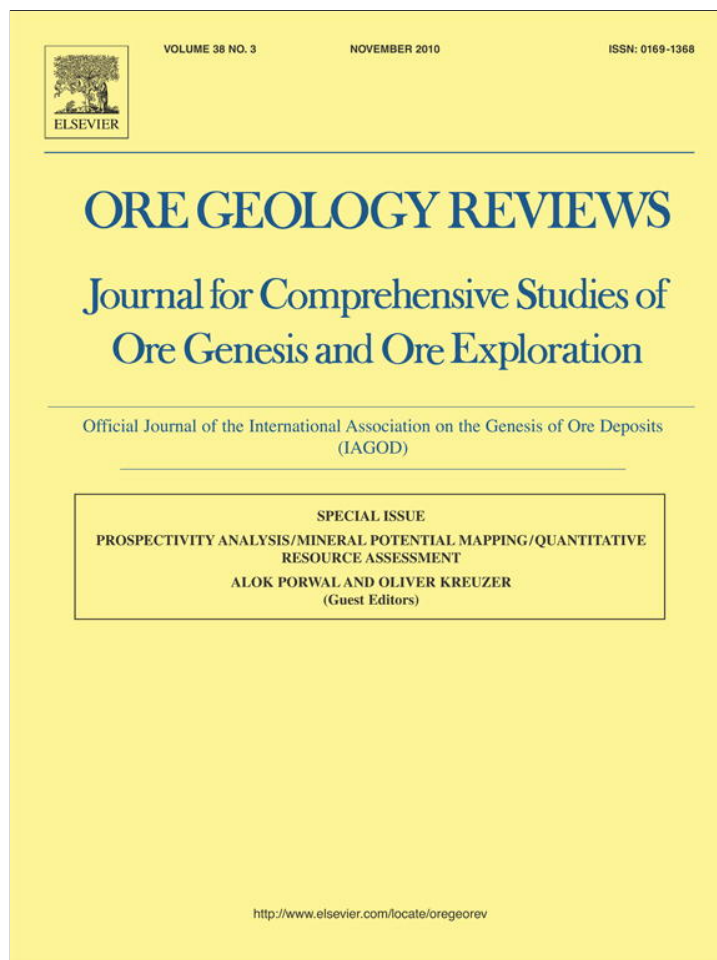


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# Developing models using GIS to assess geological and economic risk: An example from VMS copper gold mineral exploration in Oman

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## ABSTRACT

It is important to understand the financial risk involved in any business venture and recent economic conditions make this even more critical. There are a variety of tools and techniques 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 copper–gold mineralisation was created for the northern part of the Semail Ophiolite Belt in Oman and this has been used in conjunction with economic modelling to target, prioritise and plan follow-up exploration. Individual predictor themes of geology, geochemistry and geophysical data were combined into a single predictive map for VMS copper–gold mineralisation. The immediate benefits of carrying out this type of analysis include effective data compilation, quality control 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 prospectivity model identified 79 targets above an upper threshold in the study area. Nine of the targets are known historic mines or current operations, 11 of the targets are known undeveloped prospects and 59 of the targets are new unexplored prospects. The prospectivity model was not only used to target, but also used to plan new exploration programs to collect missing data that could add the most value to developing the target. Economic factors were developed for each of the targets identified by the modelling to allow a more complete understanding of the exploration risk. This allows targets with differing geology, amounts of metal and economic factors to be compared, ranked and prioritised. An exploration risk value was calculated by combining the geological probability values with the economic parameters so that positive exploration risk values were considered to be potential investment targets whereas targets with negative risk values were considered being more of a gamble. There are twenty-six targets in the study area with positive exploration risk values, which not only confirm the study areas' prospectivity, but also economic potential. The work in Oman confirms the potential for new discoveries in the region, which even at low copper prices still make attractive exploration targets.

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## 1. Introduction

Discovery rates in the last fifty years for all metals have been falling due to increased exploration maturity and reduced real commodity prices for all metals (Blain, 2000). This has been compounded by mergers and acquisitions reducing the number of experienced mineral exploration companies and consequent loss of experienced geologists from the industry. In addition many major mining companies are reducing in-house mineral exploration, preferring to depend on acquisitions to replace and grow their resources. Consequently, few significant new mineral resource discoveries have been made in the last decade, while the demand for metals continues to increase. Current mines are rapidly being depleted and there is already pressure for new discoveries to replace resources with the shortage of metals

likely to result in increased metal prices. There is a need for exploration companies to develop new innovative techniques that will allow them to survive and grow into the future.

A variety of tools and techniques are available that when used with computer based geographic information systems (GIS) allow mineral prospectivity and economic risk analysis to be carried out, including assessing uncertainty (e.g., Henley, 1997; Partington and Sale, 2004; Hronsky and Groves, 2008). The oil industry has been using similar techniques successfully for a number of years. More recently, the mineral exploration industry has taken this approach further and with the help of spatial data modelling in geographic information systems (GIS) it is now possible to measure the probability of exploration success in relation to project economics in an objective way. Spatial data modelling is a rapidly developing predictive technique that is increasingly being used in geology (e.g. Bonham-Carter et al. 1988; Agterberg et al. 1993; Bonham-Carter 1994; Raines, 1999; Partington 2000; Partington et al., 2002; Tangestani and Moore, 2003), other spatially based sciences such as

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Archaeology (Mensing et al., 2000) and by government organisations such as Crown Minerals; the New Zealand Department of Mines (Partington et al., 2001, 2002), the United States Geological Survey (Boleneus et al., 2001; Mihalasky, 2001) and the Canadian Geological Survey (Bonham-Carter et al., 1988) for resource assessment. There are a growing number of mineral exploration companies who now believe that by using such modern statistical techniques and state of the art ore deposit models it is possible to add the greatest value to mineral assets and increase the probability of discovery of new mineral resources (Bonham-Carter et al. 1988; Partington et al., 2001; Partington and Sale, 2004; Partington and Mustard, 2005; Archibald and Holden, 2009).

It is critical that all the factors involved in the processes being modelled are understood and replicated in the model for spatial data modelling techniques to be effective. A variety of predictive maps need to be created that replicate the mineral system being modelled. This means the final map not only integrates all the digital data available but also the knowledge of the process being modelled. Ore deposit models are at the core of most exploration target ranking schemes and include a complete array of process factors of ore-formation, products of the mineralisation process, characteristics of the regional and local geology and structure, inferences about the tectonic setting, and grade and tonnage data. However, the weakness of these models is that they tend to focus on the differences between deposit types rather than emphasise similarities that can be used as predictive variables when targeting. It has been recognised more recently that mineral deposits are the focal points of much larger systems of energy and mass flux, similar to those described for petroleum systems (Wyborn et al., 1994; Kreuzer et al., 2008; Hronsky and Groves, 2008). The mineral systems approach is essentially an adaptation of the petroleum systems approach. Even though mineral systems are generally thought of as being more diverse and complex than petroleum systems, the critical parameters of ore deposit formation can be reduced to those geological factors that control the generation and preservation of mineral deposits, and the processes that are involved in mobilising ore components from a source, transporting and accumulating them in more concentrated form and then preserving them throughout subsequent geological history. Ore deposit formation is precluded where a particular mineral system lacks one or more of these essential components. Being process-based, the application of the mineral systems approach is neither restricted to a particular geological setting nor limited to a specific ore deposit type; indeed, the flexibility of this approach allows for multiple ore deposit styles to be realised within a single mineral system, thereby acknowledging the inherent natural variability among ore bodies. Applied to mineral exploration, the mineral systems approach requires identification at various scales of the critical ore-forming processes and ingredients that can be mapped that characterise a particular mineral system. These diagnostic features can then be used as guides in area selection and exploration targeting.

