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The use of Machine Learning Algorithms for Mineral Prospectivity Mapping in the Giyani Greenstone Belt

Simon, Eliah, Sesebula
Department of Geology and Mining, University of Limpopo

Summary

This study applies a machine learning approach within a mineral systems framework to improve gold mineral prospectivity mapping in the Giyani Greenstone Belt, South Africa. An artificial neural network, specifically a radial basis functional link network (RBFLN), was trained using 37 known gold occurrences, with 27 for training and 10 for validation. Exploration proxies were selected to represent critical mineral system components, including lithology, proximity to the Hout River Shear Zone (HRSZ) and subsidiary structures, distribution of iron formations, and alteration indices (Hashimoto, chlorite, ACNK, and Spitz). The model achieved classification accuracies exceeding 85% for known deposits and over 80% for predicting previously unrecognised mineralised zones. These results demonstrate the capability of data-driven models to capture complex, nonlinear relationships among geological and geochemical variables. The approach provides a reproducible workflow for delineating highly prospective zones in greenstone-hosted systems, supporting efficient, targeted mineral exploration.

Theory / Method / Workflow

A mineral systems framework guided the selection of exploration proxies to capture key geological, structural, and geochemical controls on gold mineralisation. Geodata sets were compiled and spatially modelled within a GIS environment. To ensure balanced model training and reduce bias arising from class imbalance, an equal number of non-deposit locations were generated using a weight of evidence (WofE) approach, providing representative background samples for contrast with known mineralised points (e.g., Bonham-Carter 1994; Carranza 2009). More recently, studies emphasise that balancing the number of positive (deposit) and negative (non-deposit) samples improves model reliability and avoids over-favouring the majority class in machine-learning-based prospectivity models (Yousefi et al. 2024). The RBFLN algorithm was then trained on 27 known gold occurrences alongside WofE-generated non-deposit points, learning the spatial correlations between mineralisation and input features. The remaining 10 occurrences were used for validation and performance testing. Model outputs were classified into probability zones, delineating areas of high, moderate, and low prospectivity.

Results, Observations, Conclusions

The radial basis functional link network successfully reproduced known gold mineralisation zones with over 85% accuracy and predicted new, high-prospectivity areas with over 80% confidence. High-probability zones coincide with the spatial distribution of the HRSZ and iron-formation units, validating the structural and lithological controls expected within the orogenic gold mineral systems model (*Figure 1.1*). The findings confirm that integrating geological knowledge with machine learning enhances predictive accuracy and supports data-driven exploration targeting in greenstone belts.

Figure 1.1: *Gold prospectivity map generated using a radial basis functional link network trained with 40 neurons (radial basis functions) over 140 iterations on 27 known gold occurrences and an equal number of weights-of-evidence generated non-deposit points. Probability zones are classified as highly, moderately, low and very low prospectivity, illustrating spatial correlations between mineralisation and key geological, structural, and geochemical controls. The map also highlights the association of the mineralised zones with the Hout River Shear Zone and iron formation, providing a predictive tool for targeted exploration and areas warranting further field investigation.*

Novel/Additive Information

This study demonstrates one of the early applications of the artificial neural network in mineral prospectivity mapping within the Giyani Greenstone Belt. By combining machine learning with the mineral systems approach, the workflow offers a transferable method for other greenstone-hosted gold provinces, reducing exploration risk and improving the efficiency of target generation.

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