The Geochemical Anomaly: Distinguishing Between True and False Anomalies Using GIS Technology

Harris, J.R.[1], and Wilkinson, L.[1]

1. Geological Survey of Canada

Geochemical data sampled from various media are commonly used in mineral exploration programs to assist in targeting areas for specific mineral deposits. Areas characterized by anomalous concentration of a major oxide or trace element, defined by a given value above or below a *background* concentration, are commonly sought as favourable exploration targets. However, defining a true geochemical anomaly can be fraught with problems. This paper presents a methodology for processing geochemical data using GIS technology to assist in identifying anomalies that are more likely due to alteration/mineralization (e.g., a true anomaly in the mineral exploration sense, as opposed to a false anomaly attributable to some other physical, chemical or artificial effect). A GIS (Arc/Info) is used as a central archive and analytical engine for much of the spatial analysis. In addition statistical analysis packages (Statsgraphics, Splus) are used to perform some of the numerical analyses. Geochemical data are transferred to and from the GIS as simple ASCII files.

Geochemical data sampled from till, lake sediments and rock from two areas in Canada, one in the Lac de Gras area in the Northwest Territories and the other in the Swayze Greenstone Belt, Ontario, are used as test data sets. Figure 1 shows the location of each area.

Figure 2 summarizes the processing methodology. The first step is to identify false anomalies that may be caused by analytical variability, differing analytical methods (e.g., INNA vs. XRF) or differences in sample pattern between two surveys over the same geographic area. Figure 3 shows contour maps of Au concentration in soil over the Swayze Greenstone Belt. Au has been chosen as an example as Au is a difficult element to analyse due to the nugget or particle sparsity effect. Figure 3a shows a contour map of Au concentration (ppb) constructed using one half of the split duplicate samples (47) used to assess data quality, while Figure 3b is constructed using the same method only using the other half of the split duplicate population. Figure 3c is a map showing the difference between Au concentration from Figure 3a and b. Individual anomalies have been numbered to facilitate identification with respect to the following discussion. A fairly high correlation coefficient (~.8) between the two contour maps (Figures 3a and 3b) indicates that the maps are similar. However, the difference between anomalous Au analyses is critical. Table 1 compares the two split-duplicate Au populations on a sample-to-sample basis. Note that the anomalies caused by samples 45, 46, 2 and 33 (see Figure 3c) are characterized by significantly different Au concentrations. These differences are due to analytical variability. The absence of anomalies number 44 and 45 on Figure 3b (emphasized by large differences on Figure 3c) suggests that these may be *false anomalies* due to analytical error.

The effects of lithology or surficial cover on background geochemical levels can be accounted for by normalizing each sample to geology. Harris *et al.* (this volume) present a methodology for accomplishing this task using a GIS.

Once possible false anomalies have been identified on the raw or normalized data, the data are separated into background and anomalous populations. Several statistical methods for defining anomalous populations can be used and may include the following:

1. exploration knowledge (i.e., it is known that within an area of ultramafic rocks > 400 ppm Zn is anomalous),
2. statistical methods using percentiles, standard deviations,
3. visual inspection of QQ or probability plots,
4. area/concentration method (Cheng *et al.*, 1994), and
5. weights of evidence (Bonham-Carter, 1994).

The *weights of evidence* method requires *a priori* knowledge (i.e., knowledge of existing mineral occurrences) while the other methods do not require pre-existing knowledge. The probability plots are the simplest and most effective method for determining thresholds, as natural breakpoints on the cumulative curves can be easily identified. Data above upper breakpoints may represent anomalous populations that are related to alteration or mineralization effects.

Thresholding geochemical data into background and anomalous populations is a statistical operation that does not necessarily account for spatial variations due to geologic, chemical and biophysical factors that may also produce anomalous populations of a given element. Thus, the final step in the processing methodology is to screen the anomalies for other effects that are not related to alteration (in the case of rock geochemical data) or mineralization. In the case of analytical variability, discussed above, some of the anomalies may simply be a result of this variability or may be related to alteration/mineralization. In order to evaluate these difference the Au soil anomalies were compared to Au anomalies in other sampling media, primarily humus, till (fine and heavy fraction), lake sediments, and rock (whole-rock analysis) as well as known Au occurrences. This was accomplished by using the map *overlay* functionality of the GIS.

