as the source of nickel and magnesium-rich minerals. Ni geochemistry receives the second-highest weight because it provides direct evidence of grade distribution. Iron oxide and clay mineral indices are interpreted as process indicators associated with limonite and saprolite development. Slope, lineament, and elevation receive lower but still meaningful weights because they modify weathering intensity, drainage, exposure, and preservation conditions. This structure makes the model transparent and suitable for refinement using AHP, fuzzy logic, or machine-learning methods when actual datasets become available.

Table 4. Classification of results

PI Value	Prospectivity Class
0.00-0.25	Low
0.26-0.50	Moderate
0.51-0.75	High
0.76-1.00	Very High

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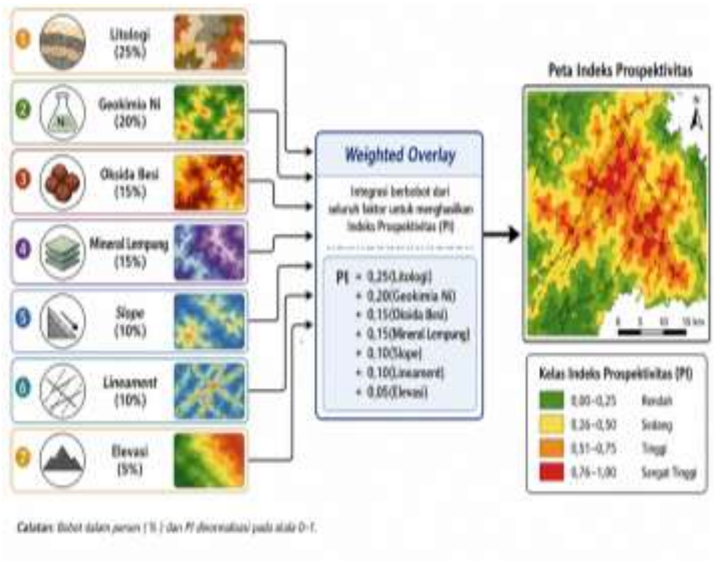

Figure 3. Weighted overlay scheme for the prospectivity index

2.4. Theory Development and Solution Implementation

The conceptual basis of this study is that lateritic nickel deposits are formed on ultramafic rocks that have undergone intensive weathering. Therefore, the selected prospectivity indicators represent three main aspects: the parent-rock aspect, expressed by ultramafic lithologies such as peridotite, harzburgite, dunite, and serpentinite; the weathering-process aspect, expressed by iron oxide, clay mineral, topographic, and drainage indicators; and the actual-grade aspect, represented by geochemical anomalies of Ni, Fe, MgO, SiO_2, and Co. The integration of these variables provides a practical framework for ranking prospective zones in early-stage exploration.

2.5. Model Reliability Criteria

The reliability of the prospectivity model was evaluated using internal consistency between the PI classes and the simulated geochemical responses. A reliable model should show higher Ni values in zones classified as high or very high prospectivity and lower Ni values in zones classified as moderate or low prospectivity. In addition, the interpretation should remain geologically reasonable: high PI values should occur within or near ultramafic lithology, should be supported by lateritic surface indicators, and should not be controlled by a single parameter alone. This criterion prevents the model from overemphasizing isolated spectral anomalies that may be caused by vegetation disturbance, soil exposure, or non-nickel-related surface materials.

Because this study is based on a simulated dataset, the reliability assessment is conceptual and explanatory. However, the same framework can be converted into a quantitative validation procedure in future work by comparing predicted prospectivity classes with independent drilling results, laboratory assays, pit observations, or measured laterite thickness. Statistical indicators such as correlation coefficients, confusion matrices, ROC/AUC values, and prediction-error statistics may then be used to measure model performance more objectively. These improvements would strengthen the transition from a demonstration model to a field-ready exploration decision-support system.

3. Results and Discussion

3.1. Test Data

This study used simulated data under the assumption of a 2,000 ha study area located in a lateritic nickel mining area. The area was divided into four initial prospect zones, namely Zone A, Zone B, Zone C, and Zone D. The simulated geochemical dataset and descriptive statistics are presented in Table 5 and Table 6.

