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Objectivity through mineralogy: application of spectrographic data and machine learning for improved geotechnical characterisation of porphyries

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Abstract

A primary objective of geotechnical characterisation is the progressive reduction of uncertainty in our understanding of rock mass character to support the development of reliable mine design and operation. A critical part of this process is the investigation of the sources of natural variability in rock strength parameters. The development and increasing use of spectrographic core imaging as part of resource drilling programs and accessibility to machine learning (ML) tools for data processing presents an opportunity for improved understanding of the sources of variability by allowing for more robust interrogation of correlations between mineralogy and associated influences on rock strength.

Ongoing studies for an underground porphyry project in Indonesia provided an opportunity to investigate the use of a Random Forest (RF) algorithm to develop a high density, downhole record of Point Load Index (PLI) strength. This RF tool combines the output of multiple decision trees to reach a single result based on two data sources: 1) comprehensive mineral composition from hyperspectral core imaging, and 2) rock hardness from high density dynamic rebound index testing. Through this approach, it was possible to augment the spatial coverage of available strength index testing and provide sufficient data density to support the development of a block model of rock strength in three-dimensional space.

In this paper, the authors outline the approach taken to develop and train the RF algorithm, limitations in the current methodology, the results and associated confidence in the outputs, and learnings to be considered in future applications.

Keywords: *machine learning, rock mass characterisation, rock strength, spectrographic data*

1 Introduction

Geotechnical characterisation of porphyry rock masses aims to reduce uncertainty through progressive improvement in the quantity and quality of available data to support the development of a reliable mine design and operation. Modern tools and technologies have allowed for improvements in our ability to objectively characterise deposits, including the use of spectrographic core imaging, dynamic hardness testing, and the use of machine learning algorithms for data interrogation.

This paper will outline the approach taken to develop and train a Random Forest (RF) algorithm to estimate rock strength in terms of the Point Load Index (PLI, $I_{s(50)}$) based on a dataset comprising actual point load testing data, core mineralogy composition, and dynamic hardness testing. The results and associated confidence in the outputs will be examined. Considerations for future applications and further refinement of the RF algorithm will also be described.

2 Geologic and geotechnical data collection

The geologic complexity of most porphyry systems results in relatively high variability in mineralogic and geotechnical characteristics. Investigation of the sources of this variability beginning at early stages of the project can add value through the early recognition of geotechnical hazards and proactive mine planning.

Conventional methods of geotechnical data collection require loggers to make qualitative estimates or assessments of the characteristics of drillcore which have the potential to introduce additional bias and variability to datasets. Modern tools and technologies such as spectrographic core imaging and dynamic hardness testing allow for more objective data collection from drillcore. A brief introduction to these tools is provided as follows:

- Spectrographic core imaging technologies can quantify the mineral composition of the core exterior based on the electromagnetic signature of the minerals under specialised sensors. The data generated by spectrographic core imaging allows for the mineral composition of the core to be analysed quantitatively, which is a technological advance in terms of being able to assess the influence of mineralogy on rock mass strength.
- Dynamic hardness testing tools drop an engineered tip under spring force against the test surface while measuring the impact and rebound velocities. The hardness of the core exterior can be measured with these devices. This approach correlates well with conventional field hardness estimates using a geological hammer and provides a more objective measure of rock hardness.

The following subsections will provide descriptions of the geological and geotechnical data used as inputs for the developed machine learning model used to estimate rock mass strength.

2.1 Point load testing

The point load test (PLT) is a relatively inexpensive test that is a component of most rock core logging programs for caving projects. The PLT is carried out by subjecting a core sample to an increasing load between two conical platens until the sample fails by splitting. The PLT can be carried out as either an axial test (with loading parallel to the core axis) or as diametral (with loading perpendicular to the core axis). The ASTM (2017) standard (ASTM D5731–16) outlines the specific testing methods to be followed. A Point Load Index strength value, $I_{s(50)}$, is recorded based on the failure load, loading orientation, and sample dimensions.

