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Integrated 3D modelling and associated machine learning targeting: the Jaguar Greenstone Belt example.

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SUMMARY

Mira Geoscience completed an integrated interpretation in the Jaguar Greenstone Belt (JGB), in Western Australia, on behalf of Round Oak Minerals (now Aeris Resources). The 3D structural and stratigraphic regional model, consistent with geophysical data sets was the foundation for the exploration model. The targeting and prospectivity analysis were based on quantifying exploration criteria and explicitly representing these criteria in the exploration model for sub-seafloor replacement-style Volcanic Hosted Massive Sulfide (VHMS) deposits.

First, the regional geological model was built from geological constraints (mapping, drill holes) but also developed in close integration with potential fields data, producing a viable starting model for geologically constrained inversion to solve for rock property variations within geological domains. When the model thus constructed was submitted to geologically constrained inversion to reconcile unexplained response as property variations within those domains, sensible/stable property variations were recovered in the inverted model, which it was possible to interpret in terms of alteration and potential targets.

The exploration criteria were translated using the integrated 3D model to create exploration vectors that were representative of the mineral system. In other words, these vectors were numerical realisations of the various targeting criteria. The prospectivity analysis at Jaguar used a Machine Leaning approach, namely Random Forests, to generate a 3D Mineral Potential Index based on different combinations of input exploration vectors. This resulted in identification of 41 separate targets within the JGB.

Key words: 3D integrated modelling, geologically constrained gravity and magnetic inversion, prospectivity analysis, machine learning, Volcanic Hosted Massive Sulfide (VHMS), Jaguar, Bentley, Teutonic Bore.

INTRODUCTION

The overarching aim of this project was to undertake an integrated approach to modelling and prospectivity analysis over the Round Oak Minerals (ROM) tenements in the JGB. The area of interest was approximately 61 × 28 km (Figure 1), aligned with the NNW-trending Gindalbie Domain, which is host to the Jaguar, Teutonic Bore and associated deposits.

The area is prospective for Volcanic Hosted Massive Sulphide (VHMS)-style deposits (e.g. Jaguar, Teutonic Bore, Bentley, Triumph, and Daimler). The goal of the integrated interpretation was to advance the geological understanding of the area, by developing a 3D geological model consistent with the geophysical data sets, while extracting as much useful information as possible from the down hole geochemical and spectral data. The model has subsequently provided a basis for exploration over the JGB.

While geophysical modelling plays an integral role in developing the geological model, the geological model also serves as a well-conditioned starting model for geologically constrained inversion. Inversion solves for rock property anomalism within the modelled geological domains which may be interpreted in terms of prospectivity, or simply indicate parts of the model that exhibit additional geological complexity.
Machine Learning (ML) algorithms were used to cluster the geochemical and spectral data according to alteration footprints (proximal, distal, barren) as well as attributing geochemical lithology to the samples (e.g. felsic, intermediate, mafic). This information was taken into consideration during model development and prospectivity analysis.
ML was also used for prospectivity analysis. Exploration vectors (numerical representations of the exploration criteria) were developed, and values were assigned to the entire 3D model. The ML 'Random Forest' algorithm was used to process all of the exploration criteria and to predict prospectivity for each cell of the model. Based on the prospectivity analysis, and careful review of individual exploration criteria and down hole information, 41 new targets were identified.

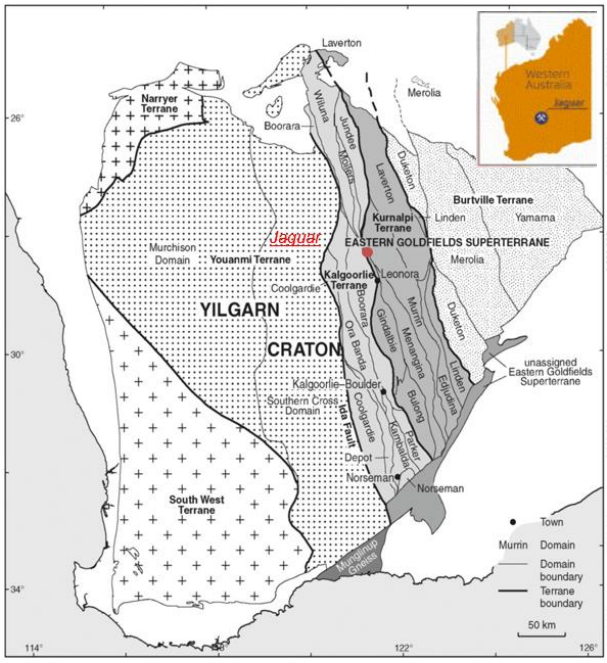

Figure 1. Archean Yilgarn Craton, Western Australia, showing the six terranes, modified from Cassidy et al. (2006).

