EXPLORATION TARGETING USING GIS: MORE THAN A DIGITAL LIGHT TABLE

G A PARTINGTON[1]

INTRODUCTION

The use of computers in mineral exploration in the last twenty years has dramatically changed the way we carry out exploration targeting (e.g. Bonham-Carter, 1994; Bonham-Carter et al., 1988; Mihalasky, 2001; Rattenbury and Partington, 2003; Partington and Sale 2004; Partington 2009; Carranza, 2009). This is especially true in the last five years where computer and GPS technology has developed to the stage where it is possible to digitally locate, accurately store, visualise and manipulate geological data at the scale of a mineral system. These tasks are commonly carried out using a Geographic Information System (GIS), which has become as an important tool to a geologist as his hammer. The aim of this paper is to provide a brief review of the techniques available to explorers using GIS and discuss the advantages and problems associated with using GIS techniques for exploration targeting.

MINERAL SYSTEMS AND EXPLORATION MODELS

Ore deposit models are at the core of most exploration target ranking systems and usually 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 (Hronsky and Groves, 2008). If we are to use GIS technology to help us with exploration targeting it is critical that all ore forming factors are understood and mapped (e.g., Archibald and Holden, 2009). GIS provide us with the tools to process raw geological, geochemical and geophysical data to create a variety of predictive maps that can be combined to replicate any mineralising system. These predictive maps can then be statistically reviewed and combined in the GIS using spatial data modelling techniques to produce a map of targets that not only integrates all the digital data available but also the knowledge of the process being modelled.

It is recognised 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., 2007). The critical parameters of ore deposit formation need to 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. 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 to the creation of predictive maps in a GIS that help with area selection and exploration targeting using spatial data modelling (Kreuzer et al., 2007; Hronsky and Groves, 2008; Archibald and Holden, 2009).

GIS TARGETING METHODOLOGIES

Spatial Data Modelling

Spatial data modelling uses digital geological, geochemical, geophysical and remote sensing data to measure the prospectivity of a chosen region (e.g. Bonham-Carter, 1994; Carranza, 2009). The various data need to be converted into raster grids where the size of the grid is usually chosen to represent the minimum scale that the data should be used at. The data can then be combined in a variety of ways as the raster grids contain cells with numerical values representing the original data. Mineral deposit locations in the region of interest can also be used to statistically constrain the assessment. The original data grids are usually reclassified to produce predictive maps, which in the case of continuous

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data like geochemical or geophysical data can be further reclassified into binary predictive maps. Predictive maps of categorical data such as geology can be reclassified into broad groups as multi-class predictive maps. The predictive maps can then be combined using a variety of techniques that are usually expert defined or data driven (e.g. Bonham-Carter, 1994; Carranza, 2009). Spatial data modelling can be carried out in most GIS using add-on software such as the Spatial Data Modeller extension developed for ESRI's ArcGIS software by Sawatzky et al., 2008. A similar extension is also available for the Mapinfo GIS software.

One of the advantages of using spatial data modelling techniques in a GIS is that you can map the unique combination of predictive map variables that contribute to the prospectivity value for each cell of the derivative map grid (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. Often the opportunity for mineral exploration lies with those targets that have moderate to high post probability values but have missing data. For example no geochemistry has been collected or there is no detailed alteration mapping in the cell. If the missing data is collected then the post probability values will be increased. Consequently, spatial data models can not only be used to target new prospects, but also can be used to plan new exploration programs to collect missing data that will add the most value to the target.

