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**PROCESSING AND INTEGRATION OF GEOCHEMICAL DATA
FOR MINERAL EXPLORATION: APPLICATION OF STATISTICS,
GEOSTATISTICS AND GIS TECHNOLOGY**

By

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Abstract

Geographic Information Systems (GIS) used in concert with statistical and geostatistical software provide the geologist with a powerful tool for processing, visualizing and analysing geoscience data for mineral exploration applications. This thesis focuses on different methods for analysing, visualizing and integrating geochemical data sampled from various media (rock, till, soil, humus), with other types of geoscience data.

Different methods for defining geochemical anomalies and separating geochemical anomalies due to mineralization from other lithologic or surficial factors (i.e. true from false anomalies) are investigated. With respect to lithogeochemical data, this includes methods to distinguish between altered and un-altered samples, methods (normalization) for identifying lithologic from mineralization effects, and various statistical and visual methods for identifying anomalous geochemical concentrations from background. With respect to surficial geochemical data, methods for identifying bedrock signatures, and scavenging effects are presented. In addition, a new algorithm, the dispersal train identification algorithm (*DTIA*), is presented which broadly helps to identify and characterize anisotropies in till data due to glacial dispersion and more specifically identifies potential dispersal trains using a number of statistical parameters.

The issue of interpolation of geochemical data is addressed and methods for determining whether geochemical data should or should not be interpolated are presented. New methods for visualizing geochemical data using red-green-blue (RGB) ternary displays are illustrated. Finally data techniques for integrating geochemical data with other geoscience data to produce mineral prospectivity maps are demonstrated. Both data and knowledge-driven GIS modeling methodologies are used (and compared) for producing prospectivity maps. New ways of preparing geochemical data for input to modeling are demonstrated with the aim of *getting the most out of your data* for mineral exploration purposes.

Processing geochemical data by sub-populations, either by geographic unit (i.e., lithology) or by geochemical classification and alteration style was useful for better identification of geochemical anomalies, with respect to background, and for assessing varying alteration styles. Normal probability plots of geochemical concentrations based on spatial (lithologic) divisions and Principal Component Analysis (PCA) were found to be particularly useful for identifying geochemical anomalies and for identifying associations between major oxide elements that in turn reflect different alteration styles. Normalization of the major oxide data to lithology was the best technique for identifying geochemical anomalies related to Au mineralization. The anomalies derived from the normalized oxides were also the better predictors of known Au prospects than anomalies derived from the raw data. Dispersal trains and up-ice source zones of anomalies in regional till data were successfully identified using the new DTIA. The production of Au prospectivity maps using the GIS was best accomplished by employing data-driven modelling methods such as the weights of evidence (WofE) as the data-driven methods better predicted the known Au prospects.

Résumé

Les systèmes d'information géographique (SIG), utilisés de concert avec des logiciels de statistique et de géostatistique, offrent aux géologues un outil puissant de traitement, de visualisation et d'analyse de données géoscientifiques destinées à des applications en prospection minérale. Cette thèse est centrée sur différentes méthodes d'analyse, de visualisation et d'intégration de données d'échantillonnage géochimique de divers milieux (roche, till, sol, humus) avec divers autres types de données géoscientifiques.

Différentes méthodes de définition d'anomalies géochimiques et de différenciation des anomalies attribuables à la minéralisation de celles attribuables à d'autres facteurs lithologiques ou superficiels (c.-à-d. les anomalies véritables des fausses anomalies) sont abordées. Pour ce qui est des données lithogéochimiques, cet examen englobe les méthodes permettant de distinguer les échantillons altérés des échantillons non altérés, les méthodes d'identification des effets lithologiques et des effets attribuables à la

minéralisation (normalisation) ainsi que diverses méthodes statistiques et visuelles de différenciation des concentrations géochimiques anormales des concentrations de fond. Dans le cas des données géochimiques obtenues dans des formations superficielles, des méthodes d'identification des signatures du substratum rocheux et des effets d'entraînement sont présentées. On présente en outre un nouvel algorithme, l'algorithme d'identification de traînées de dispersion (AITD) qui facilite considérablement l'identification et la caractérisation d'anisotropies attribuables à la dispersion glaciaire dans les données sur les tills et qui permet, de manière plus spécifique, d'identifier d'éventuelles traînées de dispersion d'après un certain nombre de paramètres statistiques.

Le problème de l'interpolation de données géochimiques est abordé et on propose des méthodes permettant de déterminer si les données géochimiques actuellement disponibles devraient ou non faire l'objet d'interpolations. On illustre de nouvelles méthodes de visualisation de données géochimiques au moyen d'affichages ternaires rouge-vert-bleu (RVB). Enfin, on fait la démonstration de techniques d'intégration de données géochimiques à d'autres données géoscientifiques pour la préparation de cartes de prospectivité. Des méthodologies de modélisation sur SIG dérivées de données et de connaissances sont utilisées (et comparées) pour la préparation de cartes de prospectivité. On démontre de nouvelles manières de préparer les données géochimiques à introduire à des fins de modélisation dans le but de permettre de *tirer le maximum des données* à des fins d'exploration minérale.

Le traitement des données géochimiques par sous-populations, que ce soit par unité géographique (p. ex. lithologie) ou selon une classification géochimique et le style d'altération a été utile pour mieux identifier les anomalies géochimiques par rapport à la roche encaissante et pour évaluer les différents styles d'altération. Les graphiques de probabilité normale des concentrations géochimiques basés sur les divisions spatiales (lithologiques) et l'Analyse des principales composantes se sont avérés particulièrement utiles pour déceler les anomalies géochimiques et relever les associations entre les principaux éléments des oxydes qui, à leur tour, sont un reflet des différents styles d'altération. La normalisation des données sur les principaux oxydes par rapport à la

lithologie s'est révélée être la meilleure technique pour mettre en évidence les anomalies géochimiques liées aux minéralisations aurifères. Les anomalies découlant des oxydes normalisés sont également plus aptes à prédire les zones d'intérêt aurifères connues que les anomalies découlant des données brutes. On a décelé avec succès dans les données du till régional des traînées de dispersion et des zones d'anomalie dont la source est en amont-glaciaire, et ce, en utilisant un nouvel algorithme appelé, dans la présente thèse, algorithme d'identification des trains de dispersion. La production de cartes figurant les zones potentielles aurifères au moyen d'un SIG a été facilitée par l'application de méthodes de modélisation dirigée par les données, comme les valeurs probantes, puisque les méthodes dirigées par les données ont été celles qui ont le mieux permis de prévoir les zones d'intérêt connues.

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Statement of Contribution

The co-authors of papers assisted in certain aspects of analysis and provided interpretative expertise. However the author was the major contributor of all material and ideas presented in the papers that comprise this thesis.

Lori Wilkinson provided invaluable help in graphic design and production of many of the figures presented in each paper as well as providing expert field assistance. She was also invaluable in assisting and developing many of the ideas presented in this thesis.

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Appendix A-2 – SQL statement (reference from Chapter 4)

Appendix A-3 – description of weights of evidence (WofE) (reference from Chapter 5)

Appendix A-4 – Summary of simulations (reference from Chapter 7)

CHAPTER I

Introduction

1.1 Rational

The objective of this thesis is to develop methods, techniques and new tools for visualizing, processing, and analysing geochemical data collected from rock, soil, lake sediments and till and integrating this data with other types of geoscience data to aid in defining potential targets for mineral exploration. Statistical and geostatistical techniques are used in concert with Geographic Information System (GIS) processing methods to produce images and maps useful for mineral exploration.

The value of this thesis is that:

- ◆ various existing techniques for the analysis, visualization and integration of geoscience data are demonstrated and further developed
- ◆ new techniques for the analysis and visualization of geochemical data are developed and discussed
- ◆ various existing and new methods for processing geochemical data are developed and demonstrated
- ◆ a new algorithm for processing till geochemical data (dispersal train identification algorithm – *DTIA*) is developed and made available to the exploration geology community

The Geographic Information Systems (GIS) used in this thesis are Arc/Info™ and ArcView™ with Spatial Analyst™, all ESRI (Environmental Research Institute) products. In addition, the weights of evidence (*WofE*) (Kemp et al., 1999) and Spatial Data Modeller (ArcSDM) (Kemp et al., 2001) add-ons to ArcView™ (developed by the Geological Survey of Canada and United States Geological Survey supported by funding from the mining industry) were used for modeling the data. *WofE* is available for free from the website listed in the references (Kemp et al., 1999). In addition, S-Plus™,

Statsgraphics™ and Surfer™ were used in concert with the GIS to process, analyze and visualize the geoscience data used in this thesis.

The Swayze greenstone belt (SGB) in Ontario is the main area for study for a variety of reasons:

- ◆ the SGB was being re-mapped (bedrock and surficial) by the Ontario Geological Survey (OGS) and the Geological Survey of Canada (GSC) at the time of the thesis research
- ◆ Large volumes of good quality geoscience data in digital formats including lithochemical, surficial and lake sediment geochemical data, were available
- ◆ interest by various exploration companies (Inco, Falconbridge, Noranda) in regional base metal and Au exploration within the study area
- ◆ interest by various mining companies and governments in the development and application of GIS technology for geological and geochemical mapping and mineral exploration

A second study area in southeastern Cape Breton Island has been included as it contains a good geochemical till dataset and provides an area with documented dispersal trains for a number of geochemical elements and is used to test the *DTIA* algorithm developed in this thesis.

1.2 Objectives

The major themes addressed in this thesis include:

- ***Geochemical Data processing***
 - a) statistical characterization of geochemical data
 - b) identification of geochemical anomalies

c) separating true from false anomalies

- altered vs. un-altered lithogeochemical samples
- normalization (lithogeochemical data)
- scavenging effects in surficial and lake sediment geochemical data
- bedrock/ surficial signatures in surficial geochemical data

d) interpolation

e) processing geochemical sub-populations

e) the effects of down-ice dispersion in geochemical data sampled from till

- *Multi-media geochemistry comparison*
- *Visualization of geochemical data*
- *Data Integration (assessment of geochemical anomalies and Mineral Prospectivity modeling)*

1.3 Thesis Organization

The thesis comprises four papers, that have been published in scientific journals, 1 in the Journal of Geochemical Exploration, 1 in Ore Geology Reviews, 1 in Natural Resources Research, and 1 in a Special Publication of the Geological Society of London. A 5th paper has been submitted for publication in Geochemistry : Exploration Environmental Analysis. These papers are found in Chapters 4 to 8 of this thesis. Each paper covers a

theme or a number of themes relevant to the overall objectives listed above. The specific themes addressed are summarized below along with a reference to specific paper(s), which addresses each theme. Table 1.1 summarizes the papers, the major themes they address and the journals they have been published in. The geoscience data used in this thesis compiled over the Swayze greenstone Belt is published as GSC Open File D3770 by Harris et al, (1999) and is included in Appendix A.

1.4 Introduction to Geographic Information Systems (GIS)

The traditional approach to the analysis of geochemical data involves the use of spreadsheets and/or statistical software packages. Often the results are plotted using proportional symbol plots, where the size of each dot is proportional to the concentration of a given element, usually ranked by percentiles. A Geographic Information System (GIS) can offer the geologist significant advantages over traditional approaches to archiving, visualizing, manipulating, analyzing, integrating and presenting geochemical data. GIS is now a firmly established technology that many mining companies are adding to their arsenal of exploration tools. These systems can and should be used by the exploration geochemical community to facilitate the storage and display of geochemical data. Furthermore, the GIS facilitates the spatial analysis and comparison of large volumes of geochemical data.

As with a *Computer Aided Design System* (CAD), a GIS employs graphic primitives (points, lines and polygons) which are the building blocks for constructing digital maps. These form the basis of the vector model which the GIS uses to store and view spatial data. The GIS also uses the raster model in which spatial information is divided into grid cells (*pixels*) containing a number (referred to as a *digital number* or *DN*) that has some user or data- defined meaning. Unlike a CAD system, the GIS utilizes a database which contains descriptive information (*attributes*) for each point, line or polygon. Thus, a geochemical sample point has a specific location, as well as a number of attributes that describe the sample, stored in an internal or external database. The data can be displayed

and queried, by any attribute or combination of attributes in the database, using a database query language (e.g. SQL - Structured Query Language) or the proprietary query language of that particular GIS software. Although the GIS can be used as a cartographic tool for producing traditional geochemical maps (proportional symbols), it also provides spatial analysis and visualization tools that can be used to analyze the statistical and spatial characteristics of geochemical data. At the present stage of GIS development, other software packages (statistical and geostatistical) are still required by the geologist in addition to the GIS, to thoroughly analyze geochemical data, both statistically and spatially. Furthermore there is a general lack of spatial statistical routines within GIS at present. However, this is beginning to change as many GIS vendors are now integrating more geostatistical and statistical tools into the GIS environment.

Paper	Title	Journal	Main Themes	Data	Focus
1. (Chapter IV)	Techniques for analysis and visualization of lithogeochemical data with applications to the Swayze greenstone belt, Ont.	Journal of geochemical exploration (JGE), Vol. 67, 1999, pp. 301-334	geochemical data processing data visualization	Lithogeochemical	- identification of geochemical anomalies using univariate and multivariate statistical methods - identification of altered and unaltered samples
2. (Chapter V)	Effective use and interpretation of lithogeochemical data in regional mineral exploration programs: Application Of Geographic Information Systems (GIS) technology	Ore Geology Reviews, Vol. 16, 2000, pp. 107-143	geochemical data processing data integration	Lithogeochemical	- lithogeochemical data processing and evaluation by sub-populations - evaluation of geochemical anomalies and alteration maps using weights of evidence modeling (<i>WofE</i>)
3. (Chapter VI)	Analysis of geochemical data for mineral exploration using a GIS: A case study from the Swayze greenstone belt, northern Ontario, Canada	Drift exploration in glaciated terrain, Geological Society of London Special Publication No. 185, 2001, pp. 165–200	geochemical data processing multi-media comparison data visualization	Surficial geochemical data (till, soil, humus), lake sediment geochemical data	- statistical characterization of geochemical data - methods for correcting scavenging effects in surficial geochemical data - identification of bedrock signatures in surficial geochemical data - comparison of multi-media geochemical data - identification of directional effects in till data
4. (Chapter VII)	A method for detecting dispersal trains in geochemical data sampled from till	submitted to Geochemistry: Exploration Environment Analysis, Journal of the Association of exploration geochemists	down-ice dispersion effects in till data	Till geochemical data	- identification of till dispersal trains - identification of directional effects in till data - DTIA algorithm
5. (Chapter VIII)	Application of GIS processing techniques for producing mineral prospectivity maps – A case study: Mesothermal Au in the Swayze greenstone belt, Ontario, Canada	Natural Resources Research, Vol. 10, No 2, 2001, pp. 91-124	geochemical data processing data integration and modeling	A variety of geochemical, geological, and geophysical geoscience data Field data	- geoscience data integration and processing techniques - geochemical data processing - comparison of methods for producing mineral prospectivity maps

Table 1.1 Summary of papers comprising thesis

CHAPTER II

Background

2.1 Study Areas

2.1.1 *Swayze greenstone belt*

The Swayze greenstone belt (SGB) is the south-western extension of the Abitibi greenstone belt (AGB), being connected to the latter by a narrow band of volcanic-sedimentary rocks that wrap around the north and south margins of the Kenogamissi granitoid complex. The SGB shares many features in common with the mineral-rich AGB to the east, but lacks any significant mineral production.

The SGB (Fig. 2.1) is surrounded by large granitoid complexes to the north, east and south known respectively, as the Nat River, Kenogamissi, and Ramsey-Algoma granitoid complexes (Heather and van Breemen, 1994). The SGB, like most Archean greenstone belts, contains a diversity of both extrusive and intrusive rock types ranging from ultramafic through felsic in composition, as well as both chemical and clastic sedimentary rocks (Fig. 2.1). A number of fold-repeated (2730-2680 ma) mafic-felsic metavolcanic packages occur. They are unconformably overlain by Timiskaming-type metasedimentary rocks, and cut by high strain zones (Heather and van Breemen, 1994; Ayer and Theriault, 1993; Ayer, 1995; Heather et al., 1995; Heather et al., 1996). The map pattern preserved within the SGB, is dominated by regional, F₂, anticlines and synclines.

The SGB contains alteration and mineralization types typical of many Archean greenstone belts. Common alteration minerals consist of epidote, chlorite, sericite, Fe-carbonate, calcite, pyrite, tourmaline, garnet, hematite, magnetite and quartz. In some cases it is difficult to distinguish synvolcanic alteration from syntectonic or late-tectonic alteration due to similar mineralogy.

The surficial geology of the study area (Fig. 2.2) is dominated by thin, sandy till mapped as bedrock-drift complex (Bernier & Goff 1993; Bernier 1994; Bernier *et al.* 1996). Glaciofluvial outwash and other glacial and post-glacial sediments occur throughout the study area, as well as several large esker complexes orientated approximately N-S to NNE-SSW. Relief is generally low except in the southern portion where rolling topography reflects underlying granitoid rocks. The EW-trending Chapleau Moraine forms a dominant topographic feature.

2.1.2 Cape Breton Island

The Cape Breton study area is located in the Mira-Framboise area on the southeastern side of Cape Breton Island, 5km south of Sydney (Fig.2). The bedrock geology is dominated by northeast-southwest striking metavolcanic and metasedimentary rocks of the Precambrian Fourchu Group (Weeks, 1954) that are separated by late Precambrian to early Carboniferous clastic and sedimentary units of the Windsor Group (Barr et al., 1992). A number of plutons intrude the Fourchu Group. Details of the surficial geology can be found in Grant (1988) and McClenaghan and DiLabio (1993). Most of the area is covered by sandy till. Glacial landforms and striations indicate that the area was affected by three major ice flow events (Fig. 2.2), an oldest easterly flow, a younger flow to the northeast and a youngest flow to the southeast (McClenaghan and DiLabio, 1993). Documented dispersal trains exist in the Yava area (McClenaghan and DiLabio, 1992, 1996) and are shown on Figure 2.2

2.2 Datasets

2.2.1 Lithogeochemical

Approximately 4500 whole rock samples were acquired over the SGB from three principal sources; Geological Survey of Canada (GSC), Ontario Geological Survey (OGS) and Falconbridge Ltd. Individual datasets and their specifications are listed in Table 2.1. Each lithogeochemical dataset comprising the final compiled dataset was characterized by a different sampling strategy, and no information was available as to the

freshness of the rocks sampled in the older datasets (Texas Gulf, Falconbridge and Petroch, assessment files). The newer datasets collected by the GSC and OGS comprised what were judged to be fresh samples in the field (Heather, oral comm., 1997; Ayer, oral comm., 1997). The major oxide data, on which this paper focuses, were generally complete for most of the datasets used in the final compilation. The oxides were analyzed using X-ray fluorescence (XRF). Wilkinson et al. (1999) provides a complete description of how this lithogeochemical database was compiled, and the various methods used for evaluating data quality and integrity. Approximately 1000 samples, from an original total of 4500 samples, were deleted from the database, as they did not pass certain screening standards set forth in the above referenced paper.

2.2.2 *Surficial geochemical*

A total of 845 geochemical samples were collected concurrently from humus, B-horizon soil and C-horizon till over the SGB, by the OGS from 1993 to 1995 (Bernier & Goff 1993; Bernier 1994; Bernier & Kaszycki 1995; Bernier *et al.* 1996) over the Swayze greenstone belt. An average density of 1 sample/4-7 km² characterized this regional survey. The -80 (<177µm) mesh fraction of humus was sampled and analyzed for a variety of trace elements using INAA and ICP-OES (aqua-regia digestion). The -230 mesh (< 63 µm) fraction of soil and till was analyzed using ICP-OES (aqua-regia digestion). More details on this survey can be found in Bernier (1994) and Bernier and Goff (1993).

Figure 2.3 shows the location of each humus, soil and till geochemical sample site within the Swayze study area. The Shunsby and Kenty mine areas (Figs. 2.1 & 2.3) were sampled in more detail to characterize the behaviour of metals in the locally sampled media with respect to glacial dispersion (i.e., orientation surveys).

A total of 324, 2 kg till samples were collected from the C-horizon of the soil profile in hand-dug pits surface pits (0.5 –1.0m deep) with an average spacing of 3 –5 km over the Cape Breton site (McClenaghan and DiLabio.,1993). An additional 166 samples were

collected around the abandoned Mindamar mine and two mineralized bedrock occurrences (Deep Cove and Blue Mountain) to document the nature of glacial dispersal in the region. More details on this survey can be found in McClenaghan and DiLabio (1993,1995). Figure 2.2 shows the location of the geochemical sample points, mineralized areas and abandoned mines. In this study the data were screened so that the topmost till sample was used at sites where pits were vertically sampled.

McClenaghan and DiLabio (1993) provide details on the geochemical analysis. The silt+clay (<0.063 mm) fraction was analysed by Inductively Coupled Plasma Emission Spectroscopy (ICP) following a partial digestion in HCl and HNO₃ (3 : 1).

2.2.3 *Lake sediment*

Data from a lake sediment geochemical survey conducted under the National Geochemical Reconnaissance Program (NGR) by the Geological Survey of Canada (GSC 1987, 1988) were used (Fig. 2.4). Only the central and southern portion of the SGB was covered by these surveys which sampled relatively large and deep lakes at an average density of 1 sample per 13 km².

2.2.4 *Geochemical quality control issues*

The surficial geochemical data (humus, soil, till) for the SGB were evaluated for quality using split and field duplicate analyses. Approximately 1 in 15 samples were split for duplicate analyses and 1 field duplicate was collected for every 20 samples. Zinc and Cu results were evaluated for quality control using Thompson-Howarth precision control plots (Thompson & Howarth 1976, 1978): both elements in all media were found to be within 10% precision levels. The lake sediment geochemical data were subjected to strict quality control measures under the NGR program (see Friske *et al.* 1988). Wilkinson *et al.* (1999) review the quality control procedures applied to the lithogeochemical data used in this paper. Similar studies were undertaken for the Cape Breton till dataset and the elements used in this thesis (Zn, Cu, Pb) were also found to be with 10% precision level.