GEOLOGICAL SETTING

Jaguar is an Archean Cu-Zn-rich volcanic-hosted massive sulphide deposit, located approximately 255 km north of Kalgoorlie, in the Teutonic Bore Volcanic Complex (TBVC) in the Eastern Goldfields Superterrane (EGST) of the Yilgarn Craton, Western Australia. The TBVC, which hosts the known massive sulphide deposits, comprises pillowed basalt, overlain by and interlayered with quartz-rich volcaniclastic units and coherent rhyolite (Hallberg and Thompson, 1985). The known deposits are subseafloor replacement type VHMS located on the main ore horizon, defined as the footwall of the Mineralised Package overlying the Footwall Sequence (Belford et al., 2015).

INTEGRATED GEOLOGICAL AND GEOPHYSICAL MODELLING

Construction of the geological model

The starting geological model was a single surface representing the "ore horizon" on which the known VHMS deposits in the JGB occur. Effective geologically constrained inversion required a starting model which was broadly consistent with the geophysical data (Pears et al, 2017). A 3D geological starting model that contradicts the measured data will typically produce an inversion result with artefacts. It was therefore important to undertake geological modelling in tight integration with the geophysical data.
Interpretation commenced with a detailed assessment of the various data sets (e.g. geological maps, drill hole data, and drill hole rock density and magnetic susceptibility data; gravity, magnetic, induced polarization, magnetotelluric, and surface and downhole electromagnetic data) with a view to establishing relationships between the geophysical responses and the geology.

3D geological scenarios were validated against the geophysical data though forward modelling and inversion. The results of the geophysical tests were appraised, and the outcomes were used to refine the model via a recursive process. Positions of geological boundaries were continually refined as interpretations evolved and additional information became available, e.g., new geological information/maps, updated geochemical interpretations of drill hole data, etc.

A 3D fault network model was constructed, which comprised thirty-two interpreted faults. Twenty-nine major geological units across the area of interest were also modelled. A 3D geological block model was constructed from the interpreted faults and geological units (Figure 2).

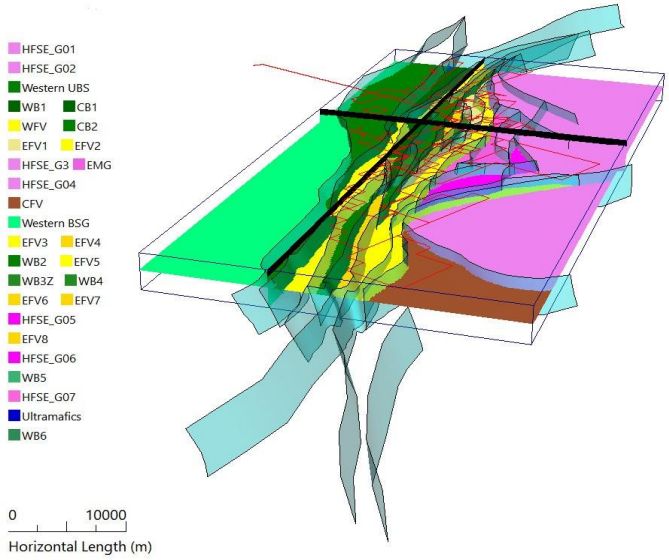

Figure 2. 3D geological model of the JGB, constructed via integrated interpretation of all available geoscientific data

Potential fields inversion applied to the geological model

Potential fields modelling was used recursively to test, validate and update the geological model at various stages during the project. The geological model developed itself was itself used as a constraint during the final potential field inversions. By specifying the geological model, attributed with density or susceptibility, as a starting model, inversion imposed the minimum amount of change required to that model to explain the geophysical data.

There were two key stages of potential field modelling: (1) Forward modelling and homogeneous unit optimisation and (2) Geologically-constrained inversion to solve for rock property variations within the geological domains.

Gravity inversion results

The final outcome from the gravity inversion was a geologically-based model with heterogeneous density variations within the modelled domains. Part of the process to achieve this result was to optimise the starting model density assigned to each geological domain. The inverted density model was found to largely preserve the geological integrity of the domain boundaries. This was a testament to the veracity of the interpretation on which the starting model was based. The main prospective horizon was not associated with a strong density contrast. This lack of contrast was consistent with petrophysical data.