In the dataset available for this study, the PLT samples are normally collected at five metre fixed intervals. A total of 1,216 valid test results (both axial and diametral) were assessed in this study. A histogram of the results is shown in Figure 1. These results provide an indication of the range of rock strength in the testing dataset, with 85% of the results between 0 and 4 MPa. There is a skew in the distribution towards weak rock strength that is consistent with observations of clay minerals in substantial lengths of core where alteration intensity is high.

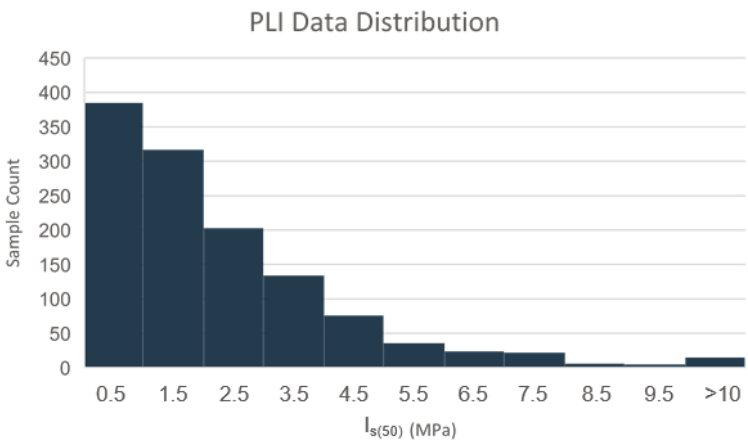

Figure 1 Histogram of valid point load index values, $I_{s(50)}$ (both axial and diametral)

2.2 Dynamic rebound hardness testing

Dynamic rebound hardness testing provides a non-destructive estimate of the rock hardness by measuring the impact and rebound velocity of the tool's impact tip against the core surface (i.e. Leeb rebound hardness test). At this project site hardness values are being recorded on approximate 10 cm intervals and are then averaged over fixed 1 m interval lengths to provide a mean hardness value.

Figure 2 provides a comparison of the mean hardness values recorded with the dynamic rebound tool against ISRM (Brown 1981) hardness testing and PLI results. Both comparisons demonstrate that the dynamic rebound tool provides a useful estimate of rock hardness.

