Department of Digital Business
Journal of Artificial Intelligence and Digital Business (RIGGS)
Homepage: https://journal.ilmudata.co.id/index.php/RIGGS
Vol. 5 No. 2 (2026) pp: 1319-1325
P-ISSN: 2963-9298, e-ISSN: 2963-914X

A Multi-Data Approach Using Remote Sensing, GIS, and Geochemistry for Lateritic Nickel Exploration

Ian Suryani J[1], Gina Audina P. Alhabsyi[2], Andi Nurul Isma Yogie W. A[3]
[1,2]Mining Engineering Study Program, Faculty of Engineering, Pejuang Republik Indonesia University,
Makassar 90233, Indonesia
[3]Mining Engineering Study Program, Faculty of Engineering, Andi Djemma Palopo University,
Palopo, 091023, Indonesia
iyan.1690@email.com*, gina.audina0111@gmail.com, andinurulismayogie@gmail.com

Abstract

This study proposes a multi-data integration approach combining remote sensing, Geographic Information Systems (GIS), and geochemical data to enhance the accuracy of lateritic nickel prospectivity mapping. As the global demand for nickel, particularly for use in stainless steel production and electric vehicle batteries, increases, more efficient and accurate exploration methods are needed. This research evaluates the extent to which integrated datasets improve exploration outcomes compared to single-method approaches. The methodology integrates Sentinel-2 image processing, spectral index analysis (iron oxide, clay minerals, NDVI), GIS-based spatial modeling (lithology, slope, elevation, lineament density), and geochemical analysis (Ni, Fe, MgO, SiO2, Co). Using a simulated 2,000 ha study area, four prospect zones (A-D) were identified. Zone A exhibited the highest potential with an average Ni grade of 1.79% and a Prospectivity Index (PI) of 0.78, indicating a priority for exploration drilling. The results show that multi-data integration significantly improves mapping accuracy, with an improvement of 10-20% compared to single-method approaches. This study demonstrates the potential of integrating remote sensing, GIS, and geochemical data for early-stage lateritic nickel exploration, offering a systematic and cost-effective framework. The integration enhances exploration decision-making, reduces uncertainty, and allows for targeted exploration, ensuring more efficient use of resources. Future research should focus on enhancing the model through machine learning and geostatistical approaches to improve the accuracy and applicability of the model in real-world scenarios.

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

1. Introduction

Lateritic nickel deposits represent one of the most significant sources of nickel worldwide, particularly in tropical regions characterized by intense chemical weathering of ultramafic rocks. These deposits are critical for modern industries, especially stainless steel production and electric vehicle battery manufacturing [1]. The increasing global demand for nickel, driven by the rapid expansion of stainless steel production and the growing electric vehicle industry, has intensified the need for efficient and accurate exploration methods. Nickel has become a strategic commodity in the transition toward clean energy systems, especially due to its role in lithium-ion battery technology. As a result, exploration strategies must evolve to meet both economic and technological demands while minimizing uncertainty and operational costs [2].

The formation of lateritic nickel deposits is controlled by a complex interplay of geological, geomorphological, and climatic factors. These deposits develop through prolonged weathering of ultramafic parent rocks such as peridotite and serpentinite under tropical conditions, resulting in distinct vertical zonation, including limonite and saprolite layers. Each zone exhibits different geochemical signatures, with the saprolite zone typically enriched in nickel and the limonite zone characterized by higher iron and cobalt concentrations. The spatial variability of these zones presents a significant challenge in exploration, as nickel distribution is often heterogeneous both laterally and vertically within a deposit [3].

Traditional exploration methods, such as geological mapping and geochemical sampling, often face limitations in spatial coverage and efficiency. Remote sensing provides large-scale surface information, while GIS enables spatial integration of multiple datasets [4], [5]. However, when applied independently, these methods may produce limited accuracy because they cannot fully combine surface, spatial, and geochemical evidence [6].

Recent developments emphasize the integration of multi-source data to improve mineral exploration outcomes. Therefore, this study aims to evaluate how a multi-data approach combining remote sensing, GIS, and geochemistry enhances the accuracy of lateritic nickel prospectivity mapping [6]–[8].