The mineral system concept has been used in this study to assess the prospectivity of the study area and develop predictive maps for use in spatial data modelling and resultant exploration targeting (e.g., Wyborn et al., 1994). Predictive maps have been developed that describe possible source, transport, trap and metal deposition. The review has focussed on testing the validity of using the volcanogenic massive sulphide (VMS) copper–gold mineral system model for modelling the area and for helping exploration planning and prioritisation of follow-up exploration on the areas currently held under tenement. The requirements and processes involved in this type of modelling and risk analysis are presented and examples from mineral exploration in Oman for VMS copper–gold mineralisation are described that demonstrate the value of these techniques in a commercial context.

Oman has only recently developed its oil based resources and although copper has been mined from the region since biblical times, modern mining and exploration are new to the country. Consequent-

ly, unlike countries such as Australia, Canada and New Zealand; Oman lacks fundamental pre-competitive digital geological, geochemical and geophysical databases that allow spatial data modelling to be carried out. Therefore the first and most time consuming task in this study was the development of a digital database of geological, geochemical, geophysical and mineral occurrence data. Fortunately, although modern mineral exploration is at an early stage, the Semail Ophiolite Belt is one of the best studied geological environments in the world. The wealth of research information was compiled into a GIS, mainly from paper based sources, and integrated with paper based data from historic exploration. The resulting GIS covers an 18,780 km<sup>2</sup> area in the Sohar Region over the main historic mines in the Northern part of the Semail Ophiolite Belt (Fig. 1). The study area is constrained by the available geological and geophysical information, which limits the targeting of new areas for VMS copper–gold mineralisation in the south east of the Ophiolite Belt.

## 2. VMS copper–gold mineralisation in Oman

The Sohar Region has a history of copper mining in the volcanic rocks belonging to the Semail Ophiolite Belt dating back to the Bronze Age (Fig. 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 (Ministry of Petroleum and Minerals, 1995; Close and Gordon, 2003). The Semail Ophiolite Belt is a large intact thrust slice comprising 8–12 km of upper mantle peridotites and 4–7 km of oceanic crustal rocks (Fig. 2). Although the ophiolite appears to have been emplaced as one internally consistent thrust sheet, it was subsequently disrupted by various normal faults and out-of-sequence thrusts. Most of the mantle sequence is composed of tectonised harzburgite, which represents the residual mantle from partial melting of fertile primary spinel lherzolite at pressures in excess of 20 kbar. Early high-temperature orthopyroxene fabrics in the harzburgites probably represent mantle flow patterns that appear to map the presence of mantle diapirs below the ridge. Mantle diapirs represent the feeders for the ridge segment and magma chambers are presumably centred above the diapirs, which may control the distribution of hydrothermal systems that deposited VMS copper–gold mineralisation. The upper part of the Semail Ophiolite Belt consists of as much as 2 km of pillow lavas which, in northern Oman, have been subdivided into five main lava units, ranging from laterally persistent to localised (e.g. Fig. 2). These lavas and the contact with the lower sheeted dyke complex are the host to the VMS copper–gold mineralisation.

Volcanic-associated massive sulphide (VMS) deposits occur throughout the world and the geological time column in virtually every tectonic domain that has submarine seafloor volcanic activity as an important constituent. The type of VMS deposits found in the Semail Ophiolite Belt are believed to have formed around active hydrothermal vents and black smoker deposits on a spreading ridge in an island arc, supra-subduction setting (Hannington et al., 1998). VMS deposits are major sources of copper, zinc and lead and contain significant quantities of Au, Ag, Se and Cd, as well as minor amounts of other metals such as Co and Ni. As a group, VMS deposits consist of massive accumulations of sulphide minerals (more than 60% sulphide minerals) that occur in lens-like or tabular bodies parallel to the volcanic stratigraphy or bedding. They are usually underlain by a footwall stockwork of vein and stringer sulphide mineralisation and hydrothermal alteration (Fig. 3). They occur on the seafloor or fossil seafloor in ancient rocks and may occur in any sedimentary or volcanic rock type; however, the predominant hosts are intermediate to mafic volcanic rocks or fine-grained, clay-rich sediments. The host rocks surrounding the massive sulphides often have very strong hydrothermal alteration and are sometimes converted completely to chlorite, clay minerals and epidote. Mineralisation consists of iron

