Developing Models using GIS to Assess Geological and Economic Risk: An Example from Mineral Exploration in Oman for VMS Copper Gold Mineralisation.

Greg Partington
Kenex Pty Ltd, PO Box 2145, Marmion, WA 6020, Australia.

Abstract: It is important to understand the financial risk involved in any business venture and the current economic conditions make this even more critical. There are a variety of tools and techniques now available that when used with modern GIS and the mineral system concept allow sophisticated economic risk analysis to be carried out, including assessing uncertainty. A Weights of Evidence model for VMS Cu-Au mineralisation has been created for the northern ophiolite belt in Oman and this has been used in conjunction with economic modelling to target, prioritise and plan follow up exploration.

Keywords: VMS Cu-Au type mineralisation, Weights of Evidence, Oman, economic risk, mineral systems concept.

1 Introduction

The commercial world has just become tougher and understanding the financial risk involved in any business venture is even more crucial. This is especially the case for mineral exploration. Fortunately, there are a variety of tools and techniques now available that when used with modern GIS allow sophisticated economic risk analysis to be carried out, including assessing uncertainty (Kreuzer et al., 2007; Hronsky and Groves, 2008). The requirements and processes involved in this type of modelling and risk analysis are presented and examples from mineral exploration in Oman for VMS Cu-Au mineralisation are described that demonstrates the value of these techniques in a commercial context.

2 VMS Cu-Au Mineralisation in Oman

The Sohar Region in northern Oman has a history of copper mining in the volcanic rocks belonging to the Semail Ophiolite dating back to the Bronze Age (Figure 1). Mining and exploration companies have continued to operate in the region west of Sohar in modern times and these companies have discovered approximately 44 M tonnes of 1-2% Cu in three deposit groups including Lasail, Ghuzayn and Aarja (Figure 1). The type of volcanogenic massive sulphide deposit found in the Semail Ophiolite are believed to have formed around active hydrothermal vents and black smoker deposits on a mid-ocean ridge similar to the Mid-Atlantic Ridge today.

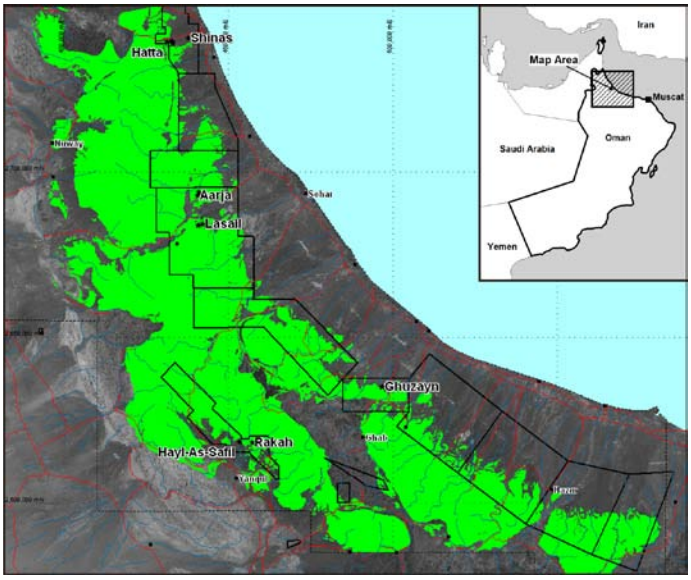

Figure 1. Location of mapped Ophiolite lithologies (in green) in relation to known mines (stars) and tenements (black polygons) in the northern Semail Ophiolite Belt.

More than 150 massive sulphide prospects have been discovered along the 500-km strike length of the Semail Ophiolite. Most are clustered in groups about 25-50 km apart, with many smaller sulphide occurrences in each group. The Geotimes Unit, a sequence of basaltic pillow lavas up to 1.5 km thick, hosts the main massive sulphide deposits, as well as gossans and Fe- and Mn-rich sediments. The morphology, ore types, mineralogy, and geochemistry of the deposits are similar to the deposits of Cyprus. However, the deposits in Oman in contrast are characterised by highly variable bulk compositions, and locally possess distinctive polymetallic ores, particularly gold. All major mines and most prospects, including Hatta, Lasail, Aarja, Bayda, Ghuzayn, Rakah, Hayl-As-Safil and adjoining ore bodies (Figure 1), are not only at the top of the Geotimes Unit or just within the Lasail Unit, but also less than several kilometres from either ultra high-level intrusive complexes or interpreted primary syn-volcanic faults associated with the Lasail phase of magmatism. The deposits are found in distinct graben-like structures and exhibit a strong structural control on mineralisation, sub-parallel to the regional sheeted dike swarm (i.e., the spreading axis). These deposits are spatially related to volcanic centres that had high associated heat flow and hydrothermal fluid discharge focused through key structural zones marked by altered and demagnetised rocks.

