INSTITUTO DE INGENIEROS DE MINAS DEL PERÚ

proEXPLO 2019

corescan SOLVE GEOSOLUTIONS

The Predictive Power of Hyperspectral Core Imaging, Applications to Grade and Geometallurgical Parameters

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May 20-22, 2019

XI CONGRESO INTERNACIONAL DE PROSPECTORES Y EXPLORADORES

EXPLORACIÓN MINERA: CIENCIA, INNOVACIÓN E INVERSIÓN ESTRATÉGICA

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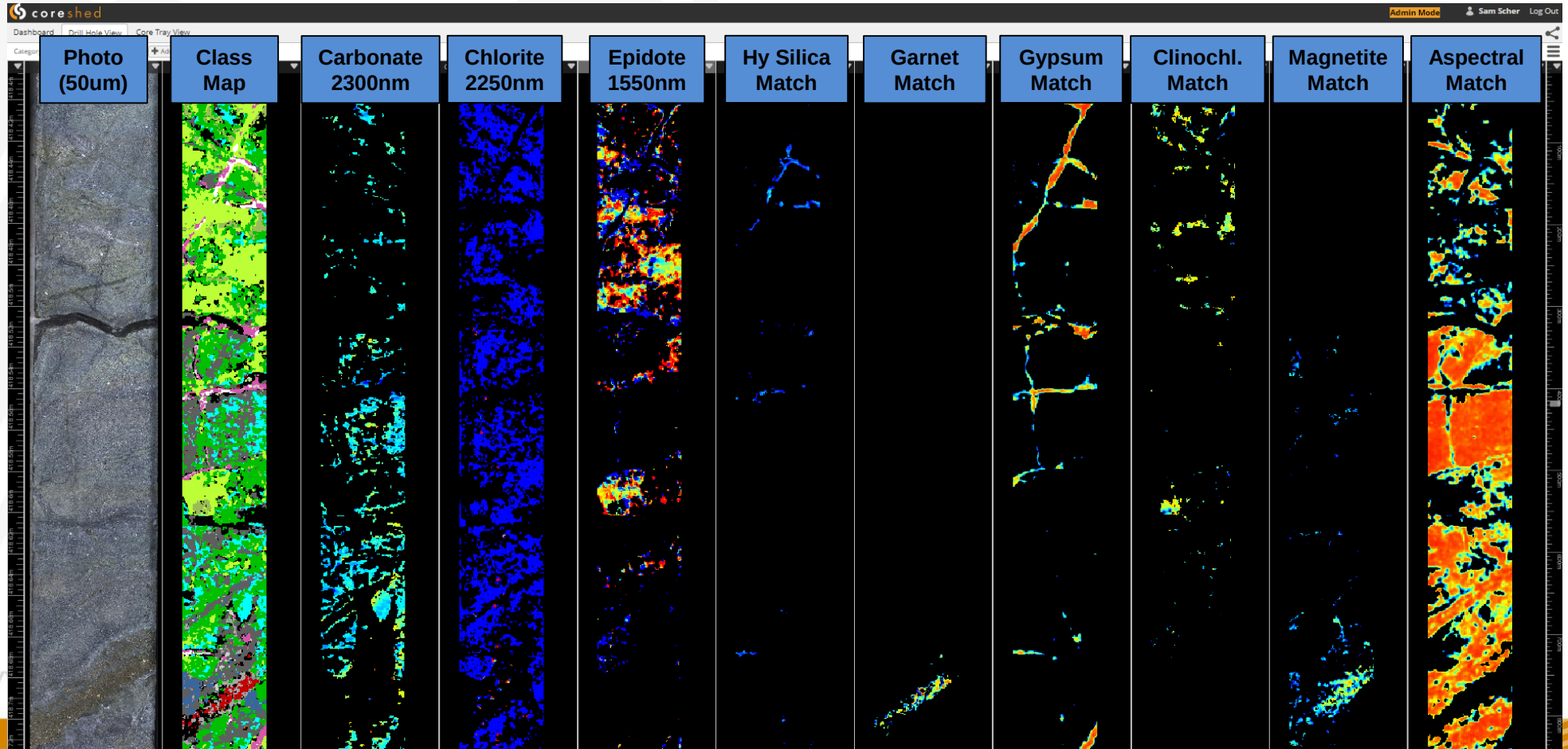
Machine Learning & Corescan

