Predictive mapping of the gold mineral potential in the northern Swayze Greenstone Belt, ON, Canada

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Background:
The Swayze Greenstone Belt (SGB) is an Archean greenstone belt, comprising of felsic to ultramafic intrusions overlain by metasedimentary rocks. It hosts mesothermal gold deposits that are structurally controlled and are associated with pervasive alteration signatures.

Problem:
Mineral deposits are becoming increasingly difficult to locate; new methods are required to locate undiscovered deposits in both greenfield and brownfield exploration areas.

Solution:
Mineral prospectivity mapping (also known as mineral potential mapping) is a method for determining locations where a mineral deposit is more likely to occur in an area by integrating multiple spatial layers. Machine learning tools such as weights of evidence and radial basis function are used to combine and analyze multiple spatial layers to define regions favorable for mineral deposits. The weights of evidence technique is outlined in the poster presentation.

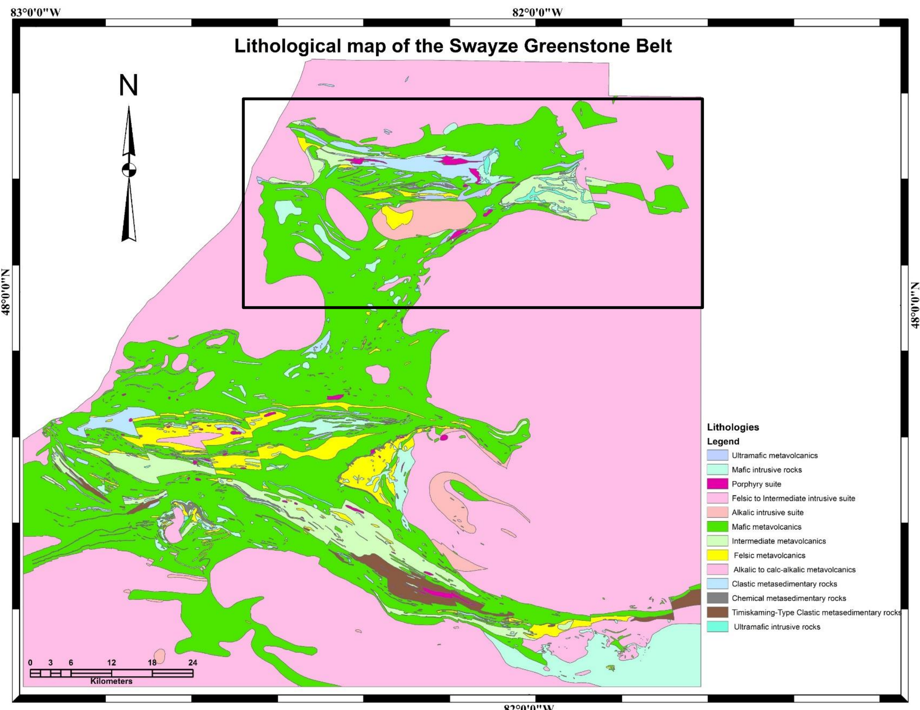

Figure A : The geological map of the Swayze Greenstone Belt (SGB) from Ayer and Trowell (2002).

Theory and methodology:
The study uses ArcGIS and ArcSDM (Spatial Data Modeler) software to integrate evidential layers in the weights of evidence tool. Weights of evidence uses Bayesian statistics to evaluate each evidential layer by statistical means using the 'calculate weights' tool. The tool assigns weights by determining spatial relationships between input training points of known deposits and evidential layers to outputs a table of the weighting coefficients: (W+, W-) and the contrast, C.