3 The Mineral Systems Approach

The mineral system concept (e.g., Wyborn et al., 1994) has been used in this study to assess the prospectivity of the study area and develop predictive maps for use in Spatial Data Modelling. Predictive maps for possible sources of metals come from the rocks that are part of the upper crustal sequence and more importantly rocks that were close to the ancient seafloor at the time mineralisation was forming. These lithologies have been mapped in the study area and used to create predictive maps for sources of heat and metals. The source fluids and metals within a mineral system have to be able to migrate in a focussed way to a site of deposition for economic quantities of metals to be present. The main fluid pathways that are important in this case are provided by syn-volcanic faults and mapped alteration. The presence of hydrothermal fluids is also confirmed by the presence of magnetic lows along some of the early faults. VMS Cu-Au mineralisation forms when metal rich hydrothermal fluids meet cooler water or water-rich rocks or sediments. Consequently, the main regional control (trap) on mineralisation is the paleo seafloor. This can be mapped from geological information, including the presence of pillow basalt, presence of seafloor sediment, presence of iron and manganese in sediment and presence of sulphide alteration.

The efficiency of the processes controlling the deposition of the metals of interest in a mineral system is critical to the grade and continuity of economic mineralisation in any ore deposit. Many of the controls on metal grade are also directly and indirectly related to the lithological and structural traps present as well as fluid chemistry and physics. The geological mapping in the study area is not detailed enough to allow an assessment of sulphide distribution or type and intensity of alteration present. Consequently, the best evidence for the efficiency of metal distribution comes from geochemical anomalism for gold, copper and zinc in rock and drill samples. There is also evidence that some of the mines are associated with magnetite and pyrrhotite alteration and should consequently be associated with magnetic highs. If present these would be a direct measure of the scale of mineralisation.

4 Prospectivity Modelling

Weights of Evidence modelling requires the creation of a variety of predictive maps for a particular deposit, based on the relevant mineral system model. These predictive maps are then statistically analysed using training data to test their predictive capacity, which allows the calculation of a spatial correlation value or weight (e.g., Bonham-Carter, 1994; Partington and Sale, 2004). In this case, the training data were drawn from mineral deposit locations for hard rock VMS Cu-Au mineralisation, including Hatta, Lasail, Aarja, Bayda, Ghuzayn, Rakah, and Hayl-As-Safil deposits. The predictive maps are then combined using the weights to calculate the probability of undiscovered mineral resources over a regular grid (e.g., Bonham-Carter 1994).

The Weights of Evidence model was created using predictive maps that represent all stages of the mineral system model (Table 1). The predictive maps for the model were chosen as having the best regional coverage, a significant spatial association with the mineral system model being considered and where possible not to duplicate predictive map patterns. The predictive maps listed in Table 1 were added after the map values for each cell were weighted by their W+ and W- spatial correlation values (Table 1). The model was developed using Arc-SDM software through Spatial Analyst in ArcGIS 9.2 (Sawatzky et al., 2008).

Map	Variable	W+	W-
Volcanic and syn-volcanic lithologies.	Source	1.95	-2.42
VMS mineral occurrence clustering.	Source	3.48	-2.61
Syn volcanic faults.	Transport	2.25	-1.85
Bends along syn-volcanic faults.	Transport	2.84	-1.49
Lithological contacts that map the presence of the ancient seafloor.	Trap	2.63	-1.48
Alteration mapped by magnetite destruction in volcanic lithologies.	Trap	2.75	-1.89
Gossan outcrops.	Trap	4.30	-1.93
Areas of high magnetic contrast.	Deposition	1.44	-0.70
Areas with anomalous copper values.	Deposition	2.35	-0.97

Table 1. Predictive maps used in the model with weights.