Expert Systems

The simplest type of exploration targeting is where individual datasets are viewed together by the explorer and used to subjectively interpret areas of interest (e.g., Bonham-Carter, 1994; Carranza, 2009). More sophisticated spatial data modelling can also be carried out where maps, on which the chosen input variables are represented by a series of integer values, are combined together using arithmetic operators. This type of analysis takes no account of the relative importance of the variables being used or how each predictive map should be combined. Fuzzy Logic techniques address the problem of the relative importance of data being used and offer a variety of methods for combining data (e.g., Tangestani and Moore, 2003). The technique is a popular and easily understood method for combining exploration datasets using subjective judgment (Bonham-Carter, 1994; Carranza, 2009). Each exploration dataset to be used is converted into a classified predictive map that is assigned fuzzy membership functions (values between 0 and 1). These weightings express the degree of importance of the various map layers as predictors of the deposit type under consideration. The predictive maps are then combined by a variety of fuzzy operators (e.g. fuzzy AND, fuzzy OR, or fuzzy SUM) according to a scheme that may be represented with an inference network. The output from the Fuzzy Logic model is a map showing mineral favourability, combining the effects of the input predictive maps.

Data Driven Systems

Data driven systems such as Weights of Evidence, Logistic Regression and Neural Network techniques, in contrast use statistical spatial analysis of the map layers being used with a training data set to make less subjective decisions on how the map layers in any model are combined (e.g., Agterberg et al., 1993; Looney, 1997; Raines, 1999). In Weights of Evidence for example, the predictive maps created from the original data are statistically analyzed using training data to test their predictive capacity, which allows the calculation of a spatial correlation value or weight (e.g., Bonham-Carter, 1994; Carranza, 2009). These weights are then used to guide whether and how the predictive maps are combined. This statistical spatial analysis of the predictive maps is as important for exploration targeting as the spatial data modelling as the analysis provides information on the data that best predict mineralisation and provides information on interrelationships between data sets that may improve exploration planning.

CASE STUDIES

IOCG Prospectivity in Namibia and Zambia

An example of an expert system model is provided by Peters et al., 2009 where a prospectivity model for iron oxide-copper-gold (IOCG) mineralisation was developed for Namibia and Zambia. The model was based on the mineral systems approach and used the Fuzzy Logic modelling technique. The Weights of Evidence technique was not appropriate for this area because of a lack of documented mines to use as training IOCG sites for a data driven model. Weight of Evidence techniques have been used to create spatial data models of similar mineral systems in Australia, such as the Mt Isa region. This study aimed to incorporate the knowledge gained from these Australian models to constrain the Fuzzy Logic based Namibian and Zambian model.

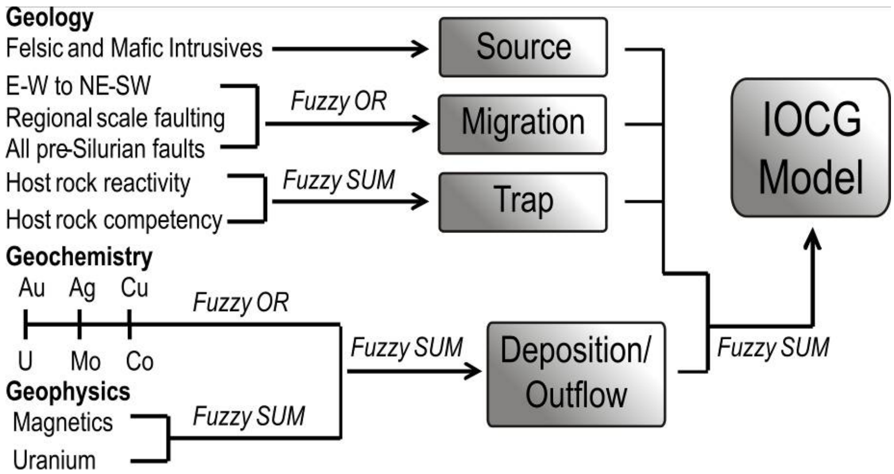

Figure 1. Fuzzy Logic decision tree shows how the predictive maps were combined using Fuzzy Logic operators to create the intermediary mineral systems maps and the final IOCG model for Namibia and Zambia.