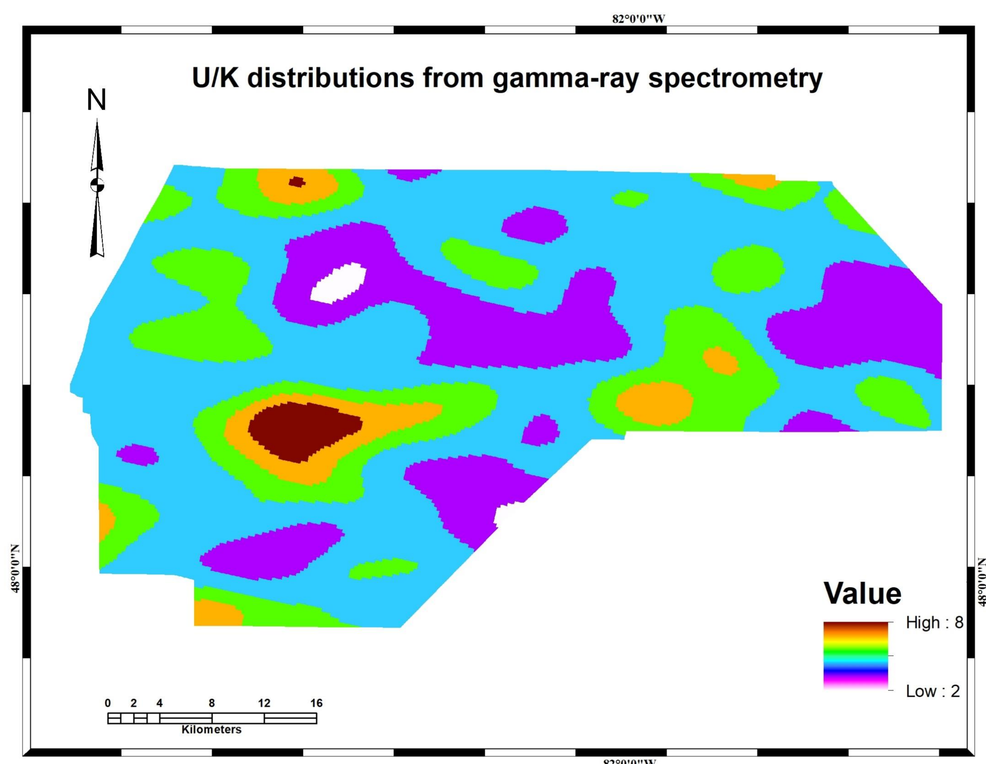

Figure B: U/K distributions

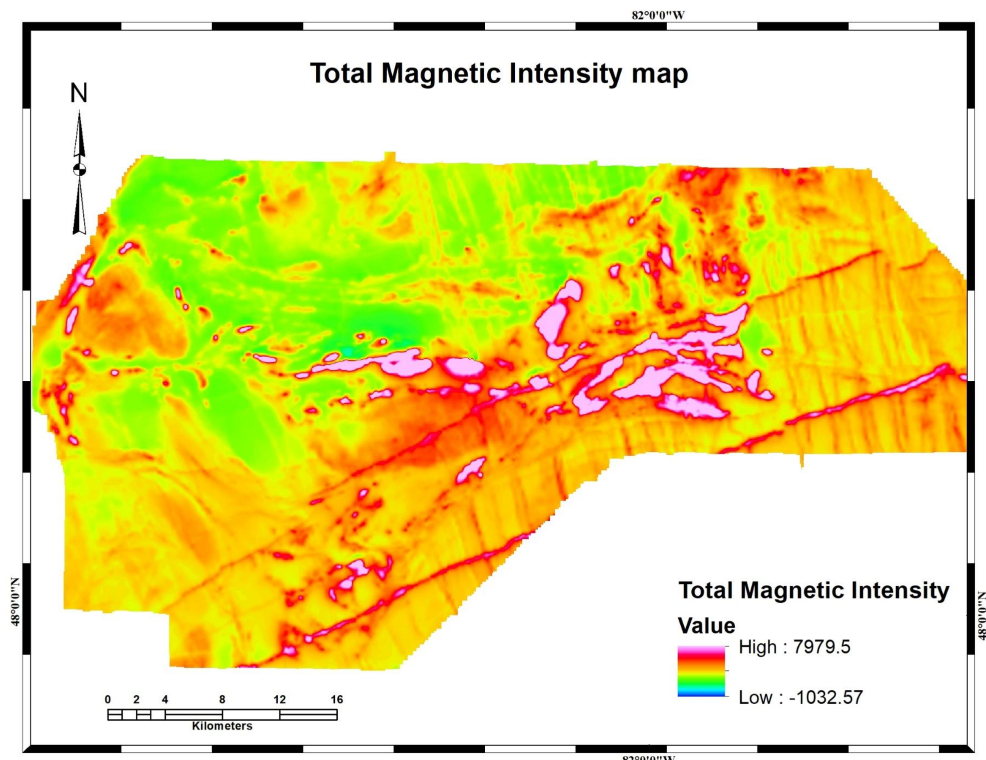

Figure C: The total magnetic intensity map

Cross validation techniques such as computing the success rate curve (SRC) and prediction rate curve (PRC) are used to check the ability of the model to predict unknown and known deposits in the study area and a cumulative area posterior probability curve (CAPP) is used to reclassify the posterior probability map (Porwal et al., 1990; Carranza, 2004).

