



MINERAL POTENTIAL MAPPING USING AN EXPERT SYSTEM AND GIS

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ABSTRACT

Noranda Mining and Exploration Inc., is applying expert-driven, fuzzy logic data integration techniques to identify new exploration targets in mature mining camps. The procedure to implement a data integration study has evolved into a well-defined process that coordinates human resources, technical databases and computer modelling software. The process begins with an expert panel defining and capturing the relationships between an exploration target and exploration measurements in an inference network. The inference network employs Boolean operators, fuzzy logic and Bayesian methods to model the judgement, reasoning and decision making process behind target compilation. Input maps are then created using the spatial analysis functions of a Geographic Information System (GIS). Modelling is performed outside the GIS and is based on a raster overlay procedure. It is driven by the same set of rules developed by the expert panel and captured in the inference network. Results are followed up with GIS generated target reports and detailed compilation that are then used as a basis to stake ground and to fund future exploration programs.

An expert system study of the Bathurst Mining Camp was completed in early 1996 to help evaluate open (unstaked) ground in anticipation of the release of a government sponsored airborne survey (magnetic, electromagnetic and radiometric survey). This study resulted in the development of an inference net model based on the Halfmile Lake VMS deposit. The results highlighted 10 priority targets on unstaked ground. Two areas were staked immediately and three additional targets were staked at the time of the airborne release owing to new information. The procedure for the development and implementation of the model is presented in this paper along with some of the results.

INTRODUCTION

Noranda Mining and Exploration Inc. is applying expert-driven, fuzzy logic data integration techniques to identify new exploration targets in mature mining camps. In these camps the majority of near surface deposits have been discovered and current exploration activities are oriented towards locating hidden, sub-cropping or deeply buried deposits. To assist in this search, explorationists have at their disposal a wide array of survey techniques which measure geological conditions that can be indicative of a mineralizing event. Each survey measures a different physical, chemical, or geological property of the earth's surface or near surface.

In mature mining camps, many exploration surveys have been conducted and the obvious targets have been evaluated. Along with the obvious targets, each survey generates many subtle anomalies that have remained untested because they are often attributed to non-mineralizing geological phenomena. Nevertheless, some of these weaker anomalies do represent mineralization and data integration techniques have

been used to develop targets from them by looking for the coincidence or near coincidence of weak anomalies from multiple data sets.

Until recently the ability to integrate different survey information has been limited to direct overlays using either hard-copy (light table) or digital techniques (imaging systems, CAD systems, etc.). Overlay techniques are useful in exploration but do not easily provide for the weighted comparison of related but different surveys, nor do they account for the uncertainty associated with geological interpretations drawn from survey results. Recently, with the introduction of Geographic Expert System (GES) concepts (Campbell *et al.*, 1982; Katz, 1991), the weighting and uncertainty characteristics inherent in the data compilation process have been successfully modelled by computer systems. Data integration studies are not new in mineral exploration but traditionally have involved time-consuming manual compilation work. Expert system modelling automates the compilation process by providing a first pass assessment of an area's mineral potential. The net effect is that scarce human resources are focused towards areas that offer a higher chance of success in the early stages of exploration.

Noranda Mining and Exploration Inc. has conducted twelve GES studies since 1993. It was recognized early that this technology represented an opportunity to consolidate available human and technical resources into a process that would provide a competitive advantage in the field. Over time a pattern has developed regarding the role that each company resource plays in the targeting modelling process. This paper reviews the process as it has come to be known and uses a recent study of the Bathurst mining camp to demonstrate various aspects of it.

The Bathurst mining camp is situated in northern New Brunswick, Canada and is underlain by bimodal volcanic and metasedimentary rocks of the Middle Ordovician Tetagouche Group (Langton, 1992) (see Figure 1). It represents an area of approximately 2000 km² and is host to more than 30 significant massive sulphide deposits including two current and four historic producers. The largest deposit is Brunswick #12, owned and operated by Noranda Mining and Exploration Inc., with past production and current reserves estimated to be 161 million tonnes of lead-zinc ore grading 3.55% Pb, 8.90% Zn, 0.32% Cu, 99.0 g/t Ag (Luff, 1995). In recent years, the Bathurst Camp has been the focus of an exploration technology initiative (EXTECH-II) which has generated several new data sets and geological concepts. This initiative was expanded to

include a federal and provincial government sponsored, high resolution, multiparameter (magnetics, radiometrics and electromagnetics) airborne (AEM) survey flown in 1995 and released on July 31, 1996.

In anticipation of the AEM survey results and as part of ongoing GIS and data management initiatives, an expert system model for the Bathurst mining camp was undertaken in the fall of 1995. This model focused on the Halfmile Lake VMS deposit type, the characteristics of which are well summarised by Adair (1992). The main objective of this study was to identify and prioritize open (unstacked) and under-explored ground with high potential to host a significant base metal deposit. Information compiled and managed in a GIS since 1994 provided the data source for this study.

INFERENCE NETWORK DEVELOPMENT

The modelling process began with an expert panel defining the relationships between an exploration target and various survey responses. To document the exploration model, company experts were brought together for a two-day modelling session. The panel consisted of eight