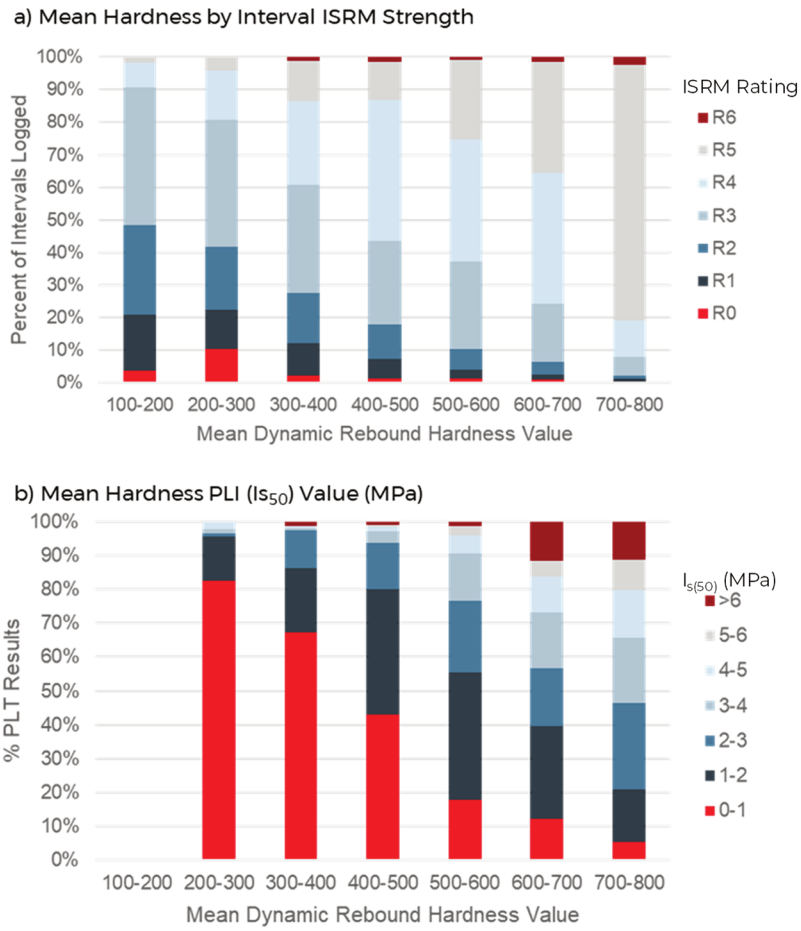

Figure 2 Comparison of mean dynamic hardness test value with (a) representative interval ISRM R-strength ratings and (b) point load index, $I_{s(50)}$

The key findings from review of the hardness testing data are as follows:

- The mean dynamic hardness values are generally less than 300 (see Figure 2) in very weak rock ($I_{s(50)}$ < 1 MPa). There are no PLT samples where the mean dynamic hardness value was <200, likely because the material was considered too weak for point load testing. Logging biases (e.g. logging the hardness of intact rock pieces within a predominantly weak intervals) may have affected the ISRM data where the mean dynamic hardness value was <200.
- Interval mean hardness readings demonstrate strong correlations with corresponding ISRM Field Strength (Brown 1981) and $I_{s(50)}$ for mean hardness readings >300 (i.e. increasing rock strength with increasing mean dynamic hardness value).
- The relatively high resolution and objectivity of the dynamic rebound hardness data relative to other datasets (e.g. ISRM hardness, which requires a minimum sample size, or PLT data, which can be biased in terms of sample selection) makes it a useful index for estimating intact rock strength.

2.3 Spectrographic core imaging

The alteration domains in porphyry deposits are often used as a basis for geotechnical domaining. The typical alteration domains for a porphyry deposit are as shown in Figure 3, however, there is often greater complexity than represented on this schematic. The definition of alteration domains for a deposit tends to evolve and increase in complexity as the deposit is drilled.

Historically, alteration logging and subsequent model development has relied on visual interpretations and limited field testing of mineral assemblages by logging geologists. Modern core imaging technologies provide an opportunity for greater objectivity in the determination of alteration mineral assemblages along a drillcore. The dataset generated by spectrographic core imaging at the project site supplying the data for this paper provides estimates of the modal percentages of key minerals along the core surface on 1 m interval lengths.

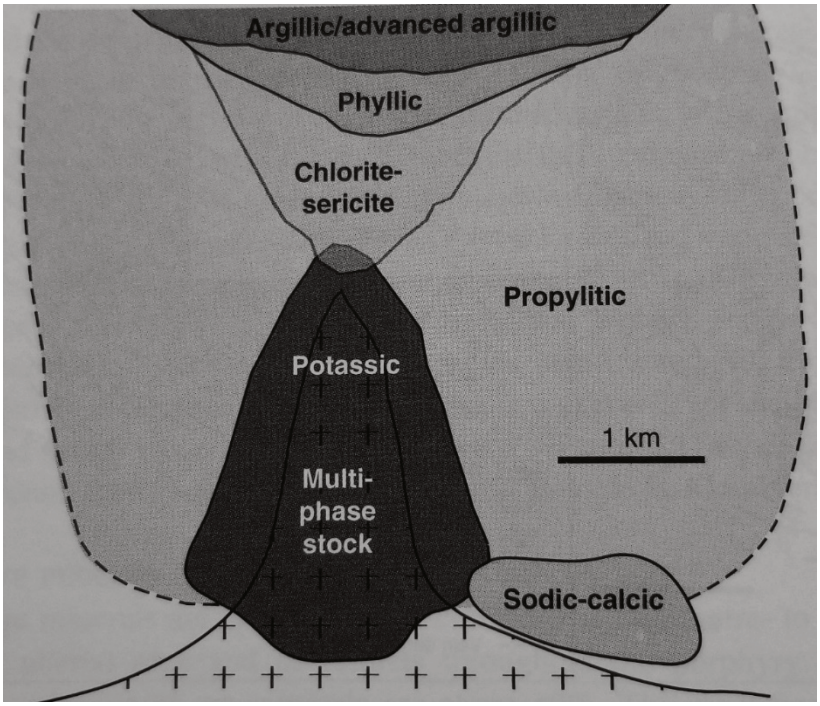

Figure 3 Cross-section through a porphyry deposit showing an idealised distribution of different alteration facies (Ridley 2013)