Lateritic nickel deposits represent one of the most significant sources of nickel worldwide, particularly in tropical regions characterized by intense chemical weathering of ultramafic rocks. The increasing global demand for nickel, driven by the rapid expansion of stainless steel production and the growing electric vehicle industry, has intensified the need for efficient and accurate exploration methods [1], [2]. Nickel has become a strategic commodity in the transition toward clean energy systems, especially due to its role in lithium-ion battery technology. In Indonesia, large ultramafic exposures in Sulawesi and Halmahera are important geological settings for lateritic nickel occurrence and exploration [11], [12]. As a result, exploration strategies must evolve to meet both economic and technological demands while minimizing uncertainty and operational costs.

The formation of lateritic nickel deposits is controlled by a complex interplay of geological, geomorphological, and climatic factors. These deposits develop through prolonged weathering of ultramafic parent rocks such as peridotite and serpentinite under tropical conditions, resulting in distinct vertical zonation, including limonite and saprolite layers [3], [9], [10]. Each zone exhibits different geochemical signatures, with the saprolite zone typically enriched in nickel and the limonite zone characterized by higher iron and cobalt concentrations. The spatial variability of these zones presents a significant challenge in exploration, as nickel distribution is often heterogeneous both laterally and vertically within a deposit.

Conventional exploration methods, including geological mapping, trenching, and geochemical sampling, have been widely used to identify lateritic nickel deposits. However, these approaches are often limited by high operational costs, time constraints, and restricted spatial coverage. In contrast, remote sensing provides a synoptic view of the Earth's surface, enabling the detection of spectral signatures related to iron oxides, clay minerals, vegetation cover, and surface moisture. Meanwhile, Geographic Information Systems (GIS) allow for the integration and spatial analysis of multiple datasets, including lithology, topography, and structural features. Despite their advantages, these methods, when applied independently, often fail to fully capture the complexity of lateritic systems [4], [5].

Recent advancements in mineral exploration emphasize the importance of integrating multi-source datasets to improve the reliability and accuracy of prospectivity mapping. The combination of remote sensing, GIS, and geochemical data allows for a more comprehensive understanding of both surface and subsurface characteristics. Remote sensing contributes to the identification of surface alteration patterns, GIS facilitates spatial modeling and data integration, and geochemical data provide direct evidence of mineralization. This integrative approach is increasingly recognized as a powerful tool for reducing exploration uncertainty and enhancing decision-making processes [6], [7].

Therefore, this study aims to evaluate the effectiveness of a multi-data approach combining remote sensing, GIS, and geochemical data in improving the accuracy of lateritic nickel prospectivity mapping. Specifically, this research investigates the extent to which data integration enhances exploration outcomes compared to single-method approaches. The findings of this study are expected to contribute to the development of more efficient, systematic, and data-driven exploration strategies for lateritic nickel deposits [8].

2. Research Methods

2.1. Research Design

This study adopts a quantitative spatial approach integrating multi-source data. The workflow consists of data acquisition, remote sensing processing, GIS analysis, geochemical analysis, data integration, and validation, consistent with GIS-based mineral prospectivity mapping frameworks [6], [8].