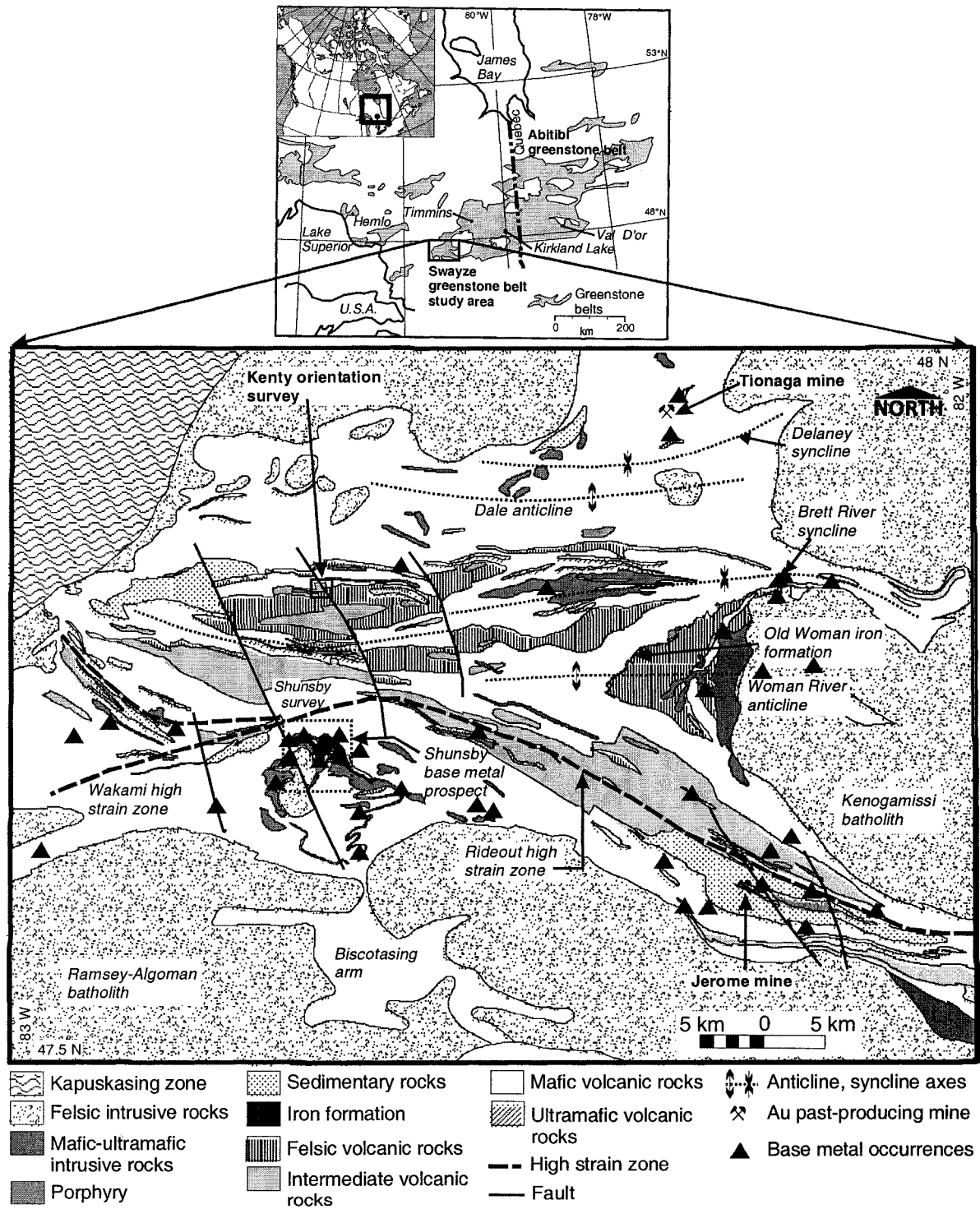


Figure 2.1 Study area and regional geology – Swayze greenstone belt (SGB)

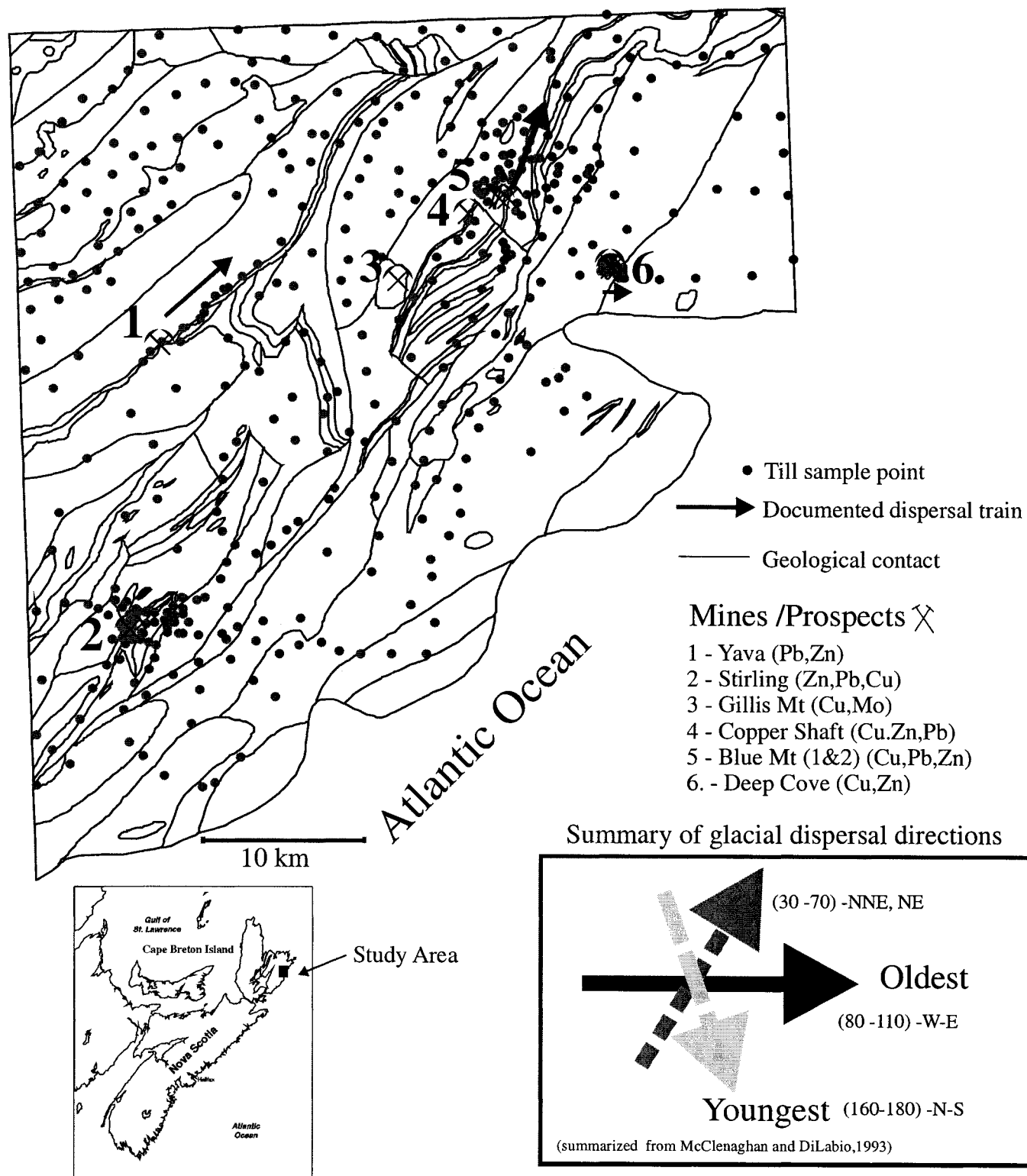


Fig. 2.2 Cape Breton Study Area

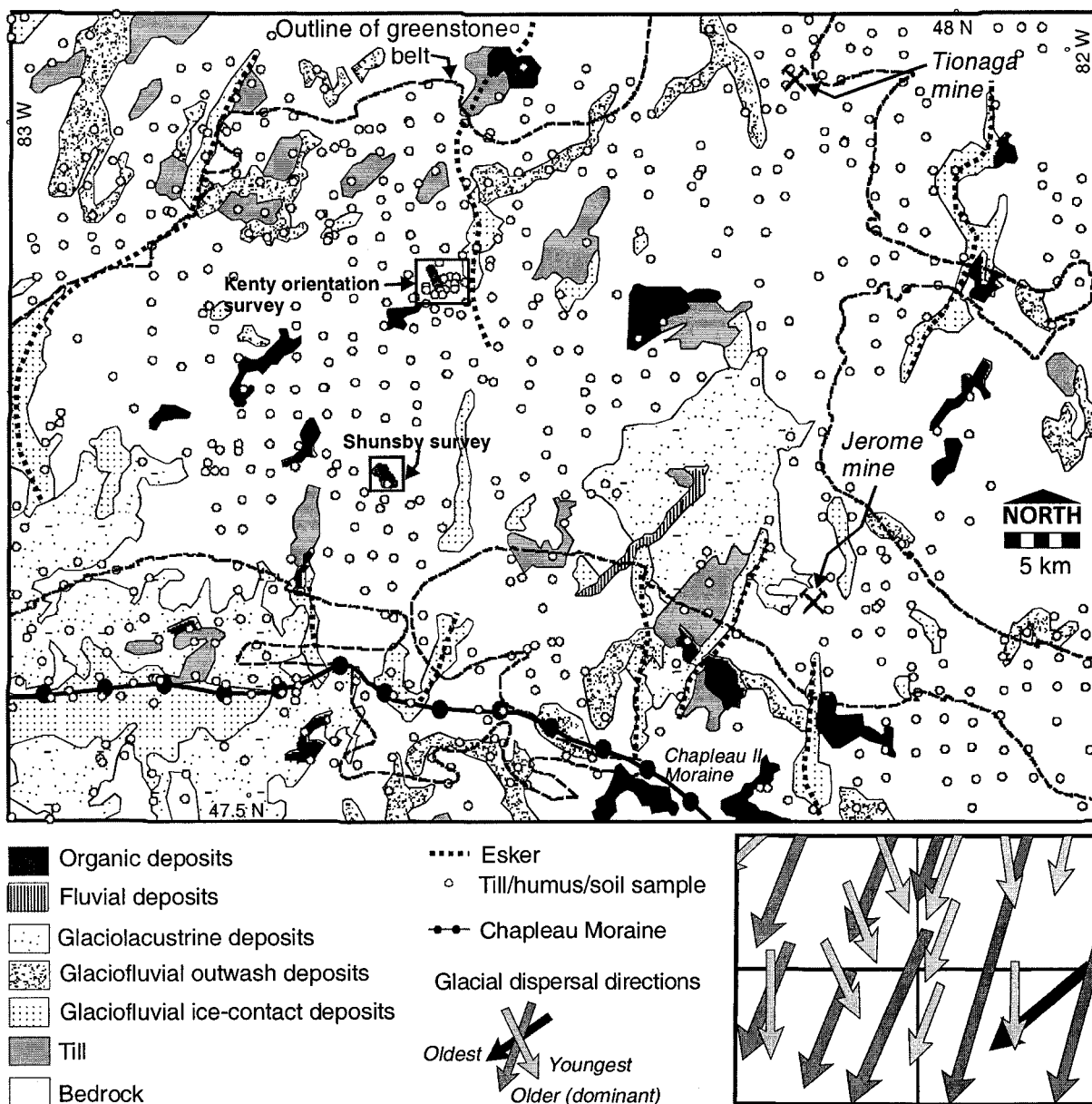


Figure 2.3 Surficial geochemical samples and surficial geology - SGB

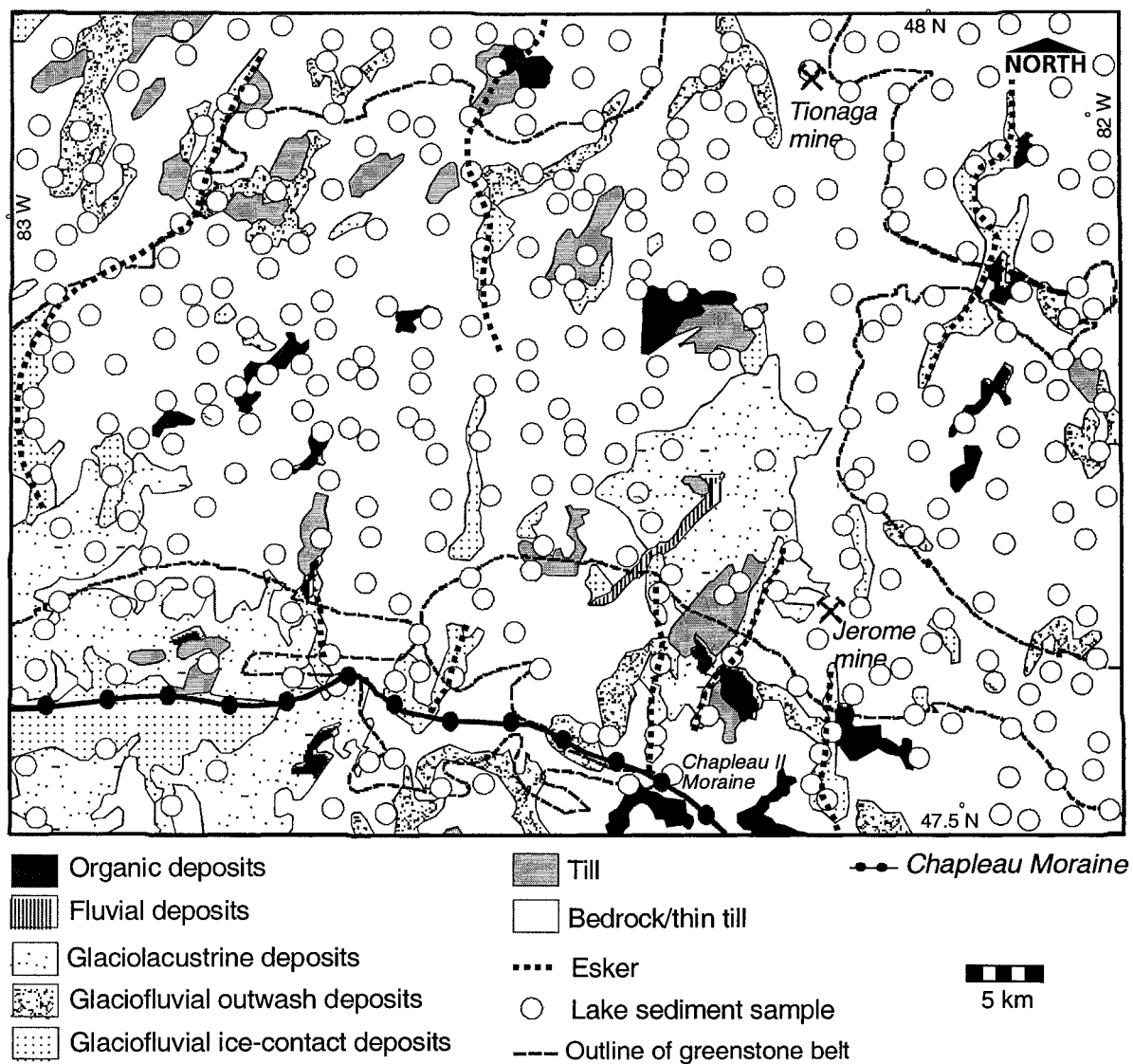


Figure 2.4 Lake sediment samples and surficial geology - SGB

CHAPTER III

Summary of Major Research Results

3.1 Introduction

The research issues addressed in this thesis comprise published papers, as previously mentioned (Table 1.1) and are presented in Chapters 4 through 8. This chapter provides a summary of the major research themes and results enabling the reader to capture the main points of the thesis in one chapter.

3.2 Geochemical data processing

3.2.1 *Statistical Characterization of geochemical data*

Before applying map visualization and analysis procedures, geochemical data should be evaluated to characterize statistical distributions. Howarth (1983), Garrett (1991) and Grunsky (1986, 1997) provide thorough reviews of techniques used to characterize frequency distributions as well as exploratory data analysis (EDA) techniques for geochemical data. These techniques form the basis for further analysis, which includes methods for separating anomalous geochemical concentrations from background and methods for visualizing the spatial characteristics of the data. Descriptive statistics such as histograms, normal probability plots and box and whisker plots provide insights into the statistical distribution of geochemical data. GIS complements statistical analysis by providing many methods with which to visualize the spatial characteristics (distributions) of the data.

One of the big advantages of GIS is the ability to divide geochemical data into separate populations on the basis of map-based spatial divisions. This is critical for geochemical (especially lithogeochemical) data as the statistical analysis and anomaly definition can be affected by background lithological variations. For example, a MgO anomaly in felsic rocks will often be characterized by a much lower concentration level than in a mafic

lithology. Analyzing geochemical data on the basis of lithological groups obviously makes better sense for both mapping and exploration than treating the geochemical data as a total population. Furthermore the sub-groups don't necessarily have to be based on a geographic division but can also comprise sub-populations created by performing a selective query in the database. For example the geochemical data in this thesis have been divided for analysis on the basis of geochemical classification (i.e., Jensen classification for Archean volcanic rocks) and alteration signature (un-altered vs. altered samples) within the database. These classifications can then be plotted spatially using the GIS.

Dividing geochemical data into sub-populations based on geographic divisions was accomplished by employing a *point-in-polygon* operation (a common GIS function) that intersected each geochemical sample point, over a polygon map. This enabled simple to complex queries to be undertaken by spatial unit, thus assisting in revealing geochemical anomalies that may be suppressed or entirely hidden when considering the entire geochemical population.

This thesis has shown that by dividing geochemical data into sub-populations based on lithology, geochemical classification and alteration, a more thorough analysis with respect to alteration styles and a more robust identification of geochemical anomalies with respect to background levels can be achieved.

3.2.2 *Separating altered versus unaltered samples*

Lithogeochemical data, comprising both major oxide and trace elements, are frequently used in geological mapping and tectonic studies to classify rock types, identify chemical variations due to fractionation trends, and characterize tectonic environments.

Lithogeochemical data are also useful for mineral exploration studies by providing chemical information on alteration and mineralization patterns. The ultimate goal of the statistical and spatial analysis of lithogeochemical data for mineral exploration is the detection of zones of elevated concentrations (e.g., geochemical anomalies) of oxide or trace elements that may be reflective of mineral deposits. Since Archean metavolcanic rocks have often been subjected to minor alteration, that is often difficult to recognize in

the field (Gelinas et al., 1977), an assessment of altered versus un-altered samples is critical in any regional exploration program. In this thesis alteration is defined as representing a change in major element oxide chemistry with respect to the original chemistry of the host rock from which it was sampled. Alteration due to mineralization processes, as opposed to regional metamorphic conditions that basically reflect a difference in alteration intensity, is the focus of this thesis.

Methods used for identifying altered samples in this thesis included the following:

- excessive LOI (Loss on ignition > 8% for mafic rocks and > 4% for felsic rocks)
- excessive volatiles ($\text{CO}_2 + \text{H}_2\text{O}^+ + \text{H}_2\text{O}^-$) (> 3.8%)
- alteration indices (Hashimoto index > 49 and ACNK index > .72)
- atypical minerals based on normative mineral classification
- index of typicality (Grunsky, 1986)
- identification of anomalous trends on scatterplots

Out of a total of 3395 lithogeochemical samples, 1606 were flagged as altered, representing approximately 47% of the total number of samples. With respect to the identification of altered samples, thresholds based on the normative mineral classification and LOI were the most liberal having flagged 810 and 665 altered samples, respectively. The highest overlap between methods for identifying altered samples, as shown by crosstabulation methods conducted using the GIS, occurred between the scatterplot and alteration index methods and LOI and scatterplot methods, all of which are more sensitive to alteration in mafic lithologies. Altered samples identified using the alteration index comprised a greater number of ultramafic samples, as might be expected since MgO is an integral part of the Hashimoto alteration index calculation. The method based on normative minerals was more sensitive to alteration in felsic rocks, as the minerals used in this classification are more typical of felsic rocks. This was supported by an increase in SiO_2 , Al_2O_3 , Na_2O_3 , and K_2O concentrations in altered samples identified by the normative mineral method. The LOI and volatile thresholds were more sensitive to mafic rocks due to their higher concentration of hydrous minerals. This was supported by

increases in MgO, CaO, FeO, Fe₂O₃, and TiO₂ concentrations in altered samples identified. Trends between the altered and non-altered samples include elevated SiO₂, K₂O and MgO values, and lowered CaO, FeO and TiO₂ values for altered samples. SiO₂, K₂O and MgO enrichment reflects silicic, potassic, and chloritic alteration.

3.2.3 Identification of geochemical anomalies

An important goal for mineral exploration, with respect to the statistical and spatial analysis of geochemical data, is the detection of zones of elevated concentrations of major or trace elements that may reflect the presence of alteration and/or mineralization. A geochemical anomaly represents an area of elevated concentrations of a single element or group of elements that exceed the threshold expected for regional background (Howarth, 1983; Garrett 1991). A threshold, in this thesis, follows the reasoning of Garrett (1991) and is defined as the outer (upper and/or lower) limit of local background variation.

Many statistical and geostatistical techniques have been used to highlight or enhance trends or patterns in geochemical data. Univariate techniques addressed in this thesis involved plotting geochemical data, sub-divided by separate populations (see above), on normal probability plots. Upper or lower breakpoints on these plots were then identified and geochemical samples above or below these concentration thresholds were considered anomalous. Multivariate techniques for identifying geochemical anomalies in this thesis included various alteration indices, 3-D scatterplots of selected oxide elements and Principal Component (PCA) analysis

Normal probability plots are arguably the most practical univariate method for determining thresholds, as they are easy to calculate and simple to interpret. Although percentile ranges are often used to divide and display geochemical data distributions, percentile divisions (e.g. 50-75, 75-80, 80-90, 90-95) do not always correspond to breakpoints present on probability plots. Ideally, natural breakpoints divide geochemical

data into separate populations that may reflect different geologic or surficial processes (Grunsky 1997). Plotting probability plots of geochemical data based on lithological groups was found to be extremely effective for identifying anomalies related to alteration/mineralization.

Three-dimensional scatterplots of oxide elements, for altered samples only, thought to reflect a particular alteration style (e.g., CaO - carbonatization, K₂O - potassic alteration etc.), were plotted against relatively immobile elements, TiO₂ and Al₂O₃. These scatterplots were then inspected for unusual patterns that potentially reflect alteration. Scatterplots were found to be a useful method for visually identifying anomalous samples, especially in ultramafic and mafic rocks.

Principal component analysis was applied to the transformed oxide altered rock samples. Principal component analysis is a multivariate technique which assumes a normal distribution and combines *N* variables into linear combinations of the original variables. The overall variance of the dataset is reduced into a few new variables termed components and these components may give insight into associations between oxide elements which in turn can provide information on alteration style. A log-ratio transform of the oxide data, as suggested by Aitchison (1986) was applied to alleviate the negative effects of closure. The first and second components generated from a principal component transform of the log-ratioed altered samples were found to reflect a felsic and mafic alteration style, respectively. When the components 1 and 2 were plotted against each other (bi-plot) not only were mafic and felsic alteration styles evident on this plot but also the oxide elements that were the major contributors to alteration. Thus samples characterized by different alteration styles (i.e., chloritization, silicification, albitization, potassic metasomatism etc.) could be identified and then the spatial location of these samples were plotted using the GIS.

3.2.4 Normalization

Normalization involves processing the lithogeochemical data to de-emphasize the effects of lithology, resulting in element anomalies that are more likely related to alteration and mineralization processes (Harris et al., 1997). Many methods can be envisioned to accomplish this task; however, the method that was successfully used in this thesis involves a simple equation that involved calculating the median concentration for each oxide element for each lithologic unit. A lithology field was added to the geochemical sample table by performing a GIS *point-in-polygon* operation, whereby each geochemical sample point is intersected with the lithological map. A simple formula, calculated in the GIS database was then used to normalize element concentration for background lithology.

It was found that this simple calculation was successful at suppressing the effects of lithological signatures and enhanced anomalies within specific lithological units. Furthermore, the anomalies identified from the normalized data were found to be better predictors of known Au than anomalies derived from the raw data. Normalization, as employed in this thesis, also circumvents the problem of closure in oxide data (0–100%) as it is based on a ratio value of concentration for each geochemical sample divided by the median value of the lithology it falls in. Employing ratio values effectively opens the number space.

3.2.5 Scavenging

GIS/statistical methods can be used to screen or filter out anomalies in soil, humus or lake sediment data that may be due to factors not related to mineralization such as lithological variations and/or metal scavenging due to organic matter and Fe and Mn oxides. Many methods for screening geochemical data for scavenging effects exist. Four related methods have been employed in this thesis: (a) selective query; (b) linear regression, (c) ratios and, (d) RGB ternary maps. These methods can be applied to multimedia data from the same geographic location or to data sampled from different

geographic locations. The former involves processing the data as discrete points whereas the latter necessitates interpolating the data to produce continuous surface maps

All methods reviewed for screening for the effects of scavenging yield similar results. The selective query technique is perhaps the simplest and most effective method, as it can be applied directly in the GIS using simple query statements. Caution must be used when using the ratio method as high ratio values can result from element concentrations that are not necessarily anomalous and are below upper thresholds present on probability plots.

