EXPLORE
NUMBER 177 DECEMBER 2017
Newsletter for the Association of Applied Geochemists
www.appliedgeochemists.org

Quantitative Interpretation of Orientation Surveys

Chris Benn[1], Giancarlo A. Daroch[2], Martin Kral[2], Paul Lhotka[2] *[1]Chris Benn Consulting, 3424 West 1st Ave, Vancouver, V6R 1G7, BC, CANADA, CJBenn@gmail.com; [2]Capstone Mining Corp., 510 W Georgia St, #2100, Vancouver, BC, V6B 0M3, CANADA.*

https://doi.org/10.70499/YJVJ3537

Introduction

When exploring in new areas, preliminary field and laboratory investigations are accomplished by carrying out orientation surveys. These surveys determine: (a) the nature and extent of dispersion patterns related to mineralization, and (b) the distribution and behaviour of elements of potential interest in unmineralised areas.The parameter most often sought is the length (in the case of stream sediment sampling) or areal extent (in the case of soil sampling) of dispersion trails, as these can be related directly to the required sampling density. There are, however, problems with these quantities due to the erratic nature of geochemical data. The main problem is in deciding where the dispersion trail ends, that is, at which point do the anomalous samples become lost within the spread of background values. One or more threshold values are normally chosen to separate what is considered anomalous from what is considered background.

Orientation surveys have the potential for generating abundant data even though they comprise few samples. After analysing several sample types and/or several size fractions for many elements, it is easy to accumulate a lot of data. Common interpretation aids such as dispersion profiles and symbol plots will adequately display the data from most orientation surveys. However, it is difficult to quantify the differences seen on these diagrams. For example, one may be able to see that a particular sample type is performing better than another, but by how much? Quantifying these differences will help when balancing out the relevant factors and deciding on the most cost effective methods.

When interpreting orientation surveys a popular method of separating anomalous from background populations is to analyse the data on a probability plot and then separate the two, or more, populations by assuming that they follow a normal (Gaussian) or lognormal distribution (Sinclair 1976). The choice of the threshold(s) will not present any problems in the unlikely event that anomalous and background values are completely separated. Unfortunately overlapping populations are the norm. The more they overlap, the more difficult it is to establish sensible thresholds and hence determine dispersion distances. Stanley (2003) described a method of determining the effectiveness of any new exploration method using hypergeometric probability. The study reported here describes an additional approach acting on the suggestion by Stanley (2003) that an orientation survey allows the operator a method of deciding, *a priori*, which samples are anomalous and which are background. With an orientation survey, no assumption about the form of the statistical distribution need be made. Instead one only has to break the populations into the two, or more, groups, anomalous and background. There could be more than one background population if there are geochemically different bedrock units in the survey area. The difficulty lies in deciding how far away from a direct projection of mineralization to the surface a sample can be considered anomalous. A refinement on the above binary method is to use a threefold categorization of (1) highly anomalous, (2) anomalous, or (3) background, which provides a new "proximity indication".

The simplest and most direct way of displaying and comparing the anomalous and background samples, determined using dispersion profiles, is to construct a probability plots of each on the same diagram. If a particular element and sample type combination is working well, the different probability plots should be well separated. No statistical distribution assumption is made by using these plots; they are merely a convenient and familiar method of displaying the data distributions.

This methodology is demonstrated with two examples. The first is an orientation soil survey that tested several analytical techniques and size fractions over known mineralization in Chile, and the second a stream sediment orientation survey in Australia.

Example 1 – Sierra Amarilla area, III Region, Chile

Capstone Mining Corporation is exploring for base metal deposits in central Chile through an option agreement with Sociedad Quimica y Minera S.A. (SQM). Before starting surface sampling programs, an orientation survey was carried out over a small area of known oxide mineralization in order to determine the most appropriate sampling method and analytical technique. An orientation area at a prospect called Sierra Amarilla was selected that is located 50 km east of the city of Taltal in Region II, at a mean elevation of 1,800 m above sea level, with mostly gentle topography. The Pan-American Highway cuts through the centre of the block (Fig. 1). The region has a hyper-arid climate and is almost devoid of plant growth.