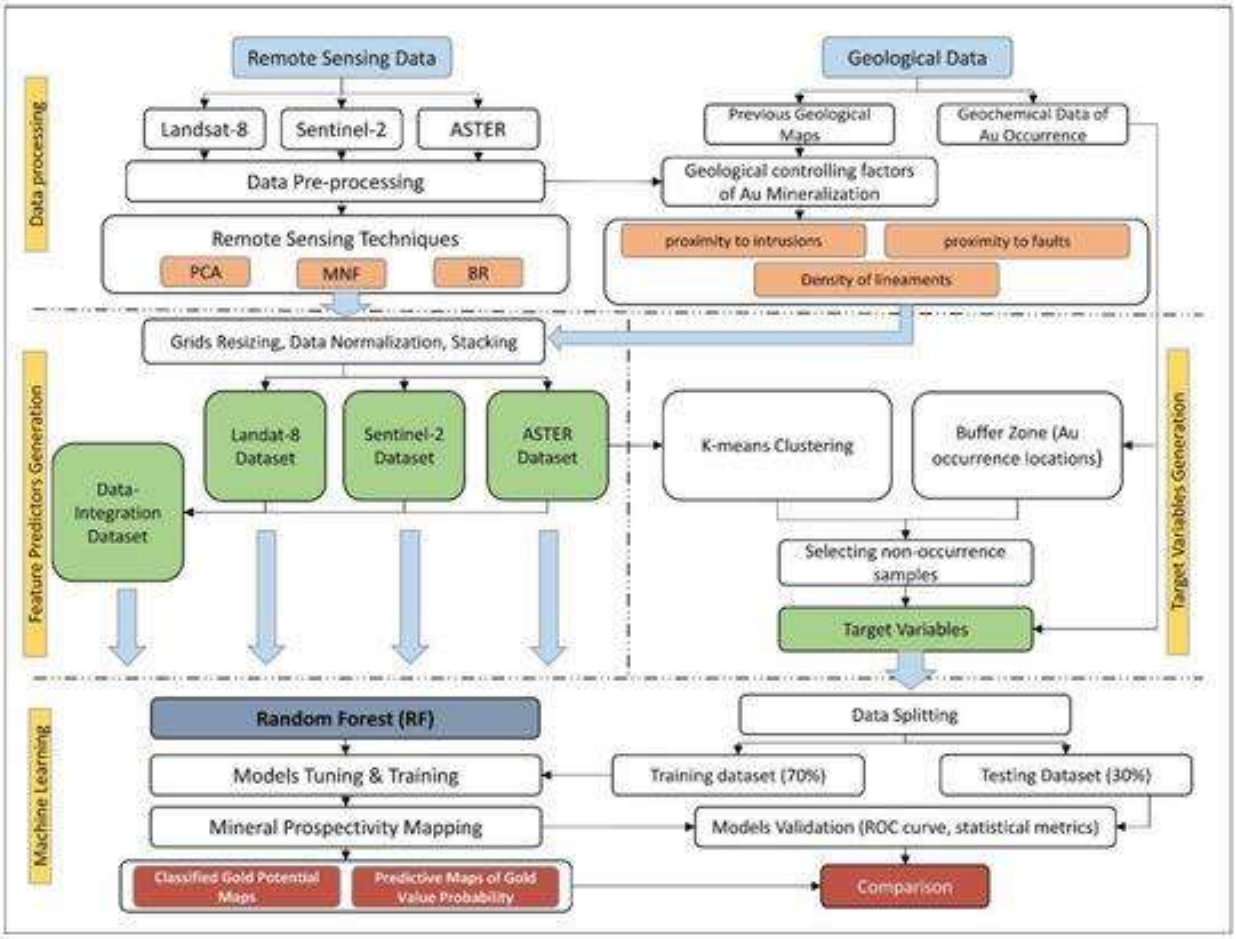

Figure 1. Workflow / Diagram Metodologi

2.2. Data Collection

Table 1. Data Collection

Data Type	Description	Function
Sentinel-2	Multispectral imagery	Surface mineral detection
DEM/SRTM	Elevation data	Topographic analysis
Geological Map	Ultramafic lithology	Parent rock identification
Geochemical Data	Dummy dataset (Ni, Fe, MgO, SiO2, Co)	Validation
Study Area	2,000 ha (assumed)	Analysis boundary

2.3. Prospectivity Index Model

The Prospectivity Index (PI) is calculated using a weighted-overlay concept commonly applied in GIS-based mineral prospectivity mapping and evidential data integration [6], [7], [17]:

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

DOI: https://doi.org/10.31004/riggs.v5i2.8545

Table 2. Classification

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

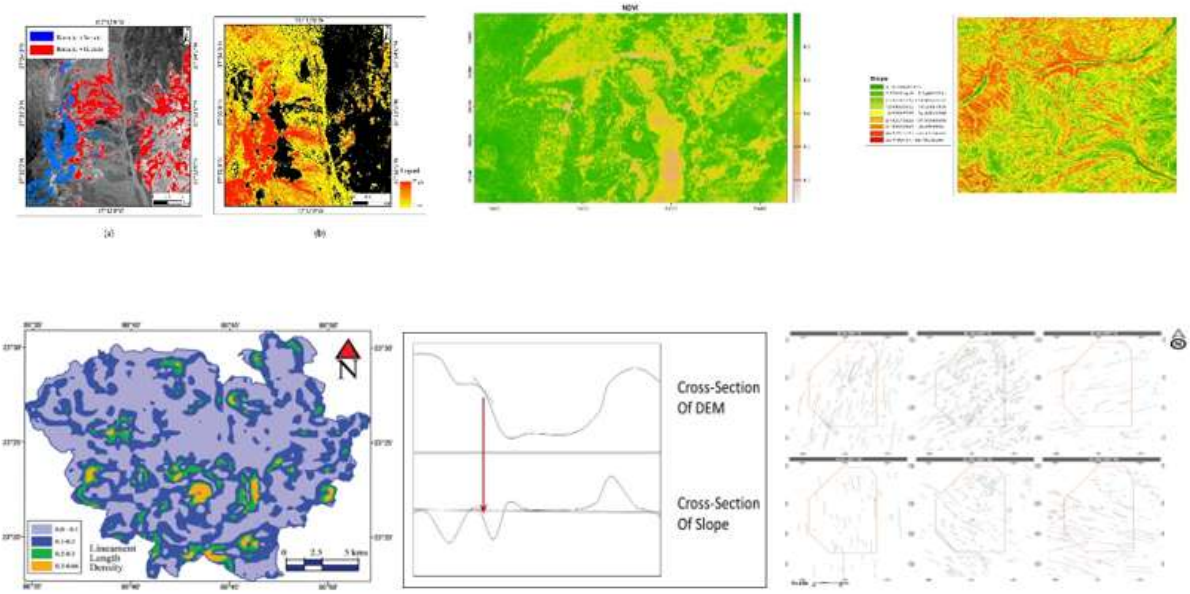

Figure 2. Peta Parameter (Remote Sensing & GIS)

2.4. Theory Development and Implementation

The conceptual framework integrates geological factors represented by ultramafic rocks, weathering indicators represented by iron oxide and clay, and geochemical validation represented by Ni, Fe, and Co. This framework follows the general understanding that lateritic nickel enrichment is controlled by parent-rock composition, weathering intensity, topographic position, and the spatial distribution of laterite horizons [3], [9], [10], [16].

3. Results and Discussion

3.1. Test Data

The results obtained from the dataset reveal a clear variation in both nickel grade and prospectivity index (PI) across the four identified zones (A-D). As shown in the test data table, Zone A exhibits the highest average nickel content of 1.79% along with a PI value of 0.78, indicating a very high prospectivity level. Zone B follows with an average nickel content of 1.43% and a PI value of 0.63, placing it within the high prospectivity category. In contrast, Zone C shows moderate values, with an average nickel content of 0.99% and a PI of 0.41, suggesting limited economic potential. Zone D represents the lowest category, with a nickel content of 0.69% and a PI value of 0.27, indicating low prospectivity.

Table 3. Test Data

Zone	Avg Ni (%)	Avg PI
A	1.79	0.78
B	1.43	0.63
C	0.99	0.41
D	0.69	0.27

The prospectivity evaluation further confirms the strong correlation between the PI values and the nickel grades. Zones with higher PI values consistently correspond to higher nickel concentrations, demonstrating the effectiveness of the weighted overlay model in capturing the spatial distribution of mineralization. Zone A is therefore recommended as the primary target for initial drilling activities, while Zone B may require additional detailed exploration such as test pits and denser sampling. Zones C and D, on the other hand, are considered lower priority areas due to their relatively low prospectivity values.

