

1. Introduction

Recent significant developments in computer and GIS techniques now make it possible to integrate the large number of geoscientific layers available in mature mining areas using data mining techniques. New insight about the mineral potential and metallogeny of these areas is gained in the process. We present a mining-camp scale mineral potential model for gold in the Val d'Or - Malartic area based on an artificial neural network.

2. Mineral potential mapping techniques and artificial neural networks

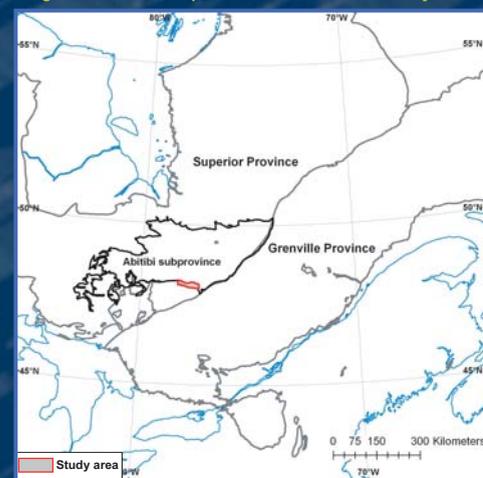
Mineral potential mapping techniques can generally be subdivided in two groups:

a. **Knowledge-driven techniques** (expert systems, fuzzy logic models, etc) are based on sets of rules that are determined by a mineral deposit expert.

b. Conversely, **data-driven techniques** (artificial neural networks, weight of evidence, etc) directly use the input data to deduce the rules that govern the location of known mineral deposits based on a set of input layers.

Artificial neural networks are a powerful data-driven technique based on the structure and interactions of biological neurons. Each neuron is a simple entity that performs a very basic processing. Neurons are interconnected to form networks. Just like their biological counterparts, artificial neural networks can "learn" from examples and apply this learning to new cases for which the result is unknown.

Figure 1: Location map of the Val d'Or - Malartic study area



4. Raw and derived input layers

The following layers were selected as inputs to the neural network:

- Competence and chemical reactivity of rocks in a cell (minimum, maximum and contrast) - based on detailed geology (Fig. 3) and theoretical chemical reactivities and competencies of greenstone belts lithologies (Fig. 4);
- Lithological complexity in a cell, calculated by the number of polygons in a cell;
- Distance to the nearest porphyry intrusion on the detailed geological map;
- Metamorphism and its horizontal gradient (Gauthier et al., 2007);
- Distance to faults of various orientations (MRNF, 2004);
- Distance to the Cadillac-Larder Lake tectonic zone;
- Bouguer gravity, total magnetic field and their first vertical derivative (Canadian Aeromagnetic Data Base, 2005; Canadian Geodetic Information System, 2005);
- Distance to geophysical lineaments of various orientations (Faure, 2003);
- Paleopressure modelling and its horizontal gradient (Faure, 2001).

Figure 3: Detailed 1:50K geological map of the Val d'Or - Malartic area (MRNF, 2004)

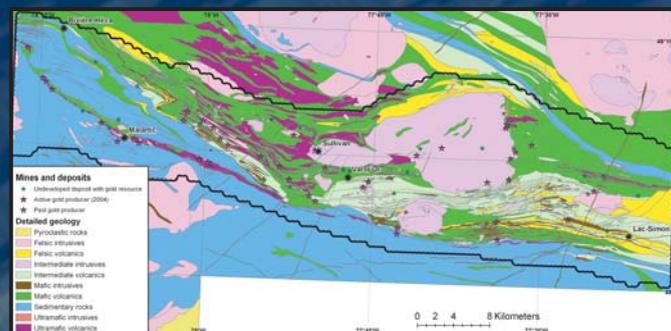
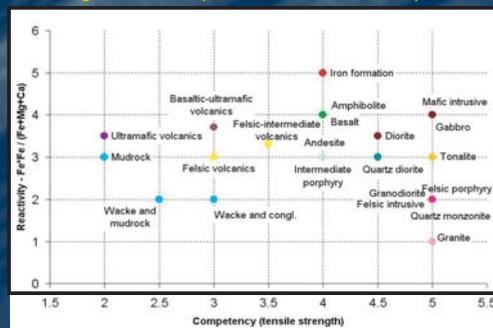


Figure 4: Competencies and chemical reactivities assigned to lithologies in the area (modified from Groves, 2002)