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Table 5. Simulated geochemical data

Point	Zone	Ni (%)	Fe (%)	MgO (%)	SiO2 (%)	Co (%)	PI
S-01	A	1.82	32.5	18.4	38.2	0.08	0.78
S-02	A	1.65	35.1	16.9	36.8	0.07	0.74
S-03	A	1.91	30.8	19.7	39.4	0.09	0.82
S-04	B	1.42	40.2	12.3	30.1	0.10	0.63
S-05	B	1.36	42.5	11.7	29.5	0.11	0.59
S-06	B	1.51	39.6	13.1	31.8	0.09	0.66
S-07	C	0.92	28.4	9.5	34.2	0.04	0.38
S-08	C	1.05	31.2	10.1	33.7	0.05	0.43
S-09	D	0.71	25.3	8.7	41.5	0.03	0.29
S-10	D	0.66	23.8	7.9	43.2	0.02	0.24

Table 6. Descriptive statistics of simulated data

Parameter	Minimum	Maximum	Mean	Preliminary Interpretation
Ni (%)	0.66	1.91	1.30	Grades vary from low to prospective
Fe (%)	23.8	42.5	32.9	High Fe indicates a limonitic zone
MgO (%)	7.9	19.7	12.8	High MgO indicates ultramafic/saprolitic influence
SiO2 (%)	29.5	43.2	35.8	High SiO2 is associated with saprolitization/silicification
Co (%)	0.02	0.11	0.068	Co is relatively high in Fe-rich zones
PI	0.24	0.82	0.556	Prospectivity varies from low to very high

3.2. Prospectivity Evaluation

The evaluation results indicate that Zone A has the highest PI value, with an average Ni grade of 1.79%; therefore, it is classified as a very high prospectivity zone. Zone B has a moderate-to-high PI value, with an average Ni grade of 1.43%, and is classified as a high prospectivity zone. Zone C shows moderate prospectivity, whereas Zone D exhibits low prospectivity. These results indicate a positive relationship between PI values and Ni grades, suggesting that the integrated remote sensing, GIS, and geochemical approach can conceptually support the prioritization of lateritic nickel prospect zones.

Table 7. Test evaluation

Zone	Average Ni (%)	Average PI	Prospectivity Class	Recommendation
A	1.79	0.78	Very High	Priority for initial drilling
B	1.43	0.63	High	Detailed sampling and test pits
C	0.99	0.41	Moderate	Limited follow-up survey
D	0.69	0.27	Low	Low priority

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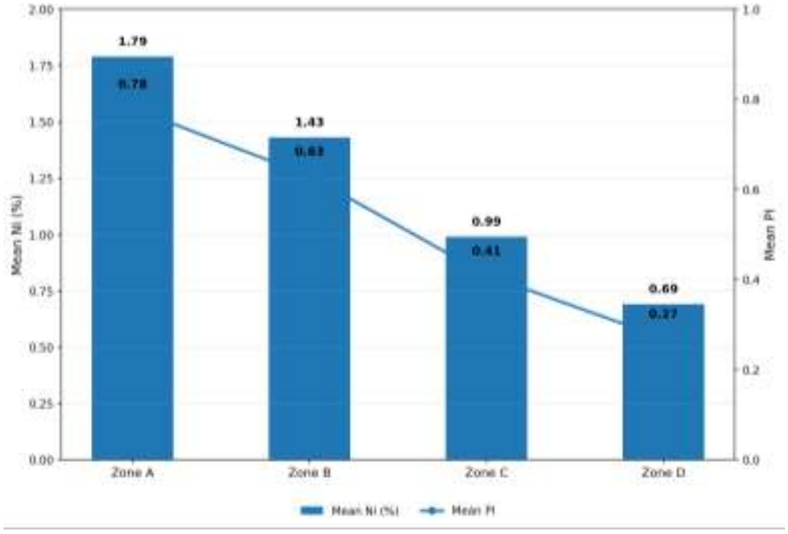