continued on page 5

Quantitative Interpretation of Orientation Surveys... *continued from page 1*

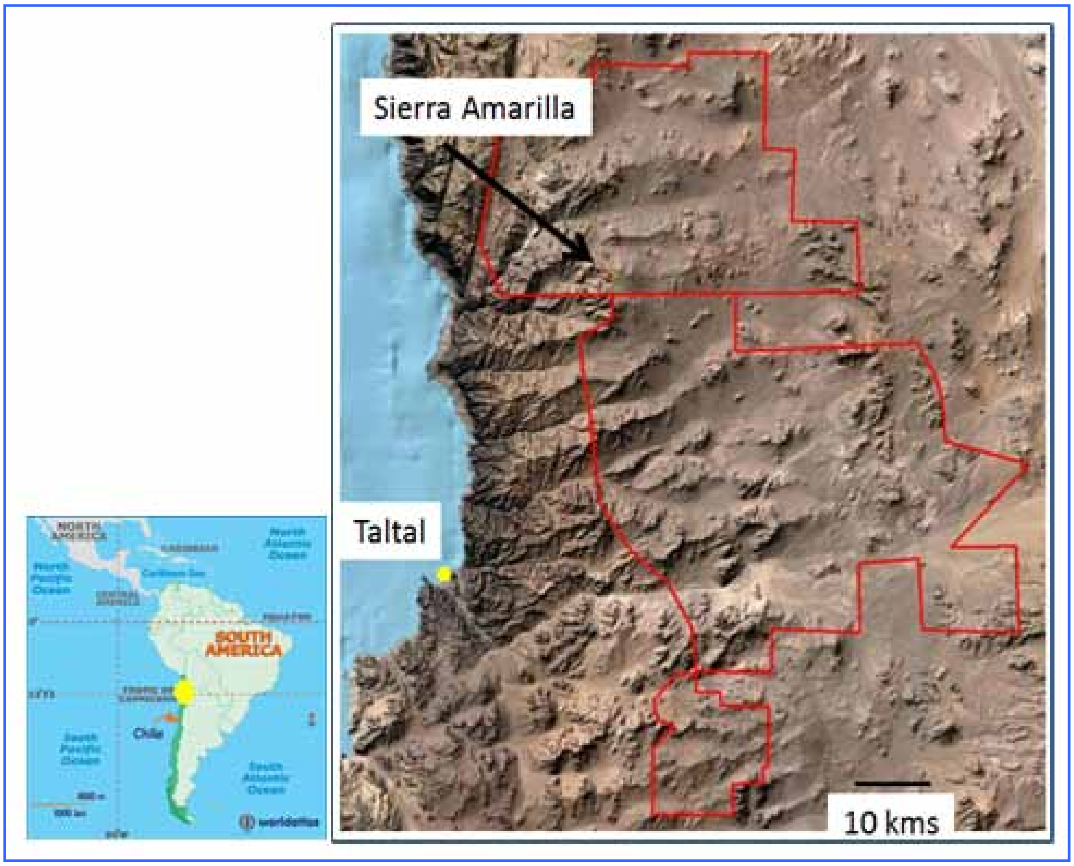
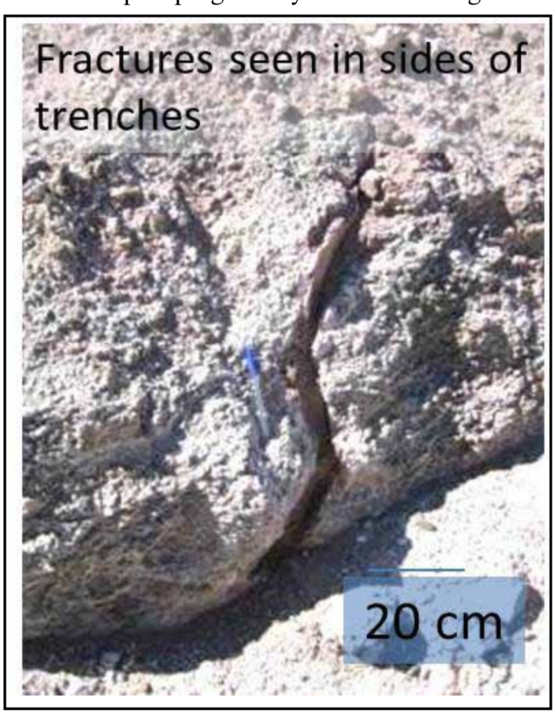


Figure 1. Location of the Sierra Amarilla orientation area, Chile.

Information from a number of trenches, shallow pits, and drillholes was used to outline a zone of manto-type oxide Cu mineralization hosted in andesites of the Cretaceous Aeropuerto Formation. Manto-type deposits are typically controlled by the permeability provided by faults, hydrothermal breccias, vesicular flow tops, and flow breccias (Sillitoe 2003). In addition to Cu, there are anomalous concentrations of Ag, Au, Zn and Pb (Tapia and Videla 2011) at the prospect. The area is covered by 5 to10 m of Tertiary gravels.

Previous work has shown that certain analytical techniques and sample types reveal geochemical anomalies at the surface of transported gravels in the Atacama region of Chile (Cameron *et al*. 2010). One possible mechanism for the formation of surface geochemical anomalies in the region is seismic pumping of groundwater from depth to the surface through the gravels. The pH of the groundwater is slightly alkaline and elements such as Mo and As can be transported as oxyanions. Support for the seismic pumping theory comes from significant seismic activity in the region and evidence of fault scarps and fractures that cut through the post mineral cover (Kelley *et al*. 2003). Recent fracturing with secondary Cu oxides forming part of the infill material can be seen in the sides of the trenches (Fig. 2a) and these could be possible conduits for the groundwater. These fractures also postdated a cemented layer of caliche developed in places within the pediment gravels (Fig. 2b).



2a

Figure 2. (a) Fractures cutting through surface material; (b) caliche developed on gravels that postdate mineralisation.

continued on page 6

Quantitative Interpretation of Orientation Surveys... *continued from page 5*

Although generally weak anomalies form at the surface, the anomaly to background contrasts can be improved by using selective leach extractions. The aim of the orientation study was to investigate the effectiveness of several surface sampling and analytical techniques in areas of transported gravel.

Three orientation lines were completed at a spacing of 150 m with samples collected every 10 m. These sampling lines were parallel to the trenches and care was taken to avoid contamination from these surface disturbances. Table 1 lists the types of samples collected at each site, and the type of analysis carried out.

Table 1. Types of Samples and Methods of Analysis (see Figure 3)

Sample	Collection Method	Analysis
A	Surface lag: 500 g of surface material sieved <2 mm, coarse retained	Pulverised and four acid "near-total" digestion method code (ALS) ME-MS61
B	Surface lag: 100 g split of <2 mm from above	Analysed by portable XRF
C	10 - 20 cm depth: thin brownish layer scraped away so reddish colour visible (due to Fe oxy-hydroxides), 1.5 kg of <2mm material collected.	Ionic Leach. Static sodium cyanide leach method code (ALS) ME-MS23. Preferentially attacks weakly adsorbed metal ions; metals associated with carbonate minerals and to some extent metals associated with amorphous Mn and Fe oxyhydroxides.