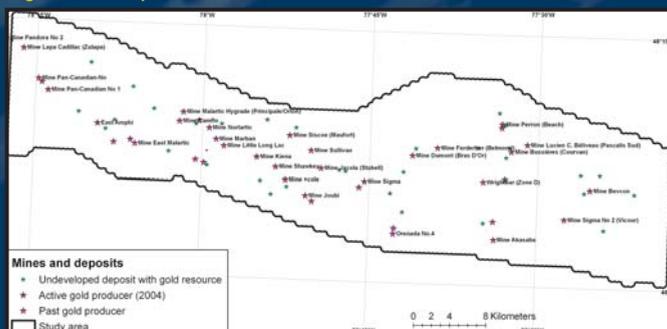
3. Study area and gold deposits

The Val d'Or - Malartic area (Fig. 1) is one of the most important gold districts in the Eastern Superior province, with a total gold production exceeding 25 million ounces (MRNF, 2006).

Only gold occurrences with defined gold resources were considered in this study. All deposits containing significant zinc or copper were excluded. More than seventy deposits in the area were retained according to the previous definition (Fig. 2). These gold deposits are of three main types:

- (1) late, undeformed quartz-carbonates-tourmaline auriferous veins (Sigma-type; Pilote et al., 2000);
- (2) deformed auriferous breccias, disseminations and quartz-carbonates veins (Kiama-type; Pilote et al., 2000); and
- (3) disseminated gold associated with syenitic porphyry intrusions (Malartic-type; Robert, 2001).

Figure 2: Gold deposits of the Val d'Or-Malartic area



5. Data processing

The Val d'Or - Malartic area was divided into 500 x 500 m cells. The model contains 4342 cells, but only 72 cells contain known gold deposits.

Training by a neural network usually requires having a subequal number of deposit cells vs. "barren" cells. To accommodate the small number of deposit cells, a technique of noise addition (Brown et al., 2003) is used to create a number of synthetic, randomly generated deposits for training. Using this idea, 2160 synthetic gold deposits were added, using a 10% uniform random noise scheme.

A feed-forward, back-propagation neural network of the generalized feed-forward type (NeuroSolutions software v4.01) was trained to recognize gold-prospective cells. Available cells were split into training (50%), cross-validation (25%) and testing (25%) subgroups.

6. Results and interpretation

Classification results on test cells

92.5% of all barren cells in the test group were correctly classified as barren. The remaining 7.5% are barren cells that are considered favourable by the network; these cells become prospective exploration targets. 91.8% of all cells containing gold deposits in the test group were correctly classified as favourable. The results indicate that the neural network is able to predict the location of known gold deposits vs. barren areas.

Output / Desired	Known as Deposit (includes synthetic deposits)	Supposed Barren
Classified as deposit by the neural network	535	78
Classified as barren by the neural network	48	965

Performance	Known as deposit	Supposed barren
Root Mean-Squared Error	0,06	0,06
R	0,85	0,86
Percent Correct	91.7%	92.5%

Sensitivity analysis

Sensitivity analysis is a method to semi-quantitatively rate the importance of inputs. It indicates that, of the 37 input layers, the 3 following layers have the most influence on gold prospectivity in the area: large competency contrasts of lithologies (Fig. 5), high average chemical reactivities (Fig. 6), and proximity to a SE-trending geophysical lineament (Fig. 7).

Figure 6: Average chemical reactivity of rocks multiplied by 10. This layer has the second most influence on gold potential calculated by the neural network

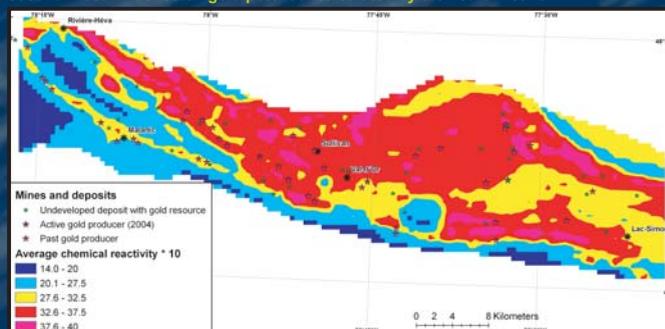


Figure 5: Competency contrasts of lithologies multiplied by 10. This layer has the most influence on gold potential calculated by the neural network