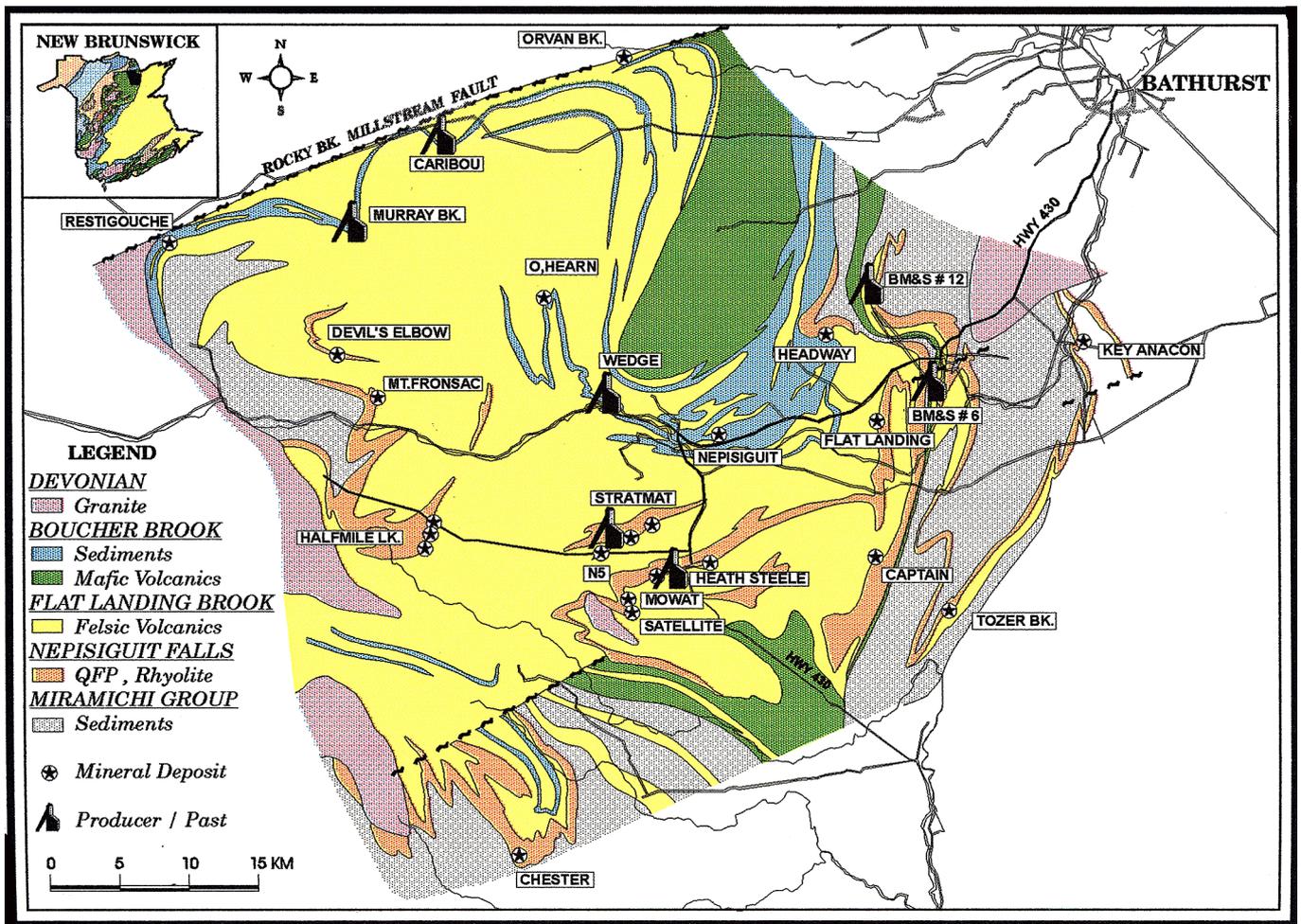


Figure 1: Location and regional geology of the Bathurst mining camp including major mineral occurrences and deposits.

professionals (geologists, geophysicists, and managers) with broad experience and an in-depth knowledge of the Bathurst mining camp. These professionals were lead through the model building process by a knowledge engineer (Reboh, 1981). The knowledge engineer guided the panel discussions through various aspects of a deposit model and carefully translated expert opinion into modelling objects. He then prompted experts to semi-quantify each of these objects, and translated the answers into modelling parameters. At the end of the model building process a diagram was produced that documented the panel's opinion of how different exploration surveys relate to each other and combine to suggest the presence of mineralization. The diagram used to document these relationships is referred to as an inference network (Figure 2).

An inference network is a logic tree that documents the decision making process of experts faced with different compilation scenarios. These were first applied to geological problems by the U.S. Geological Survey's Prospector expert system (Duda *et al.*, 1977). Inference networks are made up of many linked boxes. Boxes are termed spaces and in a GES context represent map layers. Lines that connect spaces are termed rules and document the logical relationship between hypothesis and evidence spaces. The space that is the hypothesis for one rule may be the evidence for another rule. On an inference network both spaces and rules are labelled with modelling parameters. Spaces are labelled with the name of a logical condition and with the random (prior) probability P(E) of it occurring. Rules are labelled with weighting factors

(LN, LS) indicating how evidence is associated with the hypothesis. A hypothesis space can have many relationships with underlying evidence spaces. This collectively documents how different pieces of evidence relate to one hypothesis. Each set of evidence-hypothesis spaces represents one reasoning step in the inference network and translates into one modelling step in the data integration calculation. Values that migrate up the inference network are expressed in probability terms. During modelling, each space will have a calculated (posterior) probability value assigned that can be higher or lower than its random (prior) probability, depending whether the cumulative evidence supports or contradicts the hypothesis. The final hypothesis is a synthesis of many logical steps and represents the probability that mineralization will be found in an area. This final probability value is often referred to as a *mineral potential* or *favourability* measurement.