Figure 3. Methods for collecting samples A, B, and C.

continued on page 8

Quantitative Interpretation of Orientation Surveys... continued from page 6

Field duplicates were taken and good reproducibility was shown for all elements (RSD <15%) except for Au determined by Ionic Leach, which had a RSD of 47%. Results of the orientation sampling were plotted as dispersion profiles and these are useful for showing if there is a response along the orientation lines (Fig. 4).

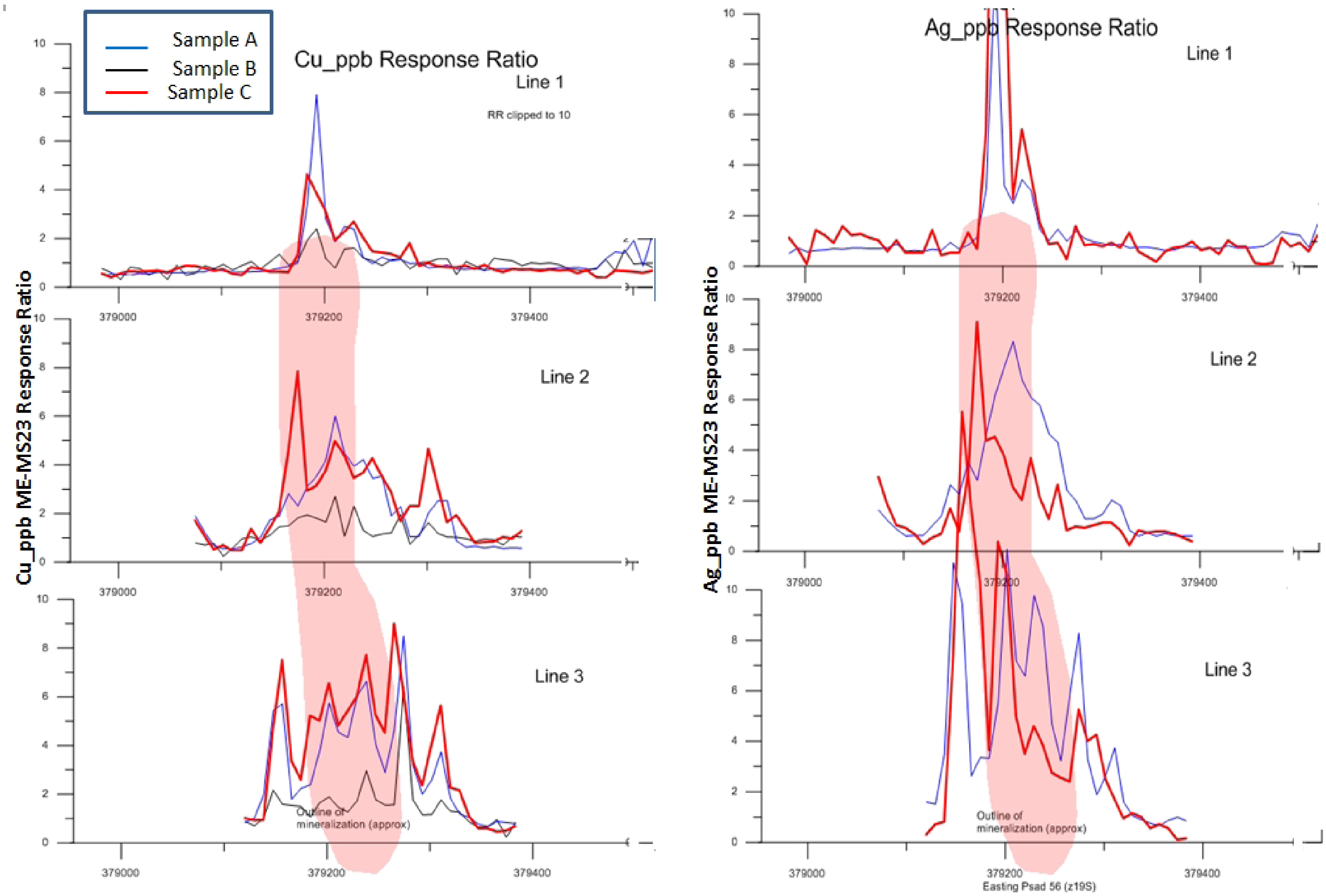


Figure 4. Dispersion Profiles for Cu and Ag for different types of samples

The outline of mineralization is shown in light red and the Y axis shows the response ratio which is the actual value divided by the first quartile. A positive response from the A (surface lag) and C (Ionic Leach) samples for Cu and Ag is apparent on all three lines, although it is difficult to determine which sample type is the best.

These dispersion profiles together with a projection of mineralization can assist in determining which samples are anomalous versus background. Figure 5 uses the profiles for Sample C to demonstrate that it is reasonably easy to distinguish between coincident samples overlying mineralization (red dots) versus flanking samples (more distal) from mineralization (green dots).

The simplest and most direct way of displaying and comparing this a priori classification of proximal mineralization and background samples is to draw probability plots for this classification for each element of interest on the same diagram.