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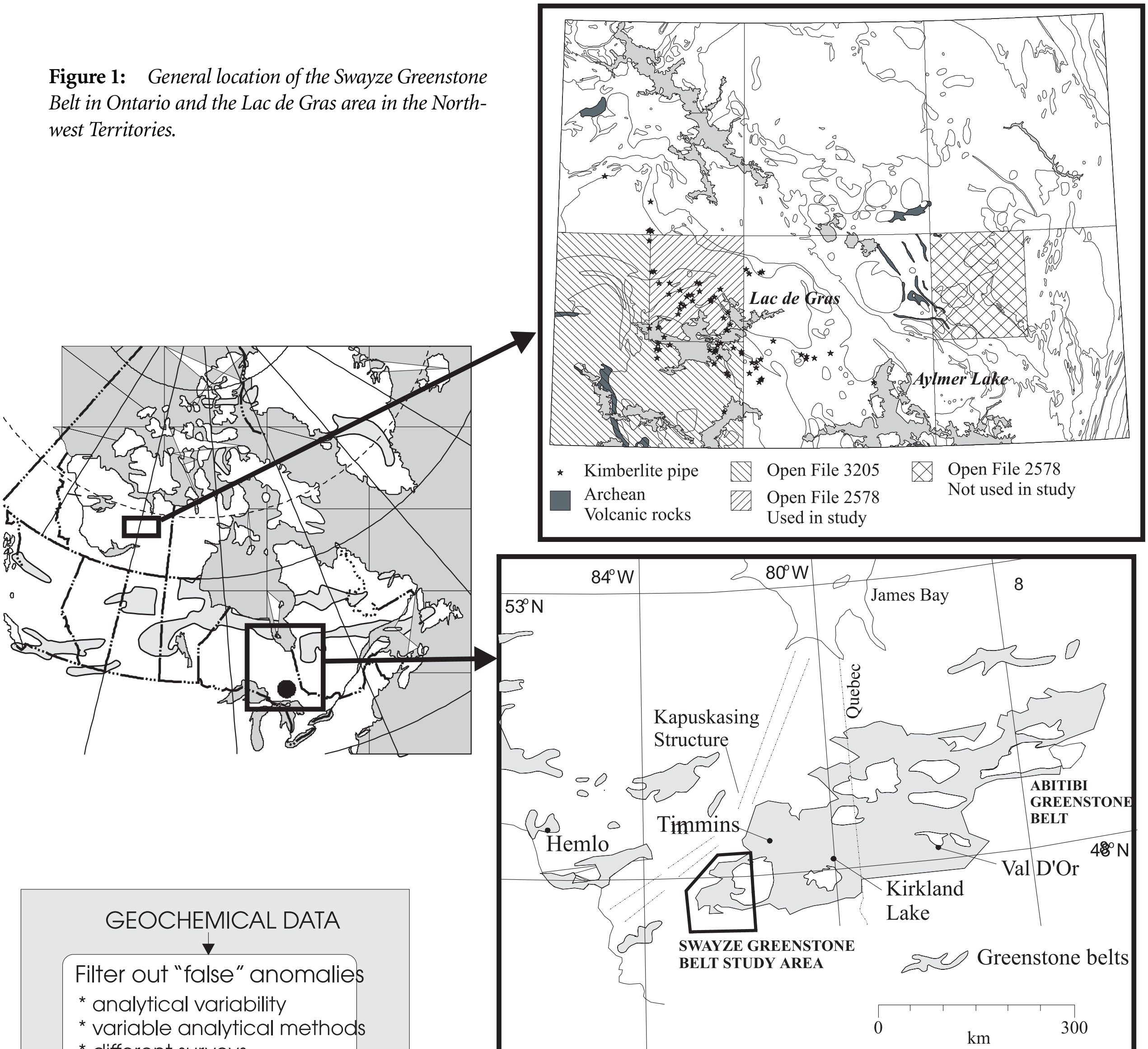
Figure 1: *General location of the Swayze Greenstone Belt in Ontario and the Lac de Gras area in the Northwest Territories.*