The prospectivity model for IOCG mineralisation in Namibia and Zambia was created using data obtained from open file historical exploration reports, published geology maps at scales between 1:250,000 and 1:1,000,000, and multi-client, open file airborne geophysics. The mineralisation models that describe the probable styles of mineralisation present are reasonably well understood and regional geological data coverage is sufficient for the use of Fuzzy Logic spatial data modelling techniques. The model combined predictive maps that represent all stages of the mineral system model (Figure 1). Felsic and mafic intrusive rocks provide information on the fluid and metal source; E-W to NE-SW trending regional scale and pre-Silurian faults provide information on migration; host rock reactivity and competency provide information on trap zones; and geophysical and geochemical data provides information on metal deposition and outflow. The predictive maps for the model were created using similar spatial variables as those obtained from the Australian examples. The predictive maps were also weighted according to the importance of each variable in the mineralisation model and relative weightings for predictive maps were kept consistent with the Australian examples. The model was developed using Arc-SDM software through Spatial Analyst in ArcMap. The final predictive model consists of a grid response theme containing the intersection of all of the input predictive maps in a single prospectivity map. The modelling has identified a number of known IOCG occurrences including the Witvlei Copper deposit in Eastern Namibia (Figure 2), and the Dunrobin Gold Mine in Zambia, confirming the predictive capacity of the model. The model also identified a number of new targets with similar prospectivity values to the known mines. Scale differences in geology files between Namibia and Zambia resulted in broader zone definition in Zambia than Namibia.

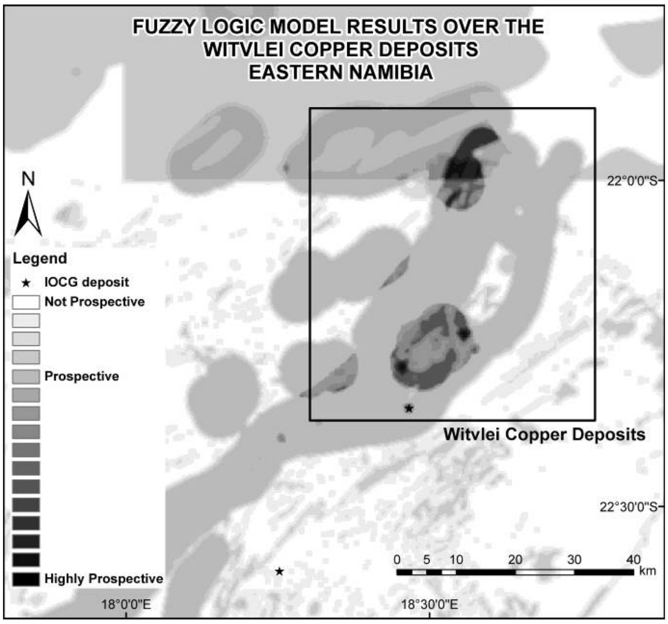

Figure 2. Prospectivity model results over the Witvlei Copper Deposit of Eastern Namibia.

VMS Copper in Oman

An example of spatial data modelling using a data driven approach is provided by Partington, in Press. The Sohar Region in Oman has a history of copper mining in the volcanic rocks belonging to the Semail Ophiolite Belt dating back to the Bronze Age. Mining and exploration companies have continued to operate in the region west of Sohar in modern times and discovered approximately 44 M tonnes of 1-2% Cu in three deposit groups including Lasail, Ghuzayn and Aarja. The type of volcanogenic massive sulphide deposit found in the Semail Ophiolite Belt 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 and the mineral system model for this type of mineral deposit is well understood.

Predictive maps were developed for possible sources of metals, which covered 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. 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 also identified by mapped alteration. The presence of hydrothermal fluids is also confirmed 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 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.

A Weights of Evidence spatial data model was created using the predictive maps described above 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 themes listed in Table 1 were added after the map values for each cell were weighted by their W+ and W- spatial correlation values. The model was developed using Arc-SDM software through Spatial Analyst in ArcMap.

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

Table 1. Predictive maps used in the model with weights and spatial correlation values.

The spatial data modelling created a map of the probability of VMS copper-gold mineralisation in the Northern Semail Ophiolite Belt for each 20m grid cell in the study area (Figure 3). The spatial analysis highlighted 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 probability map also maps those areas that have similar predictive geological variables to the known VMS copper-gold mines. 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 (Figure 3). The final stage of the model process involved reclassifying the model grid to define high priority exploration targets for VMS copper-gold mineralisation. This was done by using the prior probability as the 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 targets for exploration.