The mineral abundances generated from the spectrographic core imaging can be locally correlated with PLT results to identify 'Strong' and 'Weak' minerals, where the 'Strong' minerals are indicated with the higher $I_{s(50)}$ values, while 'Weak' minerals with the lower $I_{s(50)}$ values. The grouping of Strong and Weak minerals for the purpose of this study is based on these correlations and consideration of the Mohs hardness scale rating of the individual minerals. Figure 4 presents the correlation between $I_{s(50)}$ and these mineral groupings where minerals identified in the spectrographic core imaging, such as alunite, are positively correlated with strong rock and clay minerals are negatively correlated with rock strength.

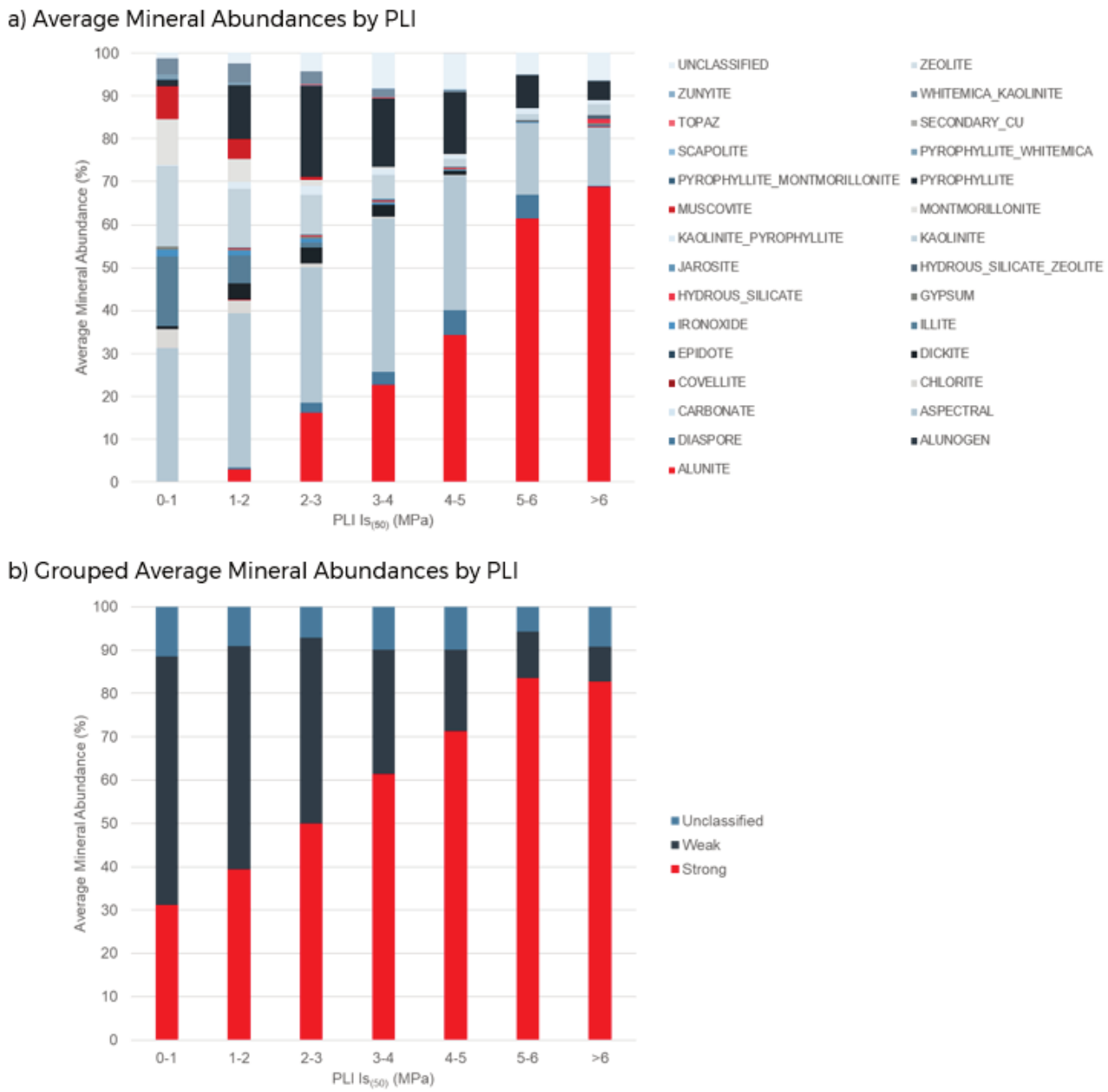

Figure 4 Comparison of (a) individual mineral abundances and (b) grouped mineral abundances with point load index, $I_{s(50)}$

3 Application of machine learning

Machine learning is a method of data analysis that automates analytical model building based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention. This allows for greater objectivity in the analysis of large datasets during geotechnical characterisation. For this study, a Random Forest (RF) algorithm was used with the objective of estimating intact rock strength in terms of $I_{s(50)}$ (PLI) from spectrographic mineralogy and dynamic hardness testing data.

RF is a type of ensemble machine learning algorithm that combines the output of multiple decision trees to reach a single result (Louppe, 2014). It was chosen for this specific application because it is a robust and computationally efficient algorithm. A synthetic $I_{s(50)}$ dataset was generated for each 1 m length of core where both spectrographic imaging and dynamic hardness testing data were available. This dataset augmented the $I_{s(50)}$ dataset by approximately 40 times (i.e. 40,007 $I_{s(50)}$ values generated for 1 m interval lengths versus 1,216 actual $I_{s(50)}$ results). This improved the downhole and spatial coverage of rock strength estimates compared

to the physical test records available for use in the subsequent development of a block model of intact rock strength.