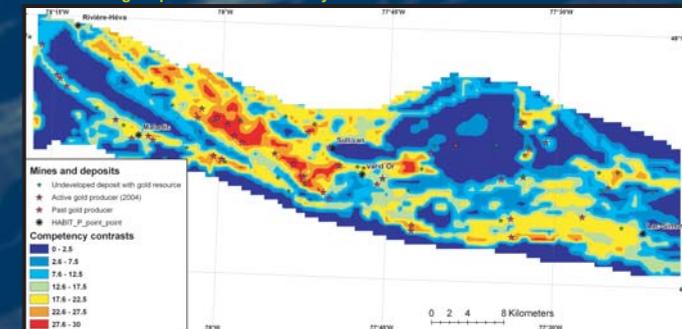
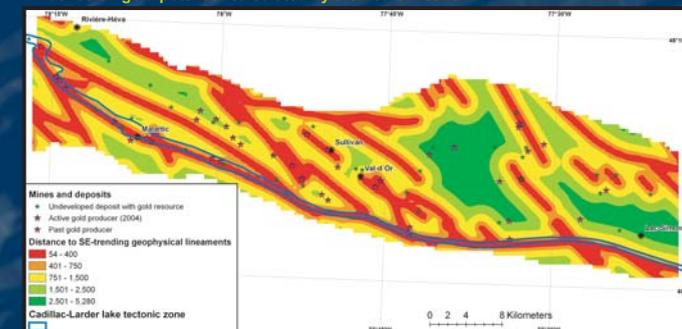


Figure 7: Distance to SE-trending geophysical lineaments. This layer has the third most influence on gold potential calculated by the neural network



7. Discussion and conclusions

The mineral potential map (Fig. 8) produced by the artificial neural network system is able to accurately classify known deposit cells vs. barren cells. It also outlines some areas that are not known to contain any deposits (Fig. 9). These areas are prospective exploration targets.

Layers that correlate most with gold potential in the neural networks model can very easily be linked to crucial local and mining-camp scale metallogenes recognized in orogenic gold deposits:

- Competency contrast of host rocks is the most important factor in defining the favorability for gold in the area. This is in accordance with the proposed precipitation mechanisms for gold in orogenic gold deposits (Mikucki, 1998). The highest amount of precipitation is likely to occur at the contact between competent and incompetent rocks, because this is where the mineralizing fluids will accumulate between seismic events.
- The chemical reactivity of host rocks is calculated by the excess amount of iron. Mikucki (1998) proposed that iron-rich rocks are important for gold precipitation because the presence of free iron triggers the precipitation of pyrite. This lowers the sulphur fugacity in the fluid and promotes the precipitation of gold transported in a sulphur complex.
- Gold prospectivity is also related to SE-trending lineaments corresponding to second- and third-order ductile shear zones parallel and subsidiary to the first-order and crustal-scale Cadillac-Larder Lake tectonic zone. This is also typical of orogenic gold deposits (Groves et al., 1998).

This further strengthens the orogenic gold model proposed for the majority of deposits in the Val d'Or-Malartic area.

Figure 9: 0.5 contour of the mineral potential map. Areas without known deposits are considered targets for gold exploration

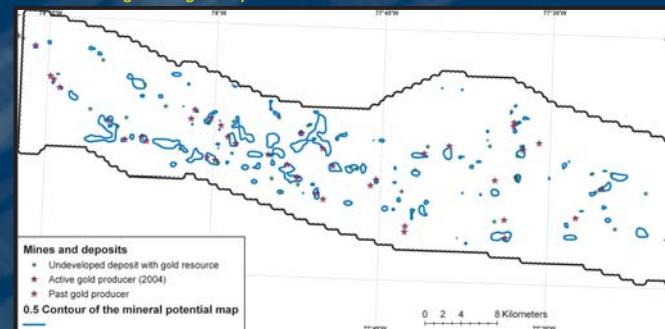
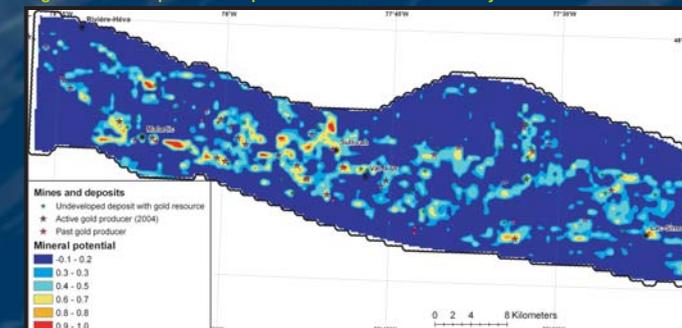


Figure 8: Mineral potential map of the Val d'Or-Malartic area by artificial neural networks



8. References

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