Data type	Format	Source
Airborne magnetics	Raster	OGS
Electromagnetics	Raster	OGS
Lithology	Polygon	OGS
Structural	Polylines	OGS
Gamma-ray spectrometry	Raster	GSC
Mineral prospects	Points	OGS
Geochemistry	Raster	GSC

Table 1: Summary of data used in GIS

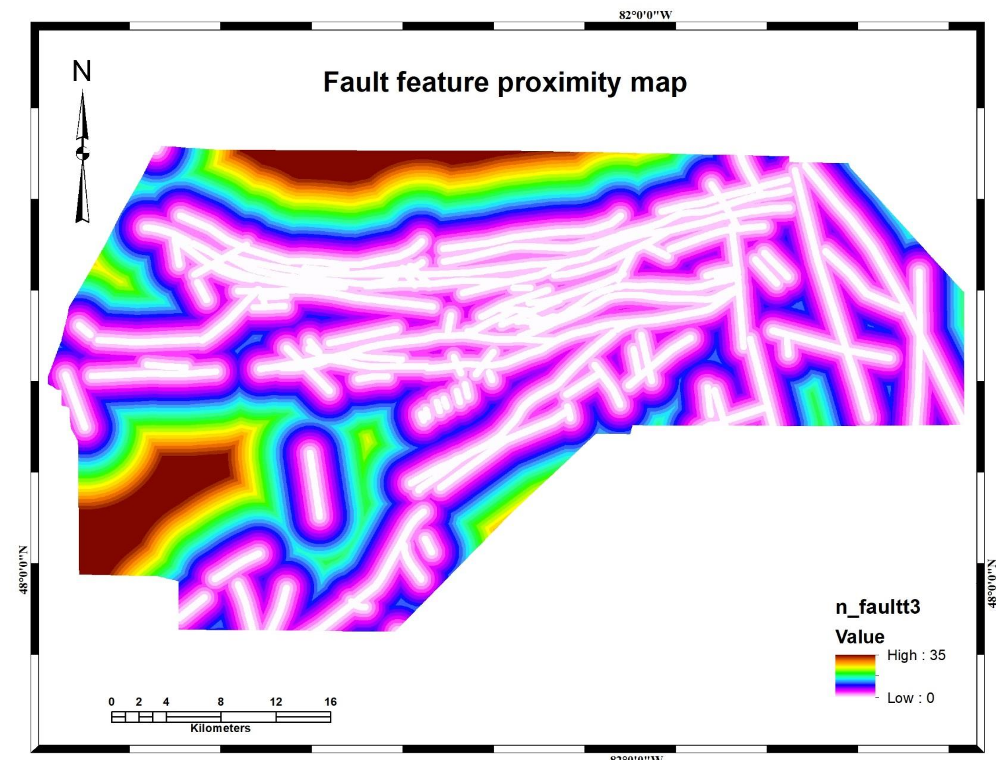

Figure D: Fault feature proximity map showing the distribution of faults.