3.2.6 Bedrock / surficial signatures in geochemical data sampled from till

Relevant questions for mineral exploration when analysing geochemical data sampled from surficial media include:

- (a) do element concentrations in surficial media vary over mapped surficial units;
- (b) is there a bedrock signature in the geochemical data sampled from surficial media;
- (c) do variations in element concentration in surficial media (till, humus, soil) reflect the concentration in the bedrock spatially and statistically;
- (d) is there a spatial relationship between geochemical anomalies in bedrock and surficial media?

The GIS can be effectively utilized to help answer these questions by employing the *point-in-polygon* procedure, discussed previously, to partition the geochemical data into separate groups based on mapped lithological and surficial units.

In the elements studied in this thesis, Zn and Cu, it was found that, with respect to Zn concentration between lithologic units, rock, lake sediments and humus had higher Zn concentrations than soil and till. Zinc concentration in humus varied sympathetically with lake sediments across lithology as did soil and till. Humus was similar to rock except over felsic volcanic rocks. With respect to Cu concentrations between lithologic units, all media varied sympathetically with lithology across ultramafic, mafic and

intermediate rocks and to a lesser extent over felsic, granitoid and sedimentary rocks. Copper concentrations in lake sediments and till were similar and varied sympathetically over all rock units. These results suggest that lake sediments and humus (at least in thin till conditions) are good media for sampling for base metal exploration as they reflect a broad geochemical signature that is reflective of bedrock variations.

Copper and even more so Zn concentrations in till (and to a lesser extent soil) were found to be related to anomalous concentrations in rock within a distance of 1 km. This, again, may reflect a stronger bedrock signature for Zn than Cu concentration in till. The GIS, using a *nearest-point* algorithm, was used to identify directional anisotropy's in geochemical data sampled from till, thus assisting in geographically narrowing down prospective targets. This is especially important for exploration in areas that are not well mapped (e.g. in areas where information on surficial units and glacial movement direction is lacking).

3.2.7 *The effects of down-ice dispersion in till geochemical data*

Collection and analysis of till is an important part of regional mineral exploration programs in glaciated terrains (Coker, 1991; McClenaghan, 1992; Shilts, 1995; Bajc, 1996; McClenaghan et al. 1997; Klassen, 1997). Glacial till (drift) comprises an unsorted mixture of rocks, clay, silt and sand derived from bedrock and mechanically modified by the physical processes of glacial erosion, transport and deposition (Shilts, 1991, 1996). However, till is deposited by a moving ice-sheet often resulting in a spatial dislocation between a till geochemical anomaly and the original up-ice anomaly in bedrock. This dislocation can be relatively small (< 1 km) or much larger (> 100km) depending on the original glacial environment and can impart a directional bias (anisotropy) on the data reflecting one or more periods of glacial ice movement.

Detailed mapping and an orientation survey, conducted before regional sampling begins are usually undertaken to gather information on till type and thickness, the distance of maximum down-ice dispersion of minerals, the direction(s) of glacial transport, the

fraction to till sample and the nature and spatial characteristics of dispersal trains. However, in some exploration programs time and cost does not permit detailed mapping or an orientation survey. The GIS in concert with geostatistics and statistical analysis can be used to assist in drift prospecting by providing information on the concerns mentioned above.

A new algorithm, termed the dispersal train identification algorithm (DTIA) is presented in this thesis for (1) identifying potential dispersal trains in a regional till dataset and (2) locating up-ice source zones (dispersal train head zones) of geochemical anomalies in till. *DTIA* requires a set of user input parameters used for simulating dispersal train characteristics. The algorithm employs a succession of wedge-shaped search regions (each one shaped like an isosceles triangle with the search point at the principal vertex) to 'look' in user-specified directions from a set of search points that may be mineral prospects, geochemical anomalies in rock or a homogeneous grid of points. The values of the till sample points occurring within the wedge are analyzed as candidates for a dispersal train using a series of criteria. The geologist specifies the length and angle of the wedge, where the length reflects the distance of down-ice dispersion and the angle is used to model a ribbon or fan-shaped dispersal train. For each search position *DTIA* calculates the average of the values within the wedge (*pmed*) the difference between wedge average and the local average (*diff*), and fits an exponential model to the within-wedge points (geochemical value as a function of distance from the search point). Candidate search points for the heads of dispersal trains are selected based on high values of *pmed* and *diff*, as well as best fit lines (fitted to the natural logarithms of geochemical values) that show high negative slopes (*b*), significant values of a test statistic for the slope magnitude (*ts*), and large negative correlation coefficients (*R*). The slope statistic, *ts*, is particularly useful in identifying candidate trains, but care must be taken to eliminate situations where the closest sample point is relatively far from the search point.

DTIA was tested on three datasets; simulated data in which dispersal trains are embedded in various levels of background noise, a dataset in Cape Breton where documented till dispersal trains exist and in the Swayze greenstone belt where no documented trains are

known. *DTIA* worked satisfactorily with the simulated data, and performed well with the data from Cape Breton. The results are particularly sensitive to both direction of search and the wedge angle, as demonstrated by plots of *ts* versus these two parameters, for known trains, using mines as search points. By systematically searching from a set of grid points, then screening out search points (and associated directions) that have (1) *pmed* values less than a threshold, (2) *diff* values less than a threshold, (3) distance of point closest to search point less than a threshold, (4) slope values less than zero and (5) *ts* values usually greater than 2, a suite of candidate search points can be plotted on the till geochemical map, colour coded by search direction. These candidate points (and associated wedges) can then be visually appraised as potential dispersal trains.

Application to the Swayze data revealed candidate trains whose directions are consistent with glacial transport directions known from data on glacial striations. Although this method shows promise as a data exploration tool, more work is needed to improve the algorithm and to test it under a greater range of conditions.

3.3 Visualization of geochemical data

Most GIS provide the geologist with a wide range of software tools with which to visualize geochemical data. The process of visualization (see Harris *et al.* 1999b, for a detailed study) involves displaying and combining geochemical with other geoscience data for the purpose of exploratory data analysis. This is important in that non-traditional geochemical maps and images can assist the geologist in identifying spatial patterns that may be important for regional mineral exploration.

Different methods of visualizing geochemical data employed in this thesis include:

- traditional proportional dot plots
- buffered points
- interpolations (kriging and inverse-distance weighted)

- 3 colour (RGB) ternary diagrams
- image combinations (fusion)
- 2.5 dimensional images

Proportional dot and pie maps are simple to construct in a GIS and, since the points are not interpolated, no potential artifacts or generalizations due to the interpolation process are produced. However, only one element can be shown at a time (unless pie plots are used), and often percentile divisions, which is the most popular method of ranking and displaying the data, may not be sensitive to natural population breaks (thresholds) in the data. Furthermore, it is difficult to compare different elements both statistically and spatially.

Variograms provided information on spatial structure enabling the modeling of anisotropy's such a glacial dispersion. Kriging was found to be the best method for interpolating geochemical data as regional geochemical patterns were emphasized and a measure of uncertainty in the interpolation process was provided. The uncertain areas were excluded from further analysis by using a masking procedure in the GIS. The interpolated geochemical data often revealed both regional and subtle geochemical patterns to a greater extent than proportional symbol maps.

Red-Green-Blue (RGB) ternary images (Broome *et al.* 1987; Harris *et al.* 1990), often used in the display of remotely sensed data, were also effective for visualizing interpolated geochemical data. These maps or images were constructed by taking three continuous surface (interpolated) geochemical maps, and displaying one in a blue, one in a green and the other in a red colour. The additive mixes of the primary colours, which results in a wide range of hues, were interpreted with respect to the varying concentrations of each geochemical element, allowing the spatial associations between geochemical elements to be visually assessed. Using variations in the additive mixture of colours, RGB ternary images were useful for the multivariate comparison of geochemical patterns, either between different elements or between the same element sampled from different media. This not only highlighted areas of anomalous concentrations but also the

patterns identified and the resulting colours shed light on surficial processes at work over a given geographic area (e.g. processes of glacial dispersion, scavenging).

Utilizing the third dimension to visualize geochemical data allowed for the comparison of at least four variables in one image, facilitating the comparison between elements or media. Combinations of geochemical data with other geoscience data such as topographic information using GIS technology (IHS transform) can revealed associations between geochemical data and other surficial factors that may be important for mineral exploration. Adding the third dimension allows for the comparison of at least four variables in one image, facilitating the comparison between elements or media. These images assisted in revealing spatial associations between different elements and/or between elements and topography.

3.4 Multi-media comparison

In this thesis Zn and Cu sampled from various media were compared with respect to concentration and the following observations were made:

- (a) Zn --- lake sediments > (humus > rock) > (till > soil)
- (b) Cu --- rock > lake sediments > till > humus > soil

The media enclosed in brackets above did not have significantly different concentrations of Zn. Zn concentrations in all media was higher than Cu. This may due to generally higher background concentrations as a function of the predominance of mafic and intermediate volcanic rocks and greater mobility. Concentrations of Cu and Zn in till were similar. The greatest amount of mixing would occur in till thus averaging out total concentration (similar to the effect of lake sediments) resulting in similar Zn and Cu concentrations at least in the clay+silt fraction of glacial till. Concentration of Zn and Cu in lake sediments and rock were the highest and typified by the highest contrast anomalies for both Zn and Cu. Soil and to a lesser extent, till (especially for Zn) had the

lowest concentrations of Zn and Cu as well as lowest contrast between anomalies and background.

The highest concentration for Zn was found in lake sediments. This is not unexpected given the relative mobility of Zn and the large catchment areas involved in lake sediment sampling. In addition, mafic volcanic rocks dominate the study area and in these rocks Zn can readily substitute in mafic-forming minerals resulting in higher background levels. The relatively high Zn concentration in humus was somewhat anomalous. The following factors may be important in accounting for this observation: (1) scavenging of Zn by organic matter and colloidal Fe and Mn oxides still present in the humus; (2) vegetation tapping mineralized bedrock directly (in thin soil/till conditions) resulting in higher concentrations in humus than in soil or till; and (3) higher background levels of Zn (see above) combined with preferential uptake of Zn by vegetation and subsequent recycling in humus. It is also noteworthy that Zn concentration in humus resulted in the best-structured variogram. This is also somewhat surprising, given that humus is generally considered to reflect element concentrations local to the sample point (i.e. small zone of influence). This result may suggest that humus has a homogenizing effect (e.g. scavenging) on more mobile elements such as Zn, thus averaging out concentrations over space, or that trees (from which the humus is derived) are efficient in gathering Zn over broad areas.

The concentration of Zn in rocks was generally less variable than Cu. Zinc exhibits both chalcophile and lithophile characteristics and can substitute readily in major-rock forming silicate minerals such as biotite, pyroxene and amphiboles; oxide minerals such as magnetite; and in sulphides (sphalerite). Copper displays chalcophile characteristics and prefers sulphides to silicates or oxide minerals. Thus, Cu will be found predominately in sulphides (e.g. chalcopyrite, covellite) whereas Zn can be found both in sulphides, and in common rock-forming silicate minerals. Therefore, high Cu concentrations may reflect primarily sulphide mineralization whereas high Zn concentrations may represent both sulphide mineralization and lithologic variations. The more homogeneous distribution of Zn between lithological units suggested that Zn concentration is more a reflection of

lithologic variations (e.g. more Zn occurring ubiquitously as a substitute mineral in mafic-forming minerals). This may reflect a general trend (or difference) between lithophile and chalcophile elements.

Copper concentration was highest in rock and given that most Cu will be found in sulphides, anomalies in Cu are more likely to reflect mineralization or extensive weathering of sulphides. High concentrations in lake sediment again may represent a mineralization signature rather than primarily a lithologic signature, as in the case for Zn. This illustrates the importance of accounting for lithologic variations using normalization techniques. Copper concentration in humus is lower than Zn in humus.

Global correlation of Cu and Zn in the various media was highest between soil and till, suggesting that in the generally thin till conditions across the belt, soil is derived directly from the till, and that the till is for the most part residual (traveled short distances generally ≤ 3 km). This suggests that either till or soil can be used as an effective medium for exploration purposes in Archean greenstone belts covered by a thin veneer of till.

3.5 Data Integration/Modeling

One of the major strengths of a GIS is the ability to integrate and combine multiple layers of geoscience data into mineral prospectivity maps showing areas favourable for mineral exploration. It is these capabilities that make GIS an extremely useful tool for mineral exploration.

The geologist has many options for processing geoscience data for input to GIS modeling procedures. This thesis presented two methods for processing geochemical data: processing as discrete (buffered) points and as continuous surface maps. Consideration of these two different processing methods is necessary, as often geochemical data will not be of sufficient density to warrant interpolation.

Once the data have been properly prepared the GIS, in concert with other statistical and geostatistical software packages, can be used to manipulate and visualize the data in order to produce a mineral prospectivity map. This thesis has employed both data-driven modelling techniques (weights of evidence (WofE) and logistic regression) and knowledge-driven techniques (boolean and index overlay) to produce Au prospectivity maps. The data-driven approach using the weights of evidence (WofE) or logistic regression techniques is objective as the weights for each evidence map are derived statistically. The weights reflect whether more gold prospects fall on a given map pattern (e.g., geochemical anomaly, specific lithology, close to a fault etc.) than would be expected by chance. However, if there appears to be a spatial association between the known gold prospects and a specific map pattern, as reflected by higher weights (W^+ and C for WofE and higher coefficients for logistic regression), the geologist still must ascertain whether this apparent association makes geologic sense.

In this thesis the index overlay method resulted in a prospectivity map that was more predictive than the boolean method (equally weighted evidence maps) indicating that expert knowledge provided by the geologist is an important part of the knowledge-driven modeling process. The data-driven prospectivity maps were better predictors of the known gold prospects which is not surprising given that the location of known prospects with respect to geochemical, geophysical and geologic anomalies comprising evidence maps drives data-driven modeling techniques. Based on the results from this thesis, it is recommended that data-driven methods be employed as a first priority providing there is a sufficient sampling of known prospects (> 30). Data-driven methods are more objective than knowledge-driven techniques and often reveal spatial associations between the known prospects and anomaly (evidence) maps that may have not been considered by the geologist before modelling was undertaken.

3.5.1 *Evaluation of geochemical data with respect to known gold mineralization*

Al_2O_3 and ferrous and ferric iron were the strongest predictors of gold prospects for the posterior probability map based on all the samples. The spatial association between anomalous iron (all samples) and gold may relate more to lithology, in this case, as 60% of the gold occurrences are found in mafic volcanic rocks, which would have naturally higher iron content. Al_2O_3 , CaO, FeO and Na_2O anomalies were the strongest predictors of gold when considering only the altered samples. However, only Na_2O is important when considering the studentised value (C/SD) which is a measure of significance of the C value. The relatively high weights (W+ and C) for CaO and Na_2O suggest that carbonatization and perhaps albitization are alteration trends spatially associated with gold mineralization. The strongest predictors of gold for the normalized data are CaO, Al_2O_3 , K_2O and FeO, all of which are important, and Fe_2O_3 , which is less significant (lower C/SD value). The anomalous CaO and K_2O indicate that carbonatization and potassic alteration (K-metasomatism and sericitization) are spatially associated with gold mineralization. The presence of iron oxides, reflected by anomalous Fe_2O_3 concentrations, may indicate an association of Fe-carbonates (e.g., ankerite) with gold mineralization. This is a common association found in many Archean greenstone belts (Hodgson, 1993). The best predictors for the ratio (mass balance) data were CaO and Fe_2O_3 . The gold potential map produced from the normalized data predicted more of the known gold prospects than the maps based on the altered, ratioed and all sample groups. The high correlation between normalized CaO and FeO, suggested an association between carbonatization and iron oxidization (ferric), possibly ankerite (Fe carbonate).

CHAPTER IV

Lithogeochemical Data – Anomaly Detection

4.1 Introduction

Lithogeochemical data, comprising both major oxide and trace elements, are frequently used in geological mapping and tectonic studies to classify rock types, identify chemical variations due to fractionation trends, and characterize tectonic environments.

Lithogeochemical data are also useful for mineral exploration studies by providing chemical information on alteration and mineralization patterns. The ultimate goal of the statistical and spatial analysis of lithogeochemical data for mineral exploration is the detection of zones of elevated concentrations (e.g., geochemical anomalies) of oxide or trace elements that may be reflective of mineral deposits. Since Archean metavolcanic rocks have often been subjected to minor alteration that is often difficult to recognize in the field (Gelinas et al., 1977), an assessment of altered versus un-altered samples is critical in any regional exploration program. In this paper, we refer to alteration as representing a change in major element oxide chemistry with respect to the original chemistry of the host rock from which it was sampled. Alteration due to mineralization processes, as opposed to regional metamorphic conditions that basically reflect a difference in alteration intensity, is the focus of this paper.

Many statistical and geostatistical techniques have been used to highlight or enhance trends or patterns (that are often termed unusual, anomalous, or atypical) in lithogeochemical data. These anomalous populations often reflect particular geologic processes such as fractionation, regional alteration, hydrothermal alteration and metasomatism. Table 4.1 provides a general summary of some of the techniques used to identify anomalous trends or populations in lithogeochemical data. These can be classified into techniques utilizing univariate, bivariate, trivariate, multivariate and geostatistical methods. Techniques applied to univariate data (histograms, probability plots etc.) are relatively simple to calculate and straight forward to apply to lithogeochemical samples. They involve identifying anomalous populations based on thresholds defined by changes in slope or groups of outliers on plots of cumulative

frequency distributions (e.g., QQ plots, normal probability graphs). Bivariate and trivariate techniques involve the identification of anomalous populations on 2D and/or 3D scatterplots or ternary diagrams (e.g., Jensen cation classification; Jensen, 1976). Multivariate methods have the advantage of analysing three or more elements simultaneously, and provide information on the association and structure between multiple elements. Principal component analysis, correspondence analysis and N-dimensional clustering have been used successfully to identify anomalous geochemical populations (e.g., Faffe and Leblanc, 1984; Grunsky, 1986; Grunsky et al., 1992; Jimenez-Espinosa et al., 1993; Grunsky, 1997).

A limiting factor in many univariate and multivariate techniques is that knowledge of spatial information is not used. Geostatistical methods such as factorial kriging (Galli et al., 1984; Sandjivy, 1984; Goovaerts, 1992; Jimenez-Espinosa et al., 1993) emphasize both statistical and spatial properties of lithogeochemical data. The approach in this paper is, thus, to analyse both the statistical and spatial characteristics of a large lithogeochemical dataset using some of the methods summarized in Table 4.1. A Geographic Information System (GIS), in concert with a number of statistical and geochemical methods, are used to analyse, manipulate and visualize the geochemical data in a variety of ways. Airborne magnetic data (OGS, 1997), and field observations of rock alteration style and intensity (Heather and Shore, 1999a-i), are used to help evaluate the alteration patterns determined from analysis of the lithogeochemical data.

The specific objectives of this study are to: (1) compare and contrast a number of univariate and multivariate methods for identifying anomalous trends (altered geochemical samples), (2) screen the identified anomalous (altered) samples with respect to regional alteration versus alteration processes that may reflect mineralization, and (3) evaluate these anomalous zones with respect to regional geology and known gold prospects.

4.2 Study area

The Swayze greenstone belt (SGB) is the south-western extension of the Abitibi greenstone belt (AGB), being connected to the latter by a narrow band of volcanic-sedimentary rocks that wrap around the north and south margins of the Kenogamissi granitoid complex. The SGB shares many features in common with the mineral-rich AGB to the east, but lacks any significant mineral production.

The SGB (Fig. 4.1) is surrounded by large granitoid complexes to the north, east and south known respectively, as the Nat River, Kenogamissi, and Ramsey-Algoma granitoid complexes (Heather and van Breemen, 1994). The SGB, like most Archean greenstone belts, contains a diversity of both extrusive and intrusive rock types ranging from ultramafic through felsic in composition, as well as both chemical and clastic sedimentary rocks (Fig 4.1). A number of fold-repeated (2730-2680 ma) mafic-felsic metavolcanic packages occur. They are unconformably overlain by Timiskaming-type metasedimentary rocks, and cut by high strain zones (Heather and van Breemen, 1994; Ayer and Theriault, 1993; Ayer, 1995; Heather et al., 1995; Heather et al., 1996). The map pattern preserved within the SGB, is dominated by regional, F₂, anticlines and synclines.

The SGB contains alteration and mineralization types typical of many Archean greenstone belts. Common alteration minerals consist of epidote, chlorite, sericite, Fe-carbonate, calcite, pyrite, tourmaline, garnet, hematite, magnetite and quartz. In some cases it is difficult to distinguish synvolcanic alteration from syntectonic or late-tectonic alteration due to similar mineralogy.

Approximately 4500 whole rock samples were acquired over the SGB from three principal sources; Geological Survey of Canada (GSC), Ontario Geological Survey (OGS) and Falconbridge Ltd. Individual datasets and their specifications are listed in Table 4.2. Each lithogeochemical dataset comprising the final compiled dataset was characterized by a different sampling strategy, and no information was available as to the freshness of the rocks sampled in the older datasets (Texas Gulf, Falconbridge and

Petroch, assessment files). The newer datasets collected by the GSC and OGS comprised what were judged to be fresh samples in the field (Heather, oral comm., 1997; Ayer, oral comm., 1997). The major oxide data, on which this paper focuses, were generally complete for most of the datasets used in the final compilation. The oxides were analysed using X-ray fluorescence (XRF). Wilkinson et al. (1999) provides a complete description of how this lithogeochemical database was compiled, and the various methods used for evaluating data quality and integrity. Approximately 1000 samples, from an original total of 4500 samples, were deleted from the database, as they did not pass certain screening standards set forth in the above referenced paper.

4.3 Methodology

Two major themes are discussed with respect to methodology: (1) the identification of altered samples using a variety of techniques, and (2) the screening of altered samples with respect to regional metamorphism and hydrothermal alteration /mineralization. Some of the techniques used for identifying altered from un-altered samples are also used for screening the altered samples (see Table 4.1). The difference is the population of samples to which each technique is applied.

4.3.1 *Identifying geochemical anomalies (altered vs. unaltered samples)*

Many methods exist for identifying altered samples (see Table 4.1, as well as Gelinas et al., 1977; Grunsky et al., 1992; Rollinson, 1993; Madiesky and Stanley, 1993; Harris et al., 1997). In this study, univariate methods (as per Table 4.1) included excessive LOI (> 8% for mafic rocks or > 4% for felsic rocks), and excessive volatiles ($\text{CO}_2 + \text{H}_2\text{O} > 3.8\%$). Multivariate methods used included an alteration index (Hashimoto index > 49 and ACNK index > 0.72), atypical minerals based on a normative mineral classification, index of typicality (Grunsky et al., 1992), and identification of anomalous trends on 3D scatterplots.

The thresholds for LOI were based on consultation with various exploration companies (Falconbridge Ltd., in particular), and government field geologists (Ayer, oral comm., 1997). Typically, regional metamorphosed mafic rocks have high LOI values due to greater abundances of hydrous minerals (micas and amphiboles). Thresholds for total volatile content were set based on upper breakpoints observed on probability plots of the data.

A total volatile ($\text{H}_2\text{O} + \text{CO}_2$) threshold of 3.8% was used in this paper to flag altered samples. This value follows thresholds determined from others working with metavolcanic rocks (Wilson et al., 1965; Brooks et al., 1969; Gelinas et al., 1977), and is justified because much of the CO_2 and H_2O occurring in Archean metavolcanic rocks has been introduced from external hydrothermal fluids (Brooks et al., 1969).