If a particular element and sample type is suitable, then the three probability plots should show clear separation between data for sample sites coincident to mineralization that are higher than those flanking to mineralization and both higher than the background samples. There is no statistical distribution assumption made by these plots. It is only when a straight line is fitted to probability plots that there is an underlying assumption of normal or lognormal distribution. These plots can be used to measure the reliability of any given threshold for a particular element and sample type combination. Figure 6 is an example

continued on page 9

Quantitative Interpretation of Orientation Surveys... *continued from page 8*

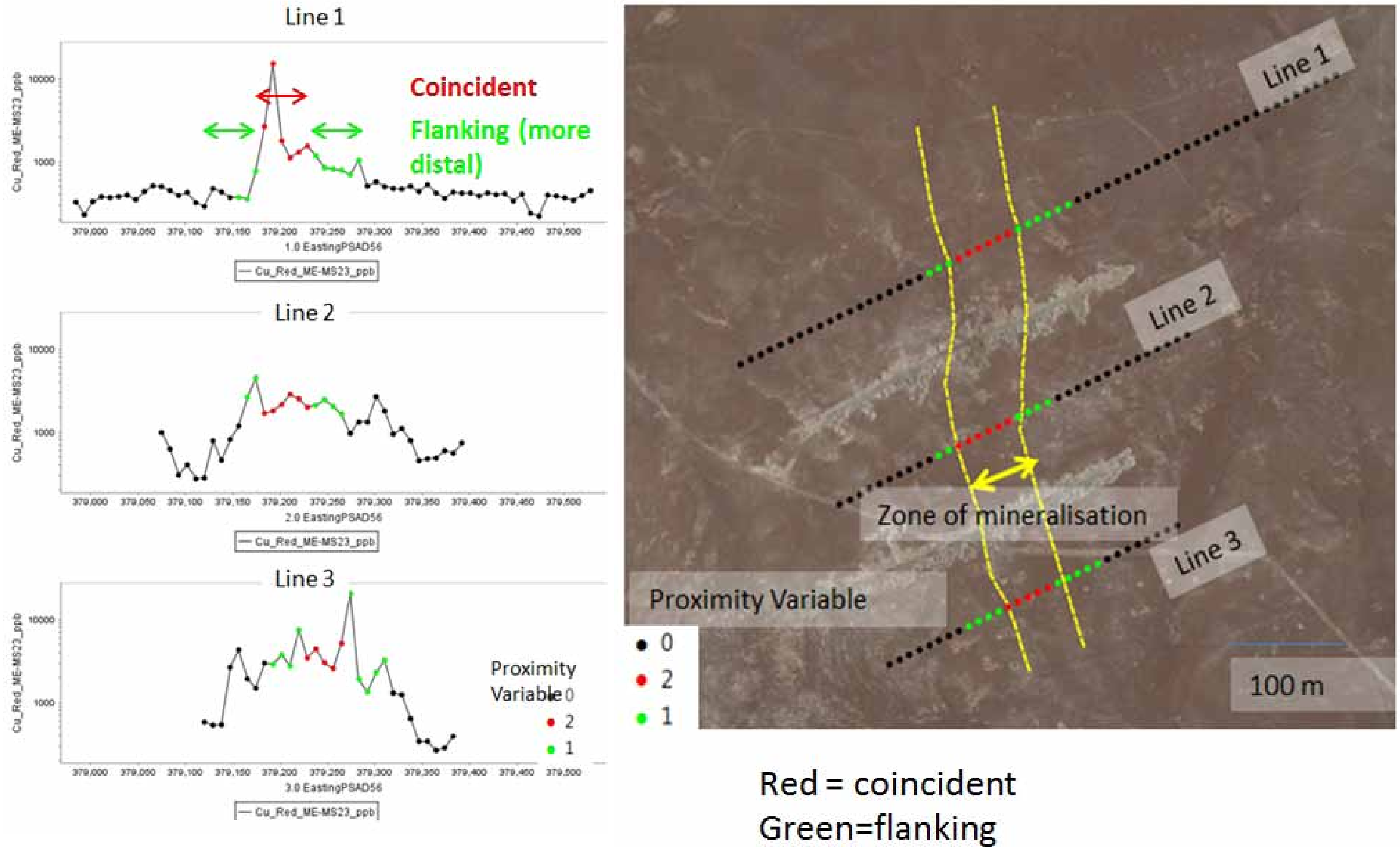


Figure 5. Profiles showing selection of samples as highly anomalous, anomalous, and background.

of probability plots for Cu content in Sample C (ionic leach analysis). Although the flanking and coincident samples are well separated from the background population, they are similar to each other suggesting little difference between the two. A probability plot for all the samples is also shown for reference.