Magnetics inversion results

Like the gravity inversion, the magnetics inversion was completed using the geological model as a constraint. The final outcome from the magnetic inversion was a geologically-based model with heterogeneous magnetic susceptibility variations within each domain. As for the gravity modelling, the first stage of inversion was to optimise the magnetic susceptibility assigned to each geological domain.

Key stratigraphic packages were more distinguishable in terms of density contrasts than magnetic susceptibility. Only a few of the modelled stratigraphic packages stood out from magnetic background, but the integrity of the homogeneous domains that did not have elevated magnetic susceptibility was preserved in the inversion result.

The main prospective horizon does not exhibit much magnetic susceptibility contrast. Subtle variations in the inverted susceptibility on this horizon may however be of exploration interest.

ANALYSIS OF GEOCHEMICAL ASSAY AND SPECTRAL DATA

Methodology

The geochemical and spectral analysis of the data were based on two successive approaches: 1) traditional alteration indices and ratio calculations and 2) a data driven approach using unsupervised machine learning. Both approaches are conducted with the objective of mapping geochemical and mineralogical changes associated with hydrothermal alteration, leading to potential VHMS deposits. This approach, referred as mineral system footprinting, used the changes in chemistry and mineralogy to produce domains at different proximity to the mineralization. This can then be rasterized in 3D space to help with understanding of the mineral system understanding and/or with targeting.
The alteration indices and ratio calculations were done using the ioGAS software, utilizing the premade calculations tool. The data driven footprints were generated using the hierarchical clustering algorithm in the Orange software environment.

Oxides lithological-alteration domains

The objective of the clustering workflow was to classify the geochemical signature of the rocks in groups that can be related to the proximity to known mineralized areas. Only the oxide data was used for this exercise given its superior spatial coverage and information gain over the trace element dataset.
A first clustering exercise (Figure 3) was conducted using the immobile elements in order to differentiate between major lithological domains within the study area. The initial composition of these different lithological domains can affect the chemical differentiation during alteration processes due to their starting geochemical compositions. Four (4) major lithological domains were found to be represented in the major element compositions (Figure 7).

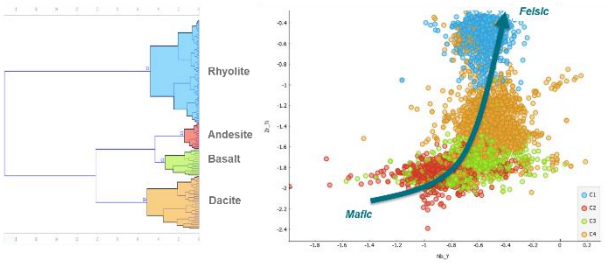

Figure 3. Oxides lithological domain classification (rhyolite – blue; andesite – red; basalt – green; dacite – orange).

Each of the domains were then presented independently through a second round of clustering using the mobile elements as input. This phase of clustering had the objective of generating groups of samples with similar signature and forming distinct populations against the distance to known mineralized occurrences. The hierarchical trees were interpreted in order to fit key groups of samples that would give good results against the distances to known deposits. The distance to known deposit validation was only undertaken on points that were within 3000m from the wireframes of the known mineralisation.
A total of 5 to 8 clusters were interpreted for each major lithological domain, in order to best represent the distances of the domains from known deposits. The interpreted clusters were then reclassified to four distance groups: 1) proximal, 2) distal, 3) distal 2 and 4) unaltered.

Spectral data alteration domains

The spectral data exhibited good spatial coverage with 28123 available entries following the removal of outliers. Once the data was pre-processed to a distribution ranging from 0-1, it was submitted to the hierarchical clustering algorithm. The resulting tree was interpreted in order to select groups of data that formed coherent groups with regards to the distance to known deposits. These clusters were then reclassified in five (5) groups representing proximity factors to the mineralization (Figure 4).

PROSPECTIVITY ANALYSIS AND TARGETING

Random Forest methodology

Machine Leaning (ML) algorithms have the potential to identify and model the complex non-linear relationships between the mineral occurrences and the evidential features (Brown et al., 2000). Random forest (RF), originally developed by Breiman (2001), is an ensemble machine learning algorithm that combines multiple decision trees and makes repeated predictions of the same phenomena represented by the training dataset.