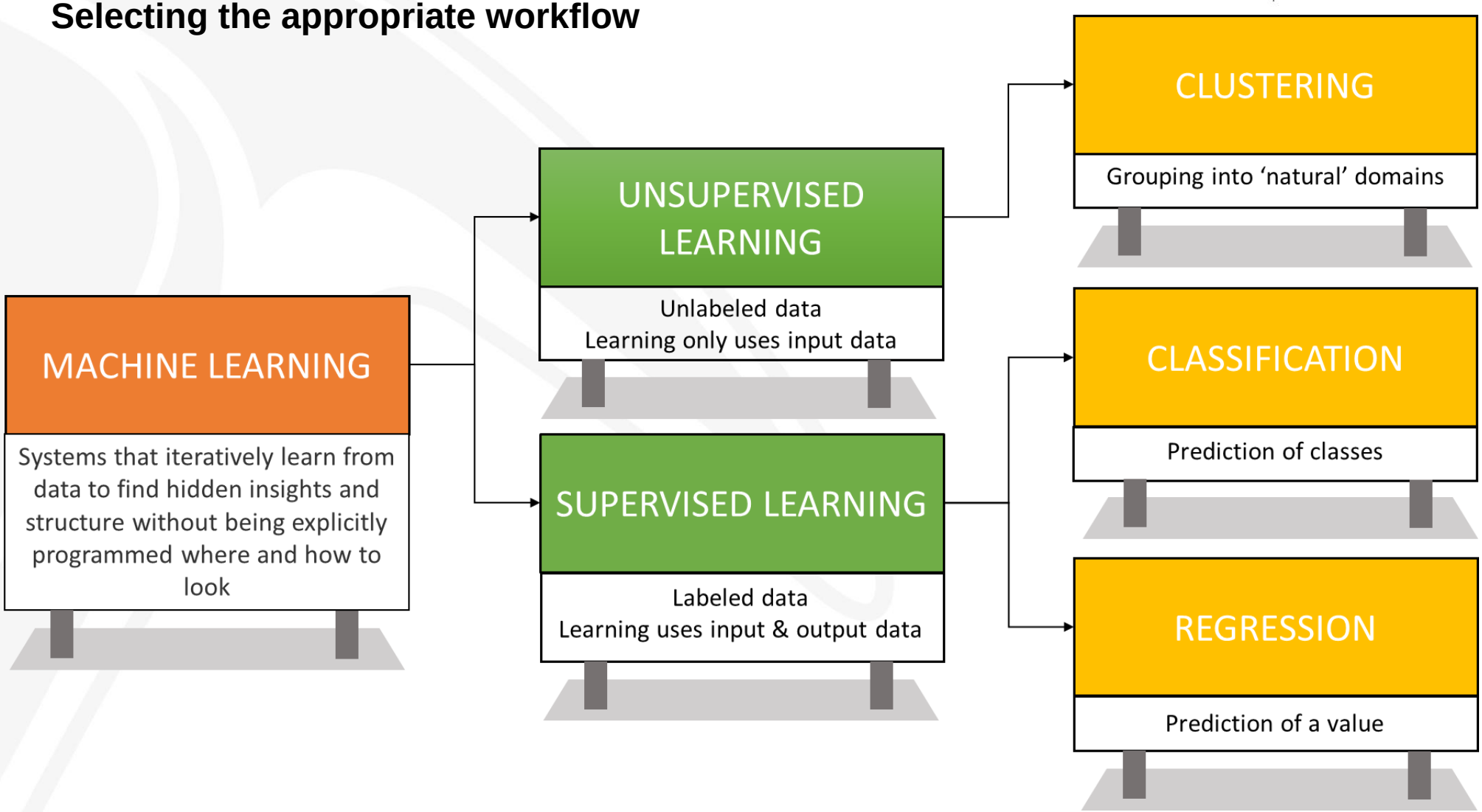
Selecting the appropriate tool

- High resolution (~200,000 pixels/meter) and consistent data.
- Once the relationship between hyperspectral core imaging (HCI) and another dataset are established, areas with no measurement or geological log can be predicted.
- The efficient use of predictive modeling may allow for significant cost reduction and to extend parameters to areas where measurements are unable to be taken.



Machine Learning

Selecting the appropriate workflow



Predicting Rock Strength Parameters

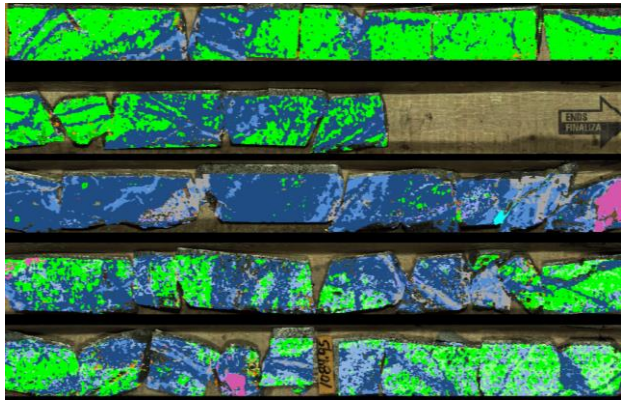
Integrating Corescan and Equotip data

- Portable hardness measurements (using an Equotip® system) collected at 2cm intervals formed the hardness parameter dataset.

- **Training set**: before performing the regression, one drillhole was removed in order to test the model , i.e. the data to train the regression model that will learn the relationship between the HCI variables and the Equotip values.

- **Test set**: the data that the model is tested on and not included in the training data.