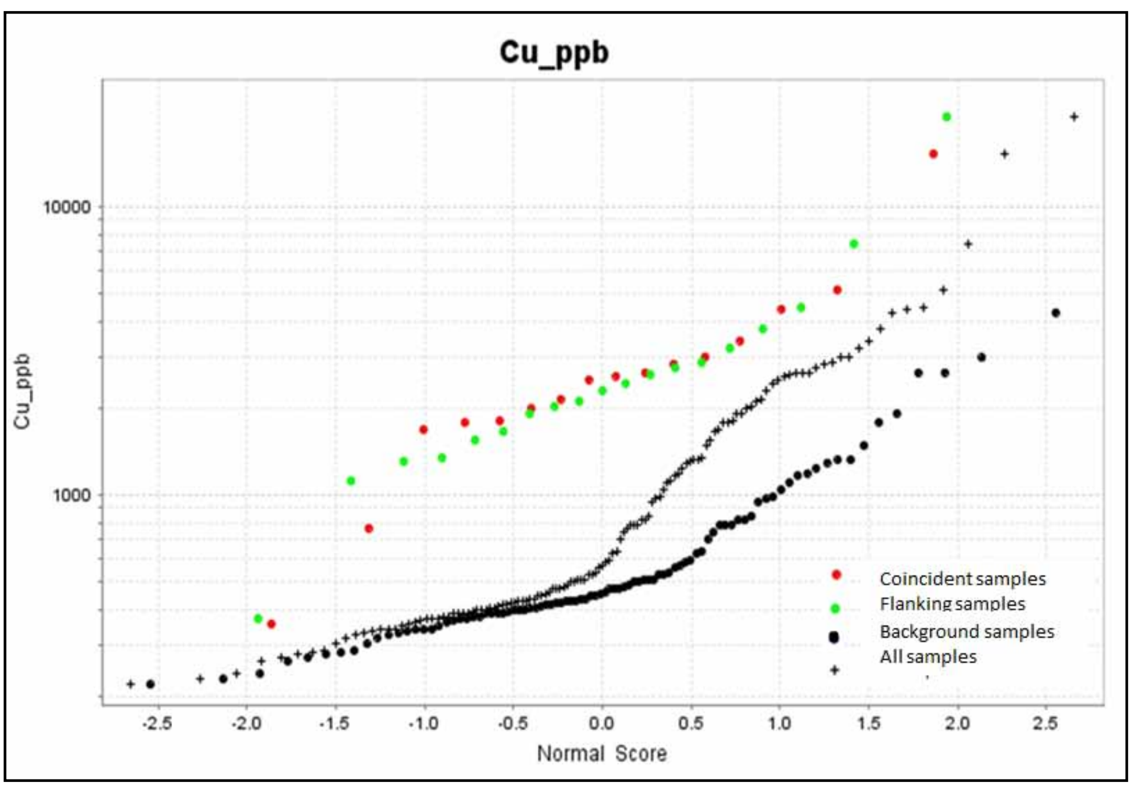


Figure 6.
Split probability plot for Sample C (ionic leach) showing the difference between coincident, flanking and background samples.

continued on page 10

Quantitative Interpretation of Orientation Surveys... *continued from page 9*

An additional feature of this type of plot is that one can measure the proportion of samples below the threshold (anomalies missed) and proportion of samples above the threshold (false anomalies). These probability plots require a subjective visual interpretation such as determining an inflection point between two different plot gradient segments. Hence, an overall measure of the separation revealed by these probability plots is needed. This can be achieved by correlating the data values with a proximity variable derived by ranking the samples using the a priori method just described. A numerical ranking system is required:

- 0 for background samples (off the dispersion tail);
- 1 for flanking samples (on the dispersion trail) but not directly over mineralisation; and,
- 2 for coincident samples close or over mineralisation

The most appropriate correlation measure is the Spearman rank correlation coefficient. This is a non-parametric statistic that quantifies the association between two variables. The higher the correlation, the better the element and sample type is at defining the mineralization. Using the Spearman rank correlation, it is possible to simultaneously compare all the elements and sample types. Table 2 shows the Spearman rank correlation coefficients for proximity variable with target (Cu, Au, Ag) and pathfinder elements (Mo, Mn, Pb, Zn), and different sample types.

Table 2. Spearman rank correlation between proximity variable and target/pathfinder elements for different sample types.

Sample	Type/Analysis	Cu	Ag	Au	Mo	Mn	Pb	Zn
A	Surface,4 acid	0.67	0.66		-0.15	0.16	0.55	-0.16
B	Surface pXRF	0.61			0.06	0.02	0.067	0.01
C	20cm depth Ionic Leach	0.71	0.61	0.43	0.43	0.51	0.57	-0.33

Target and pathfinder elements perform the best in Sample C closely followed by Sample A. Sample B performed poorly for elements other than Cu but this is probably due to the poor analytical quality of the pXRF for some elements – an example being Pb.

This measure of proximity can be used in other statistical procedures such as multiple regression to predict the proximity variable from several of the elements for a given sample type. This could result in an equation for a new variable that would highlight mineralization better than any single element alone. In this case, the proximity variable was regressed against Cu, Ag, Au, Mn, Pb for Sample C (Ionic Leach sample). The Spearman rank correlation between this new variable and the proximity variable was 0.75, which was higher than that for Cu alone (0.71) suggesting there is a small improvement using this multielement proximity variable.

Dispersion profiles for Cu and the new proximity variable composed of Cu and Ag are shown in Figure 7.

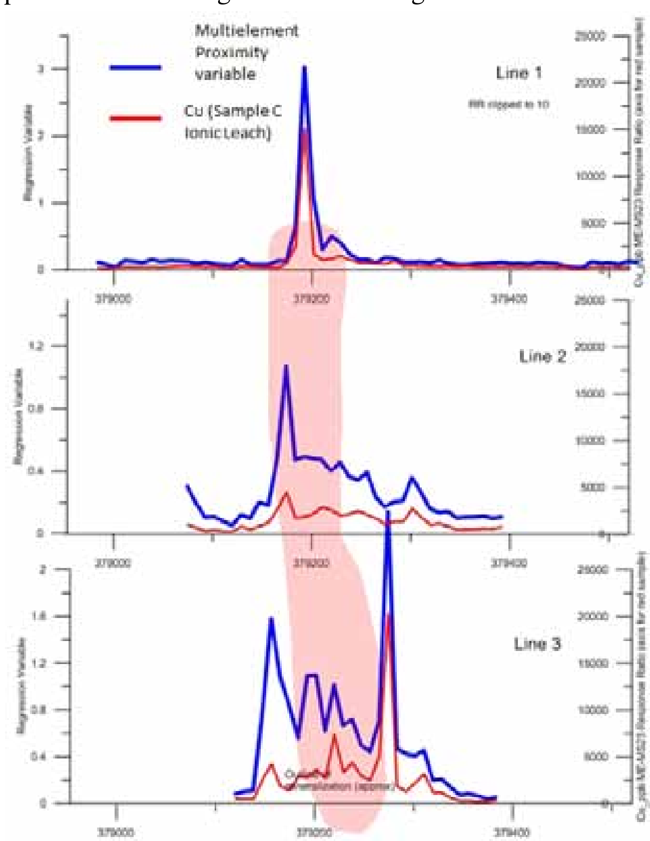


Figure 7. Dispersion profiles for Cu content in Sample C and new proximity variable (Cu +Ag).