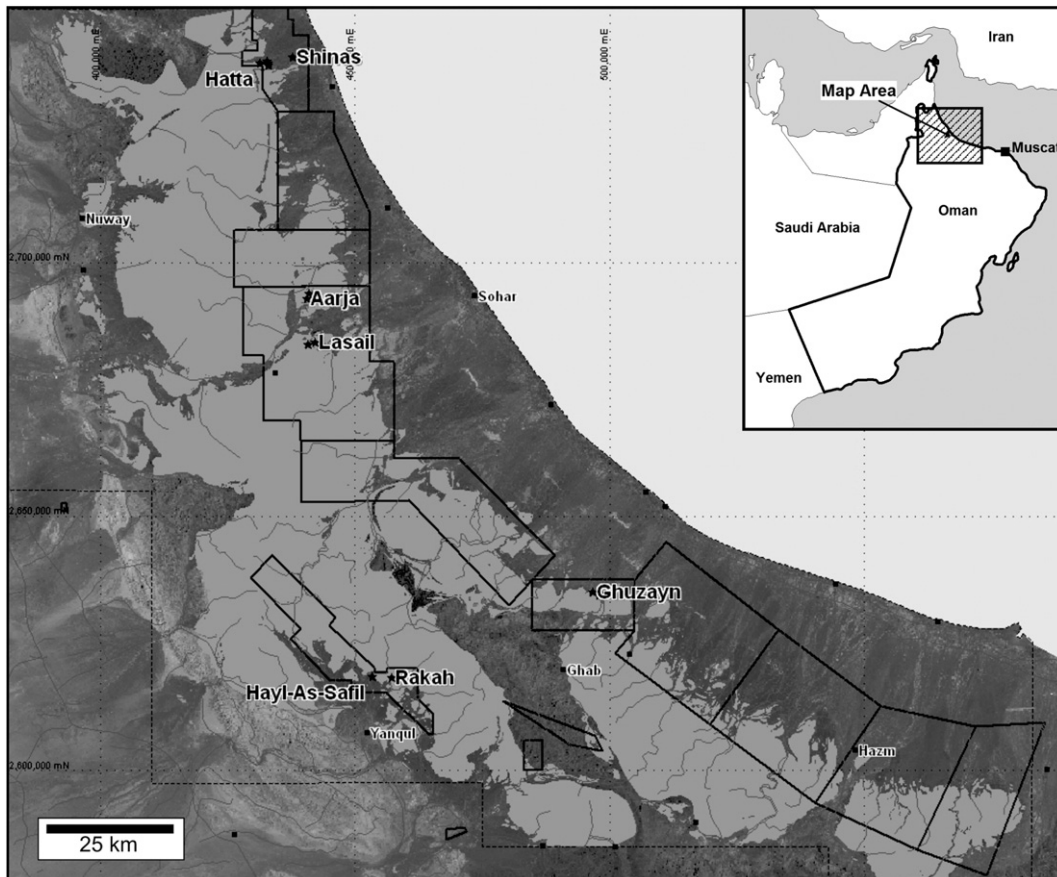


Fig. 1. Location of mapped Ophiolite lithologies (in light grey) in relation to known mines (stars) and tenements (black polygons) in the northern Semail Ophiolite Belt.

sulphide (pyrite, pyrrhotite) with chalcopyrite, sphalerite, and galena as the principal economic minerals. Anhydrite, barite and cherty silica are common gangue accessory minerals. Volcanic vent systems and

underlying dykes, stocks and sills are the sources of heat that are associated with massive sulphide systems and, as a consequence, form centres of exhalative or hydrothermal activity. Circulating waters

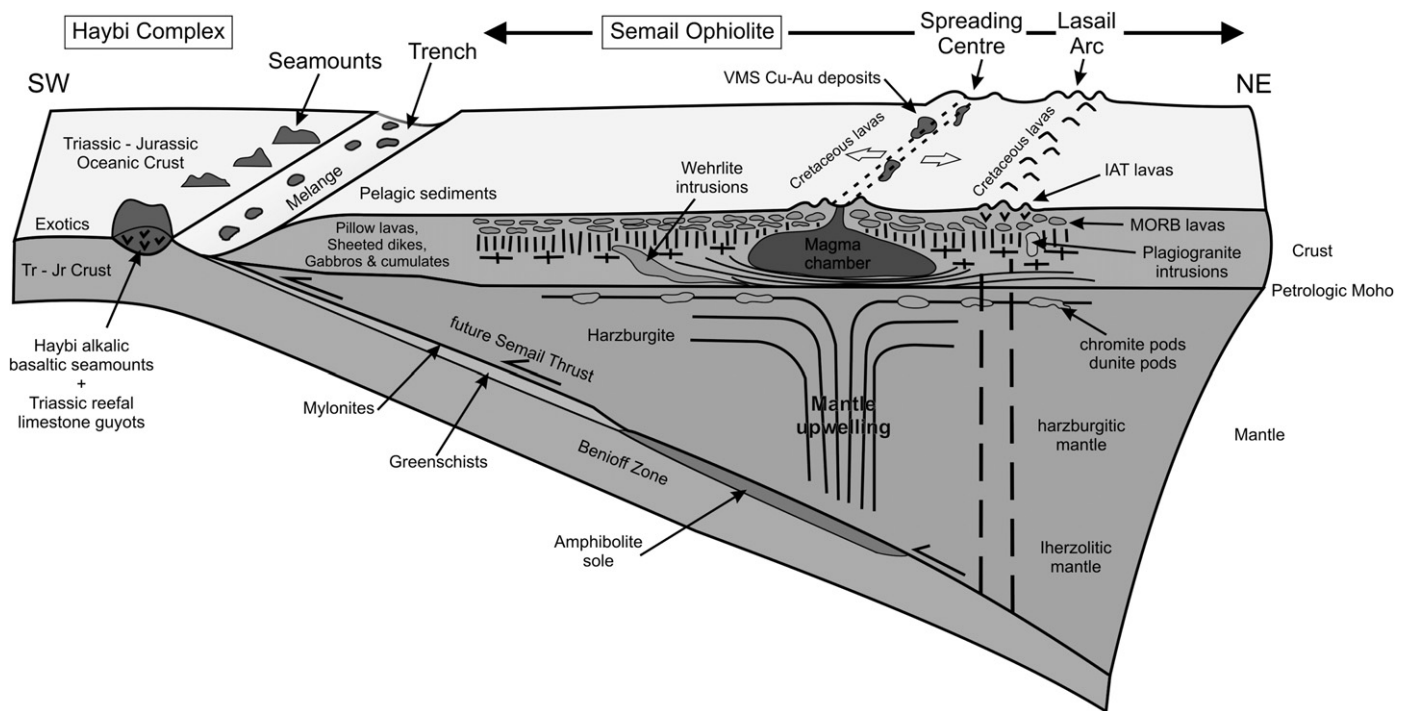


Fig. 2. Tectonic and geological settings of VMS copper-gold deposits in the Semail Ophiolite Belt.

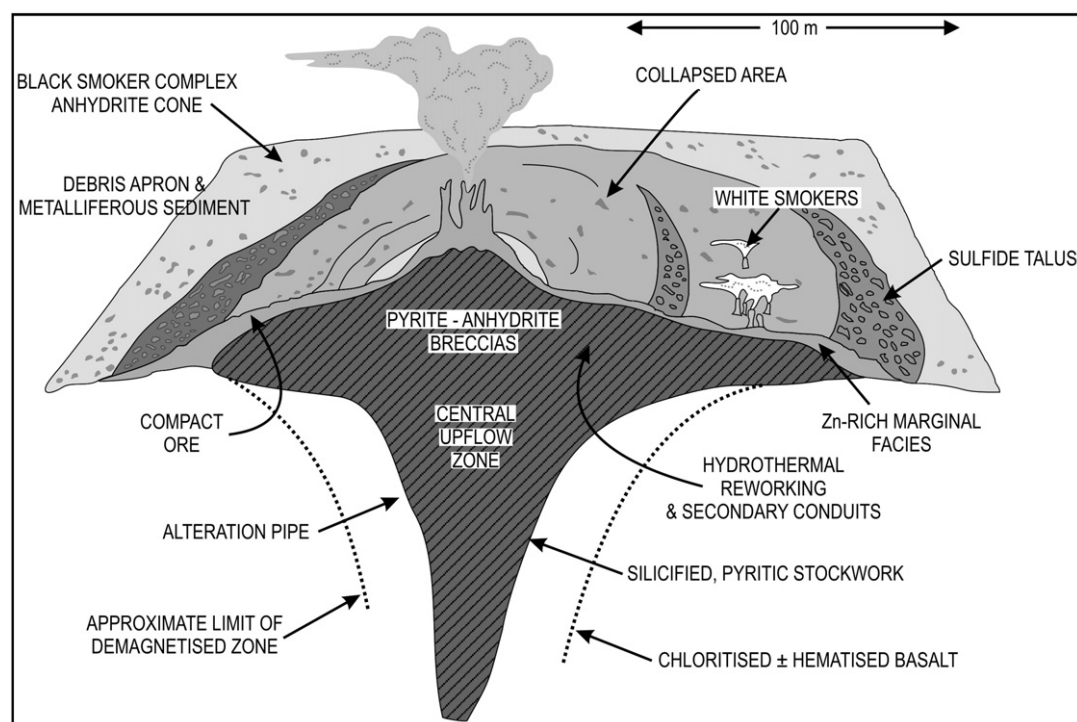


Fig. 3. Generalised section through a typical volcanogenic massive sulphide hydrothermal system.