Sci-kit Learn's Random Forest Regressor package (Pedregosa et al. 2011) was used during the RF model development. The inputs into the RF model include the mean dynamic rebound hardness value and mineral abundance percentages for 28 minerals obtained from spectrographic core imaging (29 total input parameters) (reference Figure 4a). A total of 1,216 PLT results were used in the development of the model. Only valid PLT results within the planned mining area were considered. This data was split into training and testing datasets; 80% of the data (973 observations) was used in training the model and the remaining 20% (243 observations) was used in testing the RF model.

The RF model was trained providing input data (i.e. the training data) to allow the algorithm to find patterns between the input variables and the target variable. Testing of the RF model was performed to assess and refine its estimation capabilities. A randomised grid search with cross-validation was performed with Sci-kit Learn's Randomized SearchCV package (Pedregosa et al. 2011) to determine the optimal hyperparameters to use in the model with defined iteration (i.e. the parameters of RF that control its ability to find patterns in the data). The training of the RF model also included preliminary analyses of impacts due to imbalanced input data given the skewed nature of the input $I_{s(50)}$ data (reference Figure 1). Using imbalanced data during model development can result in poorer results and, as such, imbalanced datasets are often balanced prior to model training. In the context of this study, the preliminary analyses showed good model results without balancing the data. As a result, balancing the data was deemed not necessary.

The model performance was assessed with Root Mean Square Error (RMSE). RMSE was chosen over the coefficient of determination, R^2, because RMSE provides an absolute measure of fit, while the R^2 coefficient only provides a relative measure of fit. The RMSE for the testing data was found to be 1.89 overall. This level of fit to the bulk of the range of $I_{s(50)}$ values and associated confidence in the resulting forecasts was considered adequate for the purpose of estimating intact rock strength for the current study. Further, the model was found to have a better fit for $I_{s(50)}$ values below 4 MPa and a poorer fit for values above 4 MPa (RMSE for PLI <4 MPa is 1.13, RMSE for PLI >4 MPa is 4.1). This is interpreted to be an artefact of the distribution of point load testing data towards values less than 4 MPa (see Figure 1).