continued on page 11

Quantitative Interpretation of Orientation Surveys... *continued from page 10*

Copper and Ag make by far the largest contribution to the regression model, and it is possible that the regression estimating the multivariate proximity variable could show an improvement if more elements were included in the correlation.

This case study has shown the usefulness of assigning orientation samples to background, flanking, or coincident groups prior to the analysis of data. Probability plots and Spearman correlation coefficients can then be used to determine the best elements and sample types for detecting the type of mineralization over which the survey was conducted.

Example 2 – Stream sediment orientation survey, Rhyolite Creek Au-base metal prospect, Victoria, Australia

The Rhyolite Creek Au-base metal prospect is located about 145 km ENE of Melbourne in central eastern Victoria (Fig. 8). Weak Au mineralization was explored by BHP in the 1980s. The prospect lies within a fault bounded structural window that exposes Cambrian rocks within the Palaeozoic Mount Useful Slate Belt. Mineralization is hosted by volcaniclastic units interbedded with intermediate to felsic volcanic flows and intrusives. Significant Cu-Au sulphide mineralization was discovered at Hill 800 6 km to the north.

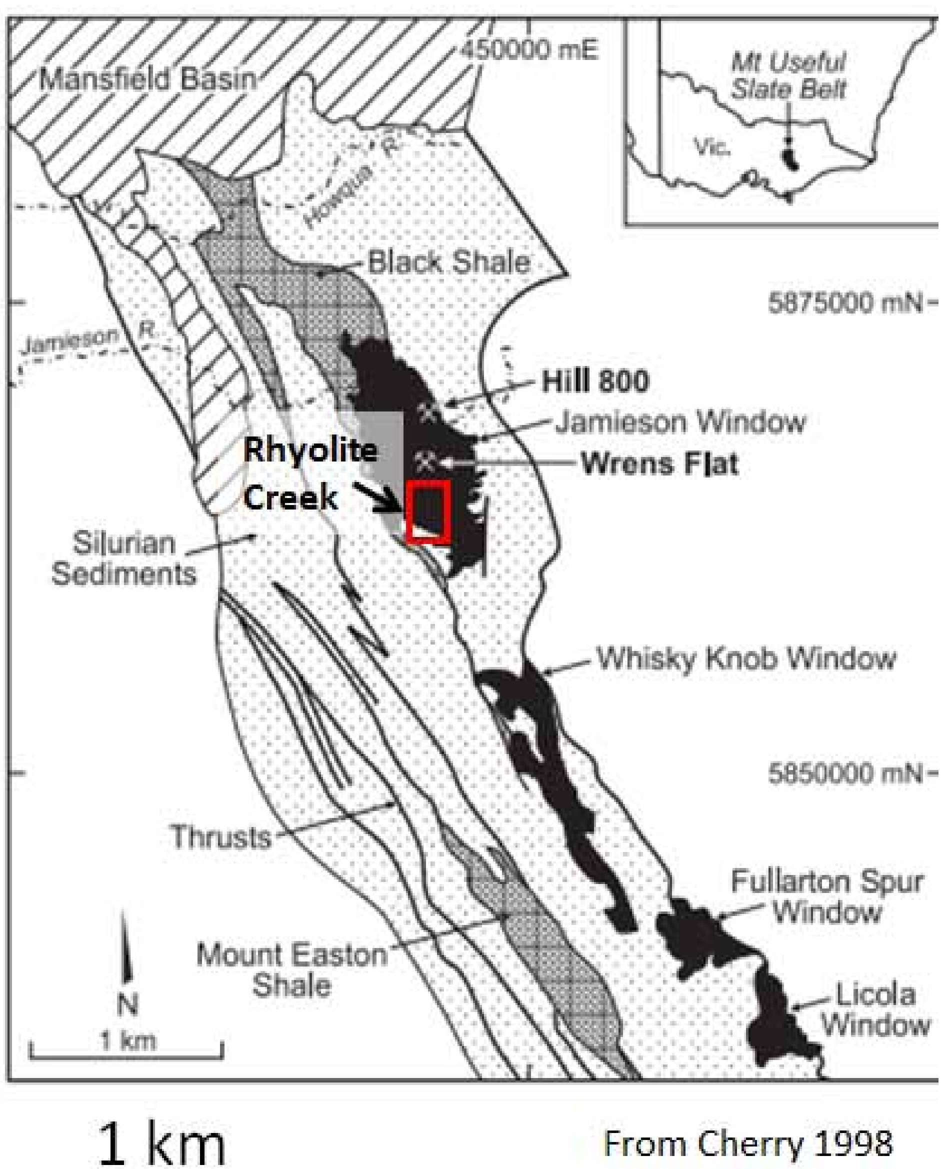


Figure 8.
Location of Rhyolite Creek Au base metal prospect Victoria. Australia

continued on page 12

Quantitative Interpretation of Orientation Surveys... continued from page 11

A stream sediment orientation survey consisting of 36 samples and 5 field duplicates was carried out downstream from known mineralization. Two types of samples were collected and analyzed:

~ 1 kg Bleg sample (cyanide active), analysis for Au.