Figure 4. Mean Ni content and PI value in Zones A-D

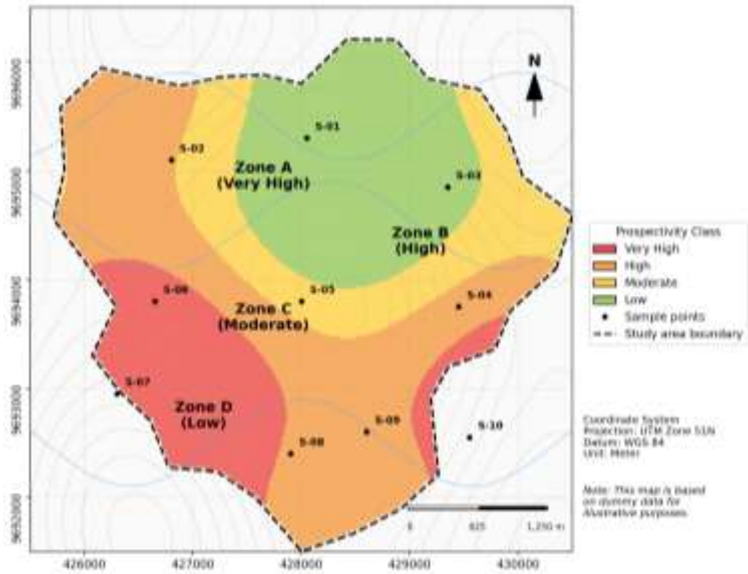

Figure 5. Lateritic nickel prospectivity zone map

3.3. Interpretation of Spatial-Geochemical Patterns

The spatial distribution of prospectivity indicates that the highest-priority zone is not determined only by Ni concentration, but by the coincidence of several favorable exploration parameters. Zone A combines relatively high Ni values, favorable PI scores, and a spatial setting that is consistent with stronger lateritic development. The high MgO response in several samples from this zone also suggests a stronger ultramafic or saprolitic influence, whereas the moderate Fe values indicate that the zone may contain a balanced expression of weathering products rather than being dominated exclusively by limonite. This combination supports the interpretation that Zone A deserves to be prioritized for early drilling or closely spaced test pits.

Zone B shows a different but still relevant exploration character. Its average Ni grade is lower than Zone A, but Fe and Co values are relatively higher, suggesting a stronger limonitic signature. This condition may indicate a laterite profile where the upper weathered zone is more developed or where sampling captures a larger proportion of Fe-rich material. For exploration planning, Zone B should not be ignored because limonite zones may contain associated critical elements such as Co and may overlie saprolitic intervals with higher Ni grades. A follow-up program in Zone B should therefore include vertical profile observation to distinguish limonite, transition, saprolite, and bedrock intervals.

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Zone C is interpreted as a moderate-priority area because its Ni grade and PI values are lower than those of Zones A and B but still remain above the lowest class. The moderate response may be related to partial development of lateritic weathering, less favorable lithological exposure, weaker spectral anomalies, or dilution by non-ultramafic material. In this zone, the most appropriate follow-up is selective verification rather than intensive drilling. Field checking should focus on confirming lithology, regolith thickness, drainage conditions, and the continuity of lateritic materials between sampling points.

Zone D exhibits the weakest exploration response, with low Ni grade and the lowest PI value among the four zones. The relatively high SiO2 values in several samples may indicate stronger silicification, dilution, or the presence of materials that are less favorable for nickel enrichment. From an exploration-management perspective, Zone D should be treated as a lower-priority area until more favorable evidence is obtained. However, it should not be permanently excluded if future mapping identifies untested ultramafic bodies, structural controls, or subsurface saprolite zones that were not captured by surface observations.

