Application of Artificial Neural Networks to geological classification: porphyry prospectivity in British Columbia

Moslem, Azarpour and Igor Morozov
Dias Geophysical Ltd. and University of Saskatchewan

Summary

An innovative approach to create a porphyry prospectivity map using geophysical, geological, structural data and artificial neural network is presented. The main challenge to create a porphyry propspectivity map is selecting the most relevant geological data and how to integrate them in order to use them as our input data for machine learning techniques. Since porphyry prospectivity map is the final results, the common approach is using geophysical inversion maps as input data and create different mathematical attributes to increase the dimensionality of the input data and increase the number of training samples in order to achieve a more reliable solution. Here, we propose a novel approach to create geological and structural maps and use them as additional training data. Finally, the results are validated using validation dataset and the accuracy shows a higher value when all geological and structural data are used.

Theory

In many geological classification problems, it is important to integrate multiple types of data to use in training step in order to reach the highest accuracy. Here, instead of making mathematical transformation of geophysical map data to increase the feature dimension, we tried using different type of geological data such as geophysical, age-constraint geological and structural data to satisfy the need for increasing feature dimension.
To predict the porphyry deposits, we used all available geological data (extract useful maps from structural data and age-constraint intrusive and volcanic data combined with 4 geophysical data) with different types and integrate them, in order to feed ANN to create prospectivity map for porphyry exploration project.

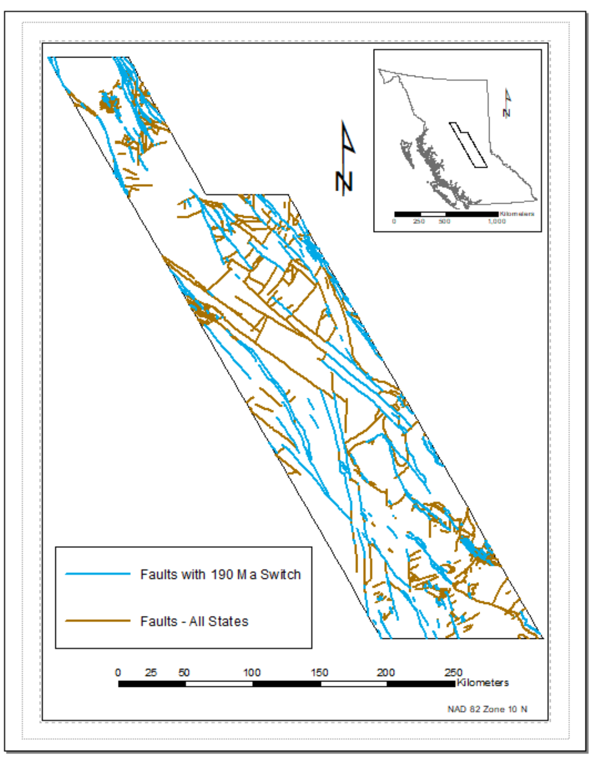
Method

Geophysical data are combined with time-constrained geological, structural, and tectonic data to produce quantitative estimates of the probability for the target mineral (porphyry).
The geophysical data in this study is provided by the Advanced Geophysical Interpretation Centre at Mira Geoscience. Maps of 3-D density contrasts, magnetic susceptibility, and inverted subsurface conductivity are the main geophysical data used in this study. These data were derived from multiple airborne gravity, airborne total-field magnetic, and airborne electromagnetic (EM) surveys, respectively.

The study area covers an about 400-km long segment of the Quesnel Terrane, in the Cariboo area of the Cariboo Chilcotin Coast region of British Columbia (BC), Canada.

The geophysical input data which are presented as spatial data are consist of TMI (total-field magnetic intensity), electric conductivity, magnetic susceptibilities at the sea level and density contrast at the sea level. In order to use other data, we converted all geological and structural data to spatial data. Intrusive and inclusive geological data are classified to 5 and 4 different age classes respectively and converted to spatial data. The geological data are consisting of five intrusive-age classes ranked from youngest to oldest and four volcanic age classes ranked from youngest to oldest as spatial data represented by map in figure 1. Also, tectonic data are studied carefully, and two structural data which are distance to the nearest fault in the regional fault database, direction (relative azimuth between 0 and 180 degrees) with respect to the orientation of the nearest fault are derived from the whole structural dataset and also two other structural dataset as distance to the nearest fault in the subset of faults that go from compression to extension and back into compression at ~190 Ma and direction from cell centroid to the nearest fault in the subset of faults that go from compression to extension and back into compression at ~190 Ma. are derived from specific time-range tectonic switches and presented as map in figure 1.