Inference networks use fuzzy logic and conditional probability operators to model relationships between evidence and hypothesis spaces. Fuzzy logic operators include AND, OR, and NOT operators and are similar to Boolean operators except that they accommodate uncertainty (Katz, 1991). Given two or more related evidence spaces, fuzzy OR logic will migrate the highest calculated (posterior) probability of the evidence to the hypothesis space (Figure 3). Fuzzy AND logic will migrate the lowest calculated (posterior) probability to the hypothesis space. And Fuzzy NOT logic will migrate the highest converse probability (one minus probability) to the hypothesis space. In fuzzy logic when the

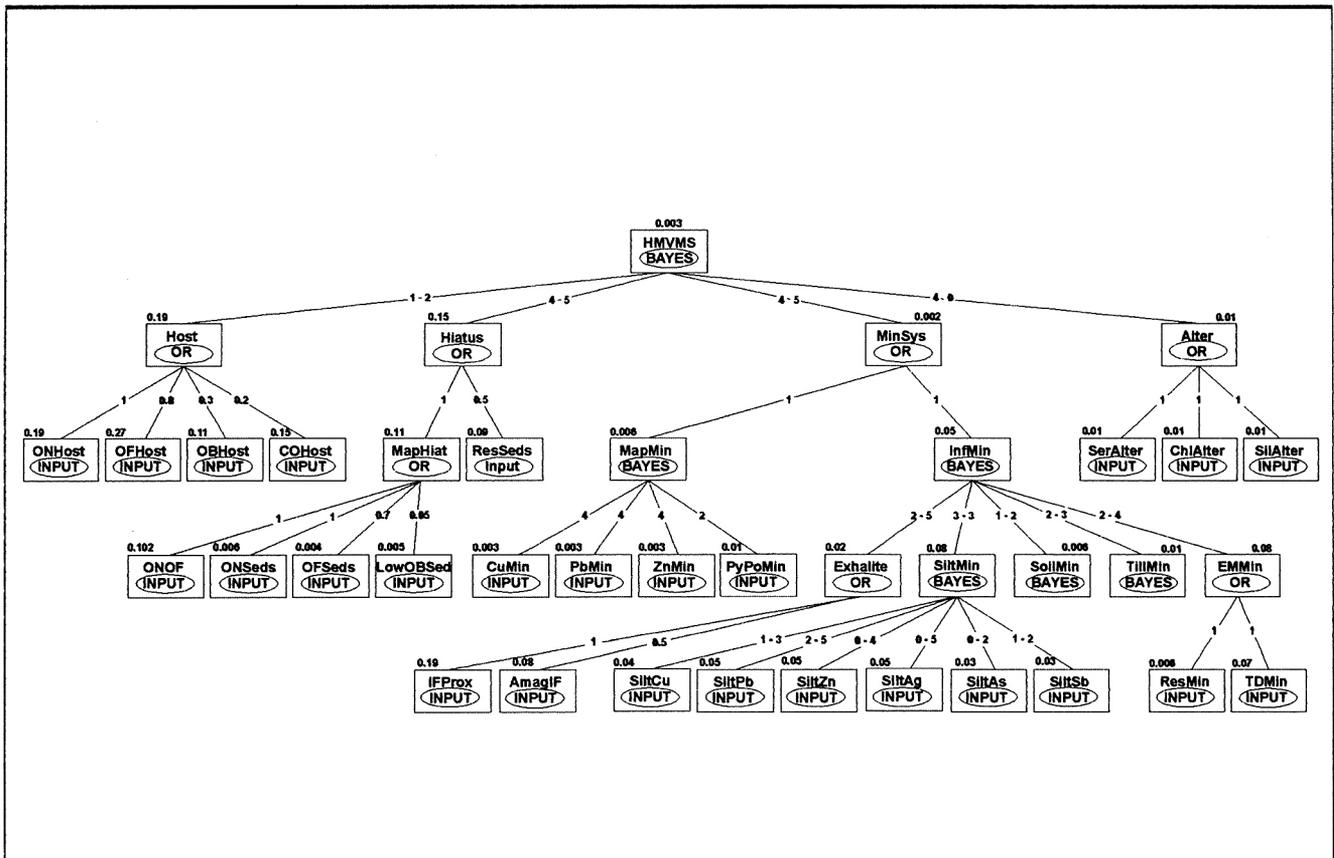


Figure 2: Inference network of the Halfmile Lake volcanogenic massive sulphide deposit model used in the Bathurst geographic expert system (GES) study.

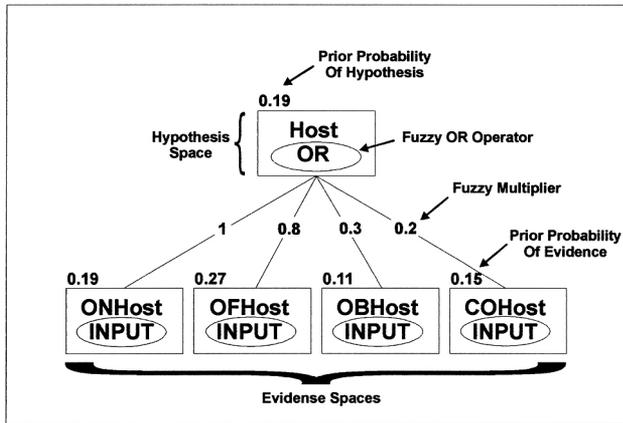


Figure 3: Example of a fuzzy logic OR operator used to migrate calculated probabilities from evidence to hypothesis spaces.

Table 1: Scaled likelihood coefficients used in Bathurst study.

Input	Meaning	LS Value	LN Value
0	Indifferent	1.000	1.000
1	Weakly	2.512	0.398
2	Mildly	6.310	0.155
3	Moderately	15.849	0.063
4	Very	39.866	0.025
5	Extremely	100.000	0.010

condition of an evidence space is unknown, the prior probability of the evidence is used in the logical comparison. All Noranda fuzzy logic operations also support a weighting factor called the fuzzy multiplier. The fuzzy multiplier is a factor applied to the evidence before any fuzzy logic comparison is made. The fuzzy multiplier is useful for fine-tuning models without having to make adjustments to input maps. In an inference network, each fuzzy operation is a logical comparison that can be thought of as emulating an expert’s decision-making process.