- **Variable importance analysis** was utilized to determine the most important mineral phases to use in an array of regression models, including robust linear regressions and Random Forest regressions.

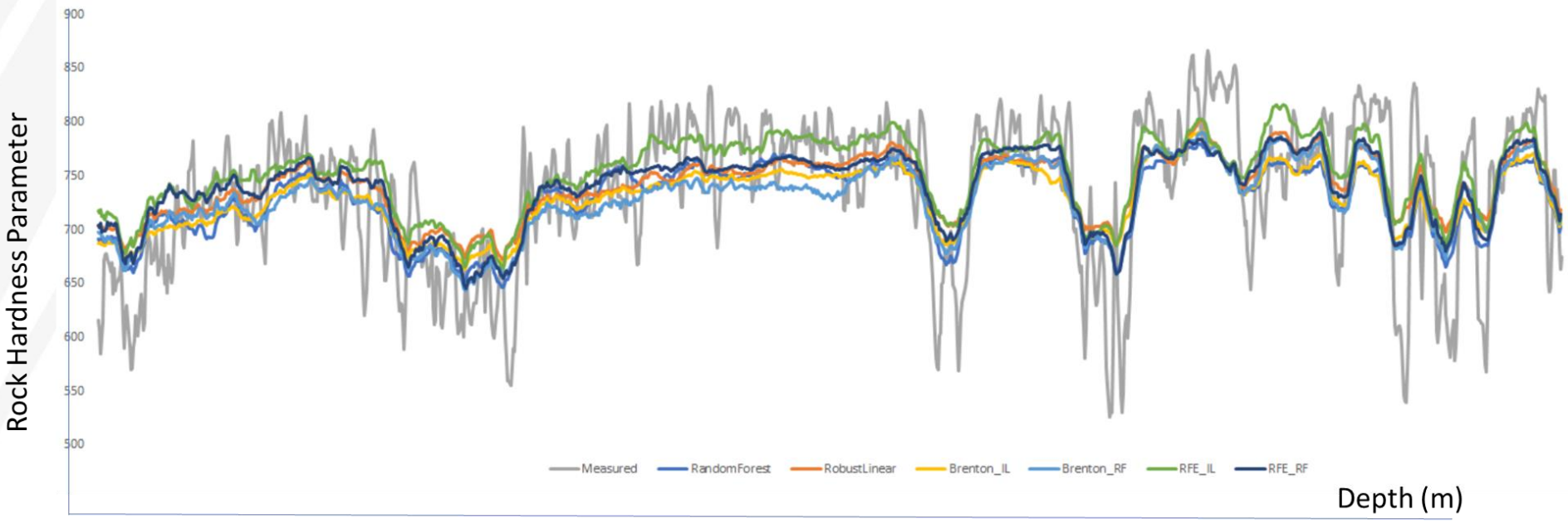


Predicting Rock Strength Parameters

Integrating Corescan and Equotip data

The above graph shows a comparison between seven different regression models (colored lines) trained on Corescan mineralogy to predict rock hardness (grey line) measured by the Equotip system.

In this case, the softer rocks have higher variability than hard rocks and chlorite shows the strongest control on the Equotip data, with high chlorite simples producing predominantly high hardness vales.