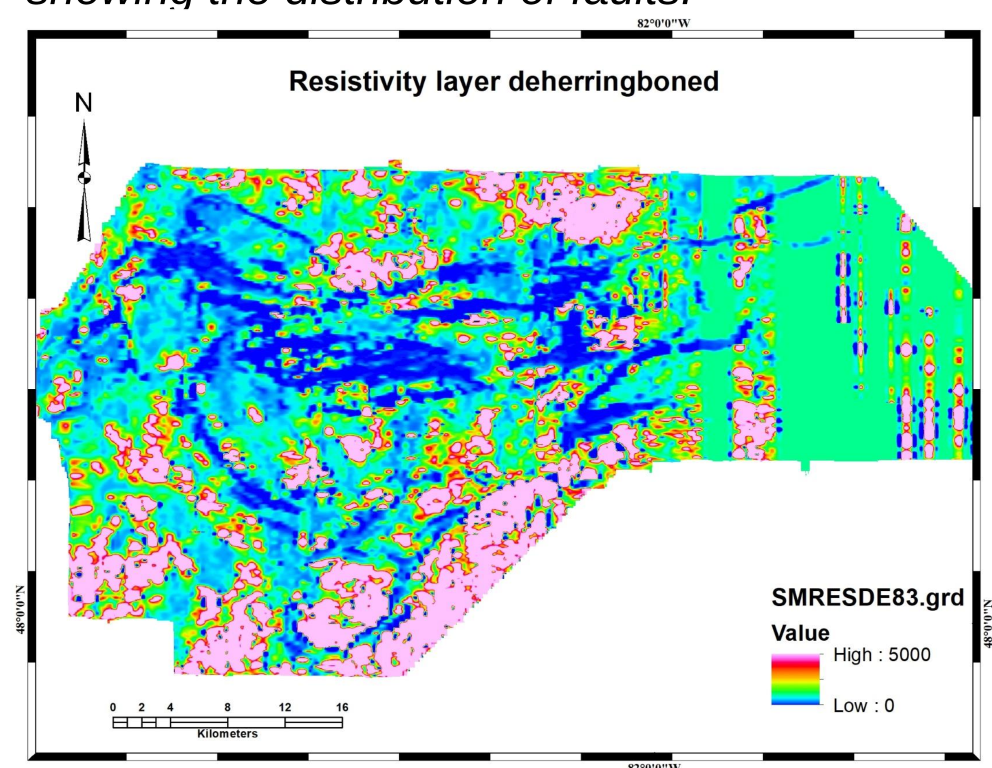

Figure E: Resistivity layer (deherringboned)

Public domain data covering the SGB was obtained from the Ontario Geological Survey and the Geological Survey of Canada (GSC) (Table 1) for this study. Evidential layers used for this study include: a lithological map (Fig. A), a U/K gamma-ray distribution map (Fig. B), a total magnetic intensity map (Fig. C), a fault feature proximity map (Fig. D), and a resistivity layer (Fig. E). The layers were chosen because they have the best spatial correlation with gold overlying the study area. Known deposits of 15 points were used for training the model in the northern SGB and 15 points were used for validation, shown in Figures (F) and (G).

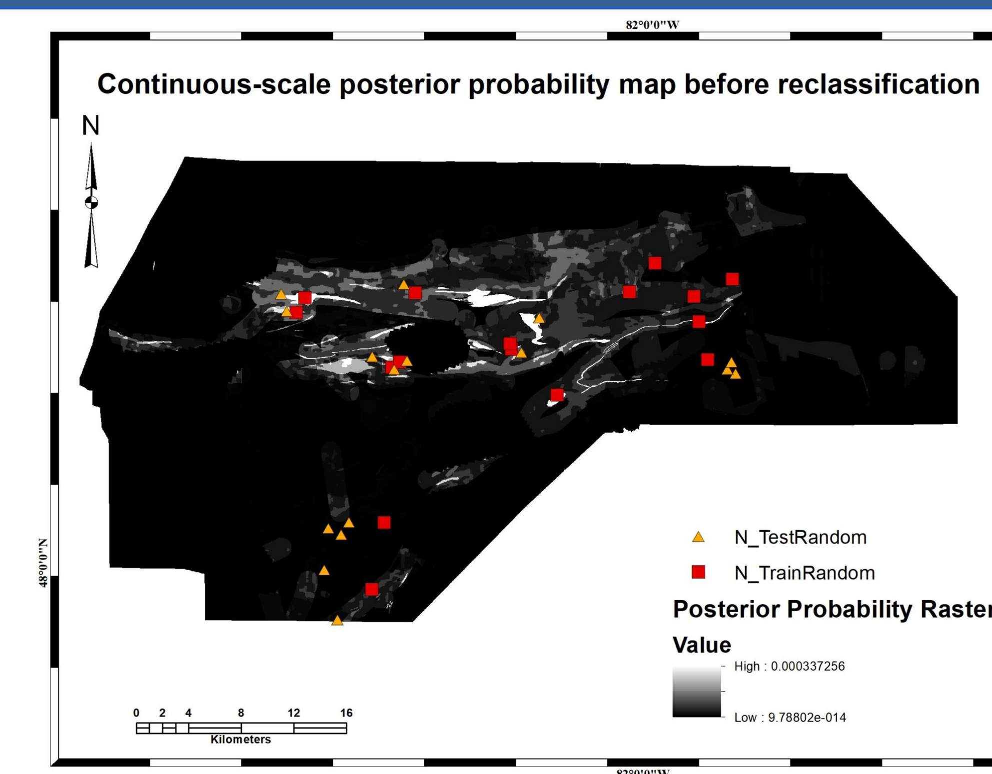

Figure F : An unclassified continuous-scale posterior probability map.