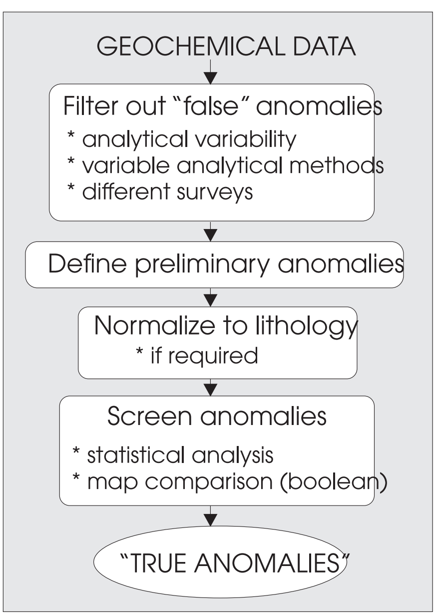


Figure 2: *Flow chart summarizes process of determining anomalies related to mineralization.*

Table 2 presents a summary of the evaluation of each anomalous zone. In this case, all the Au soil samples were used such that one population included all the non-duplicate samples and one set of the split duplicate samples (column labeled Au on Table 2) while the second population included all the non-duplicate samples and the other set of split duplicates (Au1 on Table 2). If the particular Au anomaly in soil was coincident with Au anomalies in other media and with Au occurrences then the probability of a false anomaly (due to analytical error) is reduced. Au anomalies labeled 16 and possibly 45 and 46 (Figure 3c) are thought to be due to analytical error whereas the differences in other samples (# 8, 2, 27, 33, 20 31, 40, 44) are more likely due to mineralization. The best approach when dealing with Au and possible false anomalies due to the nugget effect, is to re-sample these areas to determine whether the anomalous concentrations can be duplicated as opposed to disregarding them completely. This avoids the problem of errors of omission and commission due to the nugget effect.

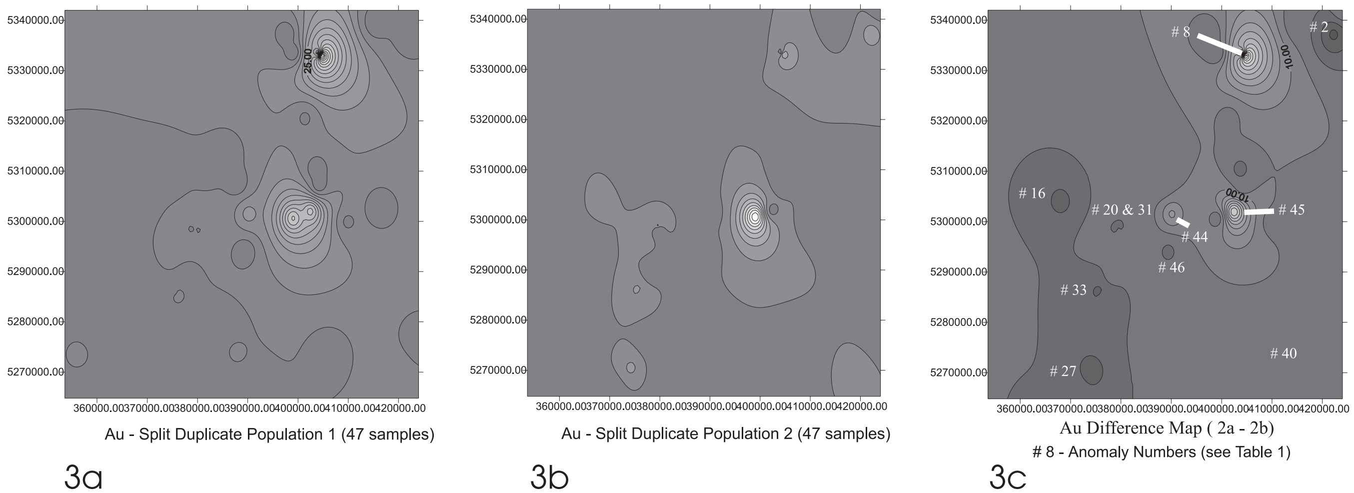


Figure 3: *(**a**) Contour map of split-duplicate Au — population 1. (**b**) Contour map of split-duplicate Au — population 2. (**c**) Au difference map.*