carry dissolved metals through fractures in the volcanic rocks around these hydrothermal centres and at times deposit sulphide minerals in the fractures themselves. Heat drives hydrothermal fluids in an upward direction to the top of the volcanic sequence, where they are vented or exhaled. The immediate change in temperature as the fluids leave the hot rock makes it impossible for the dissolved metals to remain in solution, consequently the metals precipitate at the surface of the volcanic pile. It is very common for this process to happen at many different places at the same time and many deposits have the chance of forming at a single mineralised horizon or stratigraphic level. If the volcanic pile is under water, the exhaled fluids mix with seawater and the sulphides are deposited around the hydrothermal vent, which form layers of massive sulphide material. They may be moved and carried for some distance by ocean-floor currents or they may slump into ocean-floor depressions.

More than 150 VMS 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 (Fig. 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.

The geological, geophysical and geochemical data in the GIS were used to create a series of predictive maps that represent the four critical parts of the VMS mineral system. Predictive maps of 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 inferred by the presence of magnetic lows along some of the early faults. VMS copper–gold 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 available 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, which are a direct measure of the scale of mineralisation.

### 3. Weight of evidence spatial data analysis

Weights of evidence spatial data modelling of mineral prospectivity has become increasingly popular because of the data driven approach

and transparency of results compared to Fuzzy Logic and Neural Network techniques. The 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). In this case, the training data were drawn from mineral deposit locations for hard rock VMS copper–gold 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 spatial analysis was carried out using the Spatial Data Modeller extension developed for ESRI's ArcGIS 9.2 GIS software (Sawatzky et al., 2008). The spatial correlation (prior probability) of a feature can be calculated by using the relationship of the area covered by the data variable being tested and the number of training data points. This produces a  $W^+$  result when the feature is present and a  $W^-$  result when the feature is absent. A contrast value  $C$  is then calculated from the difference. The standard deviations of  $W$  ( $W_s$  and  $C_s$ ) are also calculated as part of the contrast calculation. This provides a Studentised value of the contrast (StudC), which is the ratio of the standard deviation of the contrast  $C_s$  to the contrast  $C$ . StudC gives an informal test of the hypothesis that  $C=0$  and as long as the ratio is relatively large, implying the contrast is large compared with the standard deviation, then the contrast is more likely to be real.

As a first step in the spatial correlation calculation, a 20 by 20 m study area grid was generated over the project area, (Fig. 1). The size of the grid was chosen to represent the minimum scale that the data should be used at. Mineral deposit locations in Oman for hard rock copper and gold mineralisation were extracted from the mineral occurrence database as a training data set. The prospect database was then validated, excluding all prospects with unrelated mineralisation. A training data set was then developed from the largest copper, gold and zinc mines and projects at feasibility level under development, consisting of 13 economically viable mines and undeveloped deposits. A unit cell grid of 0.5 km<sup>2</sup> was used for the model calculations, which represents the average area covered by VMS copper–gold deposits and for this study area gives a prior probability of 0.00037. Most of the data grids were reclassified to produce classified predictive maps, which in the case of continuous data like geochemical or geophysical data were further reclassified using the posterior probability values into binary predictive maps. Predictive maps like geology were reclassified into broad groups as multi-class predictive maps. A total of 57 predictive grids were developed that map the critical processes which are required to form VMS copper–gold mineralisation. Each of these grids was then tested to assess its predictive capacity. The study area for the modelling contains a permissive region with an 18,780 km<sup>2</sup> area, which was used to constrain predictive map creation and modelling. Outcrop in the study area is more than 55%, which means geological data continuity is not a problem, especially as the magnetic data can be used to interpret from outcropping geology under cover.

A preliminary spatial analysis was carried out using the age of the lithologies in the interpreted geology layer. All the training data occur in rocks with a narrow age range between 120 and 67 Ma in the Cretaceous, with the highest spatial correlation of 4.43 returned from mafic volcanics with a maximum age of 80 Ma. This age range conforms to the mineral system model for mineralisation in the Semail Ophiolite Belt, and means that rocks that are less than 67 Ma have a low prospectivity and for this study are considered to be cover.

### 3.1. Spatial analysis of predictive maps representing source mineral system processes

The attribute rock class in the geology map was used to calculate weights to assess potential host rock control on mineralisation in the

study area. Rock classes and ages were assigned a numerical value and reclassified according to the mineral system model. As predicted from the mineral system model, mafic volcanic lithologies have the best spatial association with the Geotimes unit most important with 46% of the training data occurring in this rock type, which gives a  $C$  value of 4.37 and a StudC value of 6.92. Other rock types spatially associated with mineralisation include gossan, and sheeted mafic dykes.

Syn-volcanic intrusives were subset from the geology database and these rocks include gabbro, ultramafic and diorite intrusives. The spatial relationship of those lithologies with mineralisation was tested by buffering around the individual rock polygons. Diorite intrusives have a significant spatial association with mineralisation with 92% of the training data occurring within 4600 m of diorite contacts. This gives a spatial correlation with the training data of 3.75 and a StudC value of 3.60. The diorite intrusions mapped in the study area may be the source of the metals or have acted as a heat engine driving hydrothermal systems that stripped metals from the surrounding basalts. A more detailed mapping of the distribution of diorite intrusions is recommended from historic mapping or from prospect scale mapping in the field. There is also a strong spatial relationship between rhyolite and andesite volcanics with mineralisation with a  $C$  value of 2.13 and a StudC value of 2.78. These rocks may represent volcanic equivalents of the diorites and may have also provided heat and, or, metals to the hydrothermal systems that formed the VMS gold–copper mineralisation.