The reason we consider 190 Ma. as specific time-range is that this time-range coincide with the highest porphyry deposite in the study area. Thus, in the Quesnel area, a quick switch from compression, extension and again compression happened between 190 ma and 180 ma, which is approximately coincident with highest Cu and Au endowment.



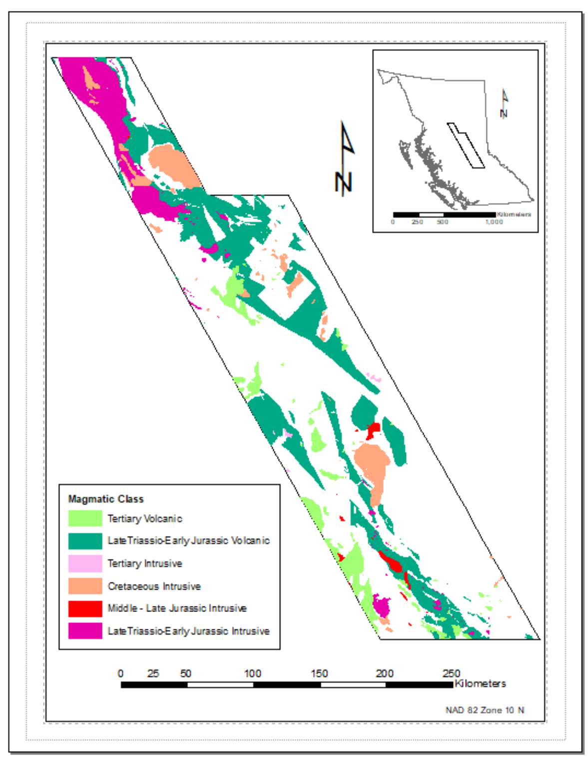


Fig 1: Mapped faults (left) and age-constraint volcanic and intrusive rocks (right).

Results

Regarding porphyry prospectivity map, the predicted prospectivity showed good correspondence with existing data, and the predicted porphyry deposits were considered geologically reasonable (figure 2). In several areas, the estimated probability of prospectivity suggests directions for further field exploration.

The total number of data points was 455, including:

142 non-prospective (with no recognized porphyry deposit) points which contain some kind of metallic mineral occurrences. Some geological features that might be common to porphyries and other deposit styles may occur at these locations. Geophysical or geochemical evidence at these locations may appear potentially porphyry-related, although caused by different or unknown deposit styles. Therefore, target label = 0 was assigned to these points. These points could be good candidates for false positive points.

66 non-prospective points in areas that have been prospected but no mineralization of any kind has been observed or reported. These points were assigned label = 0.

20 additional points selected in areas for which no prospectivity data are available, but which are considered geologically unfavorable for porphyry deposit formation. All these points were assigned label = 0.