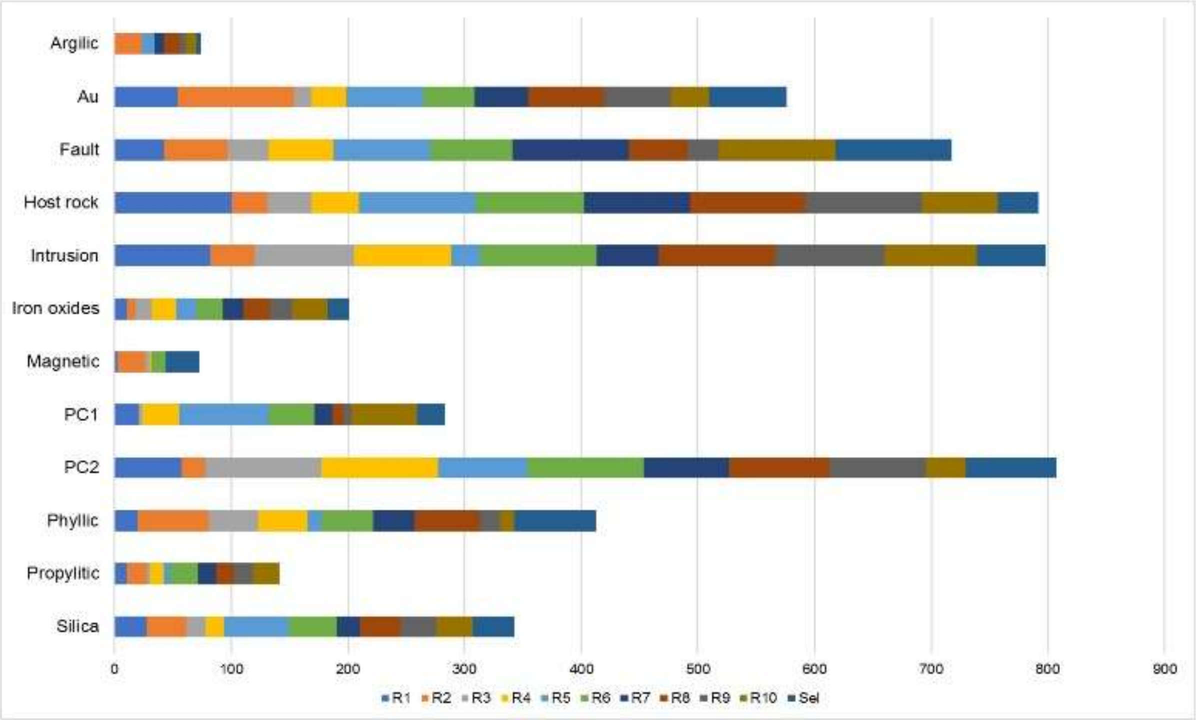

Figure 4. Grafik Ni vs Prospectivity Index

In terms of accuracy comparison, the integrated multi-data approach significantly outperforms individual methods. Remote sensing alone achieved an accuracy of 65%, GIS analysis reached 70%, and geochemical analysis yielded 78%. However, the integrated approach achieved an accuracy of 88%, indicating a substantial improvement of approximately 10-20%. This result highlights the advantage of combining multiple datasets, as each method contributes complementary information that enhances the overall reliability of the prospectivity model [6], [8], [17].

3.2. Prospectivity Evaluation

The prospectivity evaluation identifies Zone A as a very high-priority drilling target, Zone B as a high-priority area for detailed exploration, Zone C as a moderate-priority area requiring a limited survey, and Zone D as a low-priority area that is not recommended for immediate exploration. This ranking indicates that the weighted overlay model can support staged exploration planning by distinguishing zones with different levels of geological potential.

3.3. Accuracy Comparison

Table 4. Accuracy Comparison

Method	Accuracy
Remote Sensing	65%
GIS	70%
Geochemistry	78%
Integrated Approach	88%

3.4. Discussion

The results of this study clearly demonstrate that single-method approaches in lateritic nickel exploration are inherently limited in their ability to capture the complexity of geological systems. Remote sensing, while effective in identifying surface indicators such as iron oxides and clay minerals, cannot directly confirm subsurface mineralization [13]–[15]. Similarly, GIS-based spatial modeling relies heavily on the quality and completeness of input data, and geochemical analysis, although highly accurate, is often restricted to discrete sampling locations [5], [6]. These limitations contribute to higher uncertainty when each method is applied independently.