### 3.2. Spatial analysis of predictive maps representing transport mineral system processes

Structural control on mineralisation is an important predictive variable for most mineral systems. Structure, especially early syn-volcanic faults appear to be especially important in localising mineralisation. The relationship between mineralisation and faulting was evaluated for all faults and for sub-sets of different fault ages. The mapped faults were first merged into single coherent fault zones and combined with faults interpreted from geophysical and topographic data. The minimum age of faulting was then determined from the youngest age of the rocks intersected by each fault and by their relationship to thrusts related to Nappe emplacement. The faults were then classified using their maximum age, style and orientation into early syn-volcanic structures, structures synchronous with thrusting during nappe emplacement and late structures. The early faults are interpreted to be related to tectonism during sea floor spreading and these structures were probably active at the time of VMS copper–gold mineralisation. Buffering was used to statistically determine the optimum distance of the greatest number of training data from a fault. A new GIS layer was created for all faults and a subset of faults according to age was coded with relevant attributes and processed to assess the spatial correlation of each layer with the training data. The spatial correlation of all faults to VMS copper–gold mineralisation is significant with a  $C$  value of 3.47 and a StudC value of 3.35 700 m from a fault plane as predicted by the mineral system model. This analysis was repeated for different ages of faults and using a 1100 m buffer from early faults improves the spatial correlation to a  $C$  value of 4.11 with a highly significant StudC value of 5.37. This analysis suggests that areas within 1100 m of early faults are the best predictors of mineralisation.

Researchers have suggested that many mineral deposits often occur in dilatational sites along faults, including fault jogs, fault splays, fault bends and fault intersections (e.g., McCaffrey et al., 1999). An interpretation of fault bends, jogs, intersections and splays was made to test this concept in the study area. A point file of each variable was created and buffered to test its spatial association with the training data. Fault bends give a significant spatial correlation with a  $C$  value of 4.33 and a StudC value of 6.44 within the 1500 m buffer area. This suggests that bends in early faults are good predictors of mineralisation at a regional scale, which may relate to areas of greater fluid flow due to enhanced dilation. These areas are also where graben structures

are likely to form, which are important traps for mineralisation. Many mineral deposits also occur in highly fractured parts of the Earth's crust, which enhances fluid flow. These areas are often dominated by a high density of faults or veins compared to areas with low fluid flow. Fault network systems provide ideal fluid pathways that would promote the required fluid rock interaction. A fault density predictive map was created by gridding the density of faults using the kernel method in ArcView Spatial Analyst with a search radius of 5800 m. Areas of high fault density show moderate correlations with the training data at a regional scale, with a *C* value of 2.50 and a StudC value of 4.68.

### 3.3. Spatial analysis of predictive maps representing metal deposition mineral system processes

VMS copper–gold deposits form on or just beneath the seafloor, consequently geological features that can be interpreted to have formed at this interface were mapped and their spatial association with mineralisation measured. Gossans are believed to have formed as oxygenated seawater interacted with the massive sulphide on the seafloor and also by later weathering. Gossans provide strong evidence for hydrothermal processes on the seafloor. A gossan map was created by digitising gossans attributed in the regional geology and at a prospect scale from mapping done during exploration. Buffers were then created around the gossan polygons to measure their spatial association with mineralisation. The spatial correlation of gossans with the training data is very high with buffers within 700 m of mapped gossans giving a *C* value of 6.24 and a StudC value of 8.13, confirming the importance of gossans as a predictor of mineralisation.

VMS copper–gold mineralisation is also associated with iron and manganese rich sediments that form from the hydrothermal fluids that vent onto the seafloor. These sediments are the source of the Umbers that have been mined historically in Oman. Iron and manganese rich siliceous sediments, called Umbers locally, were selected from the geological database and buffers were created around the polygons to measure their spatial association with mineralisation. The Umbers have a significant positive spatial correlation with the training data, with buffers within 1300 m of mapped iron rich sediment giving a *C* value of 3.51 and a StudC value of 4.36. The hydrothermal fluids that form these sediments often deposit silica, iron and manganese up to 2000 m away from where they vent so consequently the iron rich sediments are more likely to have a larger spatial association buffer area than gossans, which form closer to where the VMS copper gold mineralisation would be deposited. The presence of iron rich sediments and gossans are significant predictors of mineralisation at a local scale.

The presence of syn-volcanic sediments should provide regional scale evidence of seafloor processes even though most sediments will have formed a significant distance from the hydrothermal centres where VMS copper–gold mineralisation was formed. All syn-volcanic sediments were queried from the geological database and buffered in a similar way to the gossans and iron and manganese rich sediments. There is a significant positive spatial association with syn-volcanic sediments, with a *C* value of 3.00 and a StudC value of 3.92. However, only 15% of the training data is associated with this predictive variable which reduces its predictive value for exploration targeting.

An interpretive map was created of areas that were at or near the seafloor during the time the VMS copper–gold deposits were forming. The contacts between volcanic units where syn-volcanic sediments have been mapped were queried from the geological database. Buffers were created around each contact and a spatial analysis was carried out to test the spatial relationship of these contacts to the training data. Most of the training data (86%) lie within 900 m of interpreted contacts giving a *C* value of 4.12 and a StudC value of 6.32. This is a significant spatial correlation and can be used to target future geochemical sampling and geophysical acquisition. The geological

mapping in the GIS is not detailed enough to subdivide individual volcanic units. A more detailed mapping of the volcanic units would improve the palaeo-seafloor interpretive map.

Geochemistry provides the best direct measure of the efficiency of metal deposition within a mineral system. The predictive geochemical maps in the GIS were created based on the pathfinder elements described from the mineral system model. Copper, gold and zinc were focused on in this study as they relate directly to ore. Average grades of rock samples from all the mines and resources were added to the geochemical database along with drill assays to provide a better geochemical coverage. Summary statistics were used for rock and drill sample data for various elements to calculate anomalous populations. Predictive anomaly maps were then created by modelling the point values into grid maps using the nearest neighbourhood technique with a 500 m sphere of influence around each point value. The copper, gold and zinc rock chip geochemistry layers have good prospect scale correlations with the training data sets across the study area as expected. Copper was split into two anomalous populations as defined by anomalies over the main mines in the study area. Copper above a cut-off of 2.8% gave a significant spatial correlation with a *C* value of 3.32 and a StudC value of 5.47 and values between 2.8% Cu and 0.75% Cu gave a significant spatial correlation with a *C* value of 1.24 and a StudC value of 2.14. These anomalous thresholds are very high for VMS copper–gold mineral districts probably due to sampling being focussed only in mineralised areas. More rock sample data are required to more accurately define anomalous thresholds for copper for the study area. All samples above 0.1 ppm Au were defined as anomalous for the gold predictive map, which gave a *C* value of 2.91 and a StudC value of 2.78. The predictive map for zinc was developed using a threshold of 1200 ppm Zn and gave a *C* value of 3.78 and a StudC value of 4.83. Both the gold and zinc predictive maps have very similar map patterns to copper, which means that either they should all be combined for the model or only one predictive map will be used to reduce potential conditional dependence problems.