227 Identified porphyry mineralization points with known porphyry deposits. These points were assigned label = 1.

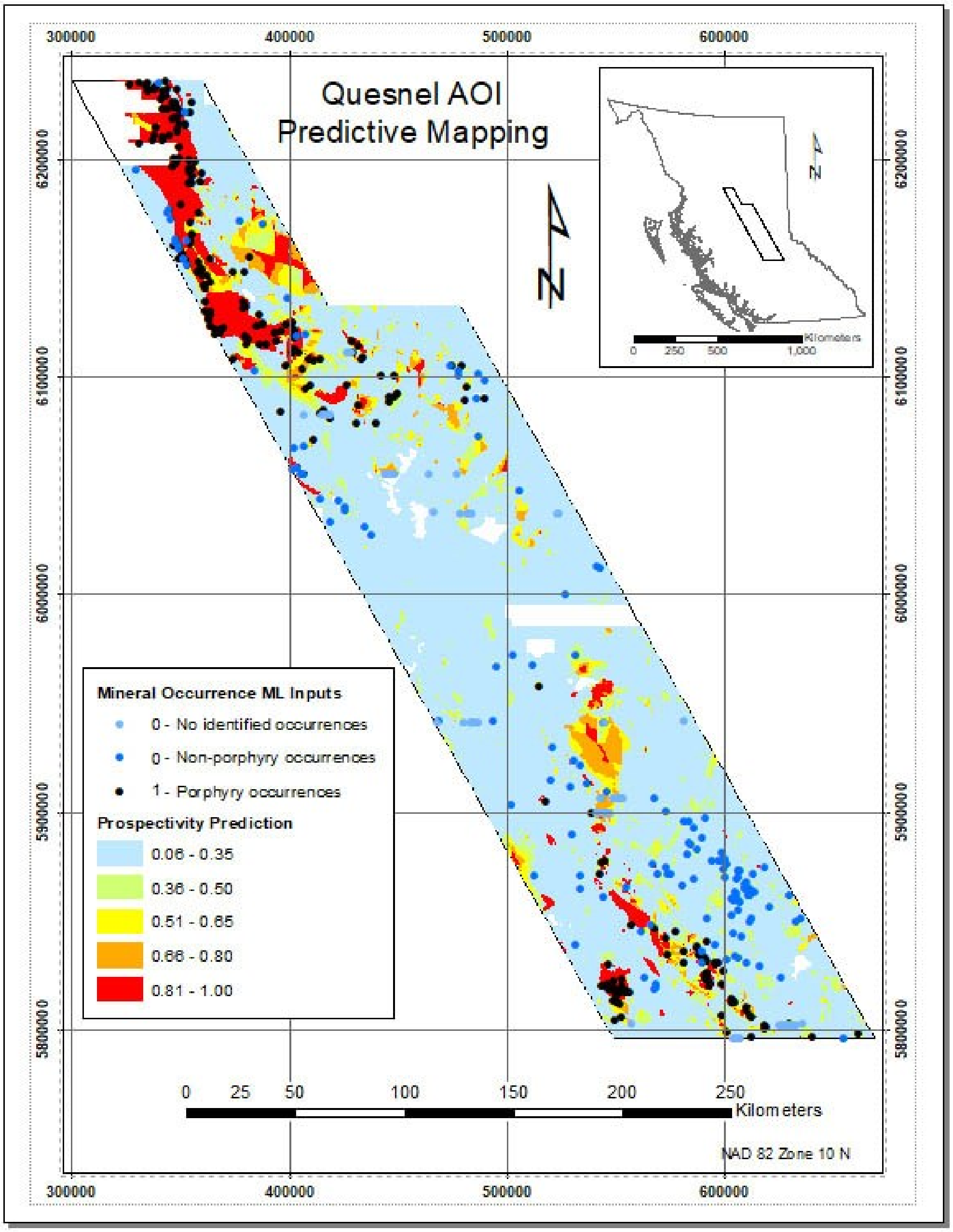


Fig 2: Predicted prospectivity map (plot courtesy of Moz Azarpour & Dène Tarkyth). Colours show intervals of prospectivity values, and blue and black dots show the data labels (legend).

geoconvention
Calgary • Canada • May 15-17 2023

Acknowledgements

Data were provided by Quest and Mira Geoscience. Griding and converting vectorized data to spatial data is done by SQL and ArcGIS software. Data analysis was performed using Matlab and Python software.

References

Phillips, N., Nguyen, T. N. H., Thomson, V., Oldenburg, D. (2009). 3D inversion modelling, integration, and visualization of airborne gravity, magnetic, and electromagnetic data: the Quest project, BC, Canada. Mira Geoscience modeling report.

Report by the University of Saskatchewan "4-D Integration" team for the 2022 Frank Arnott - Next Generation Explorers Award by the Prospectors and Developers Association of Canada. (https://www.pdac.ca/members/students/faa/2022-challenge).