Another way to model an expert’s reasoning process is to use a BAYES logic operator. The BAYES logic operator uses Bayesian methods to migrate probability values from evidence to hypothesis spaces (Bonham-Carter, 1994). Bayesian methods are based on conditional relationships that refer to the ability of one event to forecast or influence the probability of another event. For example, seismic events can forecast eruptions of volcanoes and therefore the probability of volcanic eruptions will increase if seismic events have been detected. Conditional relationships can also be thought of in terms of evidence, where evidence can range from circumstantial to *smoking guns*. In the case where there is no *smoking gun* a case can be built by compiling circumstantial evidence. The basic equation of conditional relationships is referred to as Bayes Rule (Equation 1) (Davis, 1986) and states that the probability (P) of the hypothesis (H) event occurring given some evidence (E) $P(H|E)$ is equal to the probability of the evidence with coincident hypothesis events $P(E|H)$, multiplied by the ratio of the random prob-

ability of the hypothesis (P(H)) to the random probability evidence (P(E)). From Equation 1 it can be seen that the strength of the evidence (W) is measured in terms of how many historical hypothesis events also had an evidence event occur $P(E|H)$ and by the overall rarity of the evidence (P(E)) (Equation 2). Substituting for W, we get the general equation for a BAYES logic operation (Equation 3). When experts are asked how evidence relates to a hypothesis event, they are making an estimate of W. For further information on Bayesian methods and conditional probabilities the reader is referred to the works of Bonham-Carter (1994) and of Davis (1986).

$$P(H|E) = P(E|H) * P(H) / P(E) \tag{1}$$

$$W = P(E|H) / P(E) \tag{2}$$

$$P(H|E) = W * P(H) \tag{3}$$

When using the Bayes operator the expert panel must answer two questions. First, if the evidence occurs, how strongly does it suggest that the hypothesis is true? Second, if the evidence does not occur, how necessary are the data for the hypothesis to be true? The answer to the first question is used to define a positive weighting factor called the Likelihood of Suggestivity (LS). The answer to the second question is used to define a negative weighting factor called the Likelihood of Necessity (LN) (Katz, 1991). To simplify the process of weighting evidence, experts are asked to rate the association of evidence on a scale between 0–5 where each number has a corresponding weighting value (Reddy *et al.*, 1992). The scaled likelihood coefficients (LS and LN) used in this study are listed in Table 1 and were verified by comparing modelling results with areas of known mineral potential. The objective of each Bayesian logic operation is to emulate an expert’s reasoning process in the face of uncertain interpretations and the LN and LS values used reflect this concept.

To assist in the modelling process Noranda has developed its own inference network editing software called EDIT-NET. This software allows the expert panel to quickly diagram, parameterize and create hard-copy inference networks during their development. Another feature of this software is that it will automatically generate the step-by-step processing instructions used by the inference engine to execute the model. Having this software has helped to simplify and speed up the inference network development process.

TARGET MODEL

The inference network developed by experts takes a genetic approach to target modelling which assumes ore deposits are caused by a coincidence of different geological processes (Figure 2). The target model reflects this thinking by breaking targets into their contributing geological processes. Each geological process is then defined in terms of interpreted survey information. Interpretations are based on the characteristics (amplitude, shape, etc.) of survey measurements and have different association strengths related to the geological process being qualified in the model. For example, the amplitude and shape characteristics of electromagnetic (EM) survey results were interpreted by a geophysicist to be indicative of sediment horizons that represent quiescent periods between volcanic events favourable for the accumulation of sulphide bodies (weak to strong, long formational conductors).

The EM data were also used as a basis to infer mineralization (moderate to strong, isolated conductors). Each one of these interpretations was used as a separate input to the model and each had a different weight related to how well the interpretation was thought to correctly infer the related hypothesis. EM interpretations can effectively predict the presence of mineralization near surface but not in the vicinity of large regional conductors like graphitic horizons. In the model, EM indicated mineralization (EMMin) is very strongly suggestive of inferred mineralization if present but considered only mildly necessary if not present (Figure 2). As an indicator of a hiatus in volcanic activity EM inferred sediments (ResSeds) are considered only half as favourable (0.5) as mapped sediments because EM is also indicative of faults, swamps or other near surface features. In all, 33 geological interpretations served as the basis to infer four different geological processes: emplacement of favourable host rocks; a hiatus in volcanic activity; hydrothermal systems; and, the precipitation of base metals.

A repeated theme in the exploration logic is the relationship between observed and inferred evidence. Exploration logic will accept the *concrete* evidence of an observed geological condition over evidence that was inferred by geochemical or geophysical measurements. For example, an outcrop with observed Cu, Pb, and Zn sulphides is considered to be a better indicator of nearby mineralization than geochemical anomalies because observed minerals are closely associated with this process, whereas geochemical anomalies may be many steps removed from their source. Nevertheless, in the situation where there are no observed minerals, (i.e., lack of bedrock exposure) geochemical anomalies are good indicators of buried mineralization.

GIS SPATIAL ANALYSIS

In preparation for modelling, GIS spatial query and analysis functions are used to create model input maps. The role of GIS in the preparation of model input maps is principally two-fold. First, it is used to perform spatial analysis that enhances the interpretation of survey results. As an example, spatial selects were used to determine anomalous geochemical threshold values for different underlying bedrock units (Table 2). Legitimate anomalies in low background units can be lost if threshold values are estimated from all samples. This type of spatial analysis is concerned with data processing procedures that improve the signal to noise ratio of existing data sets and will hopefully result in the identification of new, subtle anomalies.

Table 2: Summary statistics for lead concentrations in stream sediment samples over different rock units in the Bathurst mining camp (measured in parts per million).