Many alteration indices can be used for detecting the presence of alteration (see Franklin, 1997). The alteration indices used in this paper were chosen in consultation with Falconbridge Ltd., who have used them for base-metal and gold exploration in various greenstone belts throughout northern Ontario. The Hashimoto index (Ishikawa et al., 1976) is defined as follows: $((\text{MgO} + \text{K}_2\text{O}) / (\text{MgO} + \text{K}_2\text{O} + \text{CaO} + \text{Na}_2\text{O})) * 100$, and emphasizes MgO mobility over alkali depletion, and thus is useful for detecting alteration in mafic and ultramafic rocks. Specifically, this index is sensitive to the addition of MgO and K_2O as chlorite and sericite, and the loss of CaO and Na_2O by the destruction of feldspar. The ACNK index (Spitz and Darling, 1978) is defined as: $\text{Al}_2\text{O}_3 / (\text{Na}_2\text{O} + \text{CaO} + \text{K}_2\text{O})$, and is used for detecting alkali depletion while conserving Al_2O_3 . It is useful for detecting the alteration of feldspars, and thus is more appropriate for intermediate to felsic rocks. A normal probability plot was calculated for each alteration index and upper breakpoints were identified above which samples were considered altered. These breakpoints corresponded to greater than 49 and 0.72 for the Hashimoto and ACNK indices, respectively.

A normative mineral classification was undertaken using the major element oxide data. Altered samples were flagged based on atypical minerals using the following criteria; presence of hematite (or) wollastonite (or) pervoskite (or) nepheline (or) leucite (or)

kaliophilite (or) calcium silicate (or) acmite (or) sodium silicate (or) potassium silicate (or) corundum > 3%. Normative calculations assume that minerals produced in an igneous rock are the result of normal fractionation processes, whereas altered rocks do not have chemical abundances that produce expected normative minerals. The existence of normative corundum, nepheline and wollastonite in subalkaline metavolcanics, for example, is indicative of considerable alteration (Gelinas et al., 1977). Corundum indicates a peraluminous composition due to the depletion of CaO and excess Al_2O_3 , nepheline reflects addition of Na_2O , wollastonite reflects the addition of CaO, and calcite reflects the addition of CO_2 through metasomatism (Gelinas et al., 1977).

The index of typicality is a measure of how typical a sample is with respect to a reference population of samples (e.g., calc-alkaline basalts, ultramafic komatiites) established for Archean volcanic rocks within the Abitibi greenstone belt (Grunsky et al., 1992). An index of typicality of .9 means a sample has a high probability of belonging to the specific reference population, whereas an index of 0 indicates that the sample under consideration does not belong to the group, and perhaps represents an altered sample.

Altered samples can also be identified on 3D scatterplots of major element data. Unusual data trends or groups of samples on these scatterplots can be identified, and their spatial distribution can then be displayed on the geologic map of the area. Oxide elements, comprising more felsic minerals, can be plotted on 3D scatterplots to identify altered samples reflecting silicification, potassic alteration, albitization, and alkali depletion. Oxide elements reflecting more mafic minerals can be plotted to assist in identifying altered samples that may reflect chloritization, carbonatization, iron oxidization and serpentinization. Three-dimensional scatterplots of SiO_2 , K_2O , Al_2O_3 , were used to identify felsic alteration trends, and MgO , CaO , Fe_2O_3 , and Na_2O were used to identify mafic alteration trends.

Visualization of altered samples: Geochemical data can be interpolated using a variety of interpolation algorithms (inverse-distance-weighted, kriging etc.), or analysed and displayed as discrete points. One method of identifying and visualizing areas of alteration

is to construct proportional circles, where, typically, the size of the circle is proportional to concentration (see Harris et al., 1997). An alternative to this method is to construct interpolated maps based on concentration, and to combine three of these single-element maps in a red-green-blue (RGB) ternary map, an approach used widely in image processing of remotely sensed data (e.g., Sabins, 1992; Drury 1993 ; Harris et al., 1990). Another method, used in this paper, is to produce a density map based on the altered samples for each of the methods used to identify alteration discussed previously. Three alteration density maps can then be combined in a simple ternary RGB image.

The RGB ternary maps shown in this paper were produced by: (1) converting each altered sample point identified by each method to a raster cell (grid) using a point-to-grid conversion within the GIS, (2) calculating the average density of altered points for each grid cell using a 25 X 25 mean filter (~ 2.5 x 2.5 km filter size) and, (3) assigning red, green and blue colours to each of the three alteration grids (images) forming an RGB ternary colour composite map.

4.3.2 Regional metamorphism versus hydrothermal alteration/metasomatism

Once the altered samples have been identified, various graphical techniques (box and whisker plots) and statistical tests (t - test for population means, F- test for variance, Mann Witney test for median values and Kolmogorov-Smirnov test for frequency distributions) are employed to determine whether the sample populations, based on the altered and un-altered samples for each oxide, are significantly different. These tests are used in an exploratory sense, because the assumptions of un-biased random sampling and normal (or log normal) distributions are not strictly satisfied for formal tests of statistical significance.

To differentiate between altered samples resulting from alteration trends due to greenschist or amphibolite metamorphism, and altered samples resulting from local hydrothermal alteration processes responsible for mineralization, a number of methods have been used. Univariate methods include the use of geochemical thresholds, and

geochemical normalization, whereas multivariate methods include the use of alteration indices, selective querying, principal component analysis and 3D scatterplots.

All of these techniques, with the exception of the normalization method, are applied to the altered samples identified using the various techniques described in Section 4.2.1.

The normalization technique is applied to all samples, as a representative signature of background lithology is required for this technique to be effective in identifying anomalous concentrations of given elements.

Geochemical thresholds: This method involves the identification of anomalously high or low concentrations for a given major element (altered samples only) on normal probability plots. The assumption here is that anomalously high concentration of a given element in an altered sample reflects alteration related to hydrothermal or metasomatic processes. In some cases geochemical data may show distinct (anomalous) spatial patterns without anomalous high concentrations (Cheng et al,1996). Oxide concentrations for the altered samples from which thresholds are defined are based on the entire SGB, and are not divided by lithology.

Although geochemical thresholds have been variously defined (e.g., Howarth, 1983; Garrett, 1991), a threshold, in this paper, follows the reasoning of Garrett (1991), and is defined as the outer (upper and/or lower) limit of local background variation. Implicit in this definition is that regional background is dependent on lithology. An anomalous concentration of a given element in a felsic volcanic lithology may not be particularly anomalous in a mafic lithology by virtue of different background concentrations controlled by rock type. This is where normalization and selective querying (discussed in the next section) are particularly useful data processing techniques for identifying geochemical anomalies.

Many methods exist for determining thresholds for anomalous populations and include: (1) exploration knowledge applied “as rule of thumb” (e.g., it is known that within an area of ultramafic rocks > 40 wt% MgO is anomalous), (2) arbitrary methods using percentile or standard deviation values, (3) visual inspection of probability plots (Stanley,

1987; Grunsky, 1992; Harris et al., 1997), (4) visual inspection of area versus concentration plots (Cheng et al., 1996), and (5) weights of evidence (WofE) (Bonham-Carter, 1994). The WofE method requires a priori knowledge (i.e., knowledge of existing mineral prospects), whereas the other methods do not. In this paper, percentiles and visual inspection of probability plots are used to determine thresholds in major element concentrations and in the levels of derived alteration indices.

Normalization: Normalization involves processing the lithogeochemical data to de-emphasize the effects of lithology, resulting in element anomalies that are more likely related to alteration and mineralization processes (Harris et al., 1997). One method to accomplish this involves calculating the median concentration for each oxide element for each lithologic unit. A lithology field is added to the geochemical sample table by performing a GIS *point-in-polygon* operation, whereby each geochemical sample point is intersected with the lithological map (Fig. 1). The following formula is then used to normalize element concentration for background lithology:

$$Z^* = (Z/M - 1) * 100$$

where, Z^* = normalized concentration value and

Z = oxide or trace element concentration (for all samples)

M = median value of the element for the lithologic unit

Values of Z^* less than or equal to zero represent background values (e.g., $\leq$ median value for each lithological unit), whereas values greater than zero may represent anomalous concentrations. The -1 term simply adjusts samples with values greater than the median value to positive numbers (e.g., possibly anomalous), whereas those samples with values less than the median are set to negative numbers (possible background). A variation on this equation is to divide the result of Z/M by the standard deviation of each element for each lithological unit, thus accounting for the variance in element concentration for each lithology:

$$Z^* = ((Z/M) / SD) * 100$$

where, Z^* = normalized concentration value and

Z = oxide or trace element concentration (for all samples)

M = median value of the element for the lithologic unit

SD = standard deviation of the mean for the lithologic unit

Thus, a lithology that is characterized by a wide variation in element concentration (large variance and standard deviation) results in a lower normalized value for each element. The median value is used in these equations rather than the mean as it is generally less sensitive to outliers, and thus is a more appropriate estimate of average background (e.g., Garrett, 1991). The assumptions that are necessarily made in this normalization procedure is that the geologic map is accurate, that the lithological background is constant, and that the geochemical sampling is unbiased and is spatially and statistically representative of a particular lithology. The normalization equations represent an approximate correction for average values by lithology, but variability due to other sources (e.g., sampling pattern) may still be present in the data.

Selective Querying: A selective querying process was invoked which involved: (1) the calculation of probability plots for each major element (altered samples only), and selected alteration indices divided into ultramafic, mafic and felsic/intermediate lithologies as determined from a Jensen geochemical classification diagram, (2) selection of anomalous samples defined by high concentrations or ratio values (for alteration indices) from the probability plots (upper breakpoints), and (3) determining the underlying lithology for these samples and choosing only those in which the mapped lithology matches the geochemical classification (e.g., mafic geochemical classification with mapped mafic volcanic rock). This can be accomplished in the GIS by using a series of SQL (structured query language) statements. For this study, these statements are summarized in Appendix A-2. This selective querying process has the advantage of utilizing variable thresholds, as an anomalous concentration of a given element in a felsic lithology may not be anomalous in a mafic lithology. The use of variable thresholds based on different geochemical classifications, reflecting major lithologic divisions, is similar to the normalization process discussed previously. The effects of varying

lithologies on geochemical signatures are considered as well as the added effects of regional metamorphism and alteration due to hydrothermal activity and mineralization processes.

The Jensen classification (Jensen, 1976), used as an integral part of the selective query process, is based on a ternary classification of Al_2O_3 , MgO and total $\text{Fe} + \text{TiO}_2$. It is based upon the proportions of cations ($\text{Fe}^{2+} + \text{Fe}^{3+} + \text{Ti}$), Al and Mg recalculated to 100%, and plotted on a ternary diagram. The elements were selected for their variability in Archean volcanic rocks and their relative stability under low grade metamorphic conditions.

Principal component analysis and cluster analysis: Principal component analysis (PCA) attempts to describe the distribution of multivariate data using a new set of data axes (components) that are linear combinations of all the geochemical variables (e.g., Davis, 1986). Often, each component can be related to a specific geologic process (e.g., fractionation) (Grunsky, 1986). Plots (proportional circles or continuous surface maps) of these components can often reveal anomalous populations of chemically related samples.

One concern in dealing with statistical analysis of multivariate oxide geochemical data is the problem of closure. Compositional data, such as weight percentages reported for oxides, sum to 100%. Variables in a closed number system (sum to a constant) are not free to vary independently, as a change in the value of any one oxide by definition must affect the value of the rest in order for the total to remain at 100%. Aitchison (1986) has developed a method for dealing with the closure problem of compositional data based on log-ratio transformations. This method involves dividing each major oxide element by a common divisor (i.e., TiO_2 or P_2O_5), and then performing a logarithmic transformation on the resulting ratio value, thus opening the number space. In this paper, the oxides, SiO_2 , Al_2O_3 , K_2O , CaO , MgO , Fe_2O_3 and Na_2O , for the altered population of samples, were log-transformed using a relatively immobile oxide, TiO_2 , as the divisor. A principal component transform using the covariance matrix of the data was then applied to the log-ratioed, transformed data. The variance-covariance matrix was used to calculate the

principal components as the log-ratioed transformed oxides are unscaled and measured in the same units. Use of the correlation matrix results in an equal weighting of all variables (the variables are scaled to a mean of 0 and a variance of 1). Thus a large variation in one major oxide may be given as much importance as a small variation in another (Le Maitre, 1982). The first and second components were then plotted on scatterplots (biplots), and groups of samples were selected based on their component loadings, as well as their location on the scatterplots, as reflective of a particular alteration style.

Cluster analysis was also applied to the altered oxide samples and displayed on 3D scatterplots as a method of automatically delineating groups of samples based on element concentrations. Like individual components derived from PCA analysis, each cluster may reflect a different geologic process and a scatterplot of these clusters may reveal unusual trends or groups of samples. A K-means (migrating means) algorithm (Hartigan, 1975; Murtagh, 1985) was applied to sets of oxide elements thought to be reflective of a particular alteration style. The general objective of cluster analysis is to define clusters in N-dimensional space (in this study 3-D space), maximizing criteria for within group compactness and between group distinctness.

Scatterplots: Three-dimensional scatterplots of oxide elements, for altered samples only, thought to reflect a particular alteration style (e.g., CaO - carbonatization, K₂O - potassic alteration etc.), were plotted against relatively immobile elements, TiO₂ and Al₂O₃. These scatterplots were then inspected for unusual patterns that may represent highly altered samples.

4.3.3 Evaluation of geochemical anomalies

The GIS can be used effectively to compare the results of the various techniques used to identify altered samples by producing a co-occurrence map of altered samples. Small buffers, 500 meters around each anomalous geochemical sample point, were created to make a series of maps, one for each method used for identifying altered samples. These raster maps, which totaled six (based on the scatterplot, principal component, selective

query, geochemical threshold, normalization and alteration index methods) were combined in the GIS (overlaid), to produce a map showing the frequency of overlap between altered samples. The map classes reflect the number of times a particular sample was identified as being anomalous by any of the methods used to identify altered samples. Thus, a greater number of coincident altered samples reflect areas that satisfy a variety of alteration criteria and perhaps areas of more intense alteration.

The co-occurrence map can then be evaluated with respect to the known gold prospects, as compiled by Fumerton and Houle (1993), and Fumerton et al. (1993), using the weights of evidence technique (WofE) (Bonham-Carter, 1994). WofE is used to determine whether zones comprising altered samples of varying alteration intensity show a spatial association with known gold prospects. The key question in this analysis is determining whether there are more gold prospects occurring on a map pattern (areas of intense alteration in this case) than would be expected by chance. A pair of weights, (W+) and (W-), determined from the degree of overlap between the known gold prospects and the geochemical map (reflecting alteration intensity), are calculated for each map class. If there is no spatial association between the prospects and the geochemical map, then $(W+) = (W-) = 0$, and $C = 0$. A positive (W+) value indicates a positive association between gold prospects and geochemical anomaly maps. The contrast value (C), which is the difference between (W+) and (W-), also reflects the degree of spatial association between areas of intense alteration and prospects. A larger C value indicates a stronger association between gold prospects and the geochemical map. Bonham-Carter (1994) gives a detailed account of the WofE method.

4.4 Results

4.4.1 *Comparison of methods for identifying altered samples*

Figure 4.2 shows the location of the geochemical samples, divided into altered and unaltered samples, using methods discussed Section 3.1. Out of a total of 3395 samples, 1606 have been flagged as altered, by any method, representing approximately 47% of the total. Table 4.3 shows the breakdown of altered samples by method. The thresholds

based on the normative mineral classification and LOI are the most liberal having flagged 810 and 665 altered samples, respectively. The thresholds based on total volatile content and scatterplot analyses have flagged the fewest number of altered samples.

Table 4.3a is a crosstabulation among the five methods for detecting altered samples. The calculations are based on a series of 2 x 2 contingency tables (see Table 4.3b for an example) showing the frequency of occurrence of geochemical samples which were interpreted to be altered by two of the methods used to identify altered samples (e.g., norm minerals versus LOI, normative minerals versus volatiles etc.). The contingency tables show the number of altered samples identified by both methods, the number of samples identified as altered by one method and un-altered by the other method and vice versa, and the number of samples flagged as un-altered by both methods. A total of fifteen contingency tables were calculated. A measure of association between each pair of methods known as the Yule coefficient (ϕ) as quoted by Fleiss, (1991), was calculated for each contingency table and the resulting values are shown in Table 4.3a. Table 4.3b shows an example calculation of ϕ . This coefficient ranges between -1 and +1 and can be interpreted like a correlation coefficient, in that values close to 1 and -1 indicate a strong association between methods used to identify alteration. Bonham-Carter (1994) provides a more detailed discussion of this topic.

The strongest association, as reflected by ϕ , is between the alteration index and scatterplot methods and the scatterplot and LOI methods.

In Figure 4.3a, altered zones derived from the index of typicality, LOI and alteration index have been displayed in red, green and blue colours, respectively. Spatial relationships between the alteration zones can be interpreted with reference to the mix of the additive primary colours. For example, with reference to Figure 4.3b, the yellow area (B), indicates that this zone is characterized by samples with a relatively high percentage of atypical normative minerals (red), and high LOI values (green), as red plus green form a yellow colour. Areas in white (e.g., areas A, C, D, and E on Fig. 4.3b) are where all three methods used for flagging altered samples coincide. The alteration zones highlighted in colour on these ternary images, in part, reflect the density of altered

samples shown on Figure 4.2. For example, areas A, B, C, and E, annotated on Figure 4.3b, are also seen on Figure 4.2 as areas of increased density of altered samples.

Table 4.5 shows the number of altered samples by Jensen classification (Jensen, 1976), as a method to account for varying lithologies from which the samples were taken. The numbers reflect the altered samples expressed as a percentage of the total number of altered samples for each geochemical classification. For example, with reference to Table 4.5, 76% of the samples classified as BK (basaltic komatiites) were flagged by the alteration index method, and only 7% by the index of typicality. Strong trends can be seen between the alteration method and the chemical composition of altered samples flagged by each method. Ultramafic rocks tend to be identified most readily by the alteration index and on scatterplots, mafic rocks by LOI, and felsic rocks by atypical normative minerals and LOI. The index of typicality is sensitive to alteration in mafic, intermediate and felsic rocks but especially to alteration in rocks that have been chemically classified (using a Jensen ternary classification) as intermediate and felsic tholeiites.

Virtually all the altered and un-altered populations showed a significant difference for each oxide element using a variety of exploratory analysis procedures (e.g., box and whisker plots of altered and un-altered samples), as well as various statistical tests (see Section 4.3.2). These analyses and tests indicate that the methods used to detect altered samples produced distinct populations. Table 4.6 shows major element trends for the entire SGB with respect to altered and un-altered samples, based on the five methods used to identify altered samples. The direction of the arrow indicates a major element concentration higher or lower for altered samples with respect to un-altered samples. A dichotomy exists between the normative mineral and index of typicality methods, and the LOI and volatile methods, (and to a lesser extent the alteration index method), in that when the normative mineral method shows an increase in major element concentration in altered samples, the other methods generally show a decrease. The altered samples flagged by the normative mineral method show a significant increase in SiO_2 , Al_2O_3 , Na_2O_3 , and K_2O . The LOI, volatile and alteration index method show decreases in the

above major elements and increases in MgO, CaO, FeO, Fe₂O₃ and TiO₂ in altered samples.

4.4.2 Geochemical characterization of altered versus un-altered samples

Table 4.7 is a crosstabulation of altered (any alteration flag method) samples for major lithologic groups determined from a geochemical classification (Jensen cation classification). It can be seen that the ultramafic rocks have the highest percentage of altered samples, as indicated by the highest value for the ratio of altered to un-altered samples, followed by felsic rocks.

Table 4.8 provides further details on these trends by breaking the samples into individual rock types using a Jensen classification. The arrows in these tables, as in Table 4.6, indicate concentration trends of the altered samples relative to the un-altered samples, and the direction of the arrow indicates a positive or negative trend. A filled arrow indicates a strong trend and an unfilled arrow a weaker trend. This facilitates a comparison among felsic, intermediate, mafic and ultramafic lithologies with respect to dominant alteration styles. Trends between altered and un-altered samples identified using this table include a significant rise in SiO₂ in granitoid rocks, a significant increase in K₂O within felsic volcanic rocks (CR: calc-alkaline rhyolites), a significant enrichment in MgO within ultramafic rocks, an increase in Fe₂O₃ with respect to FeO within tholeiitic rocks, and an increase in CaO in picritic komatiites.

4.4.3 Characterization of altered samples

Geochemical thresholds: Figure 4.4 presents the samples for selected elements that have been identified as anomalous using thresholds on probability plots. Table 4.9 shows the thresholds selected for each element. These thresholds are quite high, corresponding to the 99th percentile of the cumulative frequency distribution for the altered samples for each major oxide (with the exception of MgO), thus, compared to the other methods, relatively few samples have been selected. These samples represent the most intensely

altered samples. The zones of most intense alteration are found in the vicinity of the Old Women iron formation (B) and the footwall felsic volcanics (Marion Formation; Heather and Shore, 1999a-i) to the iron formation, and the Shunsby area (C) (Fig. 4.4). Samples high in MgO in the central portion of the SGB (I) represent altered (chloritized) komatiites, and samples in the north, which are high in MgO, fall mostly in mafic volcanic rocks (A) and most probably reflect strong chloritization. Area A is known to contain a number of 10 –100 m wide deformation zones that are characterized by highly schistose, carbonatized and chloritized mafic volcanics (Ayer, 1995).

Normalized samples: Figure 4.5 shows the anomalous samples derived from the normalized data. Again, the anomalous samples were selected using upper breakpoints evident on probability plots. The two normalizing methods have resulted in the selection of similar groups of altered samples (see Section 4.3.2). The biggest difference between the two normalizing methods is between SiO_2 and K_2O , as indicated by correlation coefficients of 0.76 and 0.44 respectively. Correlation between normalization methods for the other oxides is in excess of 0.9. These results suggest that the spatial variation in SiO_2 (silicification) and K_2O (potassic alteration) over lithologic units is relatively large compared to other oxides.

The areas of most intense alteration occur in the Shunsby mineralized area (C), which is characterized by potassic alteration (high K_2O – see Fig.4.5), and albitization (high Na_2O); the Old Women iron formation (B), which is characterized by high concentrations of Fe_2O_3 (iron oxidization), MgO (chloritization) and CaO (carbonatization); and zones in the western SGB (E, D), which are characterized by high CaO (carbonatization), and Fe_2O_3 (iron oxidization) concentrations. Area E also has high K_2O (potassic alteration) and SiO_2 (silicification).

A comparison between Figures 4.4 and 4.5 reveals that the normalization process has generally resulted in a different population of samples being selected as anomalous than the un-normalized data. Figure 4.6 shows K_2O interpolated (kriged) using four groups of sample populations (all samples, altered, un-altered and normalized samples). The effect

of the east-west trending felsic unit, which is relatively high in K_2O (Fig. 4.6a), has been suppressed on the normalized data (Fig. 4.6b). This felsic unit is more clearly defined on the un-altered data (Fig. 4.6d), but is also evident, although less clearly, on the altered data (Fig. 4.6c). Figure 4.7 presents a series of pie charts showing the percentage of anomalous K_2O samples, defined by upper breakpoints on probability plots, by lithology for each K_2O dataset used to produce the continuous surface maps shown in Figure 4.6. A greater percentage of K_2O anomalies fall within felsic volcanic rocks for the datasets based on all, altered and un-altered samples, whereas the majority of K_2O anomalies fall within mafic rocks for the dataset based on normalized data. Thus the normalized data has identified altered samples falling in mafic volcanic rocks possibly reflecting potassic alteration. These samples would normally be overlooked using other methods due to naturally low concentrations of K_2O in mafic rocks.