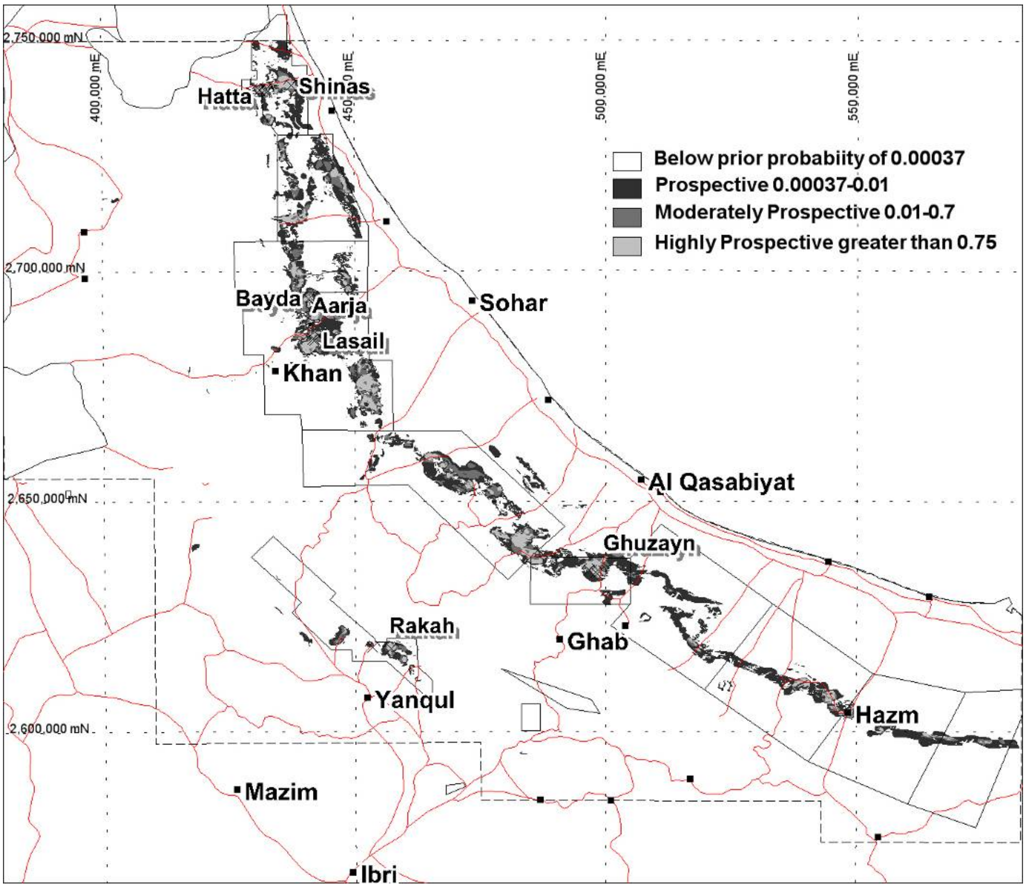

Figure 3. Reclassified spatial data model mapping various levels of prospectivity in relation to known VMS copper-gold deposits.

CONCLUSIONS

We now have the tools and techniques to use computers as an aid for targeting in mineral exploration, but several issues remain to be resolved before the use of GIS for mineral exploration targeting becomes effective and commonplace. The most important issue is that of training, as there appears to be a disconnect at the University level, with Geography departments rather than Geology departments controlling the teaching of GIS, which means graduate geologists are often not receiving appropriate training in the use of GIS to solve geological problems. Another problem with using GIS for mineral exploration targeting is data availability and data quality. In addition, most GIS only operate in two dimensions whereas the mineral systems targeted by mineral exploration are three dimensional. Consequently, we are now at the stage where computing power and modelling techniques have overtaken the availability of high quality 3D geological data and trained geologists to maximise their use.

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