The widespread development of epidote–chlorite alteration is one of the most distinctive features associated with this type of VMS copper–gold mineralisation. The alteration destroys magnetite present in the mafic volcanic units and can be recognisable in airborne and ground magnetic surveys as magnetic lows that encompass and cross lithological boundaries. Some VMS copper–gold mineralisation is also associated with magnetite and, or, pyrrhotite alteration, which causes bulls eye magnetic highs. The magnetic data were reclassified into magnetic lows and magnetic highs with a similar intensity to the magnetic anomalies adjacent to known deposits. Both data sets gave poor spatial correlation values when used directly. However when buffers were used to test the broader spatial relationship with both data sets 92% of the training data lie within 500 m of magnetic lows giving a *C* value of 4.64 and a StudC value of 6.07. Magnetic highs by contrast gave a poor spatial correlation with the training data. Magnetic gradients provide a far better predictor of mineralisation with 62% of the training data occurring in areas of high magnetic gradient giving a *C* value of 2.14 and StudC value of 3.95. The magnetic data could be levelled for the rock type to allow more precise targeting. The spatial analysis of the geophysical data confirms that these data sets can be used as predictors of mineralisation at a regional and prospect scale. The spatial analysis suggests that anomalous raw high values of magnetic data are not good predictors of mineralisation. Those areas of steep gradient contrasts are more significant predictors of mineralisation, but none of the data sets tested contained all the training data. This means that the geophysical data sets contain a significant number of false anomalies if used on their own.

## 4. Weights of evidence spatial data modelling

The spatial analysis of the individual predictive maps is as important for exploration targeting as the spatial data modelling.

**Table 1**  
Summary of key exploration criteria derived from spatial correlation analysis for VMS copper–gold mineralisation in the study area.

Exploration variable	VMS copper–gold mineralisation in Oman
Lithology	Mafic and intermediate volcanic rocks and associated sediments of the Geotimes, Lasail and Alley units and syn-volcanic mafic and diorite intrusions.
Geochemistry	Has a strong spatial association with rock samples containing anomalous copper, gold, zinc, silver, iron and manganese. See text for anomaly levels.
Structure	Mineralisation is associated with syn-volcanic faults especially at fault bends.
Geophysics	Generally spatially associated with magnetic lows and steep magnetic gradients.
Mineralisation	There is a spatial association with areas that have copper, iron and manganese mineral occurrences.
Alteration	Spatially associated with epidote and chlorite alteration assemblages as defined by magnetic lows in the volcanic lithologies and gossans.

This is because the analysis provides a range of useful information for mineral exploration as it identifies the data that best predicts mineralisation and provides information on interrelationships between data sets that may improve exploration targeting. The analysis also highlights relationships that require further research. For example, what is the spatial and temporal relationship between the diorite intrusives mapped in the study area and VMS copper–gold mineralisation? Also, the quality of the spatial analysis and creation of the predictive maps constrain the final output of the modelling. The most important variables that can be mapped for predicting VMS copper–gold mineralisation in the Semail Ophiolite Belt are summarised in Table 1.

A weights of evidence spatial data model was created using the predictive maps that represent all stages of the mineral system model (Table 2). For example, geology and spatial association with syn-volcanic intrusives provides information on source; spatial association with faults and alteration maps provides information on migration and trap; and copper and gold geochemistry provides information on the efficiency of metal deposition. 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. For example, copper and zinc have similar map patterns as they are associated geochemically and using maps with similar map patterns introduces problems with conditional dependence to the resulting model. The copper predictive map was used in preference as it relates directly to economic potential. The predictive themes listed in Table 2 were added after the map values for each cell were weighted by their  $W^+$  and  $W^-$  spatial correlation values (Table 2). The models were developed using Arc-SDM software through Spatial Analyst in ArcGIS 9.2 (Sawatzky et al., 2008).

The modelling produces up to five grids that calculate the posterior probability (an estimate of geological potential) and various measures

**Table 2**  
Predictive maps used in the model with weights and spatial correlation values.

Map	Variable	$W^+$	$W^-$	C
Volcanic and syn-volcanic lithologies	Source	1.95	–2.42	4.37
VMS mineral occurrence clustering	Source	3.48	–2.61	6.09
Syn-volcanic faults	Transport	2.25	–1.85	4.11
Bends along syn-volcanic faults	Transport	2.84	–1.49	4.33
Lithological contacts that map the presence of the ancient seafloor	Trap	2.63	–1.48	4.12
Alteration mapped by magnetite destruction in volcanic lithologies	Trap	2.75	–1.89	4.64
Gossan outcrops	Trap	4.30	–1.93	6.24
Areas of high magnetic contrast	Deposition	1.44	–0.70	2.14
Areas with anomalous copper values	Deposition	2.35	–0.97	3.32

of uncertainty and a grid response map containing the intersection of all of the input themes in a single integer theme called a unique conditions grid. Each row of the attribute table contains a unique row of input map values. The variances of the weights and variance due to missing data are summed to give the total variance of the posterior probability in these maps. The spatial data modelling has successfully modelled the probability of VMS copper–gold mineralisation in the Northern Semail Ophiolite Belt for each 20 m grid cell in the study area (Fig. 4). The prospectivity map highlights the importance of geology, geochemical and alteration maps as predictors of mineralisation, with alteration, geology and structure particularly important. Some of the areas that are geochemically anomalous also have geophysical signatures and alteration that would be expected with this style of mineralisation. The spatial data model also maps accurately those areas that have similar predictive geological variables to the known VMS copper–gold deposits. All cells with post probability values above the prior probability of 0.00037 have at least one or more of the predictive variables present and therefore have an increased probability of hosting a deposit (Fig. 4).

The final stage of the modelling involved reclassifying the model grid to define high priority exploration targets for VMS copper–gold mineralisation. This was done by using the prior probability (0.00037) as lower cut-off and the post probability values calculated for the economic mines in the region (0.5) as an upper threshold (Fig. 4). The prospectivity model identified 79 targets above the upper threshold in the study area. Nine of the targets are historic mines or current operations, 11 of the targets are known undeveloped prospects and 59 of the targets are new unexplored prospects. 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, all of which have probability values of 1.0.

One of the advantages of using the weights of evidence technique is that you can map the unique combination of predictive map variables that have contributed to the post probability values for each cell (unique conditions grid). This means you can query any combination of map variables using the GIS, and more importantly for mineral exploration targeting you can identify those cells with different types of missing data. One of the criticisms of spatial data modelling is that you only find what you already know and often the cells with the highest probability values identify known deposits or prospects. However, the opportunity for mineral exploration often lies with those targets that have moderate to high post probability values and have missing data. For example no geochemistry has been collected or there is no detailed alteration mapping in the cell. If the missing data are collected and a positive result returned then the post probability values will be increased. Alternatively if a negative result is returned the post probability values will be decreased. Consequently, the weights of evidence spatial data model can not only be used to target new prospects, but also can be used to plan new exploration programs to collect the missing data that will add the most value to the target.