Scatterplots and 3D clustering: Figure 4.8a shows a 3D scatterplot of MgO concentration plotted against two relatively immobile elements, Al_2O_3 and TiO_2 , for altered geochemical samples from mafic volcanic lithologies. Figure 4.8b shows the same plot for unaltered samples. Mafic volcanic lithologies have been chosen as they are the primary hosts of gold mineralization in Archean greenstone belts (Hodgson, 1993), and they comprise the largest volume of rocks within the SGB. A significant linear trend comprising samples that range from 15 to 40 wt% MgO can be seen on the plot of altered samples. All of the altered samples comprising this trend have been classified as either basaltic or picritic komatiites using a Jensen classification (Jensen, 1976). This linear trend may, in part, represent komatiites or alteration (chloritization) in mafic rocks, and serpentinization/chloritization in ultramafic rocks. To further define this trend, Figures 4.8c and 4.8d show MgO plotted against LOI for altered and un-altered mafic volcanic samples, respectively. The linear trend highlighted on the plot of altered samples indicates a strong relationship between samples with increasing MgO concentrations and LOI suggesting that this represents a true alteration effect as opposed to an unusual rock type. This trend is not evident in the plot of un-altered samples (Fig. 4.8d). Figure 4.8e shows the spatial location of these anomalous samples overlaid on shadowed enhanced airborne magnetic data. Over 90% of these samples fall on linear magnetic anomalies

suggesting a mafic or ultramafic lithology. The samples in the central portion of the SGB (area I) fall in ultramafic and mafic lithologies mapped by Heather and Shore (1999a-i), and reflect komatiites, with well-developed spinifex textures.

Figure 4.9a and b show scatterplots similar to Figure 4.8a and b, but K_2O is plotted against Al_2O_3 and TiO_2 . Again, the plot (Fig. 4.9a) of altered samples over mafic lithologies shows a number of interesting trends (trends 1 and 2), not present in the plot of un-altered samples (Fig. 4.9b). Figure 4.9c shows the spatial location of these samples (trends 1 and 2), as well as alteration styles recorded in the field in the vicinity of the geochemical samples. The linear trend characterized by extremely low K_2O values (trend 1 on Fig. 9a) is defined by the same samples that defined linear trends on Figures 4.8a and c, and represent regionally altered komatiites and mafic volcanic rocks, as discussed in the paragraph above. The outliers (trend 2 on Fig. 9a), characterized by high K_2O values (> 4 wt%), is defined by intermediate and felsic volcanic rocks in the western part of the SGB, oxide facies iron formation and ultramafic rocks in the eastern portion of the SGB, and mafic and felsic volcanic rocks in the northern SGB (see Fig. 4.9c).

Figures 4.10a and 4.10b show CaO plotted against TiO_2 and Al_2O_3 for altered and un-altered samples, respectively, sampled from mafic volcanic rocks (see Fig. 4.1). A K-means clustering algorithm was employed to search for five unique populations within the scatterplot. Figure 4.11a shows the statistical results (mean value in wt% for each cluster) of the K-means clustering process applied to the data (CaO , Al_2O_3 , TiO_2), and Figure 4.11b shows the colour-coded results of the clustering on the 3D scatterplot. Figure 4.11c is a map of the spatial location of the clustered samples (clusters 2 and 4 only) overlaid on an airborne shaded relief magnetics image. Clusters 2 and 4 are of interest as they are characterized by relatively high mean concentrations of CaO (9.4 wt%, and 7.7 wt% respectively), possibly representing carbonate alteration trends. Samples comprising cluster 4 also have a higher mean TiO_2 concentration that may relate to accessory minerals formed through hydrothermal alteration. Out of a total of 195 samples in the southern SGB (total of 281 for entire SGB) falling in cluster 2 (highest mean CaO), 43 fall in the mafic volcanics of the Newton Formation, 69 in mafic

volcanics of unknown stratigraphic position, 22 in mafic volcanics of the October Lake Formation and 16 in intermediate volcanic rocks of the Marian Formation (formation names after Heather and Shore, 1999a-i). The rest (45) fall within felsic volcanic or granitoid lithologies. The anomalous samples in mafic rocks are of the most interest for gold exploration as most of the known gold prospects in the SGB are associated with quartz veins hosted by carbonatized mafic volcanic rocks (Hodgson, 1993; Heather et al., 1996; Ayer, 1995).

Selective querying: Figure 4.12 a-e shows the results of the selective query process (Appendix A-2) for K_2O , CaO , Fe_2O_3 , SiO_2 , MgO , and Na_2O . Figure 4.12a (anomalous K_2O samples), for example, shows felsic altered samples (e.g., CR, TR, TA, CA) that fall on mapped iron formations and/or feldspar porphyries, mafic samples (CB, HFT, HMT) that fall on mafic and intermediate volcanics, and ultramafic samples (BK, PK) that fall on ultramafic lithologies. Note that the anomalous thresholds for K_2O are different (see Appendix A-2), as would be expected, for each lithological group being much higher within felsic than mafic and ultramafic lithologies.

Major zones of alteration on Figure 4.12 occur in the vicinity of the Old Women Iron Formation and associated footwall felsic volcanics (B) and in the western portion of the SGB. Areas of anomalous CaO are widespread along linear zones marked by magnetic anomalies (Fig. 12d). These zones are also evident on the map showing SiO_2 anomalies (Fig. 4.12c).

Principal component analysis: The PCA transform was applied to 1070 samples out of a total of 1606 samples identified as altered, because these samples had a complete analysis for the oxides under consideration (SiO_2 , Al_2O_3 , K_2O , CaO , MgO , Fe_2O_3 , Na_2O). A log-ratio transform was applied to these samples to minimize the effects of closure, as discussed previously. Table 4.10 shows the component loadings resulting from the principal component transform of the oxide data. Component one represents a more felsic alteration style being heavily weighted by Na_2O and K_2O and to a lesser extent by SiO_2 , Al_2O_3 . Component two has a stronger mafic influence being heavily weighted by MgO

and Fe_2O_3 and to a lesser extent by CaO , SiO_2 and K_2O . A scatterplot of component 1 versus component 2 reveals groups of outliers (Fig. 4.13). The vectors on this plot show the relative loadings of the first and second components, and indicate the oxides that are most influential for each group. The length of each vector is proportional to the loading (see Table 10) and the direction indicates the major oxide element that most influences each group of outliers. The locations of these groups within the SGB are shown on Figure 4.14, while Table 4.11 shows the average oxide concentrations for each of these groups. Groups 1 and 2 are heavily weighted by MgO and Fe_2O_3 and represent samples that are intensely chloritized and oxidized whereas group 3 is heavily weighted by SiO_2 reflecting silicification. Group 4 is weighted by K_2O and Na_2O (potassic metasomatism, sericitization and albitization) and group 5 is most strongly weighted by Fe_2O_3 and CaO , reflecting carbonatization and Fe-carbonate alteration. Group 6 is characterized by high Al_2O_3 , and low K_2O (alkali depletion).

4.5 Comparison between alteration zones and known gold prospects

Figure 4.15a is a summary of the major alteration zones (in the form of a co-occurrence map- see Section 3.3) identified using the various methods for identifying and characterizing alteration in this paper. The maximum number of coincident samples was six, equaling the number of input maps. The co-occurrence map has been reclassified into three categories: low, medium and high number of coincident altered samples and also shows the known gold prospects. Areas of intense alteration mapped in the field (Heather and Shore, 1999a-i) are shown on Figure 4.15b-d to help assess the alteration patterns seen on Figure 4.15a.

Table 4.12 shows the results from WofE, with respect to the known gold prospects, applied to the three map classes shown in Figure 4.15a. The same co-occurrence maps were constructed using only the methods which use variable thresholds (normalization and selective querying – Figs. 4.5 and 4.12), and the methods which did not use variable

thresholds (geochemical thresholds, scatterplots, PCA – Figs. 4.4, 4.8, 4.9, 4.11, and 4.14). These co-occurrence maps (not shown) were also tested using WofE.

It can be seen that the highest map class on the co-occurrence map based on the selective thresholds, is the best predictor of the known gold prospects (based on highest C value). The co-occurrence map based on all methods is the second best predictor, and the map based on the methods using non-selective thresholds is the least predictive. In all cases the highest map class (e.g., locations with the greatest number of coincident altered samples as determined from the different methods used to identify alteration) is the best predictor of known gold prospects.

4.6 Discussion

With respect to the identification of altered samples, thresholds based on the normative mineral classification and LOI are the most liberal having flagged 810 and 665 altered samples, respectively. The highest overlap between methods for identifying altered samples, as shown by the crosstabulation (Table 4.4a), occurs between the scatterplot and alteration index methods and LOI and scatterplot methods, all of which are more sensitive to alteration in mafic lithologies. If actual counts are used then the top three agreements contain atypical normative minerals, LOI and the index of typicality which is not surprising as these methods identified a greater number of altered samples than the other methods (see Table 4.3). Of more interest, however, is the breakdown of altered samples, by method, and by Jensen cation classification. From Table 4.5, it can be seen that altered samples identified using the alteration index comprise a greater number of ultramafic samples (BK, PK), as might be expected since MgO is an integral part of the Hashimoto alteration index calculation. The method based on normative minerals is more sensitive to alteration in felsic rocks, as the minerals used in this classification are more typical of felsic rocks. This is supported by an increase in SiO₂, Al₂O₃, Na₂O₃, and K₂O concentrations in altered samples identified by the normative mineral method. The LOI and volatile thresholds are more sensitive to mafic rocks due to their higher concentration

of hydrous minerals. This is supported by increases in MgO, CaO, FeO, Fe₂O₃, and TiO₂ concentrations in altered samples identified by these methods.

The danger with using scatterplots to detect altered samples is that geochemically unusual rocks such as komatiites can also result in unusual patterns depending on what elements have been plotted. Of the 209 samples identified as altered using the scatterplot method, 28 were not identified as altered by any other method. These samples represent either komatiites or granitoid rocks. These samples, although now classified as ultramafic komatiites (PK), are altered through MgO enrichment (see Fig. 8a and c), and were probably once basaltic komatiites (BK) or mafic tholeiites with lower MgO concentrations.

Trends in element concentrations between altered and un-altered samples can be related to lithology-specific processes. SiO₂ enrichment in granitoid rocks may represent silicification (quartz veining), or sericitization, which are known to be prevalent within granitoid rocks of the greenstone belt (Heather, oral comm., 1997). The most significant increase in K₂O between altered and un-altered samples occurs in felsic volcanic rocks (CR-ryholites), and may represent a strong potassic alteration trend. The altered ultramafic samples show a significant enrichment in MgO, perhaps representing a serpentinization (olivine to serpentine, talc, brucite) and chloritization trend. The samples classified as high magnesium and high iron tholeiites (HMT, HFT) show a significant increase in Fe₂O₃ with respect to FeO between un-altered and altered samples. This may represent strong oxidation from ferrous to ferric iron within these mafic rocks. Samples classified as picritic komatiites (PK) show a significant decrease in CaO in altered samples, and may reflect the loss of hydrous minerals, particularly amphiboles (hornblende). The difference between altered and un-altered samples with respect to Na₂O is not great, although samples geochemically classified as intermediate rocks, particularly tholeiitic and calc-alkaline dacites, do show a significant sodium depletion trend for altered samples.

Normalization appears to be effective for suppressing the effects of lithology. However, the effects of the normalization process are more easily visualized on interpolated maps (Fig. 4.6) than using discrete points (Figs. 4.4 and 4.5). A greater percentage of K_2O anomalies fall within felsic volcanic rocks for the datasets based on all, altered and un-altered samples, whereas on the normalized data the majority of K_2O anomalies fall within mafic rocks. The K_2O anomalies present on the normalized data (Fig. 4.6b), likely represent potassic metasomatism or sericitization, and may be more important for predicting gold, as gold is more frequently hosted by mafic and ultramafic rocks within the belt (Hodgson, 1993).

Scatterplots of MgO versus LOI , for altered and un-altered samples, indicate a linear trend between increasing MgO concentrations and LOI , suggesting that MgO is mobile, and supporting an alteration trend involving MgO enrichment. The occurrence of these samples on linear magnetic anomalies and within ultramafic and mafic lithologies, suggest that alteration of olivine to secondary minerals, such as serpentine, talc and magnetite may help explain MgO enrichment. These areas also coincide with mapped areas of chloritization and serpentization (Heather and Shore, 1999a-i), further supporting this interpretation. These samples are also characterized by low K_2O concentrations, as seen in the scatterplot of K_2O versus TiO_2 and Al_2O_3 . A second outlier population of anomalously high K_2O values may reflect sericitization and potassic metasomatism, especially in the iron formations and mafic volcanic lithologies. Sericitization has been mapped in the field along the Old Women iron formation. Scatterplots of CaO against TiO_2 and Al_2O_3 , for altered and un-altered samples from mafic volcanic rocks (see Fig. 4.1), contain two interesting clusters of high CaO concentrations, possibly representing carbonate alteration trends (Fig. 4.11b). These areas of carbonate and/or epidote alteration in mafic rocks may represent targets for exploration as areas of potential gold mineralization. Note that many samples comprising the cluster highest in CaO (cluster 2 on Fig. 4.11c) occur along linear belts defined by magnetic anomalies suggesting that some of the regional carbonate alteration may be due to shearing (faulting). This is also supported by the selective querying results that also show

areas of anomalous CaO along linear zones marked by magnetic anomalies. These zones are also evident on the map showing SiO₂ anomalies.

Principal component analysis results suggest that component 1, heavily weighted by SiO₂, Al₂O₃, Na₂O and K₂O, reflects felsic alteration styles (silicification, albitization, potassic alteration), whereas component 2, heavily weighted by MgO, CaO and Fe₂O₃, reflects a more mafic alteration style (chloritization, carbonatization, Fe-carbonate alteration). Plots of component 1 versus component 2 (Fig. 4.13) reveal several groups of outliers. Groups 1 and 2 reflect a mafic alteration style (highly weighted by MgO and Fe₂O₃), and occur primarily in the northern SGB. Groups 3 and 4 reflect a felsic alteration style, with group 3 occurring primarily along the Old Women iron formation. Group 5 reflects a carbonate and Fe-carbonate style. Group 6, occurring primarily in the southern SGB, shows samples high in Al₂O₃ and low in K₂O indicating alkali depletion and conservation of Al₂O₃.

Table 4.13 presents a summary of the most intensely altered zones based on alteration signature (Fig. 4.3), alteration style (Figs 4.4, 4.5, 4.8, 4.9, 4.11, 4.12, 4.14), lithology (Fig. 4.1), structure (Fig. 4.1), alteration mapped in the field (Fig. 4.15b-d), magnetic response (Fig. 8), and known major and past-producing gold mines (Fig. 4.15a).

Comparison between the alteration maps produced in this paper (Figs. 4.4, 4.5, 4.12, 4.14 and 4.15a) with alteration mapped in the field (Fig. 4.15b-d) shows a good correspondence when field stations coincide with geochemical sample locations. For example, areas of chlorite alteration identified in the field correspond well with samples identified as being chloritized (see samples displayed on Figure 4.4 and 4.5 (enriched MgO) and principal component group 2 (Fig 4.14a)) especially in areas A, B and D shown on Figure 4.15a. A high number of altered samples have been identified in zones A to H (shown on Fig. 4.15a) by all methods. These zones represent potentially the most intensely altered areas reflecting hydrothermal alteration and metasomatism. The majority of these zones are located in high strain zones (see Fig. 4.1) mapped by Heather and Shore (1999a-i) in the southern and central portions of the belt, and in the northern area by Ayer and Theriault (1993), and are associated with known gold prospects. Many

of these zones coincide with areas known to be mineralized (Shunsby zone and Old Women iron formation, respectively) while other zones do not. Area A is noteworthy as it marks the intersection of three major shear zones (Slate rock deformation zone (SRDZ), Hardiman high deformation zone (HDZ) and Deerfoot deformation zone (DDZ) – see Fig. 4.1). There are 5 identified gold prospects in this area with significant amounts of gold mineralization occurring in folded quartz veins in easterly trending deformation zones and in quartz veins in north-trending brittle faults (Ayer, 1995). The Old Women iron formation (B), a unit known to be severely altered (Heather, 1993; Heather et al., 1995; Heather et al., 1996), has been extensively drilled by Falconbridge Ltd. for base metals. This map also shows zones of less intense alteration (class 2 and 3 on Fig. 15a) that are worthy of exploration followup.

4.7 Summary and Conclusions

A large lithogeochemical dataset has been compiled over the SGB from a diverse source of both proprietary and non-proprietary geochemical datasets. The data have been screened (Wilkinson et al., 1999), and divided into two populations, one containing altered samples, identified using a number of different methods, and the other containing un-altered samples. Methods for detecting altered samples involving normative minerals, and the index of typicality are more appropriate for felsic to intermediate volcanic samples, while methods based on excessive LOI, volatile and the Hashimoto and ACNK indices are best for mafic to ultramafic samples which generally contain more hydrous minerals. Alteration trends are easily identified on 2D and 3D scatterplots, and the identified samples may then be plotted spatially using the GIS to assess relationships with lithology and structure.

Various methods have been presented for characterizing and screening the data with respect to alteration style. Selecting anomalous samples using probability plots from the altered population of samples is effective for identifying the most intensely altered samples irrespective of lithology. Screening of the geochemical data with respect to

lithology and geochemical classification can be accomplished by selective querying of the data, whereby anomalous concentrations of a given element can be identified for each lithologic unit. Comparing geochemical classifications of samples collected with mapped lithology is also a useful procedure to screen geochemical samples. Both these procedures can assist in identifying altered samples that are more likely altered due to hydrothermal/metasomatic processes as opposed to regional metamorphism. Furthermore, samples that are thought to have been altered by hydrothermal processes can be plotted on associated geology maps. This allows their spatial association with high strain zones to be assessed to help determine whether alteration is partly related to shearing or faulting processes.

Normalization of the data to account for background lithologic variations, either by using the approach based on statistical equations, or by selectively querying of the point data by lithologic and geochemical classification, is recommended. This aids in highlighting geochemical anomalies that may have originated by hydrothermal activity as opposed to being caused by gross lithologic variations. The geochemical anomaly maps produced from the normalization methods were better predictors of known gold prospects than other geochemical maps.

Multivariate techniques such as principal component analysis, and N-dimensional clustering are useful for establishing statistical relationships among more than three oxide elements. The components generated from principal component analysis often reflect a specific geologic process; in this paper, the first and second components generated from a principal component transform of the log-ratioed altered samples reflect a felsic and mafic alteration style, respectively. A log-ratio transform of the oxide data, as suggested by Aitchison (1986), is recommended when applying multivariate statistical techniques to alleviate the negative effects of closure.

Techniques that allow for variable thresholds, based on lithologic and chemical variations (selective querying and normalization), are arguably the best for characterizing alteration patterns in a lithogeochemical dataset.

Several zones of intense alteration and many scattered areas of less intense alteration have been identified throughout the SGB, using a variety of univariate and multivariate methods. WofE analysis of the spatial association between known gold prospects and alteration zones (Fig. 15a) indicates that the patterns resulting from the various processing methods applied to the geochemical data provide useful exploration guides for gold exploration in the SGB. Many of the alteration zones defined are worthy of exploration follow up.

A recommended approach to the analysis of a large lithogeochemical dataset using GIS would start by identifying altered and un-altered samples. Even when the sampling campaign is focused on fresh rocks, altered rocks are often collected because geochemical alteration in Archean rocks is often difficult to detect in hand sample. This study found that almost 40% of the samples collected specifically for lithological characterization are geochemically altered. In the second stage, the altered samples identified should be evaluated with respect to alteration style and intensity. Methods employing normalization and selective querying attempt to account for variable thresholds for defining geochemical anomalies based on geochemical classification and lithology. The maps based on these methods were more predictive of known gold prospects than those that did not account for lithologic variations. Another strength of these methods for characterizing alteration is their flexibility; the geochemical threshold can be chosen statistically (e.g. probability plots) or by exploration experience and knowledge in a given geologic environment. These methods can then be used to identify areas of most intense alteration. PCA analysis is used to determine statistical relationships between multivariate major oxide data, which identifies components that reflect either a mafic or a felsic alteration style. In the third stage, if a known set of mineral prospects are available, WofE can be employed to compare the geochemical anomaly maps with known mineral prospects, which results in a map that identifies areas for exploration follow-up. At all stages of analysis the GIS is used to plot the results of statistical analysis so resulting spatial patterns, which are critical for mineral exploration, can be evaluated.