~ 1 kg sample sieved to <200 mesh, <20+40 mesh, <40+60 mesh, <60+80 mesh, <80+200 mesh, analysis for Au (fire assay), Pb, As, Zn, Cu by 3-acid (HNO_3, HCl, $HClO_4$) digestion and AAS.

The survey was carried out in 1984 and only atomic absorption spectrometry (AAS) was available for the sample analysis at that time.

As described before in example 1, probability plots were used to display and compare anomalous and background samples. These plots still require a subjective visual interpretation to establish the overall measure of population separation.
Figure 9 shows the distribution of stream sediment samples. There was evidence in dispersion profiles that samples as far as 7 km downstream reflect the Cu-Au mineralisation.

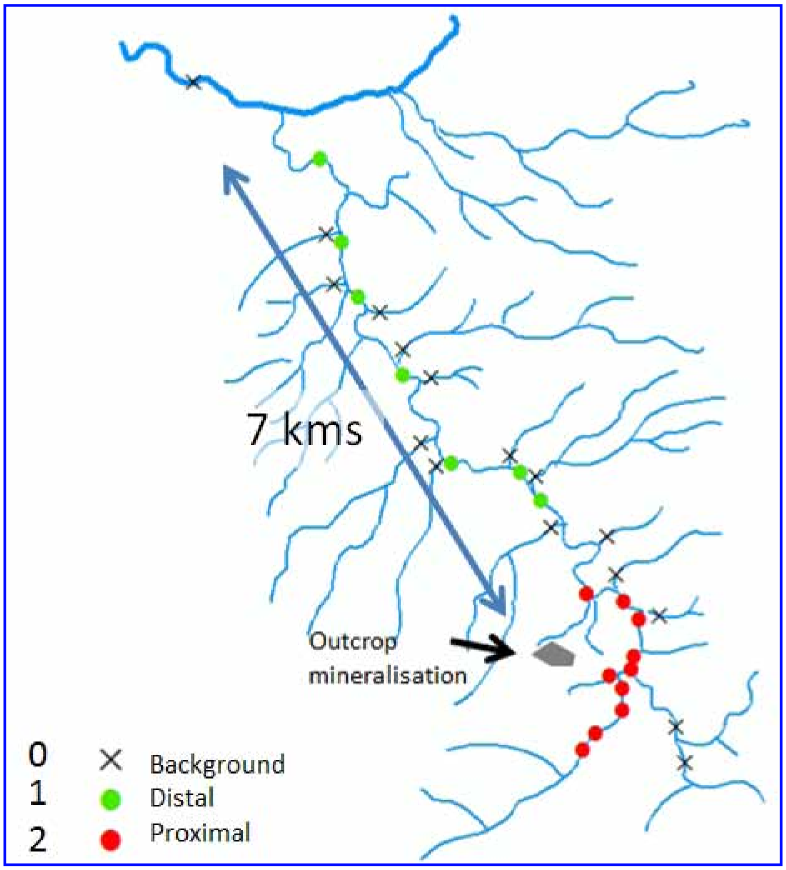


Figure 9. Distribution of orientation samples

For the orientation study, the proximity variable was given by:
0=off dispersion (background)
1=on dispersion trail 3-7 km away (distal)
2=on dispersion trail 0-2 km away (proximal)
A measure of how well a particular element and sample type identified the Cu-Au mineralization is revealed by the Spearman rank correlation coefficient between the proximity variable and analytical results (Table 3).

Table 3 Spearman rank correlations with proximity variable

	Au	Pb	As	Zn	Cu
BLEG	0.47				
<200#	0.55	0.38	0.36	0.55	0.04
<80>200#	0.04	0.34	0.21	0.49	-0.06
<60>80#	0.16	0.23	0.12	0.49	-0.07
<40>60#	0.43	0.21	0.12	0.45	-0.2
<20>40#	0.02	0.32	0.17	0.37	-0.14

For Au, the <200 mesh samples performed the best, followed by Bleg, and then <40+60 mesh. Correlations of Zn are all significant and were highest for each sample type. Lead gave the second best correlations in all sample types except <200 mesh and <40+60 mesh. The <200 mesh fraction performed well for every element except Cu.

Arsenic gave significant correlations in only <200 mesh and this poor response is explained by examining the between-element correlations. Arsenic shows a Pb-Zn-As-Au association related to the Cu-Au mineralization whereas the Cu-As association is un-related to Cu-Au mineralisation.

These elements can be combined into an equation that better highlights the Cu-Au mineralisation. This was accomplished by regressing the proximity variable against the analytical results for the <200 mesh samples. Results for each element were first log transformed because the frequency distributions are highly positively skewed. Stepwise multiple regression analysis was carried out which showed that only Au and Zn are needed in the equation. The resulting equation is:

$Y = 2.5\log(Zn) + 1.0\log(Au)$

The Spearman rank correlation between this new variable and the proximity variable is 0.71, which is higher than either Au or Zn alone (0.55). The probability plot of the regression variable is shown in Figure 10, and the map of posted values spatially shows how well the technique works.