Many of the predictive maps used in the model are not independent and consequently have similar map patterns, for example the gossans occur where syn-volcanic sediments are present. Various measures to test the conditional dependence assumption were made, confirming that conditional dependence is an issue in the model (e.g. Agterberg and Cheng, 2002; Thiart et al., 2003). This means the probability values have been overestimated and therefore should not be used as the actual statistical probability of finding mineralisation in any particular cell. The problem of conditional dependence can be addressed by excluding dependent predictive maps, combining dependent predictive maps using Fuzzy Operators or by using logistic regression. However, reducing the number of predictive maps or combining predictive maps removes important information on missing data and consequently reduces the usefulness of the model for exploration targeting and especially planning. The probability values in this model provide an objective way of ranking an area's prospectivity and

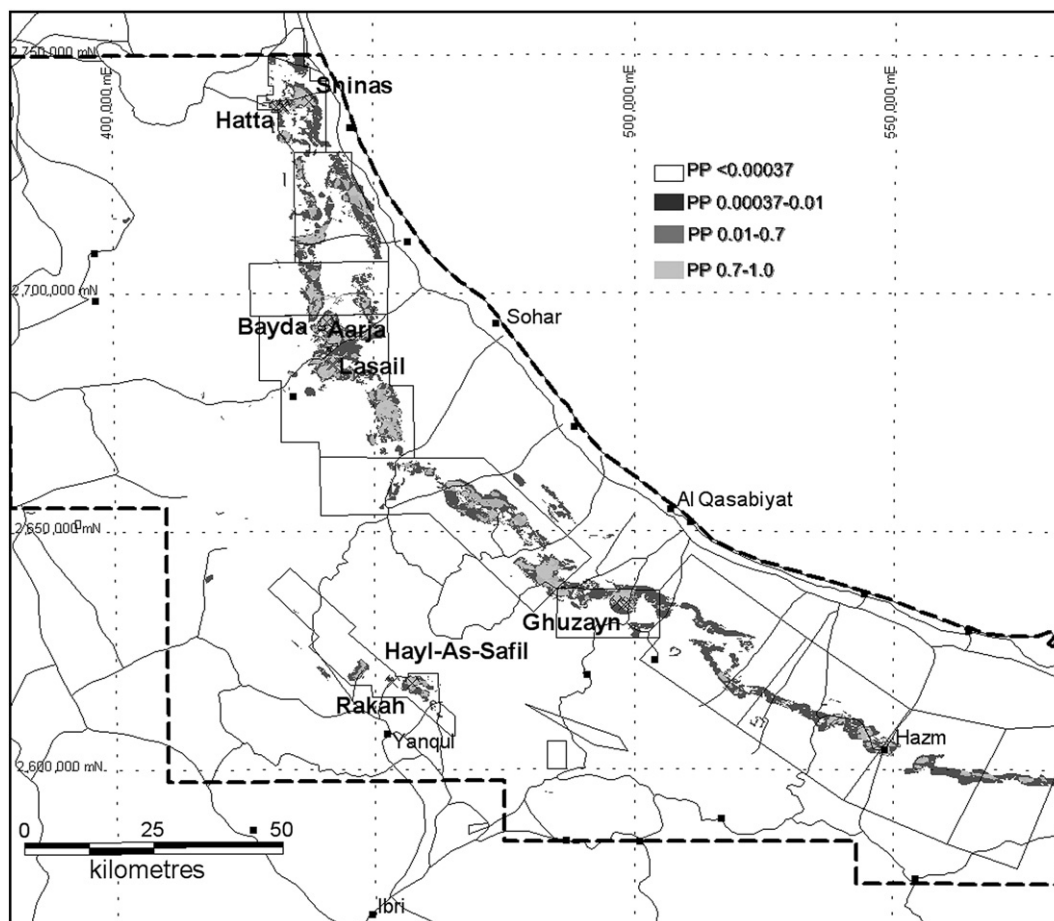


Fig. 4. Reclassified spatial data model mapping various levels of prospectivity in relation to known VMS copper–gold deposits.

highlight those areas where mineralisation may be present. These areas require field checking and more detailed geological data collected to allow drill targeting. It is also now possible to use the geological post probability values to rank other targeting methods, for example, geophysical targets defined by acquiring EM or gravity data or geochemical survey data.

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 (Sawatzky et al., 2008); 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.

##### 5. Economic modelling and exploration targeting

The spatial data modelling carried out over the study area allows an estimate of the geological potential of each cell to host VMS copper–gold mineralisation. The model does not assess the probability of an economic deposit being present nor take into account financial cost and return on any exploration investment; consequently the economic risk of exploring is unknown. It is possible to estimate the exploration risk by combining the geological probability of success with the probable cost of exploration and reward from development (e.g., Kreuzer et al., 2008). 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 a deposit with economic 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 potential net present value (NPV) of the project times the probability of success (Kreuzer et al., 2008). This allows the identification of the highly prospective targets that have the potential to offer the best returns in an exploration portfolio depending on other economic factors such as the size of the deposit, logistical factors, capital and operating costs.

A database of exploration targets was developed for the study area that lists the geological predictive variables and geological potential for each target. A list of economic parameters were also developed for each target, including potential target tonnes and grade ranges, metal prices, operating costs based on distance to the local smelter and whether a deposit is likely to be an open cut or underground operation, production rate, exploration costs based on logistics and likely capital costs. These were then combined with the geological probability values to estimate mine life, margin, NPV and the exploration risk for each target. An example of the results of this analysis is given in Table 3, including the known mines and a selection of new targets. The economic risk analysis assumes minimum, likely and maximum input variables which when simulated allow the calculation of the uncertainty of the outcome, which in this case is estimated NPV and exploration risk. The economic and geological data were then simulated using Monte Carlo simulation to calculate the chance of a positive NPV and positive exploration risk for each target (Table 3). The target areas can then be sorted and mapped according to positive and negative exploration risks (Table 3; Fig. 5).