The predicted and actual (target) $I_{s(50)}$ values are shown on Figure 5, from which the following key findings are drawn:

- The predictive algorithm's accuracy is best over the range of 1 MPa through 4 MPa. Over 50% of the training PLT values fall within this range.
- For intervals with a target $I_{s(50)}$ below 1 MPa, the algorithm tends to predict higher strengths than actual.
- For intervals with an target $I_{s(50)}$ above 4 MPa, the algorithm tends to underestimate the rock strength. This is attributed to the lack of actual PLI data available >4 MPa to train the model; only 14% of the training data have actual PLI values >4 MPa.

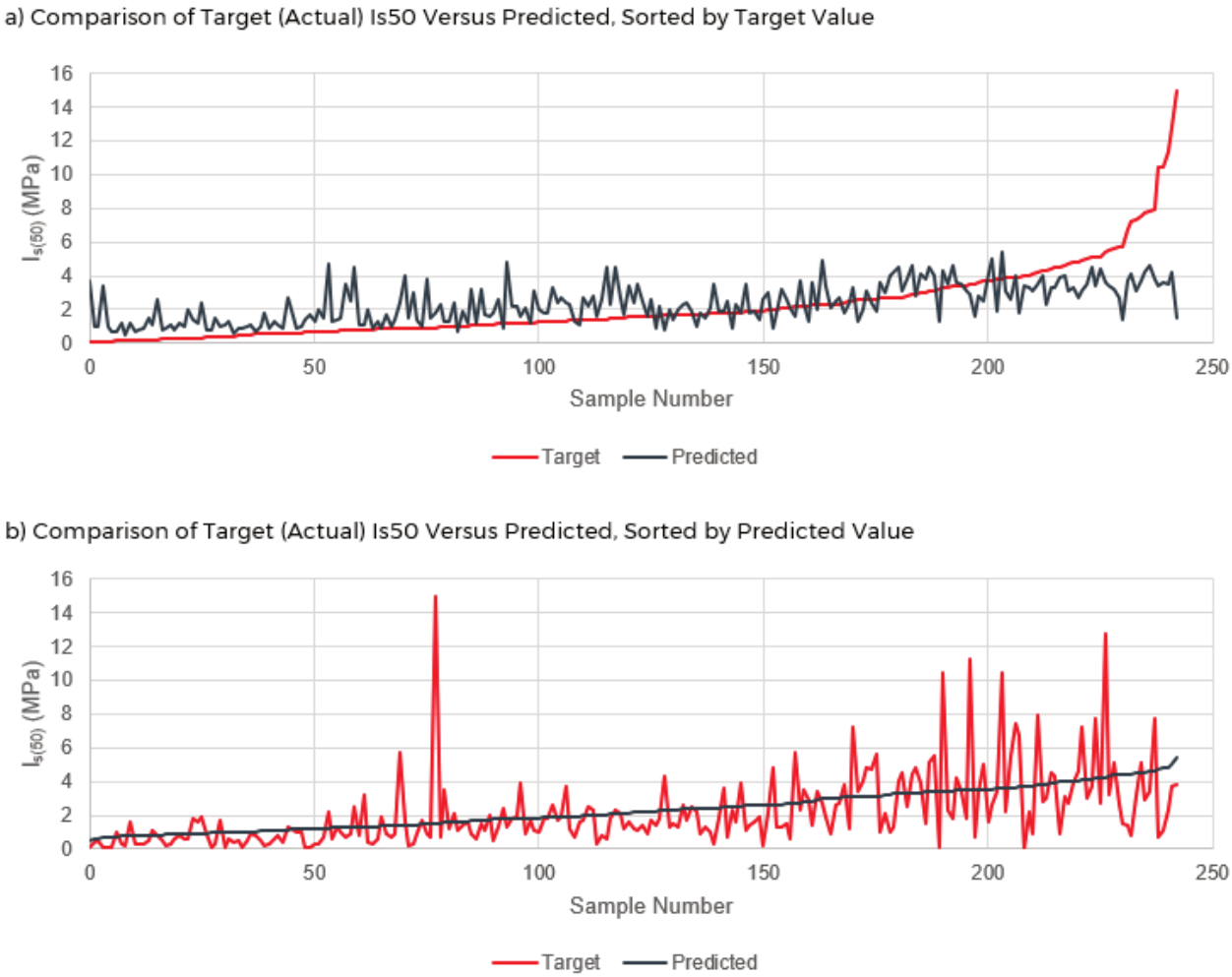

Figure 5 Comparison of machine learning $I_{s(50)}$ prediction against target $I_{s(50)}$ values sorted by (a) target value and (b) predicted value

4 Spatial validation and geotechnical modelling