Rock Unit	NUM	MIN	MAX	MEAN	S.D.
<i>Ofv1 (felsic volcanics)</i>	860	6	3515	73	175
<i>Ofv2 (felsic volcanics)</i>	229	9	787	56	76
<i>Omv2 (mafic volcanics)</i>	600	5	2580	56	155
<i>Om1 (mafic intrusives)</i>	32	16	146	38	23
<i>Os3 (sediments)</i>	412	4	688	45	65

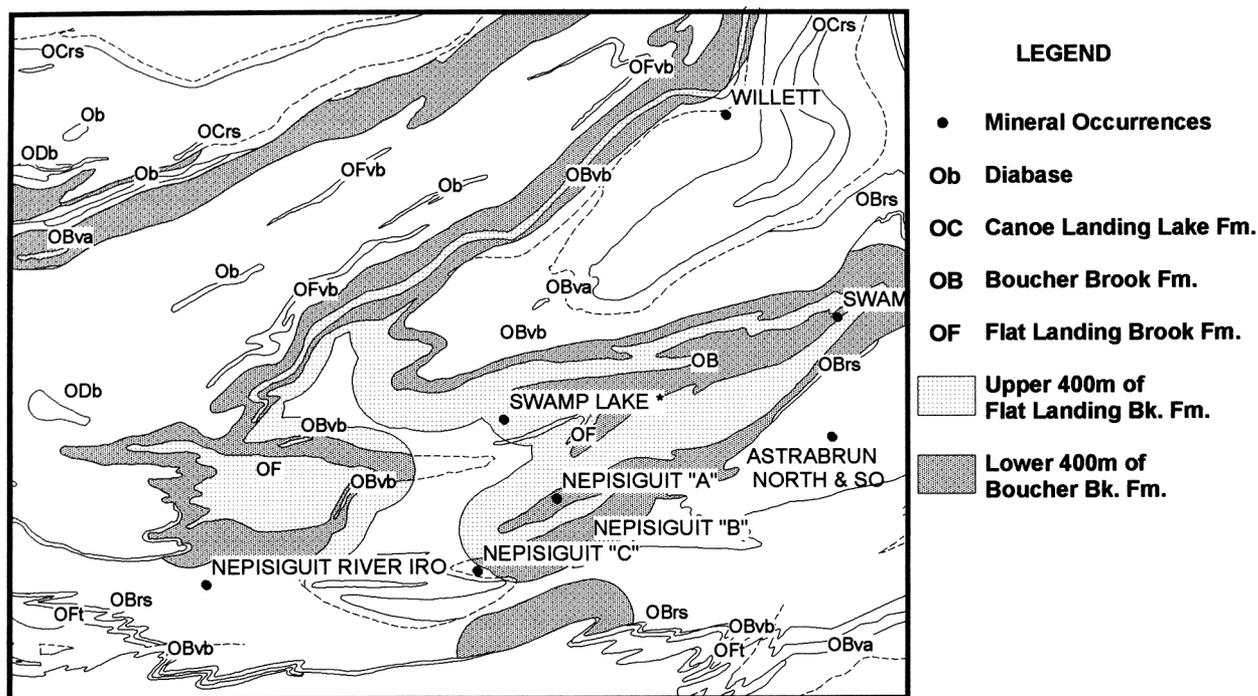


Figure 4: Result of adjacency, buffering, and clipping functions that map out the area of influence around the conformable contact between Flat Landing Brook Fm. felsic volcanics and Boucher Brook Fm. sediments.

Second, spatial analysis is used to assign areas of influence around interpreted map features. For example, buffering, clipping and adjacency functions were used to determine the upper 400 m of the Flat Landing Brook Formation that has a conformable contact with the stratigraphically younger Boucher Brook Formation. The result of this spatial analysis is presented in Figure 4 and was the basis for the LOWOBSED model input map. Assigning geologically realistic areas of influence around features is an important aspects of modelling because the procedure is ultimately searching for the coincidence of different patterns to enrich the favourability of an area.

INPUT MAPS

GIS technology was indispensable in the creation of input maps and also served as an overall data management platform. All of the interpreted maps were created in the GIS and many of them were created by having experts digitize polygons onto an interpreted drawing layer that overlaid the actual or processed survey results. Other interpretations were created with the assistance of the spatial analysis functions described above. Each interpreted polygon map had a modelling attribute defined and was assigned a probability relative to whether: the polygon indicated the interpreted feature (probability = 1), did not indicate the feature (probability = 0), or the area was not covered by this survey (no survey = -1). Polygon modelling values between 0 and 1 were also specified indicating a degree of uncertainty about the interpreted polygon's

boundary or interpretation. These were assigned to distance decay buffers around approximated boundaries or to subtle anomalies.

Once defined, all interpreted maps were clipped to a common study area and exported out of the GIS environment as co-registered raster maps. Co-registered raster maps consist of pixel or cell-based images with the same number of rows and columns. Pixels from the different maps correspond to the same geographic location and each pixel is assigned the probability value of interpreted polygons. With geological interpretations expressed in probability terms and exported as co-registered rasters, all information was in place for modelling.

EXPERT SYSTEM MODELLING

Modelling is performed outside the GIS by custom software referred to as an inference engine. The inference engine used in this study was written in-house and was based on publicly available code fragments from Katz (1991). The inference engine takes as its arguments the structure of the target model expressed as an inference network and the size of the study area expressed in pixel rows and columns. From these arguments the inference engine generates a series of modelling commands starting from the deepest levels of the inference network and working its way up the logic tree. In turn, each of the modelling commands are executed and produce one new hypothesis raster map from one or more evidence raster maps. The logic or reasoning defined in each modelling step is performed on a pixel-by-pixel basis until the entire study area has been modelled and a new hypothesis map generated (Figure 5).