**Table 3**

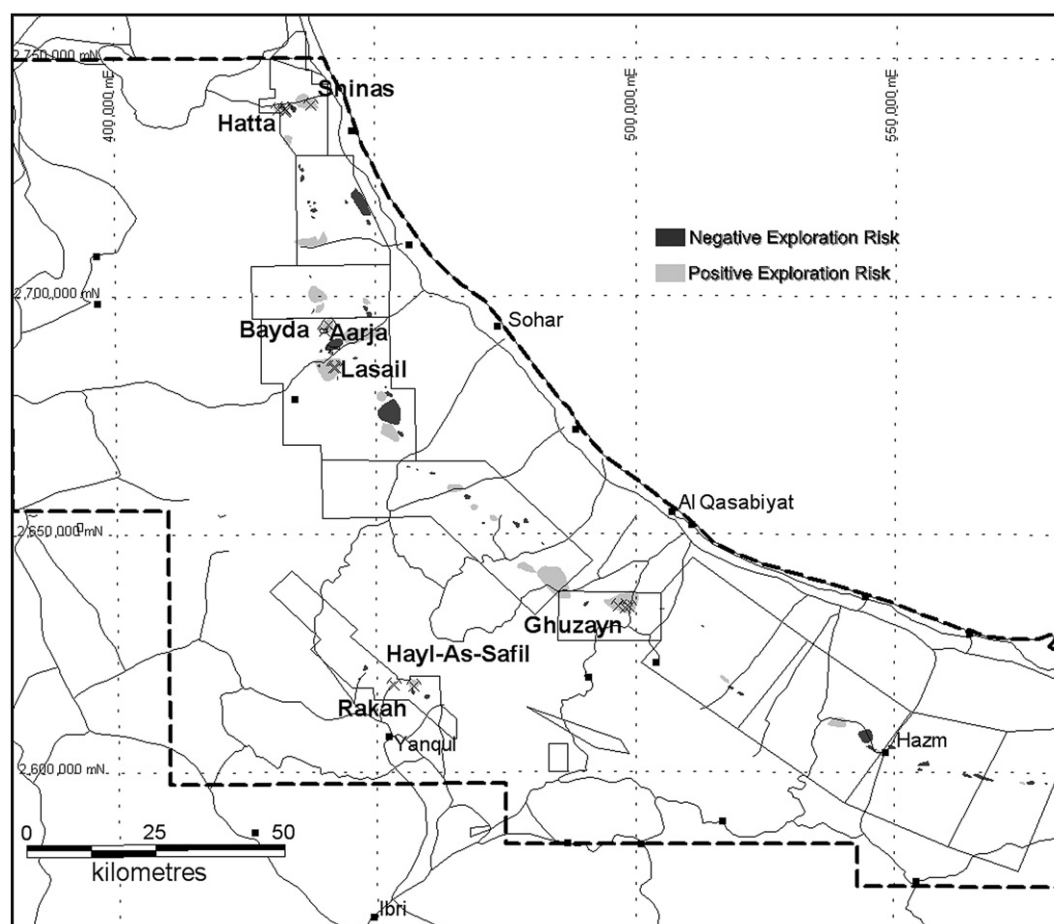
Example of ranked list of targets in the study area in relation to prospectivity ( $P(\text{ore})$ : post probability multiplied by the probability of achieving the desired tonnes and grade). The table is sorted by exploration risk and includes all the known mines (\*) and a selection of new and known prospects.

Name	Tonnes	Cu % (Target)	Au g/t (Target)	$P(\text{ore})$	NPV (\$US)	Ex risk (\$US)	Chance ex risk	Chance NPV
Lasail*	8,200,000	2.10	0.10	0.81	\$243	\$183	99.6%	99.8%
Ghuzayn 3*	9,100,000	1.60	0.20	0.81	\$136	\$97	91.1%	93.9%
Hatta*	1,500,000	3.50	1.00	0.81	\$118	\$82	99.9%	100.0%
New	7,000,000	1.60	0.50	0.01	\$164	\$68	0.0%	99.0%
Bayda*	1,000,000	3.10	1.20	0.81	\$65	\$39	97.6%	99.8%
Aarja*	3,200,000	1.50	0.20	0.81	\$59	\$35	86.1%	94.0%
Hyal-as-Safil*	8,000,000	1.30	0.60	0.45	\$152	\$27	79.7%	98.3%
New	7,000,000	1.60	0.50	0.35	\$179	\$17	69.5%	99.6%
New	7,000,000	1.60	0.50	0.35	\$185	\$17	70.0%	99.6%
Listwoenite	7,000,000	1.60	0.50	0.35	\$178	\$16	69.5%	99.5%
Hara Kilab	7,000,000	1.60	0.50	0.35	\$180	\$15	68.4%	99.6%
Wadi Fayd	7,000,000	1.60	0.50	0.35	\$178	\$14	67.1%	99.3%
New	7,000,000	1.60	0.50	0.35	\$166	\$12	63.8%	99.1%
Shinas*	2,000,000	2.10	0.10	0.81	\$25	\$7	57.0%	74.9%
Ghuzayn 2*	4,700,000	1.40	0.20	0.81	\$24	\$6	53.0%	66.1%

The economic data used in the spreadsheet are derived from a variety of sources including:

- Grade and tonnage data from a database of Troodos Style VMS deposits with a grade of 1.6% and 7,000,000 tonnes used for new targets.
- Metal prices for copper, gold and zinc were developed from the highest and lowest prices from the last three years with the likely price for copper of US\$5000 per tonne, for gold of US\$900 per ounce and for zinc of US\$2000 per tonne.

- Operating costs were developed from historic costs from the operating mines in the study area and varied according to the trucking distance to the local smelter.
- It was assumed that all targets would require a stand alone crushing and floatation processing plants and the most likely capital for these was US\$60 M.
- Exploration costs were developed from historic and current budget information and varied according to access constraints in the target area; those areas with greater slopes and at a greater elevation were



**Fig. 5.** Target areas from spatial modelling showing positive and negative exploration risks determined from economic modelling.

given higher exploration costs. The average exploration cost was US \$4 M to take a target to feasibility.

- Development feasibility costs were estimated from historic and current budget information and varied according to access constraints in the target area; those areas with greater slopes and at a greater elevation were allocated higher costs. The average development cost was US\$8 M to take a target to the decision to mine.
- A processing rate of 1,000,000 per annum was assumed in the simulation calculations.

All the geological targets defined by the modelling have positive NPVs at a US\$5000 per tonne copper price and 65 of the target areas have a positive NPV at a US\$2000 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 at lower copper prices.

As discussed above the exploration risk takes into account geological and economic risk factors by integrating the chance of failure with the cost of exploration and development and the chance of success with the probability of success. The geological probability was calculated using the model post probability values for each target and multiplying these by the probabilities for achieving the assumed grade and tonnage for each target's resource. The exploration risk value that is calculated should be considered as a measure of the risk of investment. Those exploration risk values that are positive can be considered to be a potential investment whereas those values that are negative are more of a gamble. The exploration risk values for each target are calculated in Table 3 and subdivided into investments and gambles in Fig. 5. There are twenty-six targets in the study area with positive exploration risk values, which not only confirm the study areas' prospectivity, but also economic potential. Because the exploration risk values use the post probability values from the weights of evidence modelling, they can be used to value each target, but should be used to rank those with the best comparative chance of economic success.

The economic risk analysis can now be used in scenario planning. For example, are the deposits worth developing at current copper prices or what is the minimum resource required to break even at current prices? The spreadsheet also allows the prioritisation of prospects as economic conditions change and should be used for exploration planning and business development decisions for future exploration and development.

## 6. 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 copper–gold 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, quality control 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 identi-

fication of missing data in areas of lower probabilities that if collected could increase the prospectivity of the area.

Targets developed using the weights of evidence technique need to be combined with economic factors to allow a more complete understanding of the exploration risk. 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 even at low copper prices still make attractive exploration targets.

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