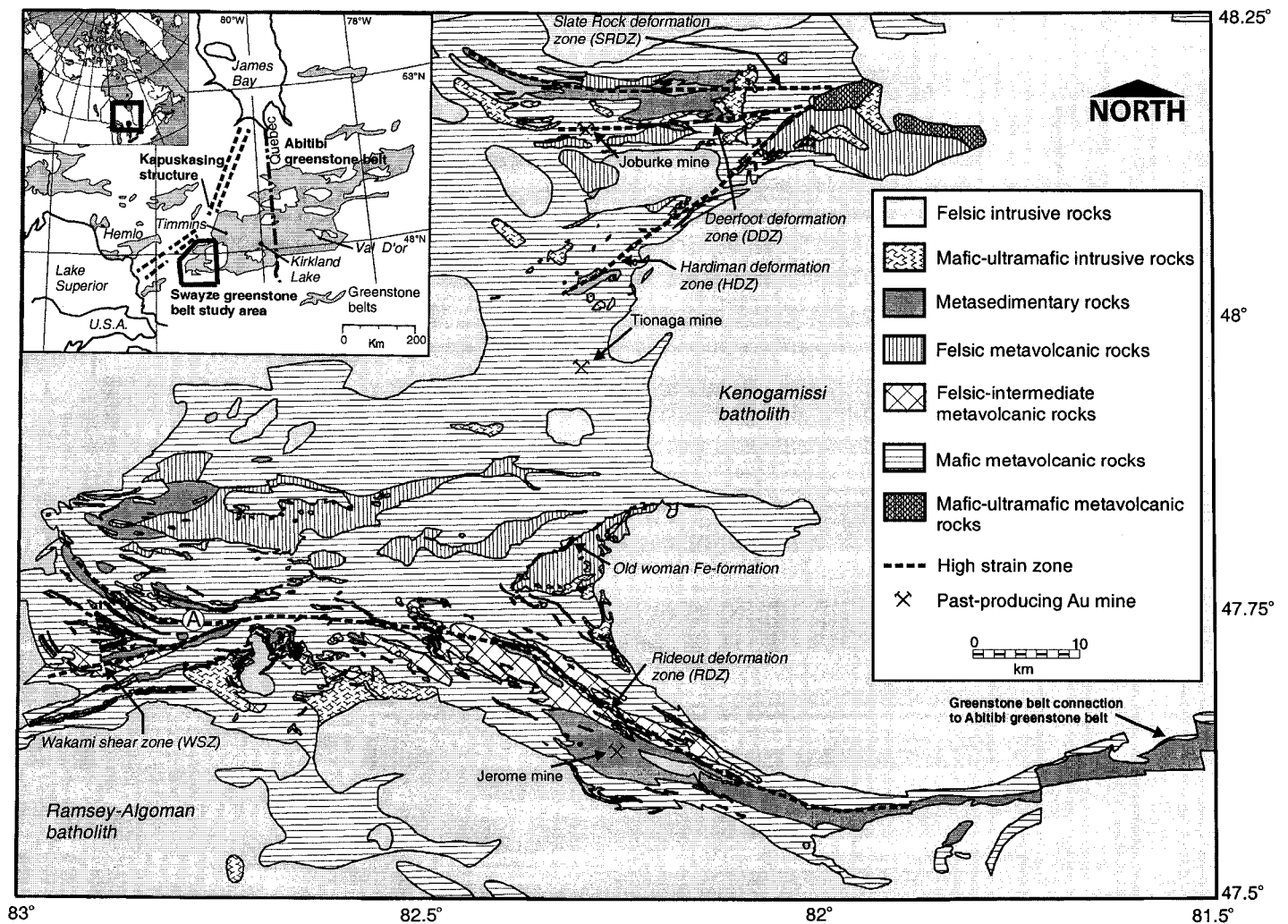


Fig. 4.1 Generalized geology and structure of the Swayze Greenstone Belt (SGB), from Heather and Shore (1999), and unpublished Ontario Geological Survey preliminary maps compiled by J. Ireland

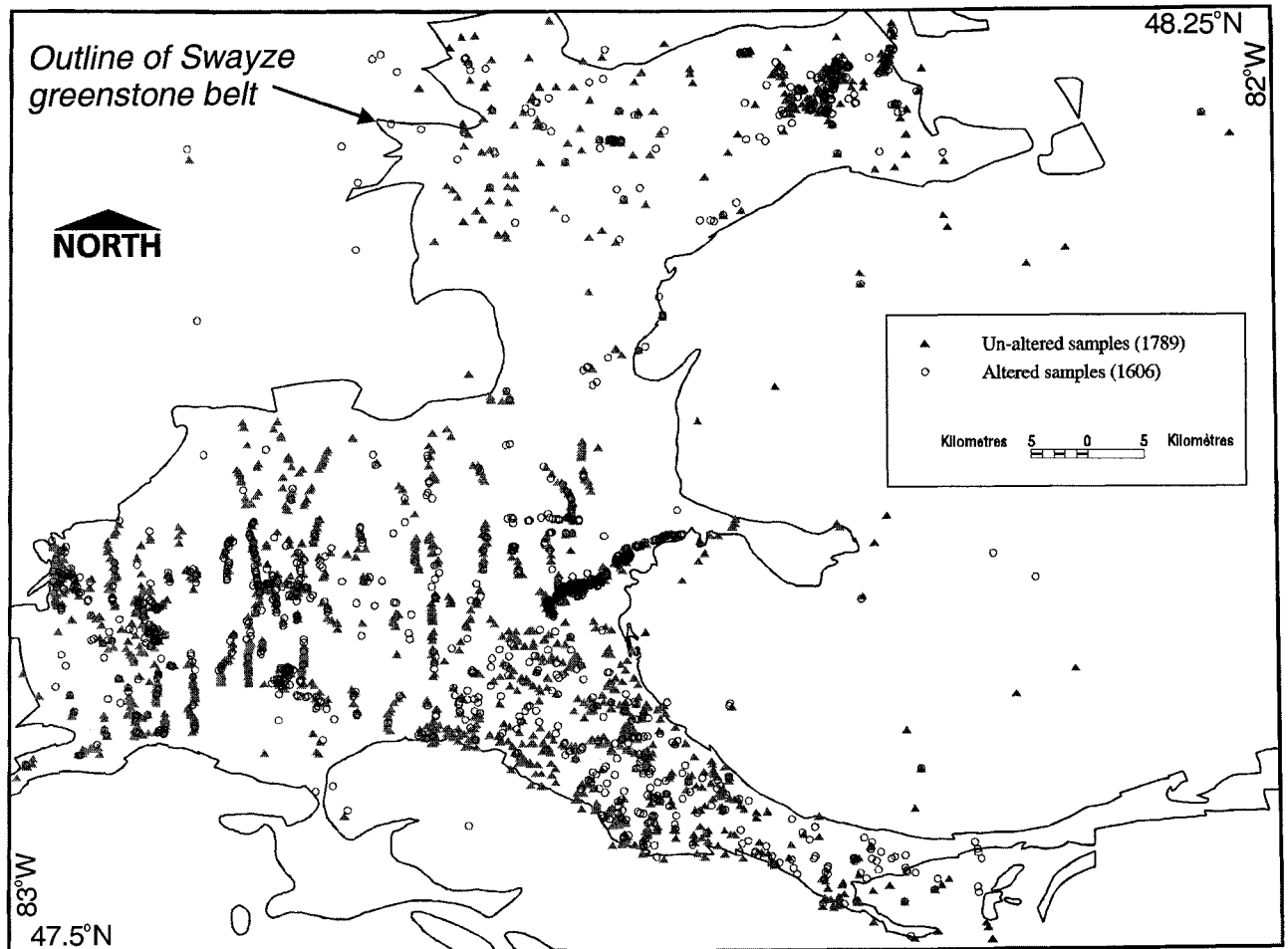


Fig. 4.2 Distribution of altered versus un-altered (any detection method) samples over the Swayze greenstone belt

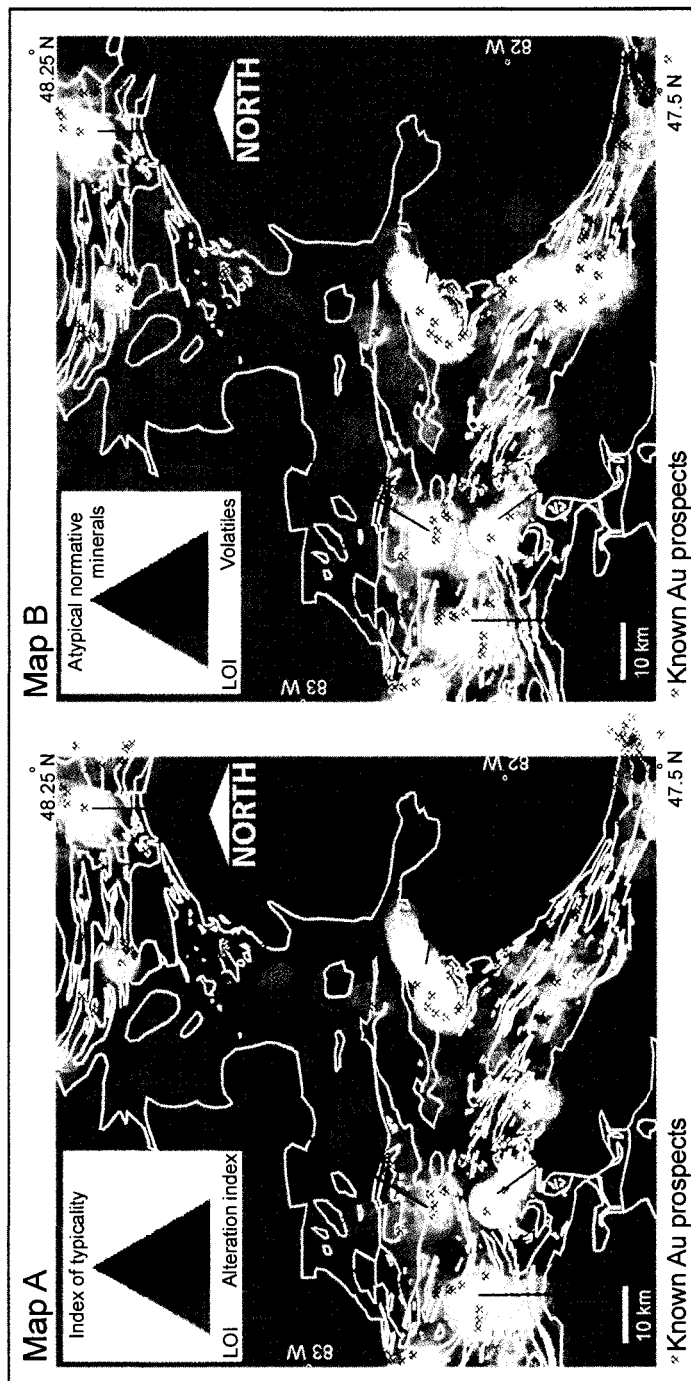


Fig. 4.3 RGB ternary alteration maps. Map A displays the index of typicality through red, LOI through the green, and alteration index through blue. Map B displays normative minerals through red, LOI through green, and volatiles through blue

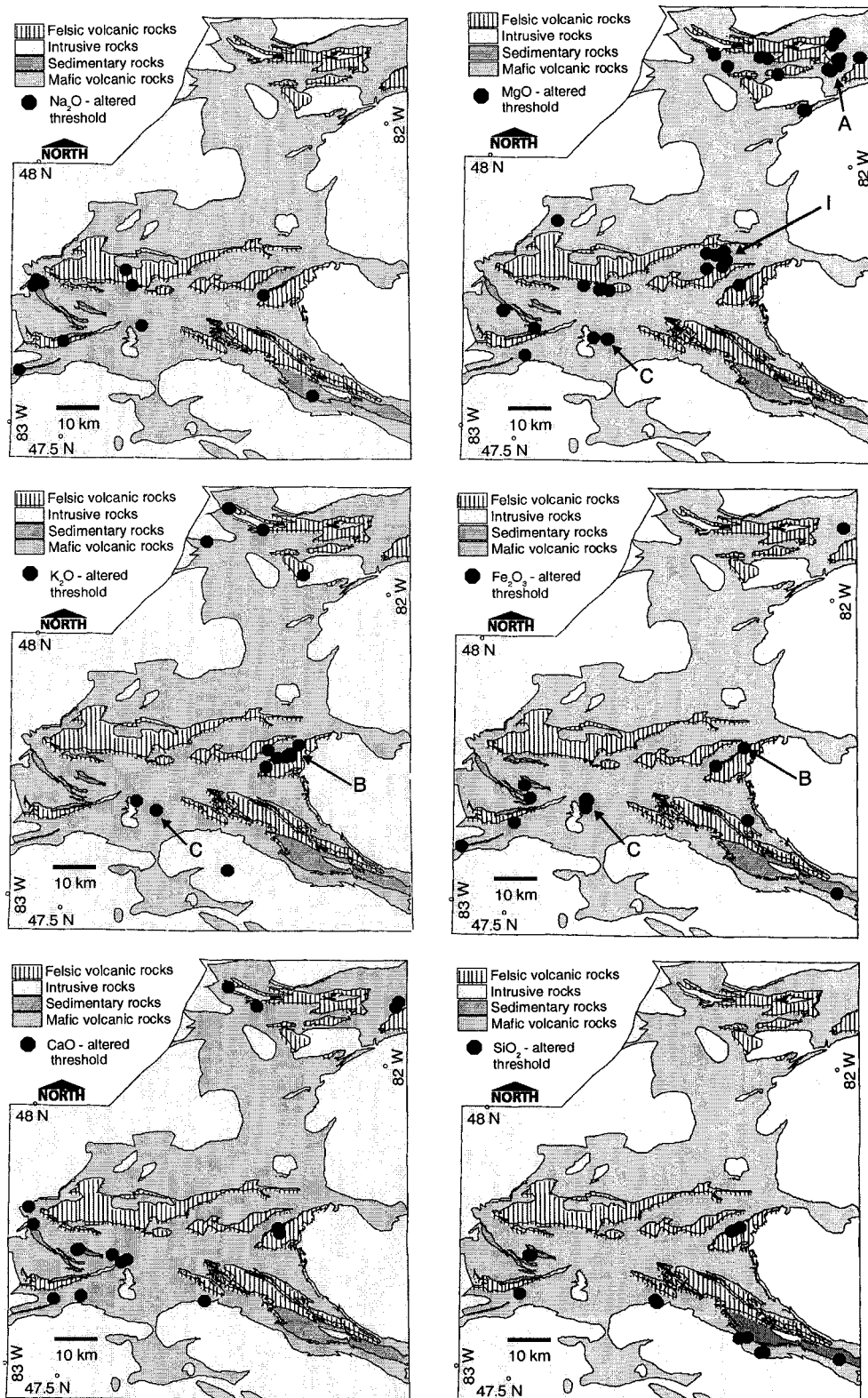


Fig. 4.4 Plots of anomalous geochemically altered samples for major oxides

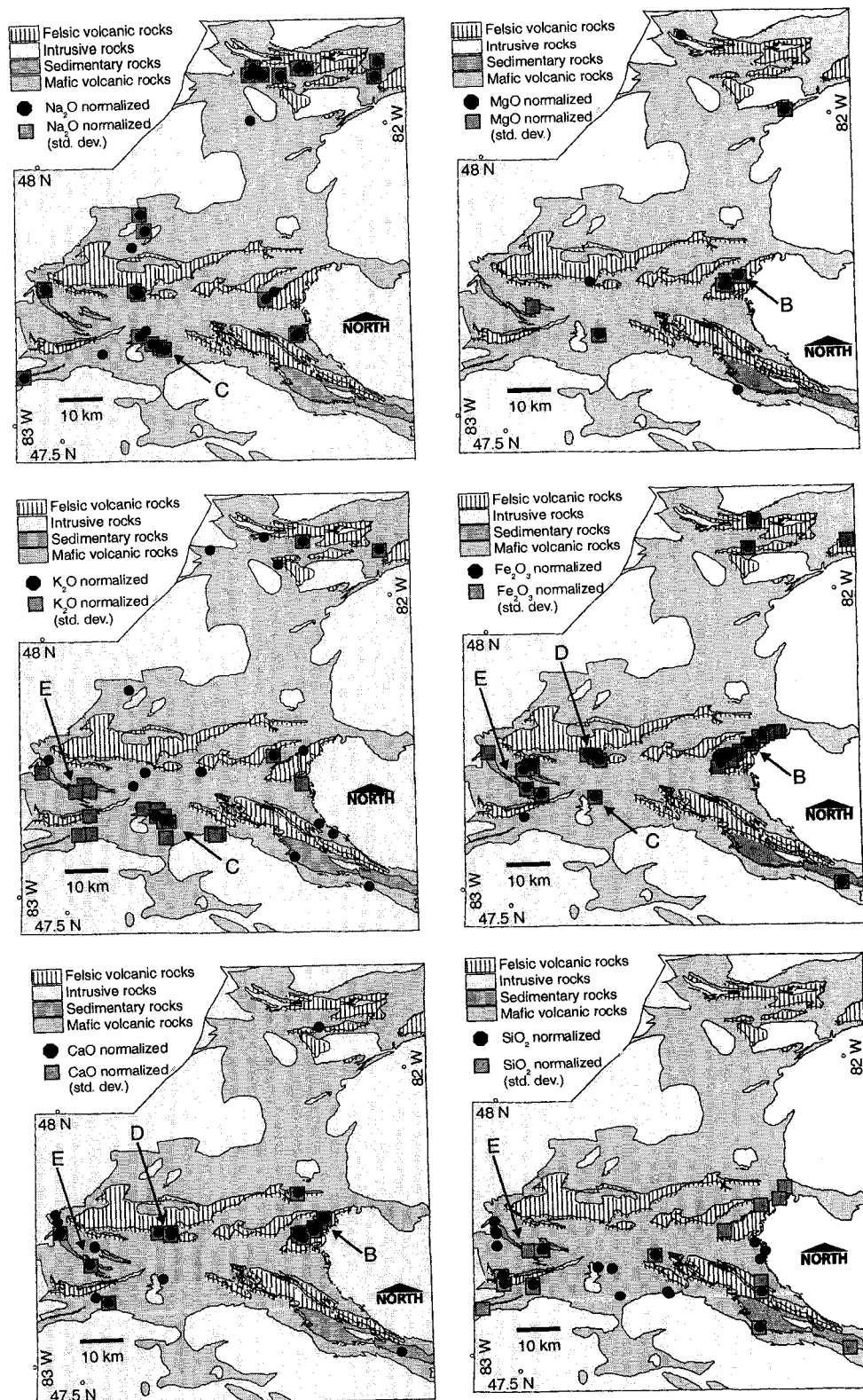


Fig. 4.5 Plots of anomalous geochemical normalized samples for major oxides. Samples are shown using two methods of normalization and std. dev. = standard deviation. (see text for description of normalizing equations)

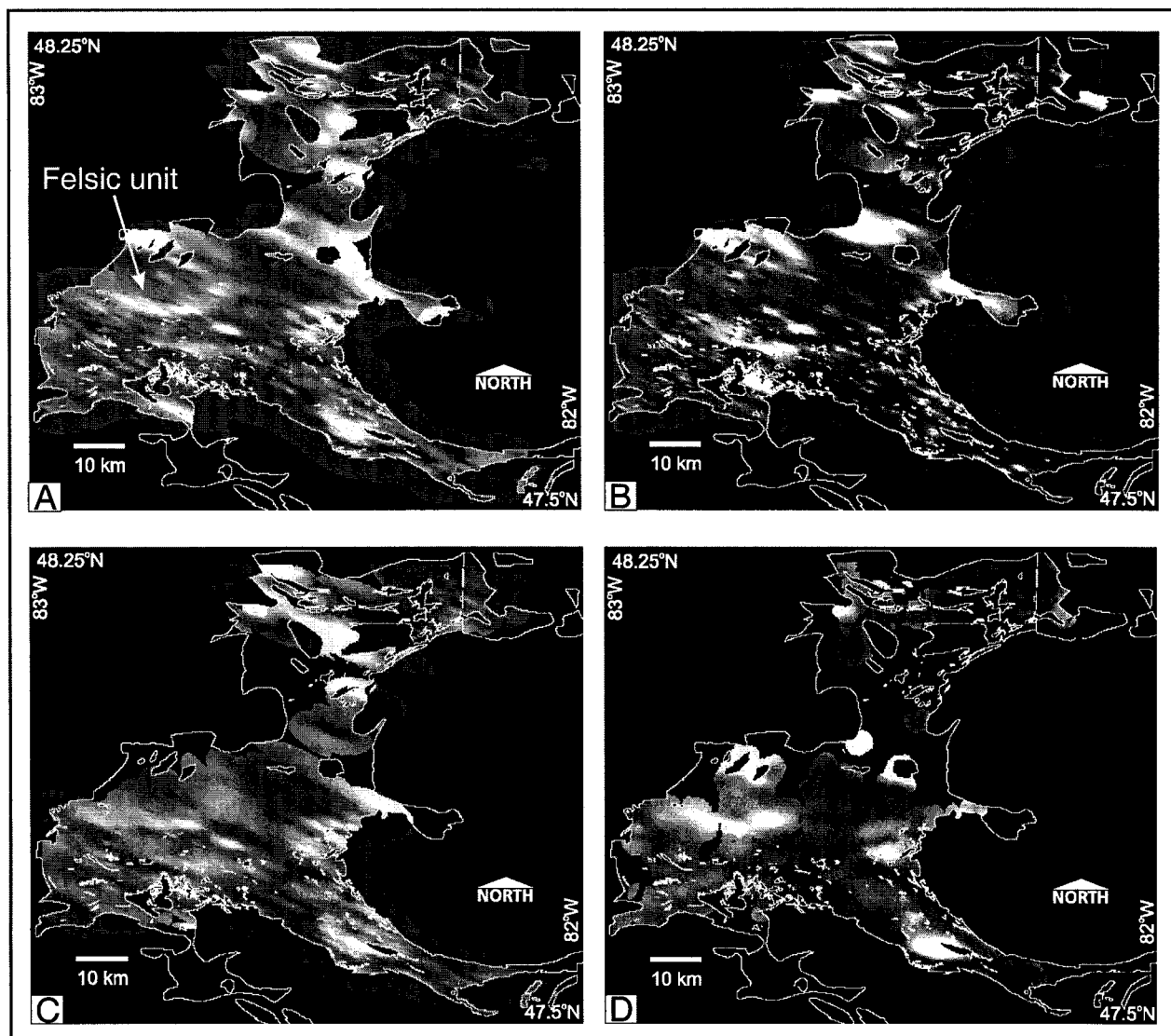


Fig. 4.6 Interpolated (kriged) K_2O maps of all samples (Map A), normalized samples (Map B), altered samples (Map C), un-altered samples (Map D)

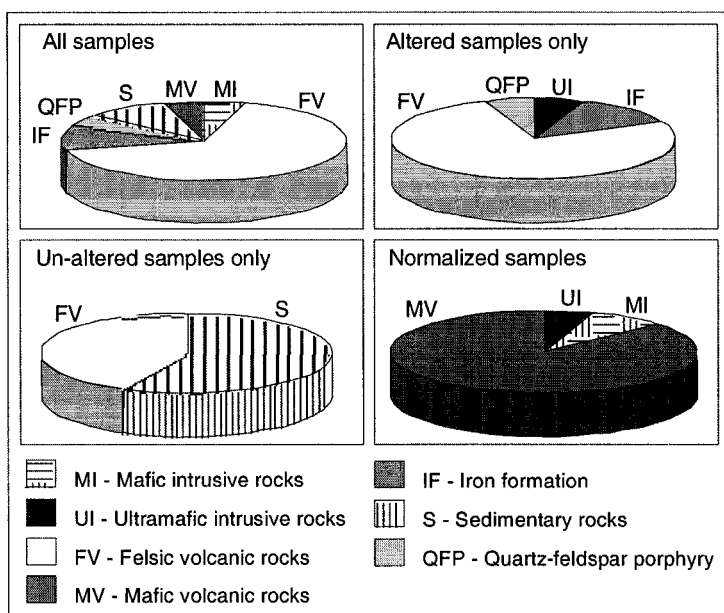


Fig. 4.7 Pie charts showing the distribution of anomalous K_2O samples by lithology for all samples, altered samples, un-altered samples and normalized samples

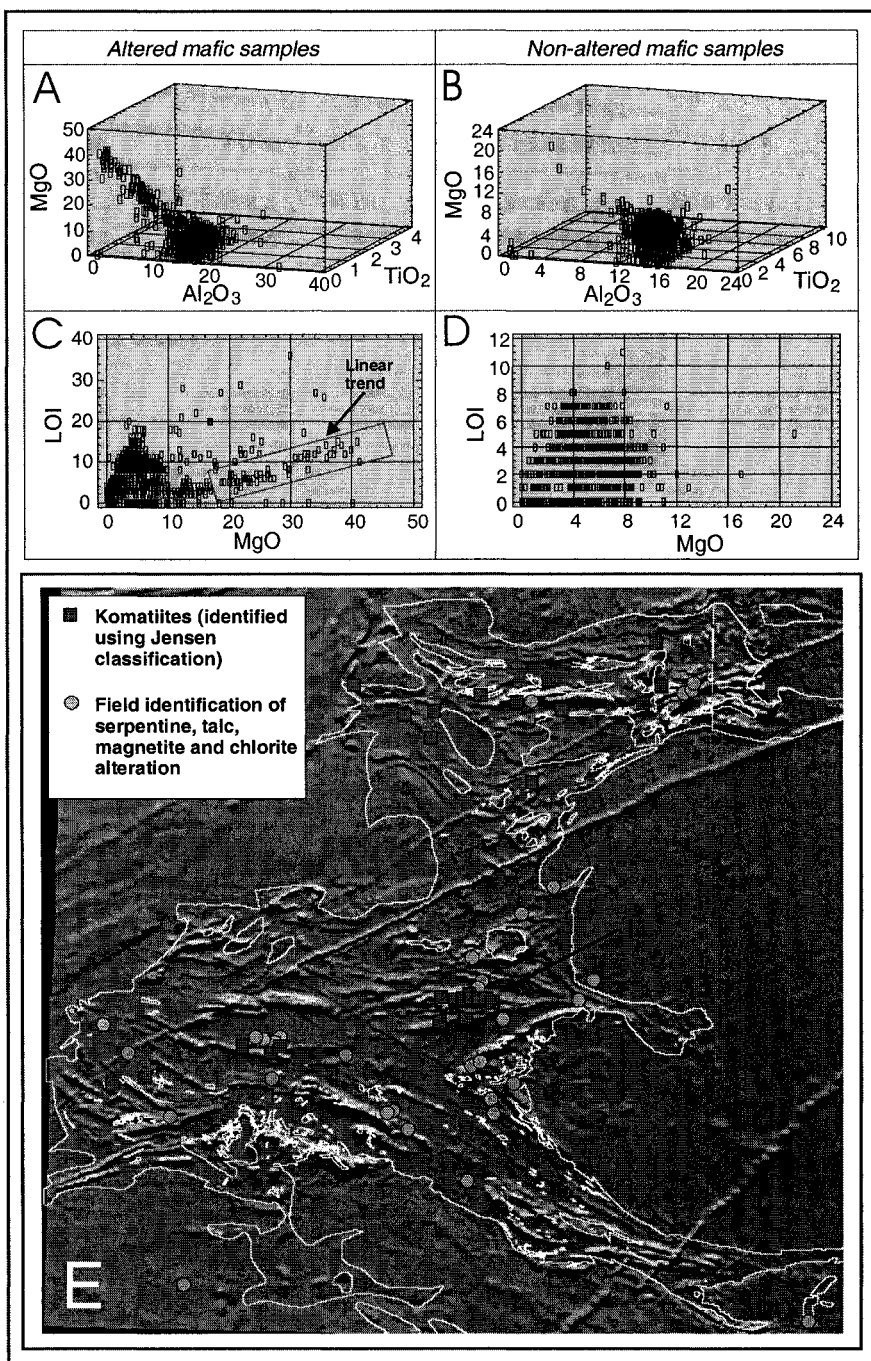


Fig 4.8 3D scatterplots: Plot A: MgO versus Al_2O_3 versus TiO_2 for altered samples; Plot B: MgO versus Al_2O_3 versus TiO_2 for un-altered samples; Plot C: LOI versus MgO for altered samples; Plot D: LOI versus MgO for un-altered samples; Plot E: Distribution of anomalous samples identified in 3D scatterplots, and areas of alteration mapped in the field. Samples plotted on airborne magnetic shadowed (shaded from the north at 30° elevation) enhanced image. Magnetic data compiled by Noranda Ltd., and provided by the Ontario Geological Survey