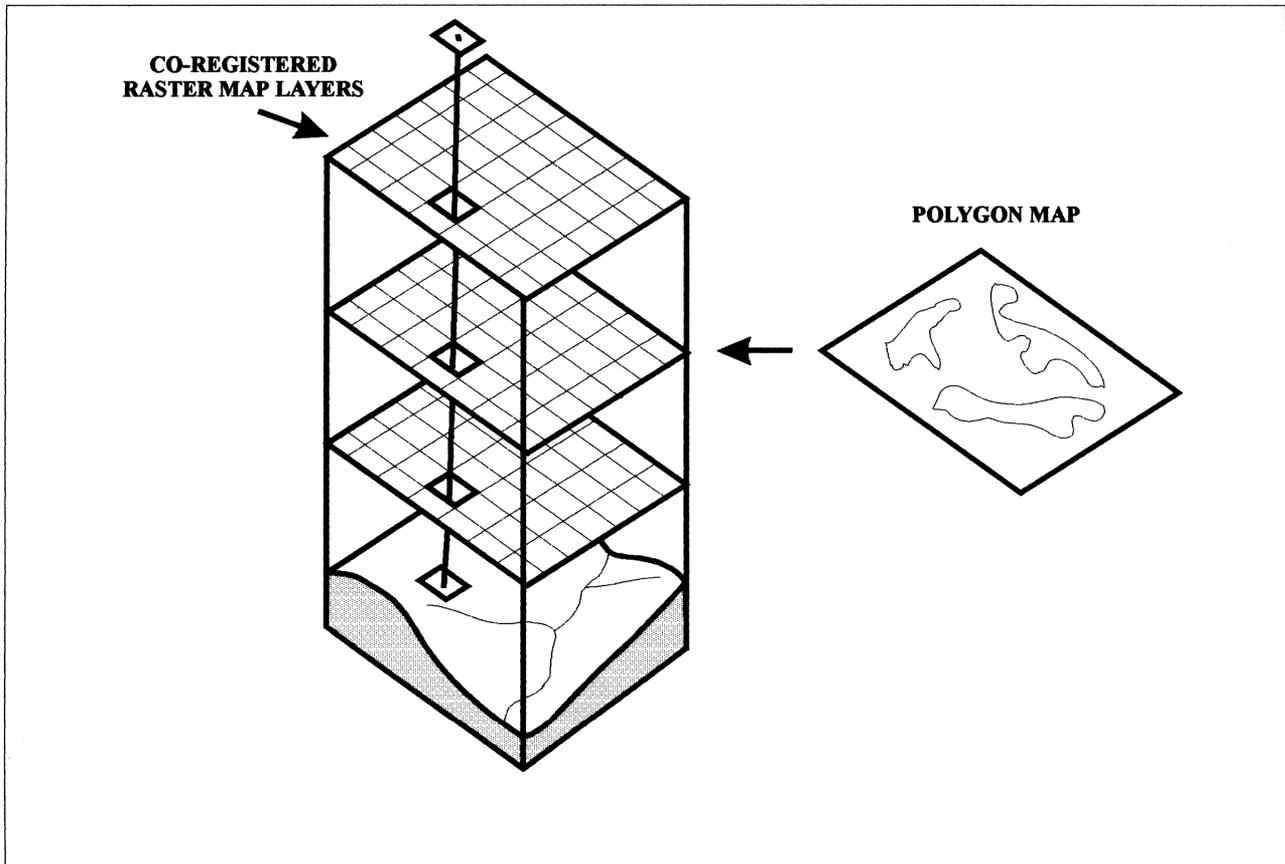


Figure 5: Modelling steps are executed against co-registered raster maps on a pixel-by-pixel basis.

The dynamic range of the modelling engine is between the probability range of 0 and 1 but is expressed as 1 byte integers using real number increments of 0.004 (1/254). The integer value 255 is reserved as a *NOT SURVEYED* flag, and when encountered the prior probability of the evidence is substituted for the pixel value. Using a 1 byte modelling engine imposes limits on resolution. Only significant differences in probability are distinguished during modelling. However, it can be argued that it is these significant differences that are of most interest to explorationists.

TARGET POTENTIAL MAP

The modelling results presented in Figure 6 represent the relative mineral potential of the Bathurst camp. Probabilities are displayed using a colour look-up table that relates each possible probability value with the appropriate display colour. The colour palette ranges from white through greys, blues, greens, yellows, reds, and purples with increasing probabilities. White (transparent) is used for the lowest four probability values to support follow-up by enhancing the effects of overlying model results

with inputs maps. Modelling results outline areas that are considered to offer higher chances of hosting mineralization and are an effective way to screen and compare targets over a large area.

Modelling results effectively outline many of the known productive areas including the Halfmile Lake, Stratamat, Heath Steele, Wedge, Murray Brook, Brunswick No.12, and Brunswick No. 6 deposits. Also of note are the stratigraphically influenced favourable horizons extending south for the Brunswick No.12 deposit. These trends are consistent with the geological models of the area.

One factor taken into account when interpreting results is the influence of missing data sets. Missing data sets decrease the confidence of modelling results because there is no evidence to either support or preclude the presence of some geological condition. Some areas outside existing airborne and bedrock mapping surveys show up as anomalous potential areas due only to favourable geochemical responses. These anomalies are an artifact of missing data sets rather than a reflection of camp-scale mineral potential. The model results were designed to be pessimistic in the assessment of mineral potential so that there would be more errors of omission than errors of commission.