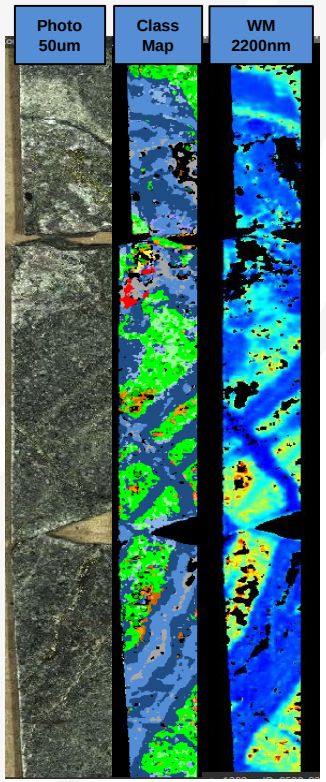


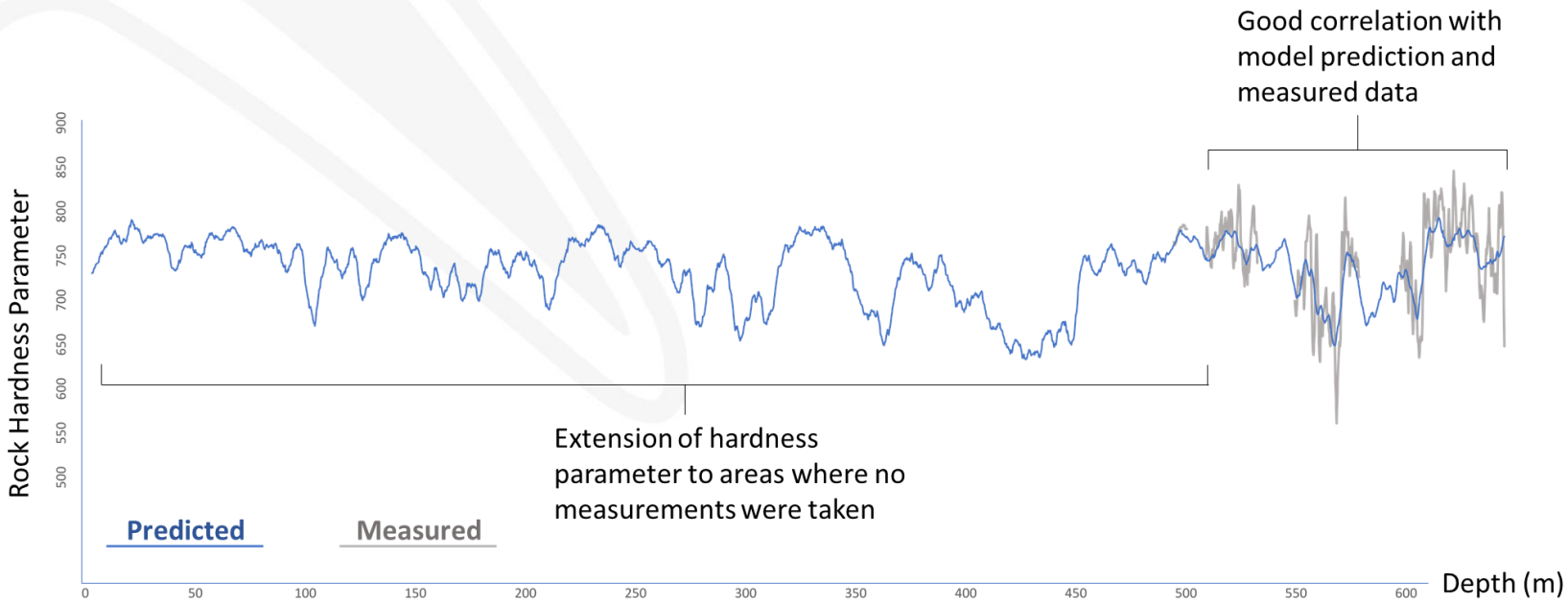
Discussion

Predicting Rock Strength Parameters

If a robust relationship between Corescan and other datasets can be identified, they can be predicted across areas where no measurements were taken.

Corescan data may be used to predict datasets that are more expensive or suffer from long lead times.





Supervised classification of Corescan data

Integrating Corescan, geochemical and geological data

Random Forest classification – we will try and predict a class from a Corescan mineral signature
Variable importance analysis – we will determine which Corescan minerals are most important to a given classification task

1. **Prediction of Au within skarns**
   a. Perform variable importance analysis to determine which minerals are the most effective at predicting Au (high-Au defined as >0.1 g/t)
   b. Build a predictive model that can predict the location of high-Au areas within the skarn

2. **Prediction of skarns**
   a. Perform variable importance analysis to determine minerals are the most effective at predicting skarns
   b. Build a predictive model that can predict the location of skarns and analyse where we see similarities and differences spatially between logged skarn and predicted skarn

Prediction of Au Probability from Corescan Mineralogy

Integrating Corescan and geochemical data

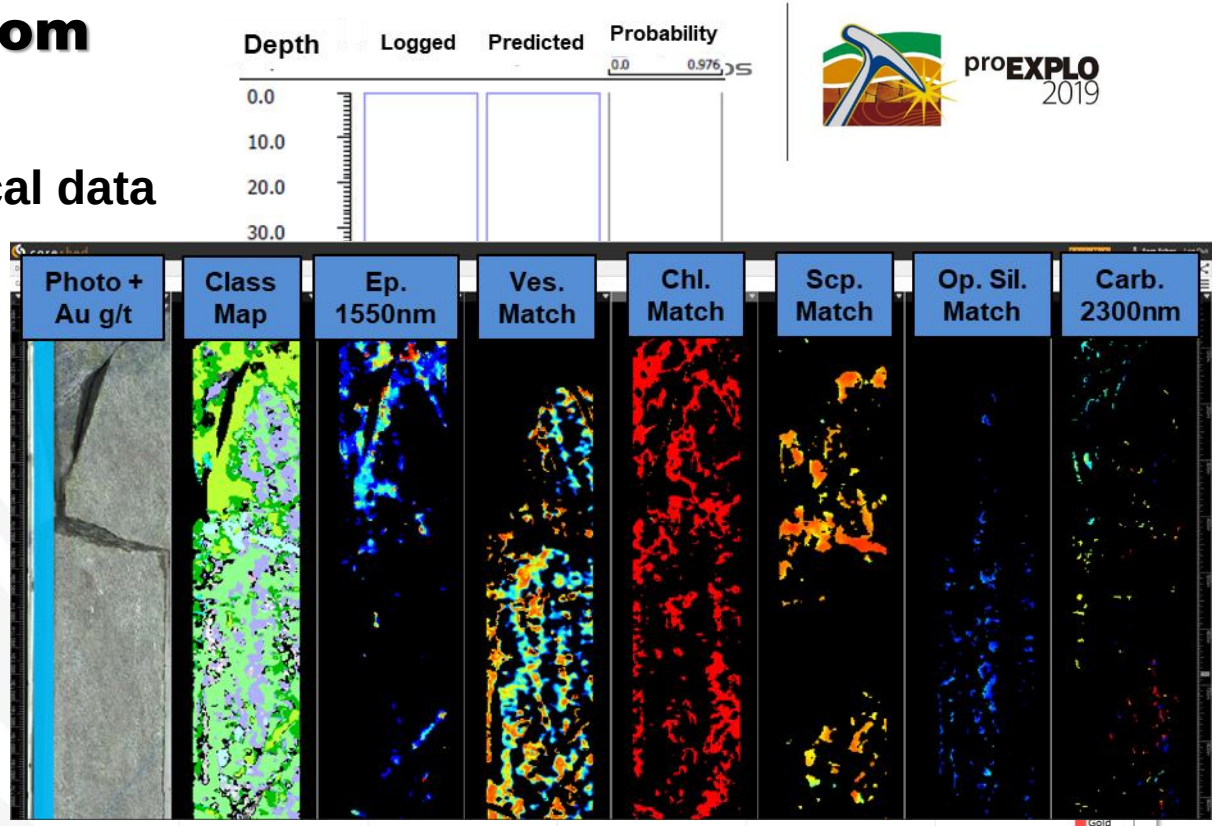
1. Divide the geology into 2 classes, high Au and low Au based on a threshold value of 0.1 g/t.