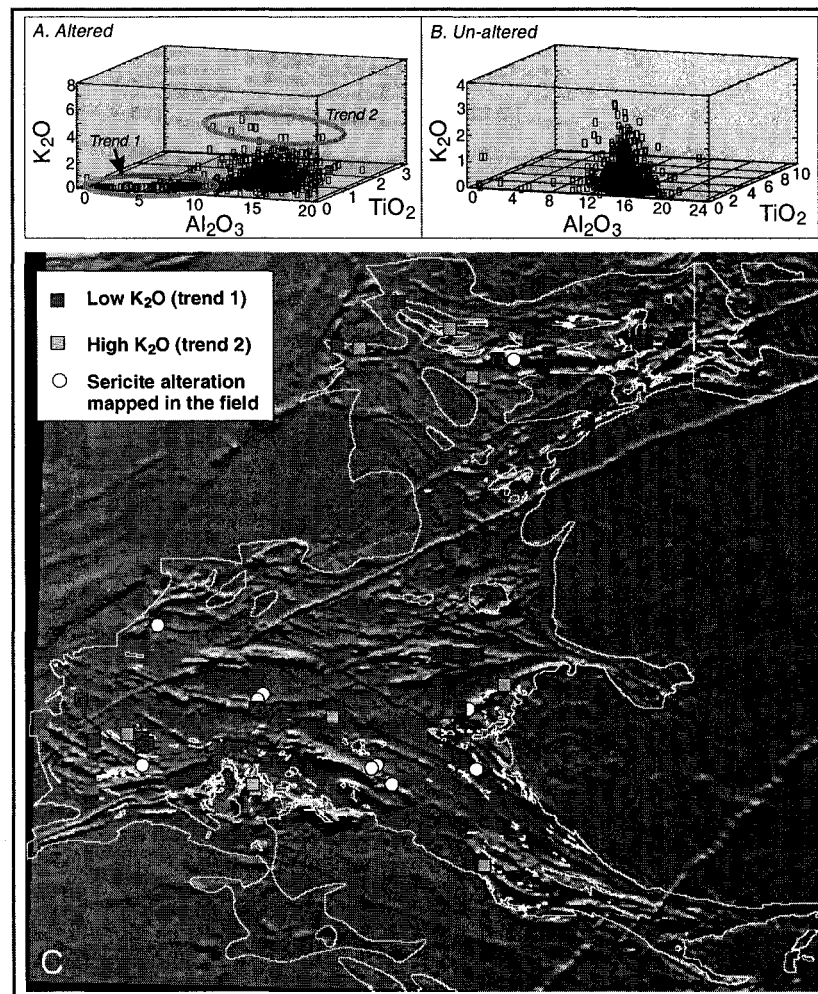


Fig 4.9 3D scatterplots: Plot A: K_2O versus Al_2O_3 versus TiO_2 for altered samples; Plot B: K_2O versus Al_2O_3 versus TiO_2 for un-altered samples; Plot C: Distribution of anomalous samples identified in 3D scatterplots, and areas of alteration mapped in the field. Samples plotted on airborne magnetic shadowed (shaded from the north at 30° elevation) enhanced image. Magnetic compiled by Noranda Ltd., and provided by the Ontario Geological Survey

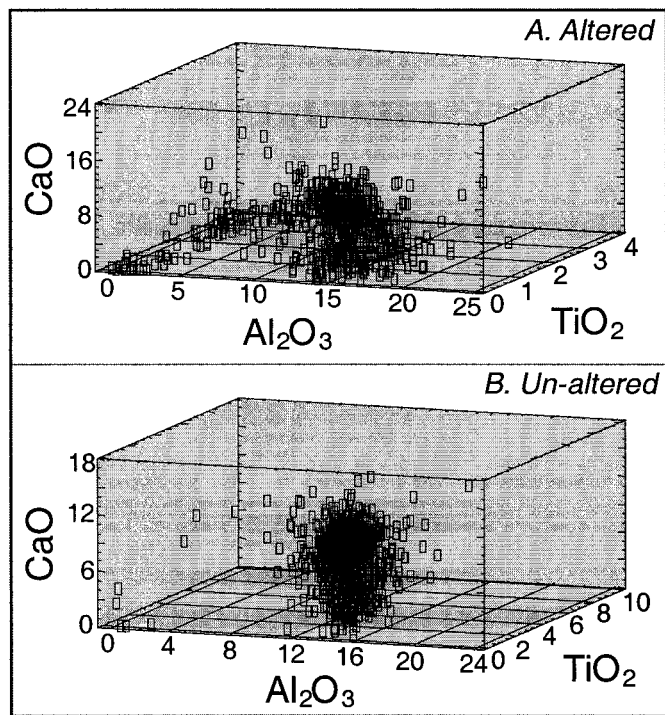


Fig. 4.10 3D scatterplots: Plot A: CaO versus Al_2O_3 versus TiO_2 for altered samples;
Plot B: CaO versus Al_2O_3 versus TiO_2 for un-altered samples

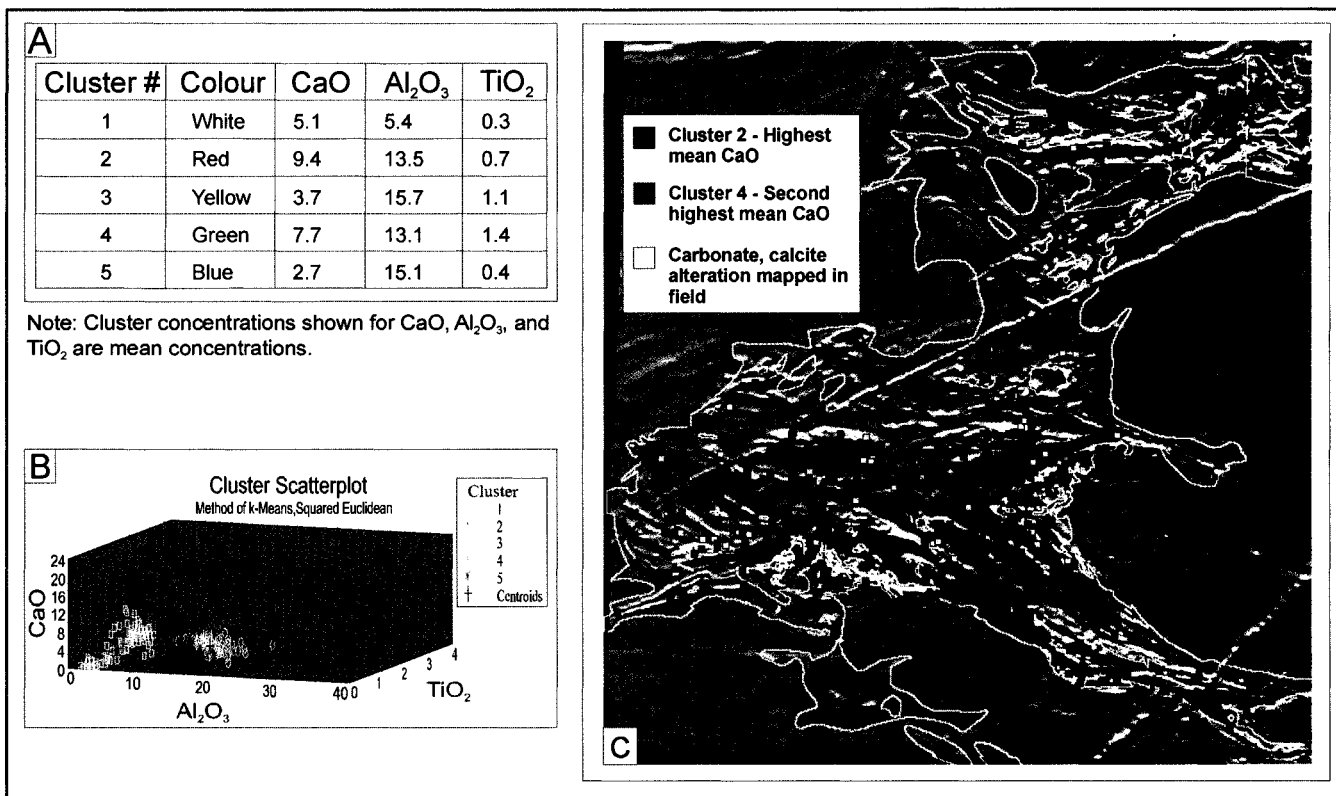


Fig 4.11 Migrating means clustering results. Plot A shows results applied to CaO, Al₂O₃ and TiO₂ (altered samples). Plot B shows 3D scatterplot of cluster results. Plot C shows the distribution of cluster 2 and 4 samples, as well as alteration mapped in the field. Samples plotted on airborne magnetic shadowed (shaded from the north at 30° elevation) enhanced image. Magnetic data compiled by Noranda Ltd., and provided by the Ontario Geological Survey

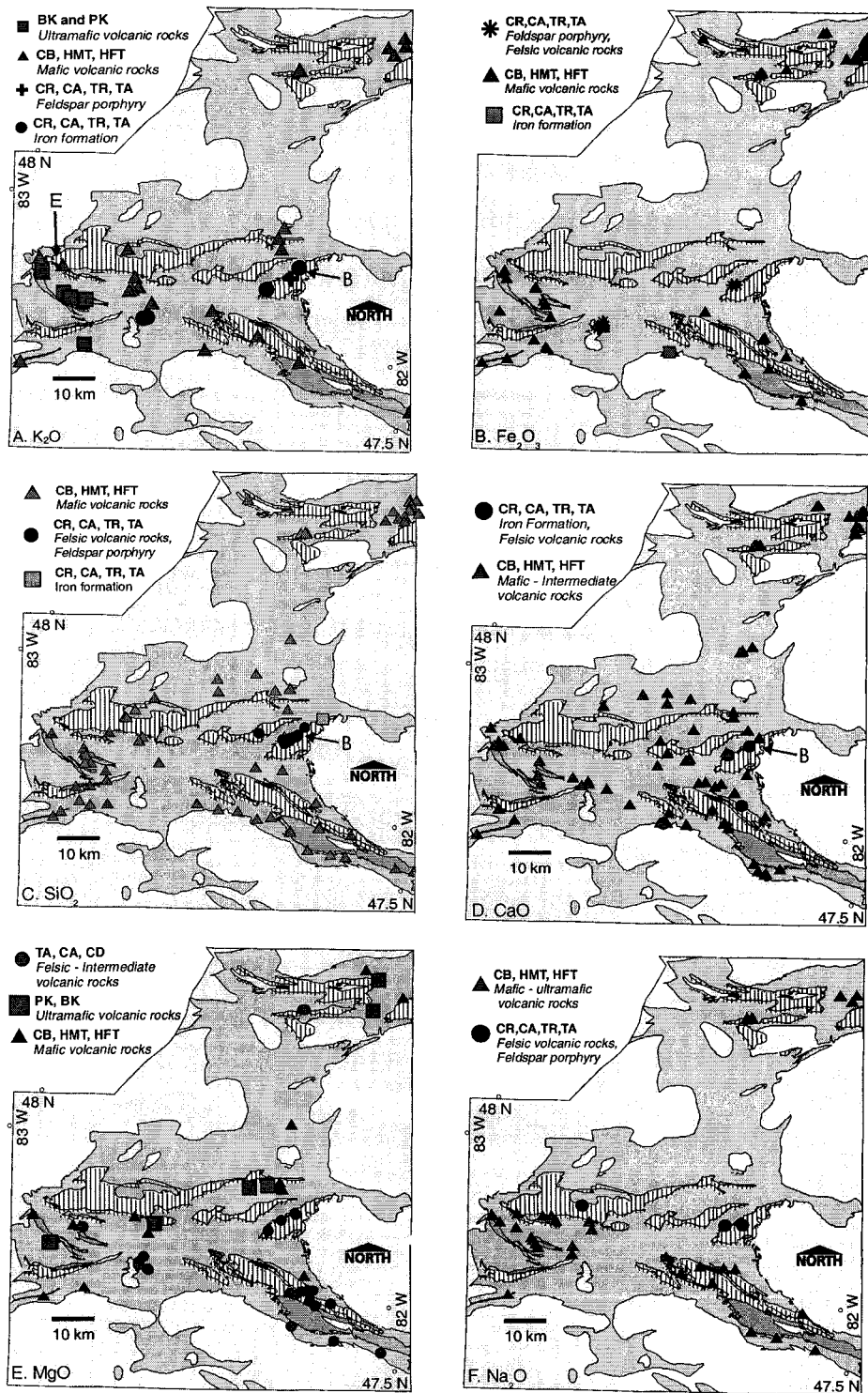


Fig. 4.12 Results of selective querying process for K_2O , CaO , Fe_2O_3 , SiO_2 , MgO and Na_2O applied to altered samples. See Appendix B for specific SQL queries

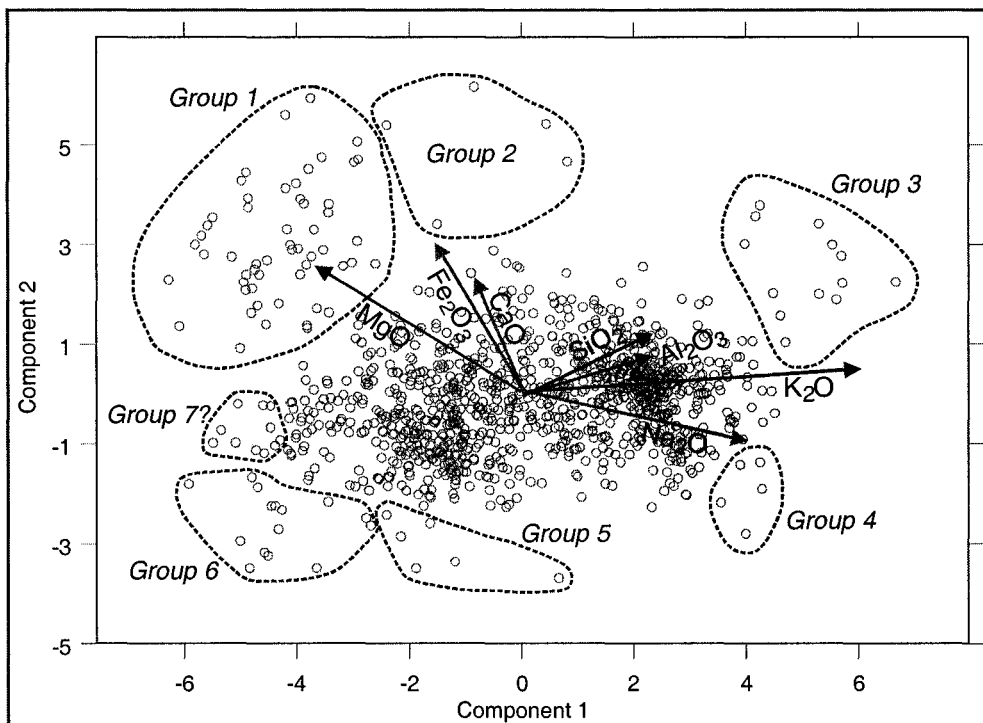


Fig 4.13 2D scatterplot of principal components 1 and 2 with groups of anomalous samples identified visually (groups 1–7). Group1 – chloritization, (iron oxidization); group 2 – iron oxidization, (chloritization, carbonatization); group 3 – silicification; group 4 – potassic alteration, albitization; group 5 – carbonatization and Fe-carbonatization; group 6 and 7 – Al_2O_3 enrichment and alkali depletion (K_2O)

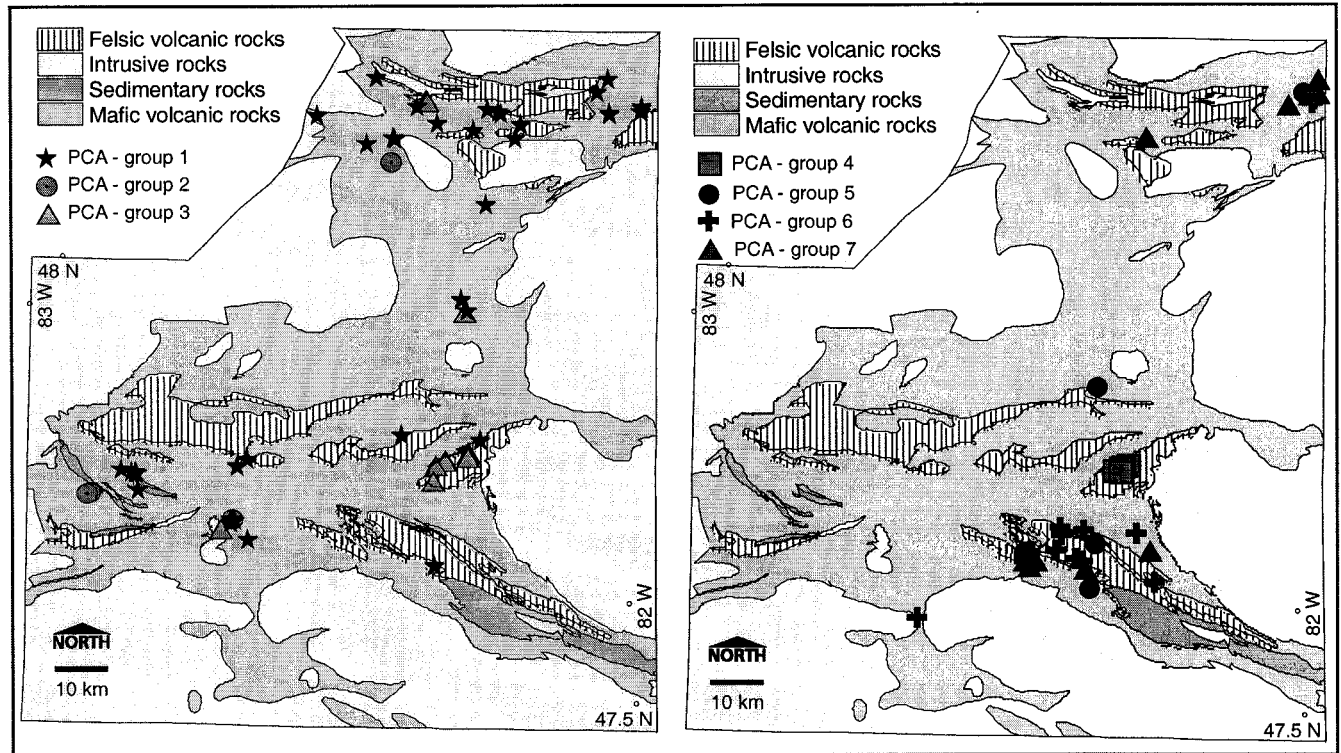


Fig. 4.14 Plot of anomalous samples identified on the principal component scatterplot (Fig. 4.13)

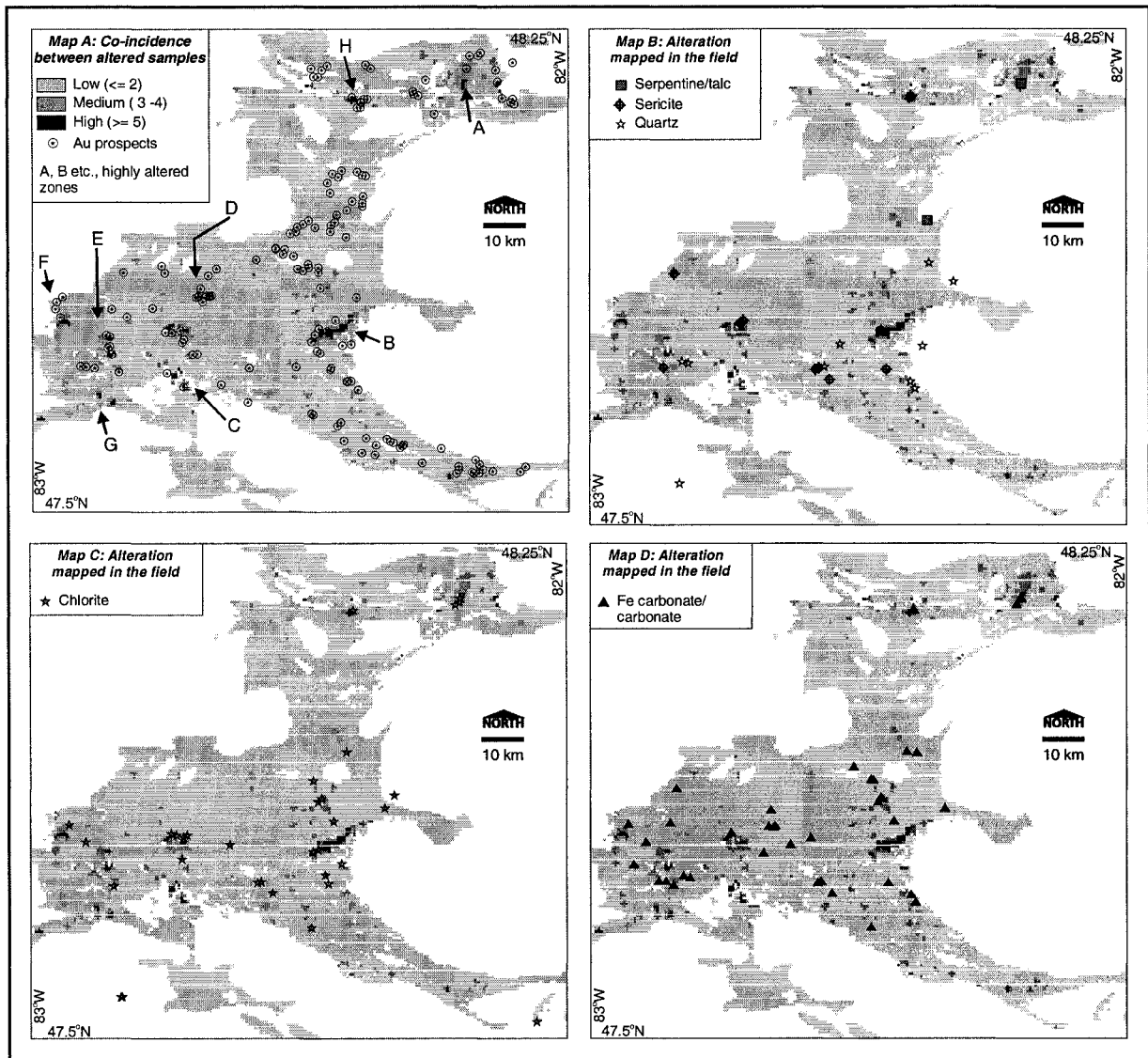


Fig. 4.15 Map A: Alteration map showing the co-occurrence of all altered samples identified using the various selection methods discussed in this paper. Sample points have been buffered to a 500m distance, and the location of gold prospects are shown as star symbols. Maps B, C, and D: Distribution of alteration, identified through field mapping (Heather and Shore, 1999)