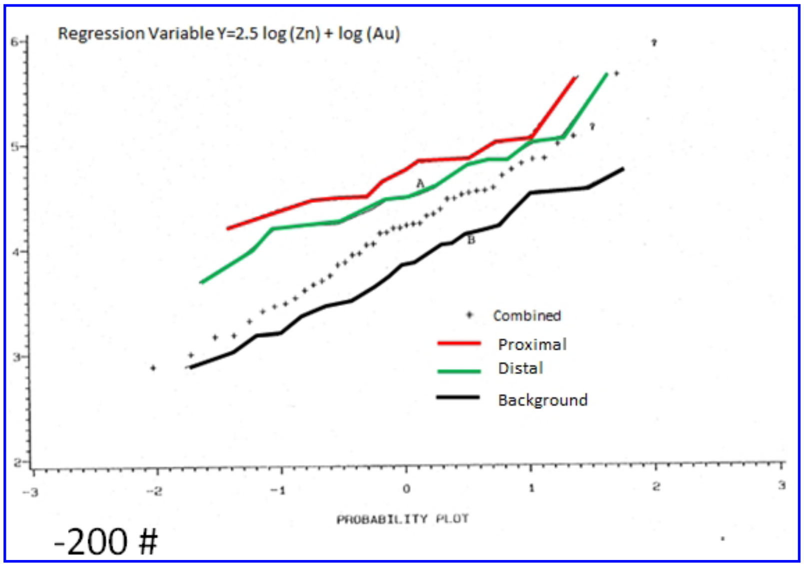
Results for the Rhyolite Creek orientation survey show that the <200 mesh sample was the most suitable size fraction for highlighting the known Cu-Au mineralisation and the elements in order response are Au > Zn > Pb> As > Cu. For Au alone, the Bleg technique also indicated the presence of the Cu-Au mineralisation.

Conclusions

These case studies have shown the usefulness of *a priori* assigning orientation samples to either background or anomalous groups based on their spatial relationships to known mineralization before further interpreting the data. Probability plots and

continued on page 13

Quantitative Interpretation of Orientation Surveys... continued from page 12



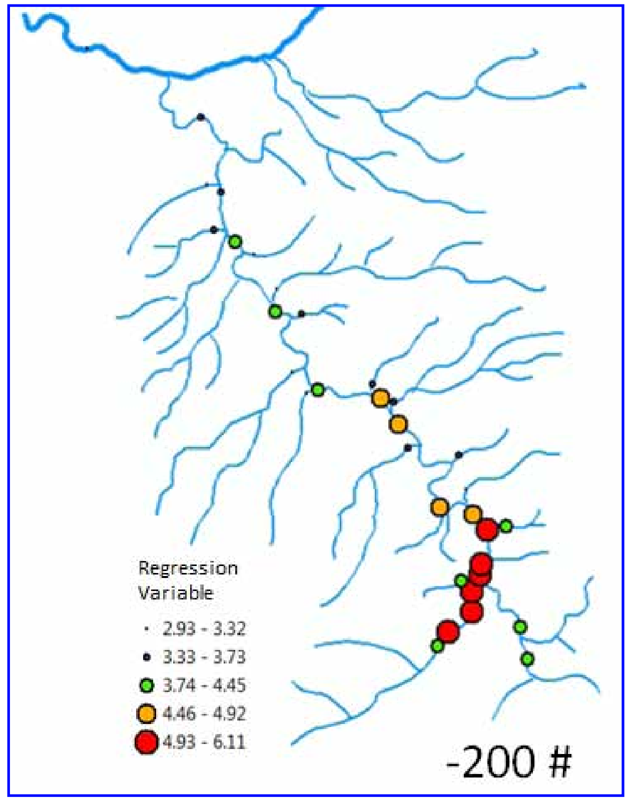


Figure 10. Split probability plot for the regression variable and location of values for the regression variable for the -200 mesh fraction of stream sediment samples.

Spearman rank correlations can then be used to determine the most suitable elements and sample types for detecting the type of mineralisation over which the surveys were conducted. The method can be applied to most types of orientation survey data and mineralisation as long as the spatial location of bedrock mineralisation is well constrained.

Acknowledgements

Capstone Mining is thanked for allowing the Sierra Amarilla case history to be published. Colin Farrelly is thanked for the developing the initial methodology and providing inspiration. Bob Garrett, Ray Lett, Graeme Bonham-Carter, Rael Lipson and Matt Eckfeldt are thanked for reviewing the article and making significant improvements.

References

CAMERON, E, LEYBOURNE, M. REICH, M, PALACIOUS, C., 2010. Geochemical anomalies in northern Chile as a surface expression of the extended supergene metallogenesis of buried copper deposits. *Geochemistry: Exploration, Environment, Analysis,* **10**, 157-169

CHERRY, D.P., Hill 800 Au-Cu Mineralization, Eastern Victoria, Regolith Expression of Australian Ore Systems. A compilation of geochemical case histories and conceptual models. 1998.

KELLEY,D.L., HALL, G.E.M, CLOSS, L.G, HAMILTON, I, McEWEN, R.M., 2003. The use of partial extraction geochemistry for copper exploration in northern Chile. *Geochemistry: Exploration, Environment, Analysis*, **3**, 85-104.¬

SILLITOE, R.H., 2003. Iron oxide –copper-gold deposits: an Andean view. *Mineralium Deposita*, **3**, 787-812.

SINCLAIR, A.J., 1976. Application of probability graphs in mineral exploration. The Association of Exploration Geochemists, Special Volume No. 4

STANLEY, C.R.,2003. Statistical evaluation of anomaly performance. *Geochemistry: Exploration, Environment, Analysis,* **3**, 3-12.

TAPIA, J. & VIDELA, M., 2011. Informe de Avance Geologia Basica Camapana 4 Ano 2011: Area de Interes Interior de Taltal GEDM Marzo, 2011. Internal report – SQM.