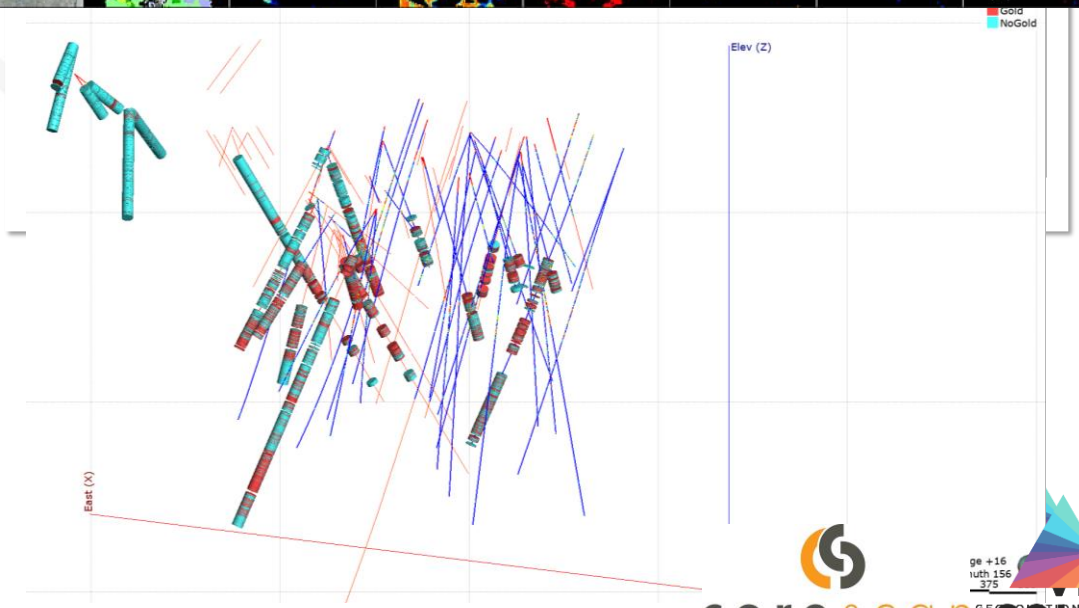
2. Select geological units of interest.

3. Perform variable importance analysis to determine the most important Corescan variables for distinguishing Au from barren intervals.

4. Choose the top variables and use them to construct a machine learning classification model that will aim to predict high Au from low Au.