3.4. Implications for Exploration Planning

The main implication of the integrated model is that exploration decisions can be organized according to evidence strength. Zone A should be used as the first drilling target because it has the strongest agreement between geochemical grade and prospectivity score. Initial drilling in this zone should be designed to test laterite thickness, vertical Ni distribution, the position of the limonite-saprolite boundary, and the relationship between MgO, Fe, and SiO2 with depth. Closely spaced surface sampling can also be used to determine whether the high-grade response is continuous or only localized around individual sample points.

Zone B should be considered as the second exploration target, especially for programs that also evaluate Co-bearing limonite potential. Test pits or shallow drilling in this zone would help determine whether high Fe and Co values represent a lateritic horizon with economic relevance or only an iron-rich surface cap. Zone C requires limited reconnaissance, while Zone D can be retained as a background comparison area. This staged strategy allows exploration costs to be distributed more efficiently, with intensive work concentrated in areas where the combined evidence is strongest.

The model also supports communication between geologists, GIS analysts, and decision makers. A prospectivity map is easier to interpret when each class is linked to a practical action, such as priority drilling, detailed sampling, reconnaissance, or postponement. This link is important because exploration models are often technically sound but difficult to translate into field programs. By presenting the output as ranked zones, the model becomes a decision-support tool rather than only a spatial visualization product.

3.5. Limitations and Future Model Refinement

Several limitations should be considered when interpreting the results. First, Sentinel-2 imagery can only represent surface conditions and may be affected by vegetation, soil moisture, land disturbance, atmospheric conditions, and mixed pixels. Second, the spatial resolution of DEM/SRTM and multispectral imagery may not capture small-scale variations in laterite thickness, boulder distribution, or lithological contacts. Third, the geochemical data used in this study are simulated, so the results should be interpreted as a methodological demonstration rather than a definitive exploration conclusion.

Future applications should incorporate measured field data and independent validation points. Drill-core logging, test-pit descriptions, laboratory assays, XRF data, and geophysical measurements would allow the model to be calibrated against actual subsurface conditions. Weighting can also be improved using expert-based AHP, fuzzy membership functions, logistic regression, random forest, or other machine-learning approaches. With sufficient field data, the model can be expanded from two-dimensional prospectivity mapping into three-dimensional laterite characterization, including estimation of limonite thickness, saprolite thickness, grade continuity, and preliminary resource potential.

4. Conclusion

Based on the results obtained from simulated data and assumptions, the integration of remote sensing, GIS, and geochemical data can be used to delineate lateritic nickel prospect zones in a more systematic and targeted manner. Remote sensing parameters such as iron oxide index, clay mineral index, NDVI, and surface moisture assist in recognizing lateritic weathering indicators, while GIS parameters such as ultramafic lithology, elevation, slope, lineaments, and distance to geological structures support the construction of the prospectivity model. Geochemical data comprising Ni, Fe, MgO, SiO2, and Co serve as the primary validation components for differentiating high- and low-prospectivity zones. Based on the simulated data processing, Zone A shows the highest prospectivity, with an average Ni grade of 1.79% and a PI value of 0.78, and is therefore recommended as the priority area for initial drilling. The revised interpretation emphasizes that the best exploration target is the area where lithological suitability, surface-weathering indicators, structural conditions, and geochemical evidence are mutually consistent. Within the simulated case, Zone A satisfies these criteria most strongly and should be tested first through systematic drilling, detailed sampling, and laterite-profile logging. Zone B remains important as a secondary target because its Fe and Co characteristics may indicate a well-developed limonitic zone, whereas Zones C and D require lower-intensity verification. Future studies should use actual field data, particularly drilling data, test pit information, and laboratory geochemical analyses, to improve model accuracy and enable scientific validation. Parameter weighting should also be developed using more objective methods such as AHP, fuzzy logic, or machine learning, and tested using statistical measures such as the confusion matrix, ROC/AUC, RMSE, or Pearson correlation. Further work may include the integration of geophysical data, three-dimensional modeling of laterite profiles, preliminary resource estimation using Ordinary Kriging, and analysis of associated elements such as Co, Sc, REE, and Cr to support critical-mineral studies.

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