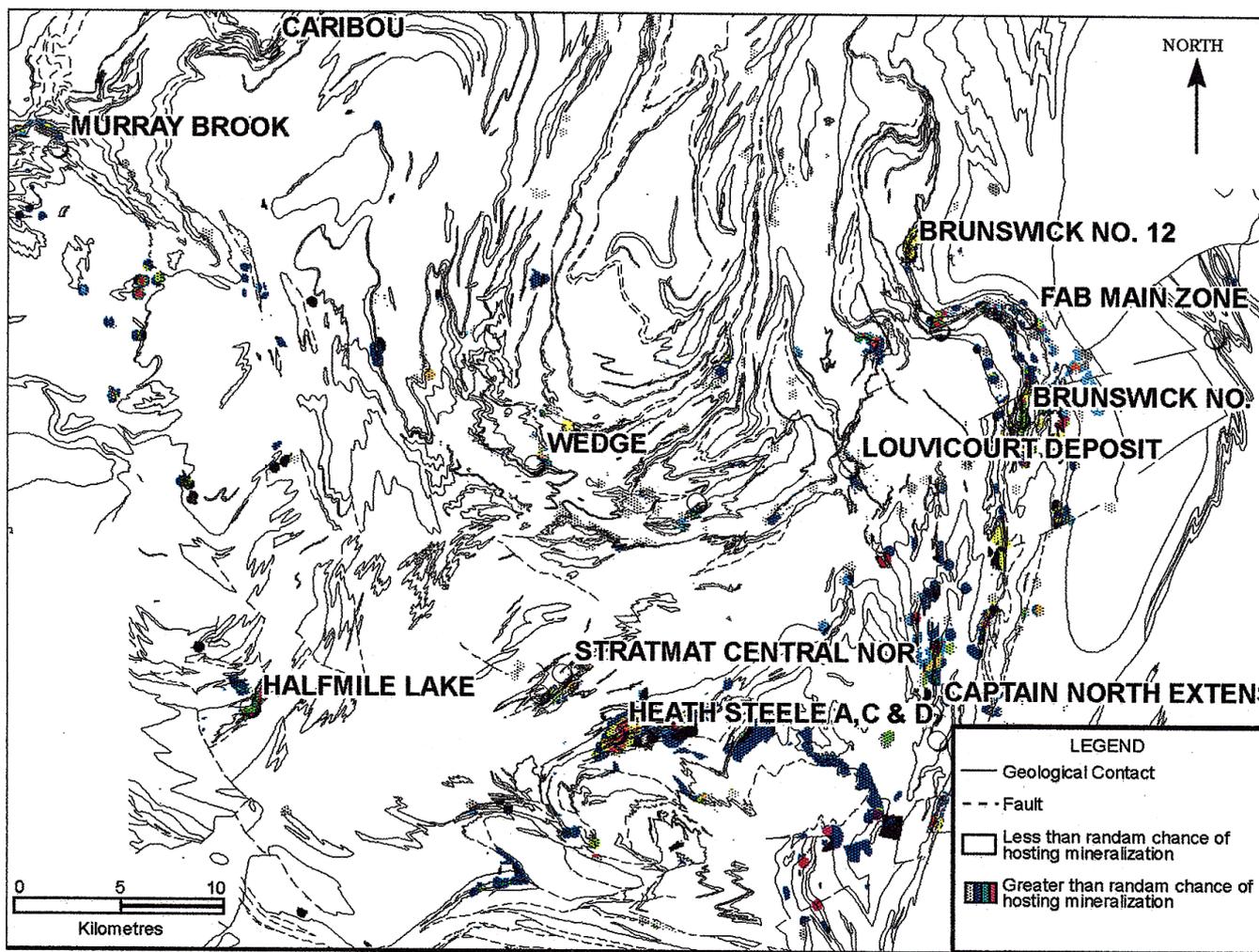


Figure 6: Target potential map of the Bathurst mining camp indicating the relative probability of an area to host mineralization.

GIS MAPPING AND QUERYING

Target models were initially followed up by importing modelling results back into the GIS environment where model input maps and the original exploration data were overlaid with positive model responses. Additional masks were overlaid to direct follow-up to areas that were unstaked. From the GIS, additional information was queried to provide further details about anomalous survey measurements. The ability of GIS to integrate and manage graphical and tabular information allowed for the quick assessment of modelling results.

TARGET REPORT

With the assistance of GIS mapping and querying tools, target reports were generated that summarized original exploration survey results in high potential areas. Target reports included a map of the area and a short summary correlating the underlying survey information with the modelling results (Figure 7). The target report served two important functions. First, it was used by geologists to verify that results reflect an expert conclusion. Should discrepancies arise between expert opinion

and modelling results, the inference network is checked for a logic error and if necessary altered and the model rerun. The Bathurst expert system model was rerun three times before it achieved satisfactory results. The second function of the target report was to put modelling results back into a context more easily communicated to other explorationists.

Consistent with the modelling objectives, only the areas of high mineral potential which were unstaked were selected for follow-up. From the model, 10 target reports were generated and forwarded for detailed compilation. In one of the high potential areas, TGS1 (Figure 7), modelling highlighted an area on a productive horizon with favourable magnetic, and electromagnetic properties that are proximal to anomalous soil survey results. This area represents a classic data integration target with the coincidence of many favourable and complementary survey results. Notwithstanding the long exploration history of the camp, the target was not tested and was on open ground. Another type of favourable target developed through modelling had moderate to low mineral potential but was proximal to additional supporting evidence. This type of adjacency association is not detected by the model unless interpreted input features are assigned a distance-related decay buffer with decreasing probability values. Each target report takes about two hours to complete and when finished is forwarded to a project geologist for more detailed and time consuming follow-up compilation and assessment.