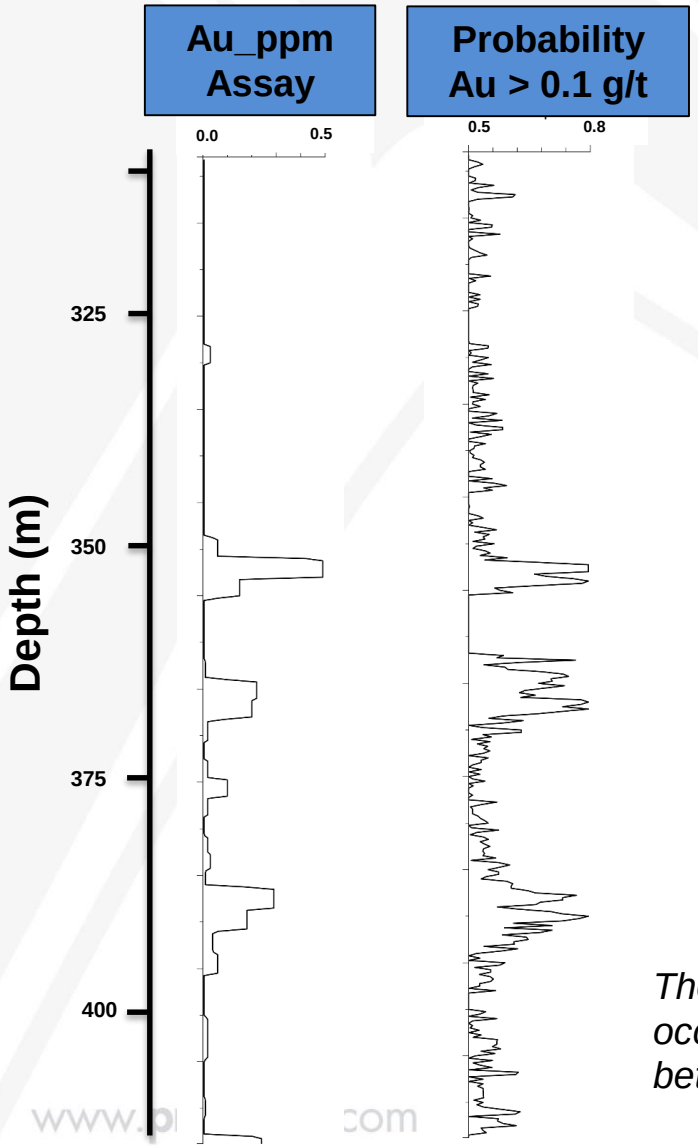
5. Train the model to learn the signature of Au in all drillholes except one; predict on the held out hole.





Discussion

Prediction of Au Probability from Corescan Mineralogy



Machine learning models can be trained to learn the signature of Au from Corescan hyperspectral core imaging mineralogical data.

If this signature is robust, then the assay variable can be predicted everywhere there is Corescan data.

The far right column shows the probability of high grade gold occurrence based on a model trained on the relationships between the Corescan mineralogy and Au assay (left column).

Prediction of Skarn from Corescan Mineralogy

Integrating Corescan and geological data

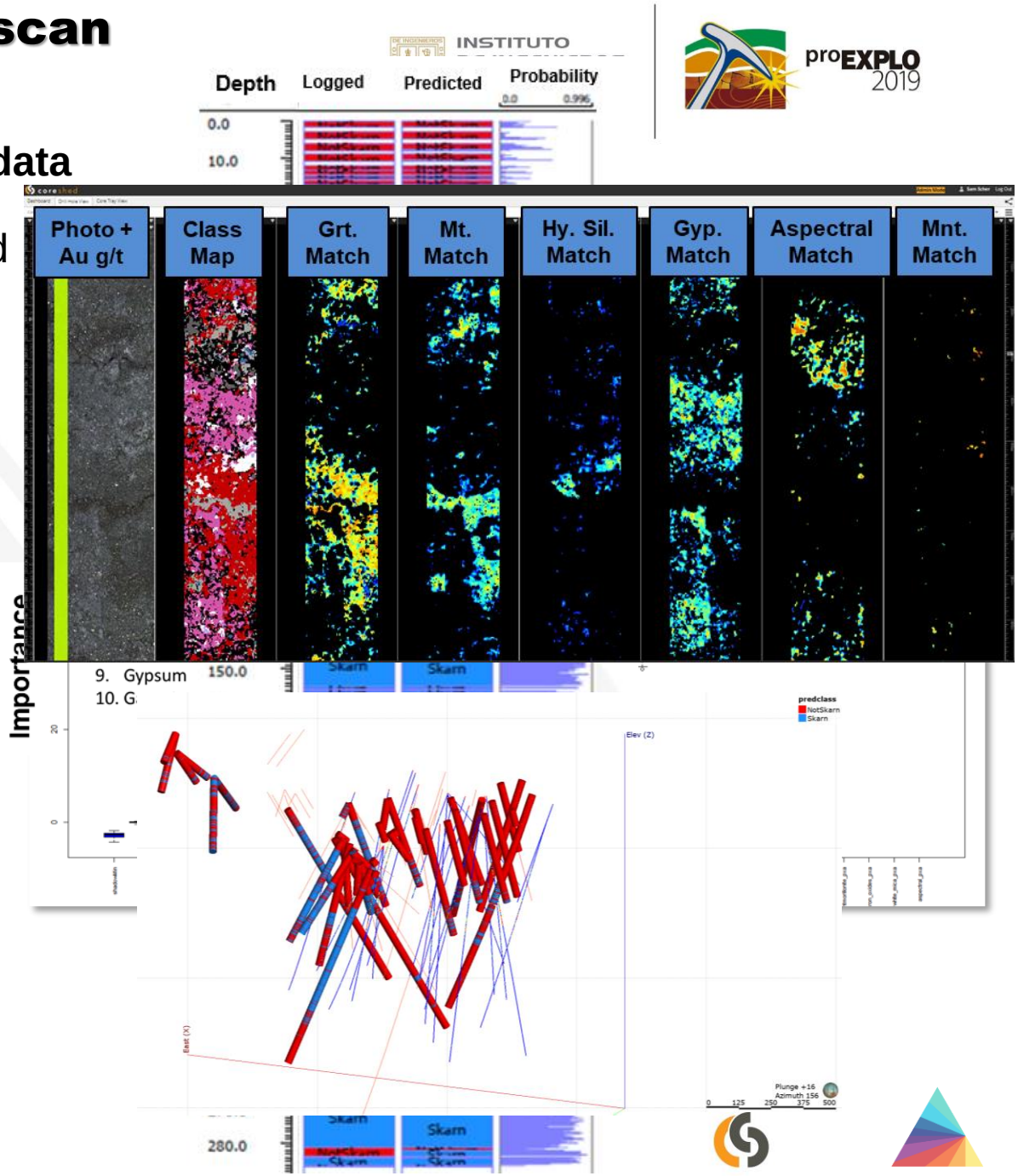
1. Divide the geology into 2 classes, skarn and not skarn (background) based on the logged lithology.