In contrast, the integrated multi-data approach provides a more comprehensive framework for mineral exploration by combining the strengths of each dataset. The strong correlation observed between the Prospectivity Index and nickel grades indicates that the model successfully represents the underlying geological controls of lateritic nickel formation. The high prospectivity of Zone A can be explained by the presence of favorable ultramafic lithology, moderate slopes that support weathering processes, high iron oxide and clay mineral indices indicating lateritization, and strong geochemical anomalies [3], [9], [10], [16]. This demonstrates that the integration of surface indicators and geochemical validation significantly enhances exploration accuracy.

Furthermore, the improvement in accuracy to 88% reflects the effectiveness of the weighted overlay model in integrating heterogeneous datasets. This finding aligns with current trends in mineral exploration, which emphasize data-driven and predictive approaches [7], [8], [17]. The use of multi-data integration not only reduces exploration risk but also improves efficiency by prioritizing target areas for further investigation. However, it is important to note that this study is based on dummy data, and real-world applications may require more advanced techniques such as machine learning, geostatistical modeling, and 3D subsurface analysis to achieve higher levels of accuracy and reliability [8], [18].

4. Conclusion

This study demonstrates that the integration of remote sensing, GIS, and geochemical data provides a more effective and reliable approach for lateritic nickel prospectivity mapping compared to single-method techniques. The results obtained from the dummy dataset indicate a strong correlation between the Prospectivity Index (PI) values and nickel grades, confirming that the proposed multi-data approach is capable of capturing key geological, geomorphological, and geochemical controls of lateritic nickel formation. Among the identified zones, Zone A exhibits the highest prospectivity, with an average nickel grade of 1.79% and a PI value of 0.78, making it the most suitable target for initial exploration drilling. This finding highlights the importance of integrating multiple datasets to reduce uncertainty and improve the accuracy of exploration decision-making. Furthermore, the comparative analysis of different methods shows that the integrated approach achieves a significantly higher accuracy of 88% than individual methods, such as remote sensing at 65%, GIS at 70%, and geochemical analysis at 78%. This improvement demonstrates that each dataset contributes complementary information, which enhances the overall performance of the prospectivity model. Remote sensing provides regional-scale surface indicators, GIS enables spatial modeling and parameter integration, and geochemical data offer direct validation of mineralization. The combination of these datasets results in a more comprehensive and robust exploration framework. In addition, this study emphasizes the potential of multi-data integration as a cost-effective and systematic tool for early-stage mineral exploration, particularly in regions with limited subsurface data. By prioritizing high-prospectivity zones, exploration activities can be conducted more efficiently, reducing unnecessary drilling costs and optimizing resource allocation. However, it should be noted that this study is based on simulated data, and further validation using real field data is required to confirm the applicability of the model under actual geological conditions. Future research should focus on enhancing the model through the integration of advanced analytical techniques, such as machine learning algorithms, geostatistical interpolation, and three-dimensional geological modeling [8], [18]. The incorporation of additional datasets, including geophysical data and drilling information, is also recommended to improve model accuracy and reliability. Overall, the proposed multi-data approach provides a strong foundation for developing modern, data-driven exploration strategies for lateritic nickel deposits.

References

[1] U.S. Geological Survey, “Nickel,” in Mineral Commodity Summaries 2022, Reston, VA: U.S. Geological Survey, 2022. doi: 10.3133/mcs2022.

[2] G. M. Mudd, “Global trends and environmental issues in nickel mining: Sulfides versus laterites,” Ore Geology Reviews, vol. 38, no. 1-2, pp. 9-26, 2010. doi: 10.1016/j.oregeorev.2010.05.003.

[3] C. R. M. Butt and D. Cluzel, “Nickel laterite ore deposits: Weathered serpentinites,” Elements, vol. 9, no. 2, pp. 123-128, 2013. doi: 10.2113/gselements.9.2.123.