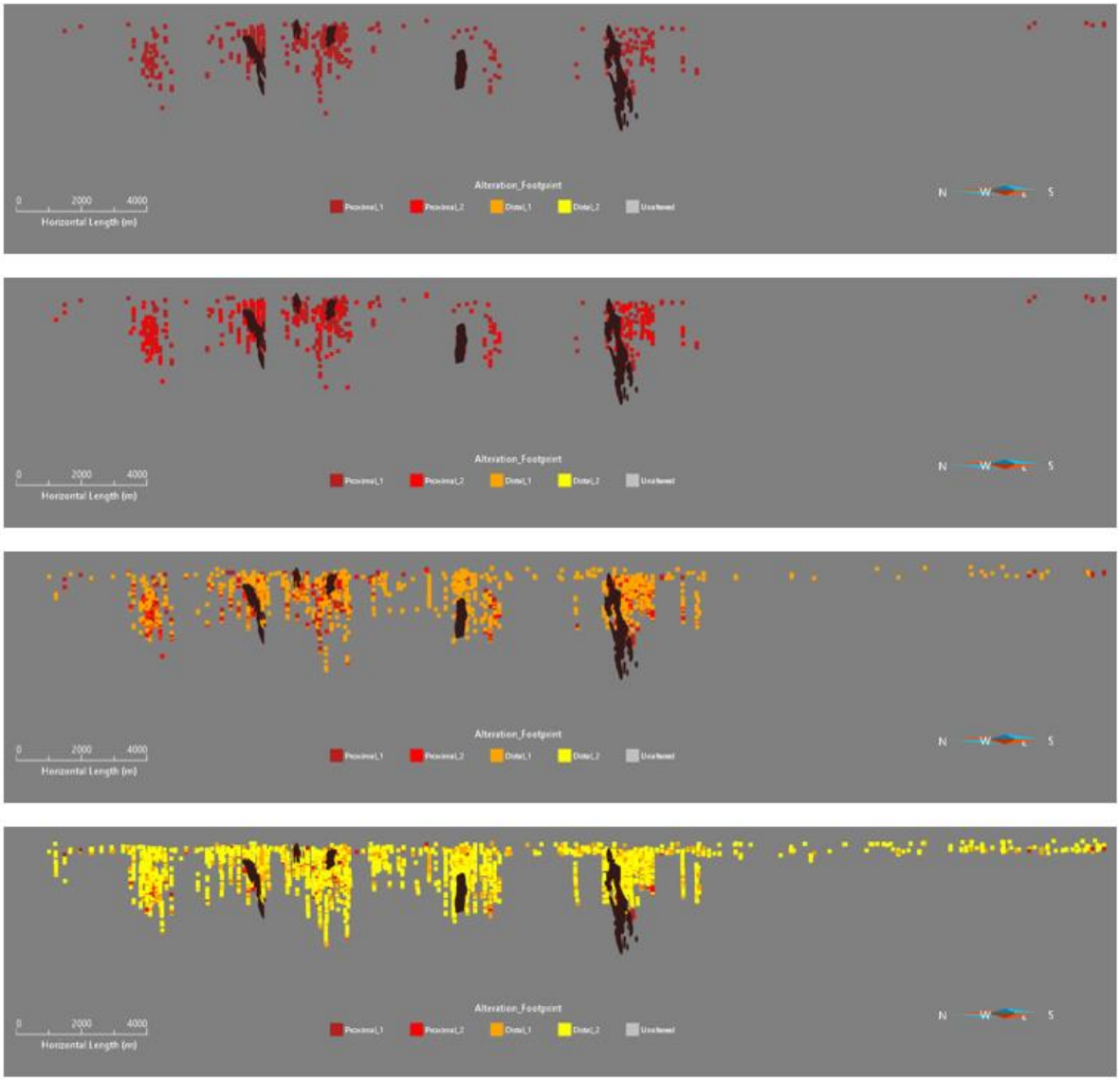

Figure 4. Long sections looking east showing spectral alteration footprints in relation to the known resource wireframes in the JGB (black). Proximal alteration signatures are shown in the top two panels and distal alteration footprint in the bottom two.

Application of machine learning methods include data preparation, model training and testing, as well as visualization of output. Tasks include integration of multi-source predictor maps, generation of input datasets, and visualization of output. The objective of the data driven approach taken here is to remove all human biases from generation of the Mineral Prospectivity Index (MPI). Hence no weights are set on entry to the algorithm. The algorithm takes the observed correlations in the datasets at the location of mineralized and unmineralized holes and seeks the same patterns where there are not drill holes, so there is no bias towards areas which have already been tested.