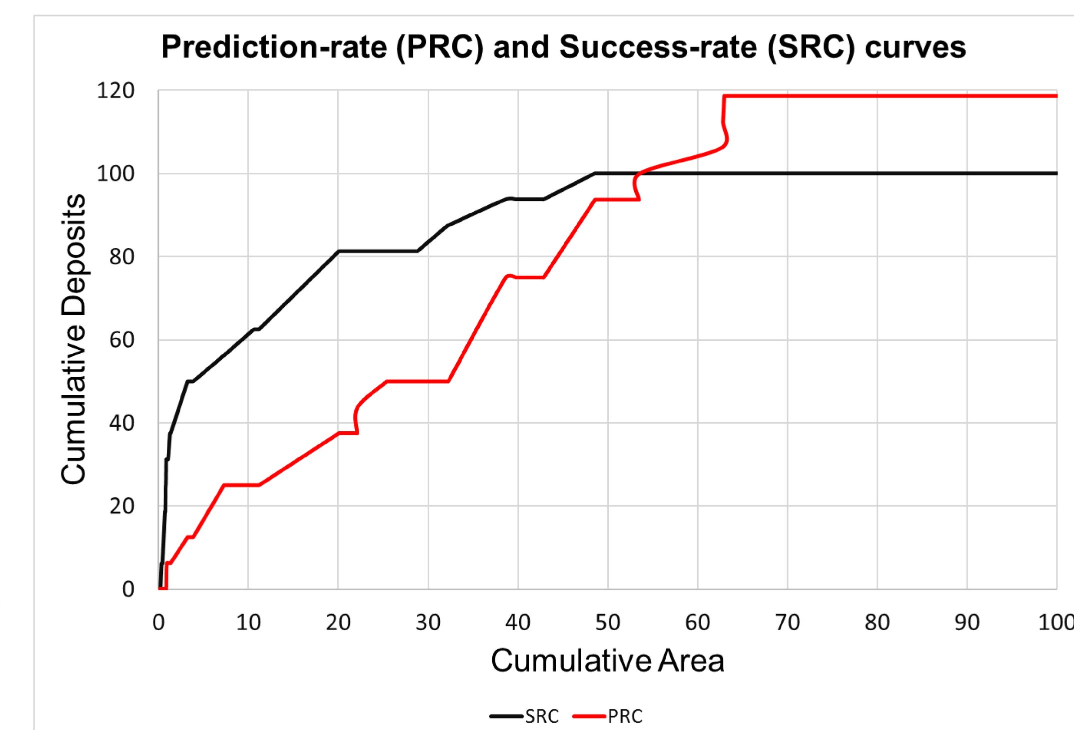

Figure G: Success rate curve (SRC) and prediction rate curve (PRC) used cross validation of the posterior probability raster.