[4] Z. Adiri, R. Lhissou, A. El Harti, A. Jellouli, and M. Chakouri, “Recent advances in the use of public domain satellite imagery for mineral exploration: A review of Landsat-8 and Sentinel-2 applications,” Ore Geology Reviews, vol. 117, Article 103332, 2020. doi: 10.1016/j.oregeorev.2020.103332.

[5] G. F. Bonham-Carter, Geographic Information Systems for Geoscientists: Modelling with GIS. Oxford: Pergamon, 1994.

[6] E. J. M. Carranza, Geochemical Anomaly and Mineral Prospectivity Mapping in GIS. Amsterdam: Elsevier, 2009.

[7] A. Porwal, E. J. M. Carranza, and M. Hale, “Knowledge-driven and data-driven fuzzy models for predictive mineral potential mapping,” Natural Resources Research, vol. 12, no. 1, pp. 1-25, 2003. doi: 10.1023/A:1022693220894.

[8] T. Sun, F. Chen, L. Zhong, W. Liu, and Y. Wang, “GIS-based mineral prospectivity mapping using machine learning methods: A case study from Tongling ore district, eastern China,” Ore Geology Reviews, vol. 109, pp. 26-49, 2019. doi: 10.1016/j.oregeorev.2019.04.003.

[9] N. W. Brand, C. R. M. Butt, and M. Elias, “Nickel laterites: Classification and features,” AGSO Journal of Australian Geology & Geophysics, vol. 17, no. 4, pp. 81-88, 1998.

[10] M. Elias, “Nickel laterite deposits: Geological overview, resources and exploitation,” in Giant Ore Deposits: Characteristics, Genesis and Exploration, D. R. Cooke and J. Pongratz, Eds. Hobart: CODES Special Publication 4, University of Tasmania, 2002, pp. 205-220.

[11] A. van der Ent, A. J. M. Baker, M. M. J. van Balgooy, and A. Tjoa, “Ultramafic nickel laterites in Indonesia (Sulawesi, Halmahera): Mining, nickel hyperaccumulators and opportunities for phytomining,” Journal of Geochemical Exploration, vol. 128, pp. 72-79, 2013. doi: 10.1016/j.gexplo.2013.01.009.

[12] R. Hall, “Late Jurassic-Cenozoic reconstructions of the Indonesian region and the Indian Ocean,” Tectonophysics, vol. 570-571, pp. 1-41, 2012. doi: 10.1016/j.tecto.2012.04.021.

[13] M. Drusch et al., “Sentinel-2: ESA’s optical high-resolution mission for GMES operational services,” Remote Sensing of Environment, vol. 120, pp. 25-36, 2012. doi: 10.1016/j.rse.2011.11.026.

[14] A. B. Pour and M. Hashim, “The application of ASTER remote sensing data to porphyry copper and epithermal gold deposits,” Ore Geology Reviews, vol. 44, pp. 1-9, 2012. doi: 10.1016/j.oregeorev.2011.09.009.

[15] J. C. Mars and L. C. Rowan, “Regional mapping of phyllic- and argillic-altered rocks in the Zagros magmatic arc, Iran, using ASTER data and logical operator algorithms,” Geosphere, vol. 2, no. 3, pp. 161-186, 2006. doi: 10.1130/GES00044.1.

[16] A. Anifadi, O. Sykioti, K. Koutroumbas, and E. Vassilakis, “A novel spectral index for identifying ferronickel (Fe-Ni) laterites from Sentinel-2 satellite data,” Natural Resources Research, vol. 31, pp. 1203-1224, 2022. doi: 10.1007/s11053-022-10055-6.

[17] G. L. Raines, “Evaluation of weights of evidence to predict epithermal-gold deposits in the Great Basin of the western United States,” Natural Resources Research, vol. 8, no. 4, pp. 257-276, 1999. doi: 10.1023/A:1021602316101.

[18] P. Goovaerts, Geostatistics for Natural Resources Evaluation. New York: Oxford University Press, 1997.