5 Results

The resulting prospectivity model comprises a raster grid containing the intersection of all of the input maps as a single integer raster. Each row of the raster attribute table contains a unique row of input map values, the number of training points, area in unit cells, sum of weights, posterior logit, posterior probability, and the measures of uncertainty. Importantly, the raster grid can be mapped by any of the fields in the attribute table, giving important information on the data influencing the result and missing information. This type of analysis usually cannot be done with other Spatial Data Modelling techniques like Fuzzy Logic or Neural Network Systems. The final stage of the modelling involved reclassifying the model grid to define high priority exploration targets for VMS Cu-Au mineralisation. This was done by using the prior probability as lower cut-off and the post probability values calculated for the economic mines in the region as an upper threshold. The prospectivity model identified 79 targets above the upper threshold in the study area. Nine of the targets are historic mines or current operations and seventy of the targets are at the prospect level of exploration. The targets in the study area range in probability values from the first ranked at 1.0 to 0.55, with 70 of the 79 targets having similar probability values to the main mines. Twenty of the targets are historic mineral occurrences or mines and the remaining fifty nine targets are new.

Various measures to test the conditional independence assumption were made, confirming that conditional dependence is an issue in the model. Most geological datasets and geochemical data sets have some form of interrelationship that may lead to an over emphasis of prospective areas. Consequently, the posterior probabilities in the model used should be thought of as relative rankings rather than actual probabilities of finding an ore body. The predictive capability of the model was also tested statistically by creating efficiency curves of the post probability map grid from the modelling with the training data and all VMS copper-gold mineral occurrences in the study area; 40 of which were not used in the initial modelling. The curve for the training data in this model gave a Success Rate value of 99.8% and the curve for the mineral occurrence data gave an Efficiency of Prediction value of 98.7%. Both measures confirm that the model has a very high predictive efficiency that is statistically valid.

6 Economic Modelling

The prospectivity modelling carried out over the study area provides a measure of the geological potential, but does not take into account financial cost and return on any exploration investment; consequently the economic risk of exploring is unknown. It is possible to calculate the exploration risk by combining the geological probability of success with the cost of exploration and reward from development (e.g., Kreuzer et al., 2007). This can be done for each target defined by the prospectivity modelling or other targeting methodology to develop a district wide exploration risk profile for each target. The probability of geological success has been calculated by the Weights of Evidence modelling, the probability of discovering chosen tonnes and grade can be calculated from grade tonnage curves and cost and revenue data can be derived from historic information updated for current costs and metal prices. The exploration risk can be calculated by multiplying the cost of exploration and development by the probability of failure and subtracting this from the NPV value of the project times the probability of success (Kreuzer et al., 2007). This allows the identification of the highly prospective targets that have the best returns in an exploration portfolio.

All the geological targets defined by the modelling have positive NPVs at a US$5,000 per tonne copper price and 65 of the target areas have a positive NPV at a US$2,000 per tonne copper price. The simulation of the NPV values provides information on the chance of each target achieving a positive NPV, with 69 of the 79 targets having better than an 80% chance of a NPV greater than zero. This analysis confirms that VMS copper-gold mineralisation remains an attractive economic target for exploration in Oman.

7 Conclusions

Spatial data modelling techniques, where individual predictor themes of geology geochemistry and geophysical data are combined into a single predictive map, are particularly useful when targeting VMS Cu-Au mineralisation in Oman. Geological data have proved to be fundamental predictors of mineral occurrences in all predictive maps and the model developed to date. An understanding of the structure and temporal development of the geology of an area is critical, especially at a prospect scale. The benefits of carrying out this type of analysis include effective data compilation, QC of digital data, understanding of critical geological factors to be used in follow-up exploration, ranking of prospects, prioritising exploration, exploration budgeting and management, understanding of risk and cost reduction.

The Weights of Evidence technique is particularly useful for exploration, especially as it is possible to derive the data and weights that contribute to any area with high probabilities from the predictive map theme. This allows the exploration manager to identify those geological, geochemical or geophysical data themes that are the best predictors of mineralisation. More importantly it allows the identification of missing data in areas of lower probabilities that if collected could increase the prospectivity of the area. The Weight of Evidence technique needs to be combined with economic factors to allow a complete understanding of exploration risk to be measured. This allows targets with differing geology, amounts of metal and economic factors to be compared and prioritised. The work in Oman confirms the potential for new discoveries in the region, which at the lower copper prices still make attractive exploration targets.

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