2. Perform a variable importance analysis to determine the most important Corescan variables for distinguishing a skarn from background.

3. Choose the top variables and use them to construct a machine learning classification model that will aim to predict the location of skarns across the deposit.

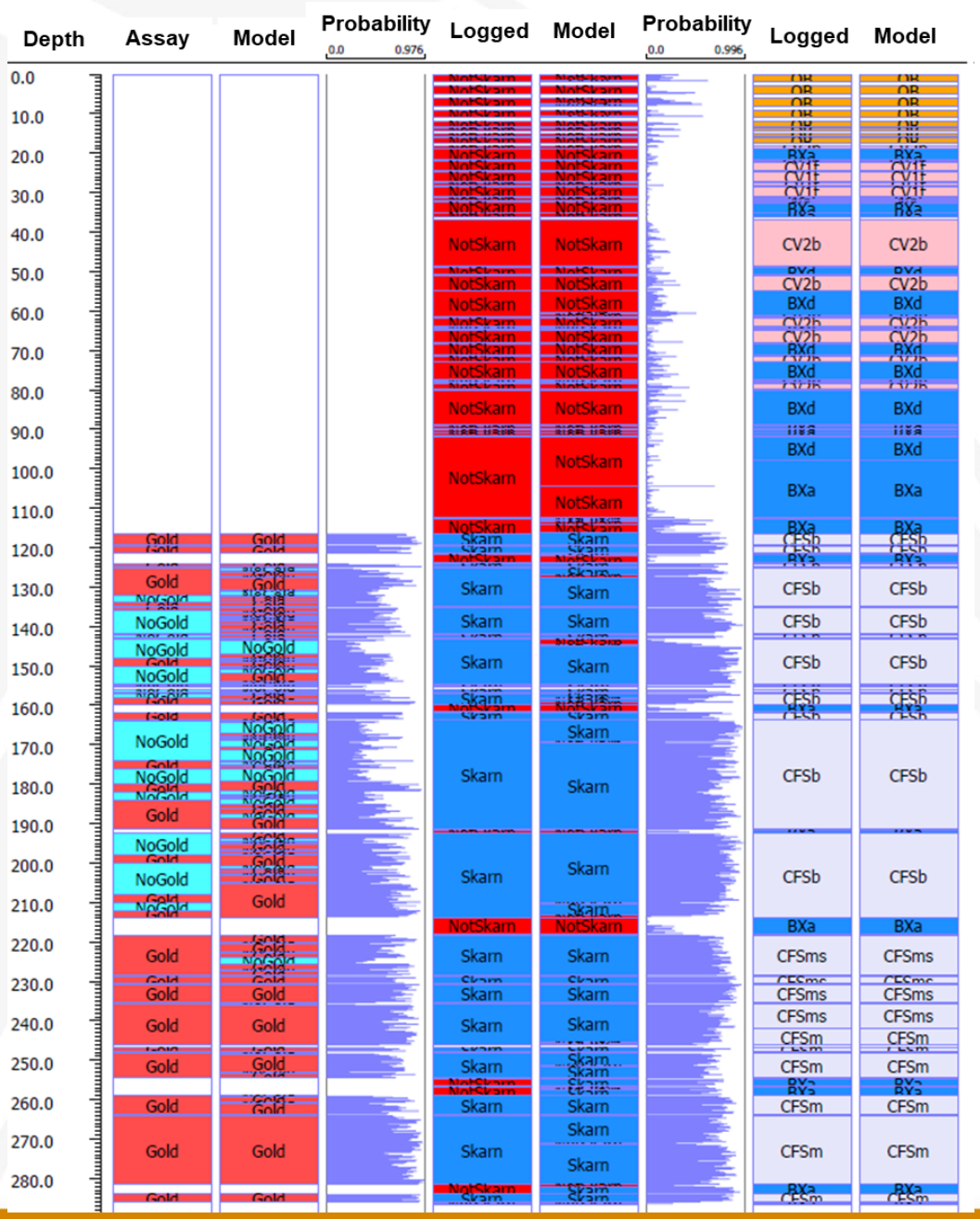
4. Train the model to learn the signature of skarn on all drill holes except one. Use the model to predict skarn presence on that held out hole.