Twenty-nine exploration vectors (otherwise referred to as 'features') were developed for the machine learning (Figure 5). These vectors are numerical realisations of the various targeting criteria. The criteria were grouped according to three conventional categories of exploration criteria: 1, Metal Source (e.g. granitic intrusions); 2, Architecture, effective conduits and circulation (e.g. structures, alteration, geophysical); 3, Metal trapping (porous geological units).

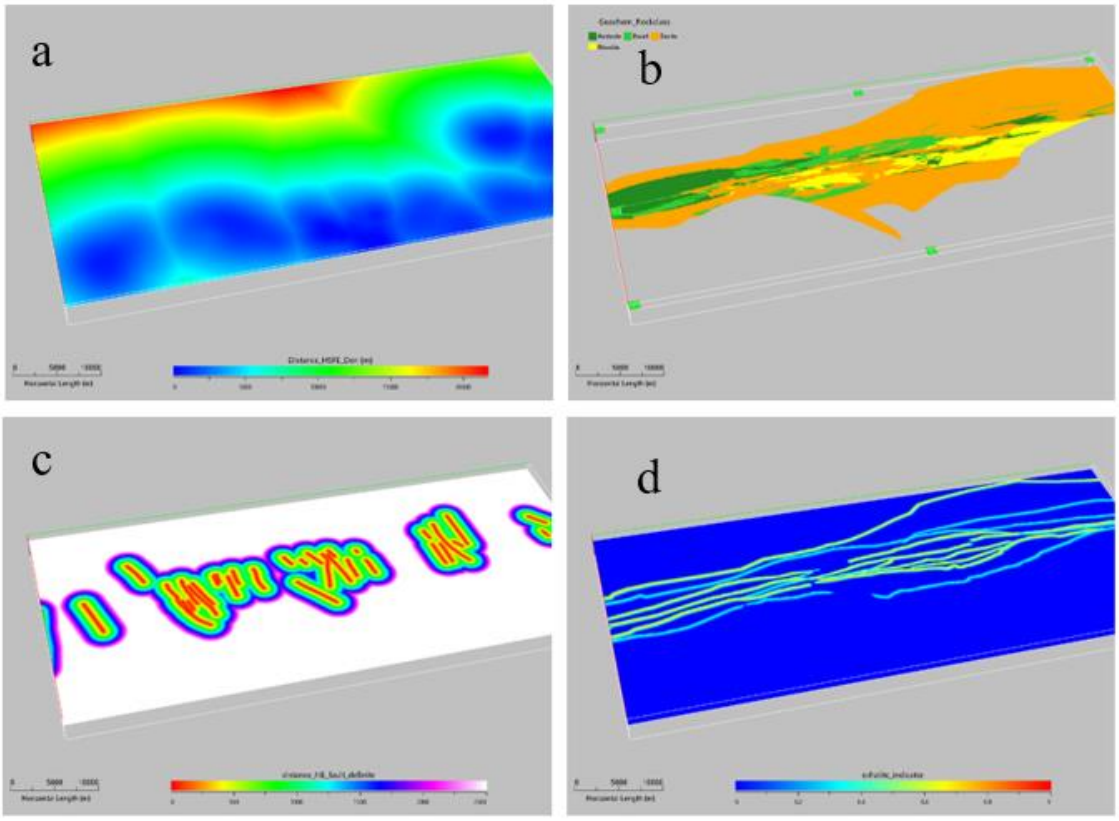

Figure 5. Examples of exploration vectors in the exploration 3D model (all can be viewed in the supplied 3D model). a. Distance to High Field Strength Element granite; b. Geochemical rock class; c, Distance to northeast-trending faults; and d. distance to interpreted exhalite.

Training and verification of the Random Forest algorithm are quite complex, and are not discussed in detail here. Considerable care must be taken when constructing suitable positive and negative examples on which to train the algorithm. When applying the predictive model, a balance must be sought between simply reproducing the known occurrences of mineralisation (overfitting) and overestimating the likely areas of mineralisation (underfitting). Validation of the results was undertaken in part by reserving 30% of the training dataset and using it in the prediction phase. This allowed the ability of the RF network to correctly recover both negative and positive examples to be assessed.

Mineral Potential Index

Once the predictive model was deemed acceptable it was applied to the cells in order to generate an Mineral Potential Index (MPI). The predictive modelling approach was conducted on several scenarios with varying learning deposits and exploration features. An MPI score was produced for each combination of learning features and learning deposits. The final Global MPI shown in Figure 6 is a weighted average of these different prediction scenarios.