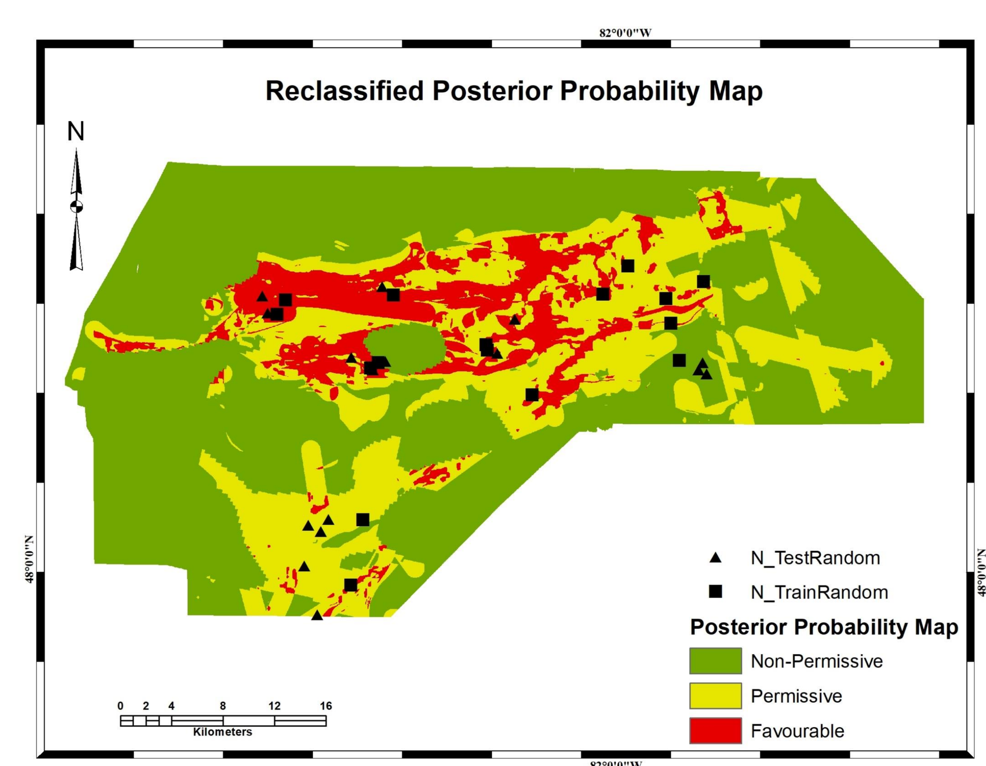

Figure I: A reclassified posterior probability map showing favorable to non-permissive regions

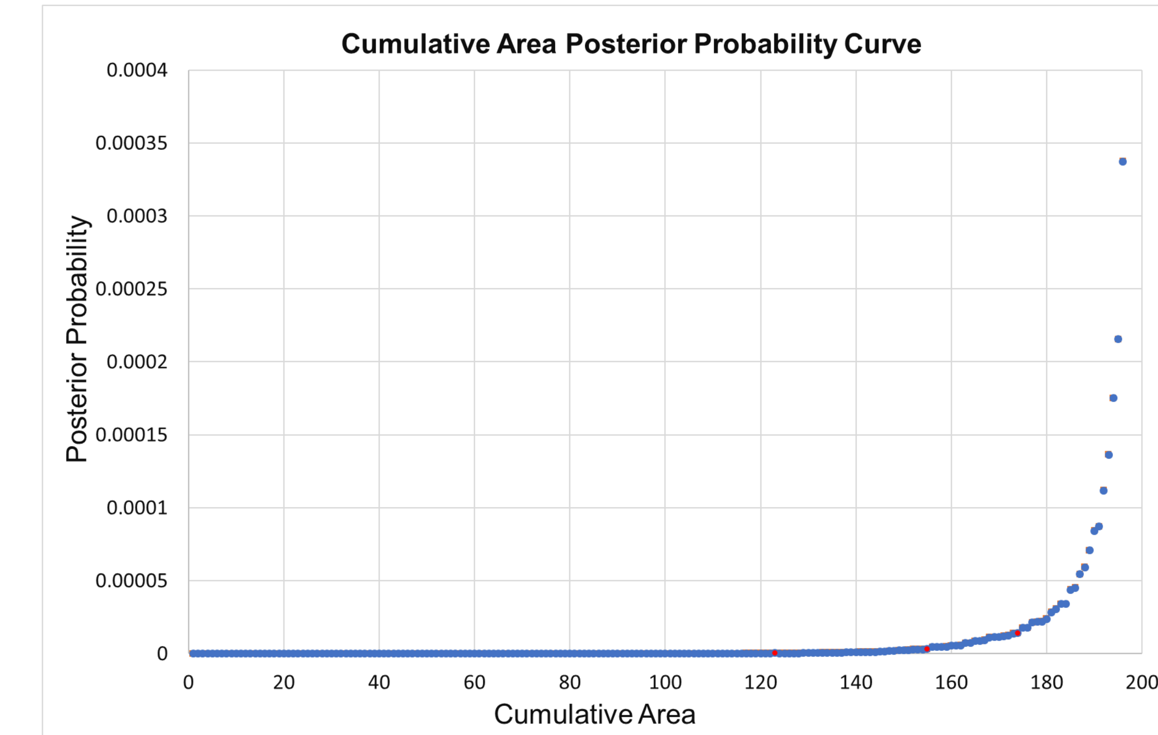

Figure H: Cumulative area posterior probability (CAPP) curve used to define class breaks for reclassification of posterior probability raster.

Results and discussions
The results show the abilities of the weights-of-evidence method to predict known and unknown mineral deposits by combining multiple spatial layers. The cross-validation methods termed SRC and PRC for determining the success-rate and prediction-rate curves are shown in Figure (G). They indicate the efficiency of classification and prediction of the model which are 87% and 69% respectively. The values are obtained by summing the area under the curves. The CAPP curve was used to reclassify the posterior probability map in Figure (F).

Conclusion
The weights-of-evidence model was able to classify and predict new and already known deposits well as shown in Figure 9. The cumulative area posterior probability curve helps for objective reclassification of posterior probability maps from a continuous scale map shown in Figure (F) to a reclassified map in Figure (I). Overall, the weights of evidence model is successful in delineating areas for further detailed exploration.

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