5. Repeat step 3 for every hole in the deposit.



Discussion

Prediction of Geological Logs



When trained model is subsequently presented with a Corescan signature (without a label), the sample can be classified into one of the trained logging classes:

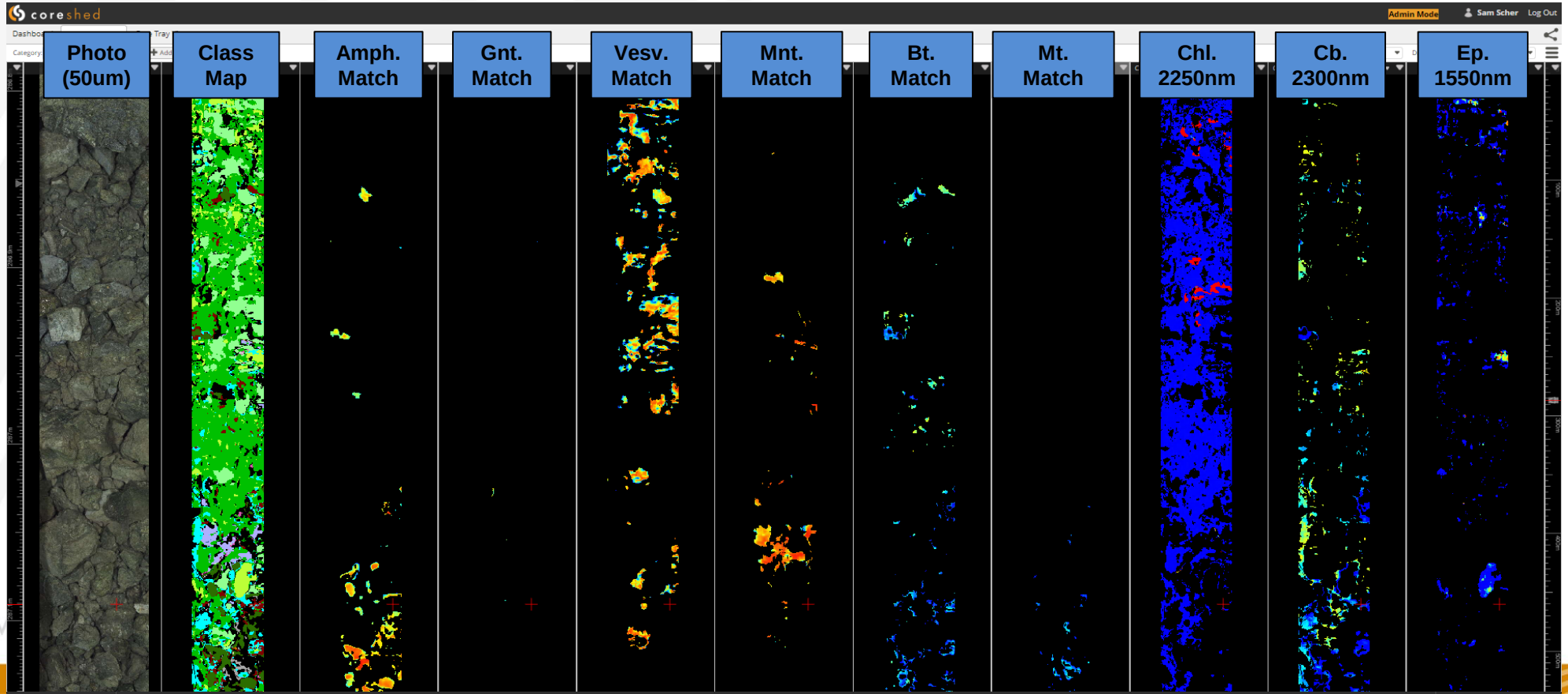
- Model outputs include the probabilities of each unit existing rather than a single hard class.
- Predicted logs present a useful **comparison** to a geologist-made log for QAQC and training purposes.

Discussion

Applications of Supervised Classification

- Training machine learning algorithms to learn the signatures of Corescan where there are parameters of interest available is an important tool for mineral exploration and exploitation allowing for timelier, well informed decisions to be made by a geologist or geometallurgist.

- If the signature is robust, as shown in the examples above, it is possible to predict Au assay, lithological/alteration domains and geometallurgical variables everywhere there is Corescan data.



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Solve Geosolutions and Corescan would like to acknowledge:

Regulus Resources
Anglo American

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