After training and testing the RF model, it was used to forecast PLI for the complete set of drillhole data where both spectrographic imaging and dynamic rebound hardness testing data were available. The forecasted values were then verified through spatial review against the interpreted alteration domains and actual PLT data. Figures 6 and 7 present examples of this review from which the following findings are noted:

- Comparison of $I_{s(50)}$ values and trends predicted along a given drillhole demonstrate good correlation with the actual PLT results (where both exist).
- The predicted $I_{s(50)}$ values provide greater resolution on the variability of the rock mass strength than could be achieved with only the actual point load testing results.

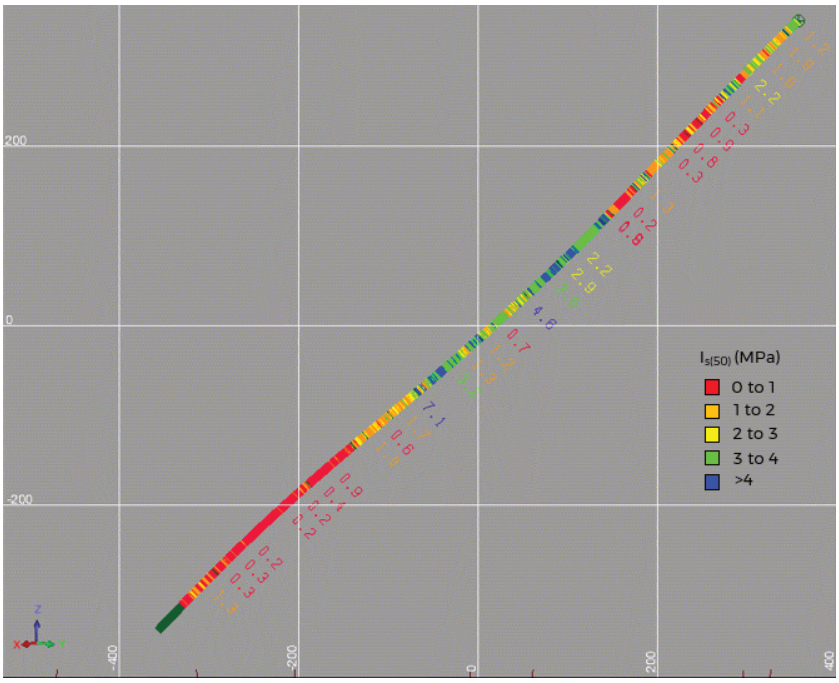

Figure 6 Individual drillhole comparison of machine learning predicted PLI (drillhole trace) alongside actual $I_{s(50)}$ data (labelled along hole)