Figure 4 is an example of how Zn anomalies in lake sediments over the Swayze Greenstone Belt were screened for anomalies that may not be due to mineralization. The green areas on this figure represent Fe and Mn anomalies, acidic conditions (e.g., pH < 4.0) and areas of high LOI (loss on ignition). These parameters were measured coincidentally with each lake sediment sample. Zn anomalies shown in red, coincident with the anomalies shown in green (yellow areas), are less likely to represent mineralization and may represent scavenging by Fe and Mn oxides, or by concentration of Zn due to greater solubility in high pH conditions or scavenging by organic matter. One has to interpret this with caution as Fe formations are hosts for base metal occurrences within the Swayze Belt. These anomalies could be further screened by comparison to linear magnetic anomalies as Fe anomalies in lake sediments coincident with magnetic anomalies are less likely due to scavenging effects

Table legend

<det = less than detection limit (INAA — 2ppb)
x = no data available
Y(w) = Yes, co-occurence with Au anomaly inother geochemical media but weak
Y(0) = Yes, co-occurrence but offset due to glacial dispersion
? = Au occurence within 1 km
Rank = 1 point for co-occurence with Au anomaly in other geochemical media and 2 points for co-occurrence with known Au occurenec

Table 1: ***Soil Au split-duplicate anomaly assessment (47 samples). Differences measured in percentiles.***

Sample #	Au (ppm)		Au1 (ppm)		Significant Difference
8	96	> 99th%	21	> 95th%	N – both > 90th%
45	47	> 95th%	3	> 70th%	Y
46	17	> 90th%	1	< det	Y
2	1	< det	12	> 90th%	Y
27	1	< det	11	>80th%	N – both < 90th%
16	1	< det	9	> 80th%	N – both < 90th%
33	4	> 70th%	12	> 90th%	Y
20	9	> 80th%	3	> 70th%	N – both < 90th%
31	10	> 80th%	7	> 80th%	N – both < 80th%
40	10	> 80th%	8	> 80th%	N – both < 80th%
44	51	> 95th%	49	> 98th%	N – both > 90th%

Table 2: ***Soil Au anomaly assessment. (Total population + Split duplicate Population = 943 samples)***

Sample #	Au (ppm)		Au1 (ppm)		Significant difference	Humus	Till	Wra	Lake	Au grain	Au ocurr	Rank	False anomaly?
8	96	>99th%	21	>98th%	N – both > 90th%	x	x	x	x	x	x	x	x
45	47	> 99th%	3	> 70th%	Y	N	Y (w)	N	Y (w)	Y	?	2	?
46	17	> 98th%	1	< det	Y	N	Y (o)	N	N	Y	?	2	?
2	1	< det	12	> 95th%	Y	x	x	x	x	x	x	x	x
27	1	< det	11	> 95th%	Y	N	Y	x	Y	Y (o)	N	3	N
16	1	< det	9	> 95th%	Y	N	N	N	N	N	?	0	Y
33	4	> 80th%	12	> 95th%	Y	Y	Y	Y	N	Y (o)	Y	6	N
20	9	> 95th%	3	> 70th%	Y	N	Y	N	N	Y	Y	4	N
31	10	> 95th%	7	> 90th%	N– both > 90th%	Y	Y	N	N	Y	Y	5	N
40	10	> 95th%	8	> 90th%	N – both > 90th%	N	Y	N	Y	Y	Y	5	N
44	51	> 99th%	49	> 99th%	N – both > 90th%	Y	Y	Y	Y	Y	Y	7	N