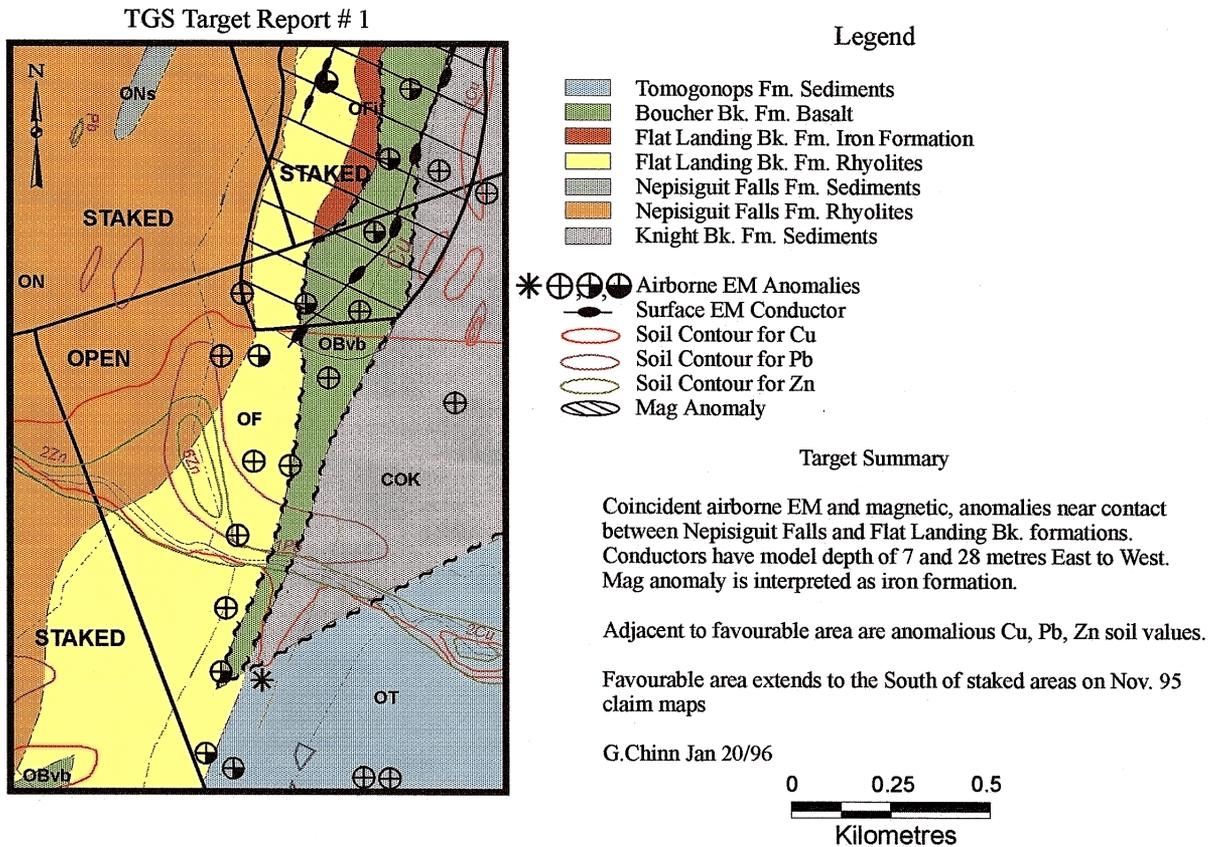


Figure 7: Example of a target report based on modelling results and translated back into a geological context for easier understanding by explorationists.

PROJECT PROPOSAL

In spite of the growing number of digital data sets available for modelling, much of the information collected over the 45-year history of the Bathurst mining camp is not digital. The second phase of the follow-up process involves a detailed search of all historical work in targeted areas and was performed by an experienced project geologist. Part of the detailed work was to search through public and private sources for additional information that would either support or preclude developing a target into an exploration project. Detailed compilations typically took a day or two to complete and the recommendations were then used as a basis to stake ground and fund future exploration programs.

Of the ten targets that underwent detailed compilation two were recommended for immediate staking and resulted in the acquisition of 158 claims. After the release of the 1995 government AEM survey, three of the other target areas were staked as the new information added to their favourability. This evaluation of new data was done within hours of the AEM release.

THE TARGET MODELLING PROCESS

The process of implementing an expert system study can be subdivided into a number of procedural steps where each impacts the quality of modelling results. The first step is to capture an expert's data compilation process and define an accurate inference network. This includes reasonable estimates of prior probabilities and the association between evidence and hypothesis events. Before model inputs are created a database must be compiled that contains technical information stored in a spatially and logically queryable format. Model input maps defined by the inference network must be judiciously produced and incorporate both the interpretation of geological features as well as spatial decay buffers needed to accommodate adjacency associations. Creating and preparing model inputs is a task well suited to a GIS with a well-developed set of spatial query and analysis functions. To implement the model, an inference engine must be developed and programmed to accept both the inference network model and interpreted maps as inputs. Modelling results must be scrutinized to verify that they accurately reflect expert deductions. Adjustments in the inference network may be needed before satisfactory results are achieved. Target reports are made for selected areas of anomalous mineral potential and are based on information used in the model. They aid in detailed compilations that are performed by experienced geologists and include a search of non-digital historical work. Recommendations from detailed compilations are used to develop a target into an exploration project. As a whole, the target modelling process has been useful for focusing on areas that offer a higher chance of success early in the exploration process. It also helps to allocate the appropriate level of technical and professional resources for solving an exploration problem.

CONCLUSIONS

Expert-driven, fuzzy logic data integration techniques were used successfully in the Bathurst mining camp to prioritize ground and identify new exploration targets. The advantages of this style of knowledge-

based compilation and mineral potential mapping are numerous. The resulting mineral potential or favourability maps help establish exploration priorities and focus efforts by windowing out large areas of unfavourable ground. The inference networks themselves provide a vehicle to communicate the geological model and the relative importance of each geological data set to all participants in an exploration program. The system can also be used to evaluate the significance of new data and new ideas in the context of the exploration model.

Over the last three years Noranda Mining and Exploration has conducted twelve GES studies. The experience gained from these studies has led to the development of a successful modelling process. Past studies cover a variety of exploration targets ranging from regional style, grassroots plays to mature mining camps and cover several different deposit models. The 1995 Bathurst mining camp GES study benefited from the previous studies, and added new understanding to the modelling process. The modelling resulted in the staking of five new claim groups and set the stage for the rapid assessment of the AEM results after they were released. All targets are based on the coincidence or near coincidence of subtle anomalies that were not obvious in the original data sets but were verified by experienced explorationists.

Mineral potential mapping is becoming more popular in the exploration industry as a result of an increase in available digital data sets and advances in GIS software. The evolution of data integration techniques will be a dynamic process, drawing on past experiences to help refine and develop better inference engines, modelling parameters and modelling procedures. Noranda Mining and Exploration Inc. continues to use and develop expert-driven fuzzy logic data integration techniques as an exploration tool to aid in the screening of large and diverse data sets with the primary focus on target generation.

ACKNOWLEDGEMENTS

We would like to acknowledge some of the people who contributed towards the preparation of this paper. Namely, Lyndon Bradish for inviting us to publish this material and for his role in directing GIS/ES initiatives. David Gower for allowing and supporting GIS/ES development from the Bathurst exploration office. Members of Noranda's GIS committee who have worked through the design of numerous technical databases and data standards. Expert panel members for their cumulative knowledge which serves as the base for the whole process. Doug Coombs for capturing and managing data sets. And Daniel Pitre who added an artistic element to every map and figure produced for this paper.

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