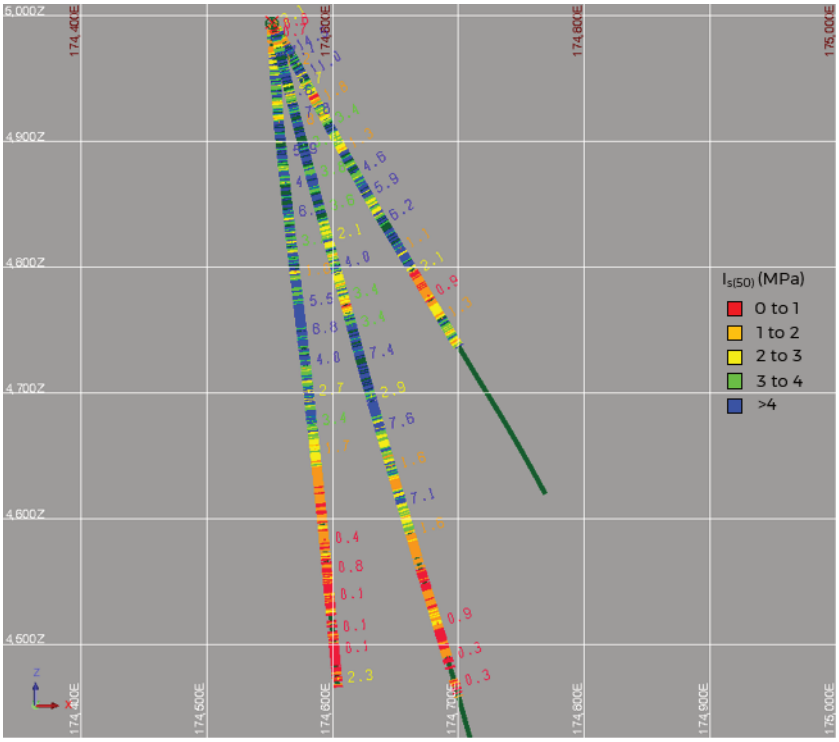

Figure 7 Drillhole cluster comparison of machine learning predicted PLI (drillhole traces) alongside actual $I_{s(50)}$ data (labelled along holes)

5 Conclusion

The predictions from this RF model were found to be useful for the geotechnical characterisation of the mining area by augmenting the available dataset of rock strength estimates. The predicted PLI dataset had a sample count of 40,007 from 78 drillholes, which is approximately 40 times greater than the original point load testing dataset of only 1,216 valid data records from 71 drillholes. While the accuracy of the forecasted

values was shown to vary over the range of strengths, the associated confidence in forecasted values was found to be reasonable for the purpose of this (early stage) study and the required levels of accuracy.

While this approach and the associated accuracy of forecasted results was appropriate for the purpose of this study, the following important limitations of the RF model are noted:

- The influence of defects and microdefects in the PLT samples has not been considered in the training of this algorithm due to limitations in the available data related to defect intensity and PLT failure types (e.g. failure through homogeneous rock versus failure along defects in the core).
- Damaged core samples of otherwise strong rock may introduce additional scatter into the results that is not representative of the intact rock strength.
- The accuracy of the RF model is limited by the quality of input data and requires accurate calibration and standardised usage of the tools used to generate the input data (i.e. the spectrographic core imaging and dynamic rebound hardness testing tools).

Future refinements of the RF model are planned to improve the accuracy of its predictions. The following opportunities for improving future applications of this methodology have been identified:

- The collection of additional PLT data for training and testing the RF model.
- While preliminary investigations of the impacts due to the skewed (imbalanced) distribution of PLI values in the training data did not suggest significant impacts to model performance, different data balancing techniques should be examined (such as synthetic minority oversampling technique or cost-sensitive learning) to improve model performance.
- Model performance could be improved with more explicit (spatial) pairing of dynamic hardness testing and PLT instead of extrapolating mean values hardness testing values over the 1 m interval from which the PLT sample was collected.
- The quality of dynamic hardness testing data could be improved by implementing a more consistent recording of null values for intervals of weak or lost core where the tool's readings are not applicable.
- More detailed hyperparameter tuning of the machine learning model could be conducted.
- Additional features could be included as inputs to the model. As an example, it may be beneficial to add microdefect intensity as an input or the variability of hardness measures for a given interval in addition to the mean. Characterising rock strength in stronger conditions requires consideration of rock heterogeneity and other factors not considered by the current algorithm.
- Additional screening and quality control on PLI results, e.g. $I_{s(50)}$ results over 6 MPa are considered outliers for this dataset and need to be investigated in greater detail and potentially removed from the training dataset.

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