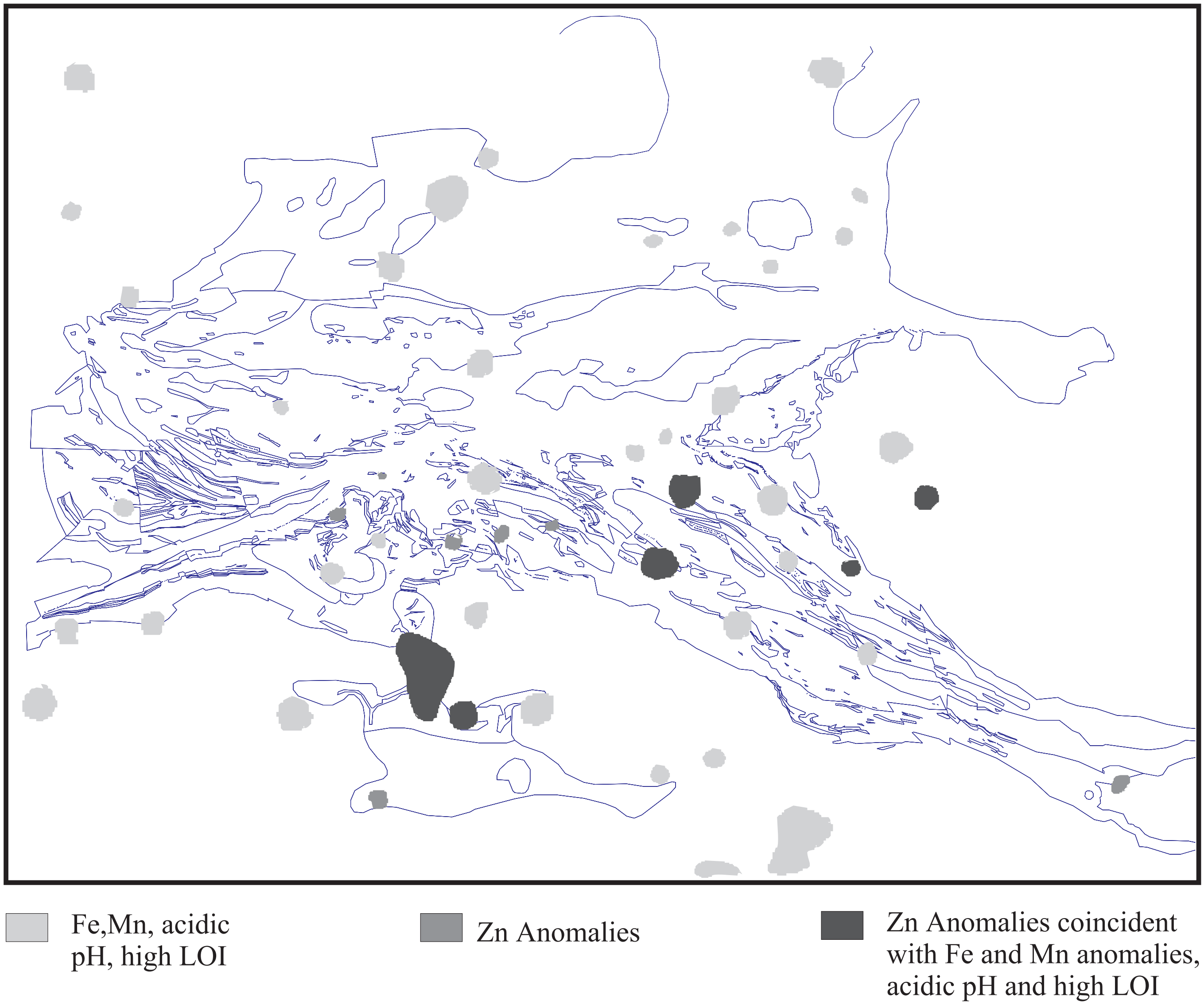


Figure 4: *Screened Zn anomalies in lake sediment.*

SUMMARY AND CONCLUSIONS

The GIS used in concert with statistical analysis software is a powerful tool for processing and visualizing geochemical data. A specific processing methodology for identifying geochemical anomalies and screening these with respect for alteration/mineralization, physical and chemical effects has been presented. This method is useful for mineral exploration as it helps to target true anomalies, thus saving time and money in the exploration process.

REFERENCES

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