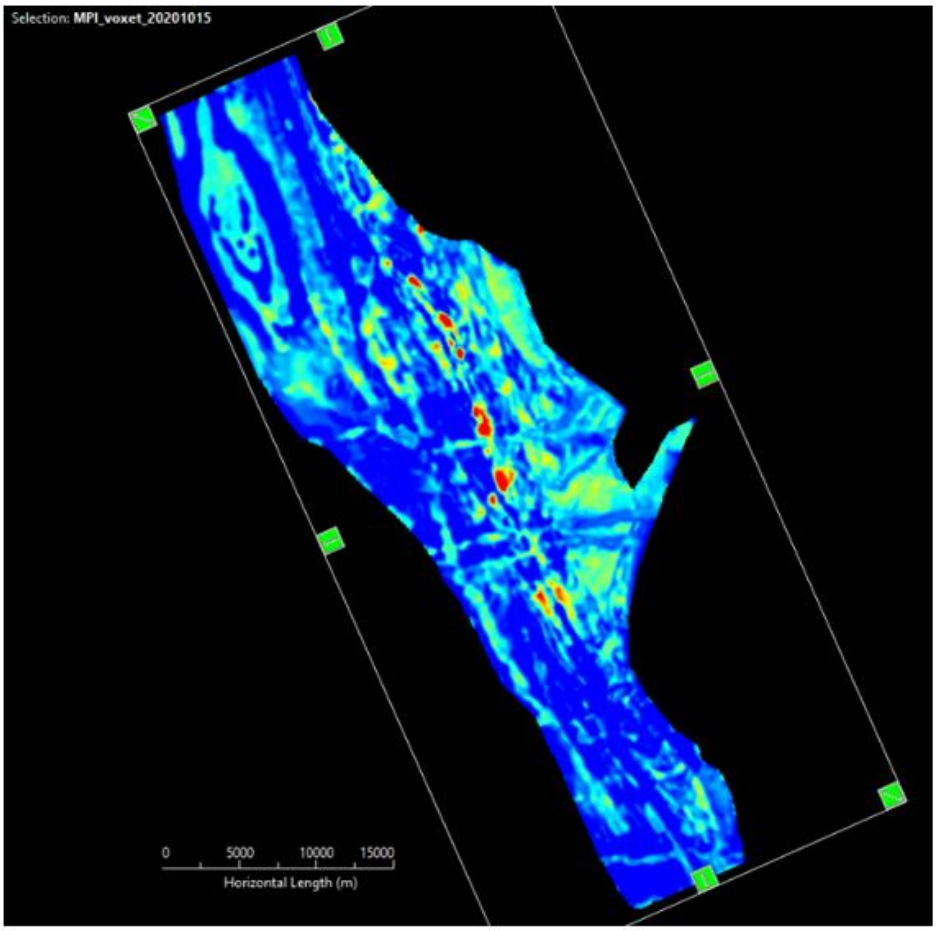

Figure 6. Global MPI score from RF. The different scores were combined through a weighted averaging process based on the standard deviation. Higher weights were assigned where variance was lower. Hotter colours denote a higher likelihood of mineralisation occurring.

CONCLUSIONS

The final integrated 3D model proved significantly useful in the generation of new exploration targets. Using a combination of structural, stratigraphic and potential field interpretation, we were able to build a regional geological framework for the JGB. This model ties locally, where possible, to the drilling, outcrop geology, and other available geophysical data (EM, DCIP, and MT data). This geological model was used as the constraint for the inversion of the magnetic and gravity datasets, creating a coherent physical rock property model composed of 29 different lithological units and 32 major faults. The stratigraphic model was used to generate a grid that proved of great use in the creation of a probabilistic geological model and interpolation and extrapolation of rock geochemical and spectral datasets. All of this information was combined to create the integrated geological framework for targeting. A phase of feature engineering was necessary to maximise exploration information from the interpreted and measured data.. The vectors were used to generate a total of 29 features in the exploration voxet. Those vectors were submitted to a data driven targeting approach named Random Forest Classification. The different prospectivity scores were then combined a Mineral Prospectivity Index for VHMS in the JGB. A total of 41 separate targets were identified in 3D.

This study represents a highly complex, interdisciplinary exploration exercise involving geochemical, geophysical and geological data. Successful implementation of this approach requires collaboration between the domain experts in the various disciplines, including the various geophysical specialties, geochemistry, exploration geology and machine learning. Although geophysics was used largely in an indirect sense, it was crucial to extending the existing geology to 3D away from drilling, and to providing a robust geological model which formed the framework for the prospectivity analysis.

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