<i>Method</i>	<i>Characteristics</i>	<i>Comments</i>	<i>References</i>
<i>Statistical - Univariate</i>			
Probability (QQ) plots	Breakpoints from cumulative probability plots.	Statistics collected for total population, or sub-divided by lithology. Data can be normalized to take account of lithological background.	Garret, 1991 Grunsky et al., 1992 Grunsky, 1997 Harris et al., 1997
Fractals	Breakpoints on plots of log concentration vs. log area.		Cheng et al., 1996
<i>Statistical classification and mathematical ratios</i>			
CPIW normative mineral classification	Identification of atypical minerals.	Statistics collected for total population, or sub-divided by lithology. Data can be normalized to take account of lithological background.	Rollinson, 1993 Franklin, 1997
Alteration indices	Ratios of major oxides or trace elements.		
<i>Statistical - Multivariate</i>			
N-dimensional clustering	Identification of outliers in derived clusters.	Data should be Log ratio-transformed to correct for closure (major oxides).	Grunsky, 1986
Regression	Prediction of response variable from a linear combination of explanatory variables.	Useful for distinguishing regional geochemical background from anomalies (expressed as residual values from linear equation).	
Principal component (PCA)/factor analysis	Linear combination of oxides and/or trace elements - identification of residuals.	Data should be Log ratio-transformed to correct for closure (major oxides).	Grunsky, 1986
Scatterplots (2D and 3D)	Identification of outliers and unusual trends.		Grunsky, 1986 Harris et al., 1997
Selective querying (SQL)	Selection of anomalous values with respect to geochemical and lithological characteristics.	Statistics collected for total population, or sub-divided by lithology. Data can be normalized to take account of lithological background. Combines statistical and spatial characteristics of the data.	
Geochemical classifications (bivariate and ternary plots)	Identification of outliers and unusual trends.		
Geochemical classification versus mapped lithology	Identification of samples where geochemical classification does not match mapped lithology.	May indicate biased sampling or incorrect geological mapping, as well as possible alteration.	
<i>Geostatistical</i>			
Factorial kriging	Determination of different spatial frequencies from analysis of a variogram and subsequent PCA analysis of each element (oxide or trace) for each spatial frequency.	Assesses both statistical and spatial characteristics of a multivariate dataset.	Galli et al., 1984 Sandjivy, 1984 Goovaerts, 1992 Jimenez-Espinosa et al., 1993

Table 4.1 Review of methods used for identifying anomalous samples (altered versus unaltered)

Dataset	Number of samples	Years collected	Analytical method^a	Source^b
J. Ayer (JA)	135	1991-1993	91 - XRF/ICP-MS/ICP-ES/AA 92 - XRF/ICP-MS/ICP-ES	OGS
K. Heather (KH)	348	1992-1995	XRF, ICP-MS, AA, DIONEX	GSC
PETROCH (PT)	646	1976-1993		OGS
S. Fumerton (SF)	1304	Unknown (variable)	XRF/ICP-MS/AA/FA	Assessment files
Falconbridge (FA)	1058	1978-1979	XRF	Falconbridge Ltd.
Texas Gulf (TG)	943	Unknown (variable)	XRF/ICP-MS	Falconbridge Ltd.

^a Analytical methods include: XRF = X-ray fluorescence; ICP-MS = inductively-coupled plasma mass spectrometry; ICP-ES = inductively-coupled emission spectrometry; AA = atomic absorption; FA = fire assay; DIONEX = Dionex ion chromatography analyzer.

^b Sources include: OGS = Ontario Geological Survey; GSC = Geological Survey of Canada.

Table 4.2 Description of lithogeochemical datasets comprising the final geochemical dataset used in this study

Alteration flag method	Number of samples	% of total samples
Atypical normative minerals	810	23.8%
LOI	665	19.6%
Volatiles	260	7.6%
Alteration index	432	12.7%
Index of typicality	413	12.2%
Scatterplot	209	6.1%

Table 4.3 Summary of the number of altered samples by each method used to identify alteration

Table 4a
Crosstabulation of altered samples by alteration flag method

	Atypical normative minerals	LOI	Volatiles	Alteration index	Atypicality index	Scatterplot
Normative minerals		0.0	-.06	.2	.28	.01
LOI			.25	.08	-.08	.3
Volatiles				.07	-.13	.15
Alteration index					.28	.62
Index of typicality						.14
Scatterplot						

- numbers represent the Yule coefficient of association (α)
 - bold numbers represent stronger associations between methods by virtue of higher coefficients

Table 4b
Frequency crosstabulation of altered samples identified using the LOI and scatterplot methods - 2 x 2 contingency table - calculation of Yule coefficient (α)

		Scatterplot		$\alpha = \frac{\sqrt{T_{11}/T_{21}} - \sqrt{T_{12}/T_{22}}}{\sqrt{T_{11}/T_{21}} + \sqrt{T_{12}/T_{22}}}$ where T = 2 x 2 contingency matrix
		Altered	Un-altered	
LOI	Altered	91	118	$\alpha = \frac{\sqrt{91/574} - \sqrt{118/2612}}{\sqrt{91/574} + \sqrt{118/2612}}$
	Un-altered	574	2612	

Table 4.4 (4a) Crosstabulation of altered samples by alteration flag method
 (4b) Frequency crosstabulation of altered samples identified using the LOI and scatterplot methods – 2 x 2 contingency table – calculation of Yule coefficient (α)

Alteration flag method	BK^a	PK	CA	CB	CD	CR	HFT	HMT	Granitoids	TA	TD	TR
Atypical normative minerals	12 ^b	9	28	16	29	71	7	6	32	19	40	42
LOI	25	57	7	20	40	15	23	15		29	45	35
Volatiles	8	17	7	9	8	1	8	7	11	6	4	29
Alteration index	76	81	9	6	8	9	11	11	10	5	18	8
Index of typicality	7	5	14	15	13	19	13	8		24	33	24
Scatterplot	21	99	1		2	4	1	1	6	2	2	2

^a Jensen cation classification. BK = basaltic komatiite; PK = picritic komatiite; CA = calc-alkaline andesite; CB = calc-alkaline basalt; CD = calc-alkaline dacite; CR = calc-alkaline rhyolite; HFT = high Fe tholeiite; HMT = high Mg tholeiite; TA = tholeiitic andesite; TD = tholeiitic dacite; TR = tholeiitic rhyolite.

^b Values are in percent, where the percentage is the total number of altered samples for a given Jensen class, divided by the total number of samples (altered and un-altered), for a given Jensen class. For example, for the alteration index, 75 altered samples were classified as BK out of a total of 99 BK samples, for a percentage of 76%. Note that columns do not sum to 100%, because it is possible for some samples to be flagged as altered by more than one method.

Table 4.5 Percentage of altered samples for each method used to identify altered samples by Jensen cation classification

Alteration flag method	SiO₂	Al₂O₃	Fe₂O₃	FeO	CaO	MgO	Na₂O	K₂O (log)	TiO₂ (log)
Atypical normative minerals	↑ ^a	↑	↓		↓	↓	↑	↑	↓
LOI	↓	↓	↑		↑	↑	↓	↓	↑
Volatiles	↓		↑ ^b	↑	↑	↑	↓	↓	↑
Alteration index	↓	↓		↑	↑	↓	↓	↓	↓
Index of typicality	↑		↑		↓	↓	↓	↑	↓
Scatterplot	↓	↓	↑		↓	↑	↓	↓	↓

^a SiO₂ is significantly higher for altered samples identified by the atypical normative mineral method, than for un-altered samples.

^b Solid arrows indicate significant difference between median element concentrations for altered versus un-altered populations; gray arrows indicate less significance.

Table 4.6 Major oxide element concentration trends of altered versus un-altered sample groups, for each method used to identify altered samples

	Felsic	Intermediate	Mafic	Ultramafic
<i>Jensen class</i>	CR, TR ^a	CA, CD, TA, TD	HFT, HMT, CB	BK, PK
<i>Number of un-altered samples</i>	121	366	1003	19
<i>Number of altered samples</i>	229	273	356	121
<i>Ratio (altered/un-altered)</i>	1.89	0.74	0.35	6.36

^a Jensen cation classification. BK = basaltic komatiite; PK = picritic komatiite; CA = calc-alkaline andesite; CB = calc-alkaline basalt; CD = calc-alkaline dacite; CR = calc-alkaline rhyolite; HFT = high Fe tholeiite; HMT = high Mg tholeiite; TA = tholeiitic andesite; TD = tholeiitic dacite; TR = tholeiitic rhyolite.

Table 4.7 Number of altered and unaltered samples in each Jensen cation classification category, and grouped into felsic, intermediate, mafic and ultramafic lithologies

Jensen classification	SiO₂	Al₂O₃	CaO	Fe₂O₃	FeO	MgO	K₂O	TiO₂	Na₂O
PK ^a	↓ ^b	↑ ^c	↓	↓		↑	↓		↓
BK	↓		↓	↑	↓	↑	↑	↑	↓
HMT	↓	↓	↓	↑	↓		↑	↓	
HFT	↓	↓	↓	↑		↓	↑	↓	
CB	↓	↓		↑	↓	↓	↑		↓
CA			↓	↑	↓	↓	↑		↓
TA	↓	↓	↓	↓	↓		↑	↑	
CD	↓		↑	↑	↓	↑	↑		↓
TD	↓			↑	↓		↑	↑	↓
CR	↑			↑		↓	↑	↑	↓
TR	↓			↑		↑	↑	↑	↓
Granitoids	↑			↓	↓	↓	↑	↓	↓

^a Jensen cation classification. BK = basaltic komatiite; PK = picritic komatiite; CA = calc-alkaline andesite; CB = calc-alkaline basalt; CD = calc-alkaline dacite; CR = calc-alkaline rhyolite; HFT = high Fe tholeiite; HMT = high Mg Tholeiite; TA = tholeiitic andesite; TD = tholeiitic dacite; TR = tholeiitic rhyolite.

^b SiO₂ is significantly lower for altered samples geochemically classified as picritic komatiites (PK), than for un-altered samples.

^c Solid arrows indicate significant difference between median element concentrations for altered versus un-altered populations; gray arrows indicate less significance.

Table 4.8 Trend of altered versus un-altered oxide element concentrations, by Jensen cation classification

Oxide	Threshold (%)	Equivalent percentile
Al ₂ O ₃	21	99
SiO ₂	78	99
MgO	28	97
Na ₂ O	7	99
CaO	14.5	99
Fe ₂ O ₃	19	99
K ₂ O	4.7	99

Table 4.9 Major oxide element thresholds, and the equivalent percentile, for altered sample populations

Oxide	Component 1	Component 2
log (Al ₂ O ₃ /TiO ₂)	0.24	0.17
log (SiO ₂ /TiO ₂)	0.25	0.33
log (Fe ₂ O ₃ /TiO ₂)	-0.09	0.50
log (MgO/TiO ₂)	-0.25	0.66
log (CaO/TiO ₂)	0	0.27
log (Na ₂ O/TiO ₂)	0.45	-0.19
log (K ₂ O/TiO ₂)	0.77	0.22

Table 4.10 Eigenvectors (component loadings) for the first two principal components, calculated from a log-ratio transform of major oxide elements, using the variance-covariance matrix of only the altered samples

PCA- group	SiO₂^b	MgO	Na₂O	CaO	Fe₂O₃	TiO₂	Al₂O₃	K₂O
group - 1 ^a	38.9	23.5	0.119	5.0	11.4	0.29	5.8	0.02
group - 2	42.3	23.1	0.47	3.4	9.9	0.07	9.06	0.08
group - 3	73.3	0.63	3.1	1.0	1.4	0.06	14.7	3.7
group - 4	76.4	0.038	4.5	0.87	0.97	0.2	13.4	2.0
group - 5	54.8	2.5	2.6	13.3	22.2	1.09	13.9	0.73
group - 6	49.4	4.5	3.0	6.0	4.08	1.56	14.9	0.03
group - 7	48.2	5.8	0.94	9.8	8.5	0.98	13.2	0.01

^a group 1 altered samples identified from plot of principal component 1 versus principal component 2 (see Fig. 13).

^b values in weight %

Table 4.11 Average major oxide element concentrations for altered sample groups identified using principal component analysis (see Figure 4.13)

<i>Map Class</i>	<i>Area (km²)</i>	<i>No. of Au prospects</i>	<i>W+</i>	<i>W-</i>	<i>C</i>	<i>Rank^a</i>	<i>Combined rankings^b</i>
All methods (Fig. 15)							
Lowest co-occurrence	2633	107	-0.14	1.25	-1.40	3	
Medium co-occurrence	122	17	1.11	-0.09	1.20	2	4
Highest co-occurrence	21	6	1.85	-0.04	1.89	1	2
Selective thresholds (normalized)							
Lowest co-occurrence	2761	116	-0.09	1.23	-1.34	3	
Medium co-occurrence	86	11	1.03	-0.05	1.09	2	5
Highest co-occurrence	17	5	1.89	-0.03	1.92	1	1
Non-selective thresholds (not normalized)							
Lowest co-occurrence	2688	119	-0.05	0.77	-0.83	3	
Medium co-occurrence	84	6	0.41	-0.02	0.43	2	6
Highest co-occurrence	44	7	1.23	-0.03	1.27	1	3

^a Rank is based on C (Contrast) values between map classes within all methods, selective and normalized thresholds, and non-selective threshold.

^b Combined rankings looks at C values between all 9 map classes.

Table 4.12 Results of the weights of evidence statistics applied to the alteration co-occurrence maps, and known gold prospects

Area	Significant alteration	Alteration style	Lithology	Structure (See Fig. 1)	Field alteration	Known gold?	Geophysical signature	Comment
A	Atypical normative minerals, LOI, volatiles, alteration index	Fe, Ca, K, Mg, Si, Al	Mafic volcanic rocks	HDZ, SRDZ DDZ	Serpentine, talc, chlorite	Y		
B	Atypical normative minerals, LOI, atypicality index	Si, Mg, K, Ca	Iron formation, Felsic and mafic volcanic rocks	Old Woman iron formation	Sericite, chlorite	Y	Linear magnetic anomalies	Well known base metal prospect and well explored
C	LOI, volatiles, alteration index, atypicality index	Fe, K, Ca, Mg	Iron formation, Felsic volcanic rocks	RDZ, WKZ		N	Linear magnetic anomalies	Well known Shunsby base metal prospect
D	LOI, alteration index, atypicality index, volatiles	K, Mg, Na, Fe	Mafic and felsic volcanic rocks, Sedimentary rocks		Sericite, chlorite	Y	Linear magnetic anomalies	
E	Atypical normative minerals, LOI, volatiles, alteration index, atypicality index	Mg, K, Si, Fe	Mafic and felsic volcanic rocks	RDZ		Y		
F	LOI, volatiles, atypical normative minerals, atypicality index	K, Ca, Na, Fe, Al	Mafic and felsic volcanic rocks, Iron formation		Carbonate, chlorite	Y		
G	LOI, atypical normative minerals, atypicality index	K, Ca, Si, Fe		WKZ		Y	Linear magnetic anomalies	
H	LOI, volatiles, atypical normative minerals, atypicality index	K, Ca, Fe, Si, Mg, Na			Sericite, chlorite	Y		Site of past-producing Jerome mine

A - H - see locations on Figure 15

Table 4.13 Geological summary of major alteration zones within the Swayze greenstone belt

CHAPTER V

Lithogeochemical Data – Integration

5.1 Introduction

Lithogeochemical data comprising both major oxide and trace elements are frequently used in geological mapping and tectonic studies to classify rock types, identify chemical variations due to fractionation trends, and characterize tectonic environments. Statistical and spatial analysis of lithogeochemical data for mineral exploration involves the identification of geochemical anomalies (e.g., zones of elevated concentrations of oxide or trace elements that may be reflective of mineralization). A Geographic Information System (GIS) offers great potential as a tool for analyzing geochemical data for both lithological classification and mineral exploration applications. GIS are not only capable of routine display of geochemical data, but also provide a range of spatial analysis tools with which to query, manipulate, visualize and analyze the data. For example, GIS have been used for generating exploration favourability maps (e.g., Bonham-Carter et al., 1988; Harris, 1989; Bonham-Carter, 1994; Rencz et al., 1994; Harris et al., 1995; Wright and Bonham-Carter, 1996).

The objectives of this paper are: (1) to demonstrate the application of some GIS-based methods for analyzing, interpreting and visualizing lithogeochemical data over an Archean age greenstone belt in Ontario that is presently being assessed for gold potential and, (2) to identify and interpret multi-element geochemical patterns as they relate to gold mineralization within the greenstone belt. A number of diverse lithogeochemical datasets have been assembled over the Swayze greenstone belt in northern Ontario (Fig. 5.1) by industry and government agencies (provincial and federal) to assist in on-going mapping and regional exploration. The methodologies set forth in this paper can be used to assist geologists in compiling and analyzing their own geochemical datasets with the aid of a

relational database, a PC or UNIX-based GIS and the use of visualization, statistical and geostatistical analysis software.

The material in this paper is related to a companion paper by Harris et al (1999) which focused on methods for identifying altered samples from the same geochemical database. This paper briefly reviews some of this work but deals mainly with GIS methods for processing and combining geochemical data into maps useful for gold exploration.

5.2 Study area

The Swayze greenstone belt (SGB) (see Fig.5.1) is the westernmost extension of the mineral-rich Abitibi greenstone belt (AGB), and has recently been re-mapped by both the Ontario Geological Survey, and the Geological Survey of Canada (Ayer and Theriault, 1993; Heather and van Breeman, 1994; Ayer, 1995a,b; Heather et al., 1995; Heather et al., 1996; Heather and Shore, 1999a-i). Similar to the AGB, the SGB contains a number of folded 2730-2680 Ma mafic-felsic metavolcanic packages that are unconformably overlain by Timiskaming-type metasedimentary rocks, and cut by high strain zones thought to be extensions of the major faults (Destor-Porcupine and Cadillac-Larder Lake) found in the AGB. A detailed description of the SGB geology can be found in the references cited previously.

The SGB shares many features in common with the mineral-rich AGB to the east, but lacks any significant mineral production. A detailed mineral occurrence database has been completed for the SGB (Fumerton and Houle, 1993; Fumerton et al., 1993). Historically, gold has been the principal exploration commodity in the SGB, and there have been several, small, past-producing gold mines (see Fig. 5.1). The most significant gold deposit was the Jerome Mine (Fig. 5.1), which produced approximately 56,883 ounces of gold (Fumerton and Houle, 1993).

5.3 Data analysis

5.3.1 Overview of GIS processing methods

Figure 5.2 is a summary of the data processing methodology used in this study. A number of published papers (cited on Fig. 5.2) deal with specific aspects of the processing methodology, and the reader is referred to these papers for more details. The spatial distributions and spatial associations of the major oxides are the focus of the analysis in this paper, as they comprise a more complete database than the available trace element data (Wilkinson et al., 1999), and are also useful for identifying regional alteration patterns that may reflect mineralization (Harris et al., 1999).

The data were first divided into altered and un-altered samples using a variety of methods (Harris et al., 1999). It is assumed that altered samples are more reflective of potential mineralization, whereas the un-altered samples may be more reliably used for lithologic characterization. The processing flow, at this point, was split into two streams, one in which the major oxides were spatially interpolated (e.g., converted from points to a surface) and analyzed as continuous surface maps, and the other in which only the altered samples were processed and analyzed as discrete points.

Processing of the major oxide data (see Fig. 5.2) involved separate spatial interpolations of the geochemical data for different sample groups comprising *all* samples, *altered* samples, *un-altered* samples and *normalized* samples. In addition, pseudo mass-balance (ratio) maps were also produced by dividing the interpolated map of the *altered* group of samples by the *un-altered* samples for each major oxide. By dividing the altered by the un-altered samples one can get an indication of relative gains and depletions of major oxide concentrations over the greenstone belt. Interpolation of the altered and un-altered samples was necessary to produce mass-balance maps as each sample is either altered or un-altered, and therefore the sample groups do not coincide spatially.

Normalization was employed to account for the effects of differing lithologic composition, and to produce spatial geochemical patterns potentially more reflective of mineralization than lithologic and/or regional metamorphic patterns. Binary maps showing areas of anomalous geochemical concentrations were produced from the interpolated maps, using thresholds identified from probability plots and using the weights of evidence (WofE) statistics (Bonham-Carter, 1994 and see Appendix C for more details on the WofE method). These binary¹ anomaly maps, derived from the different groups of samples for each major oxide discussed previously, were then evaluated, again by weights of evidence, with respect to known gold mineralization. WofE analysis results in a set of statistically derived weights that reflect the spatial association between the anomaly map and gold prospects. Gold favourability maps (showing areas with differing potential for gold), derived from the binary oxide anomaly maps for each of the groups of samples, were produced using WofE. These maps were compared and contrasted to determine the best processing methods, and the most effective oxides for predicting the locations of known gold prospects.

Processing of the altered samples (Fig. 5.2) identified by the various methods discussed later (e.g., excessive LOI etc.) involved dilating (known as *buffering* in GIS terminology) each sample location to a distance of 1 km to create binary maps. These maps have a value of 1 for any location within 1 km of an altered sample, and 0 elsewhere. The altered samples were visualized in various ways: as simple binary maps, proportional bubble (dot) maps, and as raster red-green-blue (RGB) ternary maps facilitating the identification of alteration patterns throughout the greenstone belt. The binary alteration maps, created by buffering, were then compared to the known gold prospects using WofE to establish which were the best predictors of gold mineralization. A gold favourability map based on the altered samples was also produced and compared to the gold favourability maps derived from the major oxide data.

⁴ a binary map consists of areas of anomalous geochemical concentrations which are assigned a value of one and areas of background concentration which have a value of zero.

Some of the data analysis procedures required use of additional software not contained within the GIS. The import and export of the data to the GIS was accomplished through the use of ASCII text files (and associated header files when required) or popular database formats such as Excel®, DBase®, and Microsoft Access®. WofE analysis was performed using a newly written application for Arcview® and Spatial Analyst® (part of the Arc/Info® family of GIS software) by the Geological Survey of Canada⁵.

5.3.2 *Lithogeochemical database compilation*

In a regional compilation program it is likely that data have been collected at different times, by different organizations using different sampling strategies and analyzed by different laboratories using different analytical techniques. Wilkinson et al. (1999) provide details on the problems involved and solutions invoked in assembling this database. To summarize, they encountered problems in the data compilation process involving what they termed first-order and second-order problems. First-order problems involved missing analyses, uncertain geographic locations for samples, and non-unique sample identifiers. Second-order problems included the interpretation of zeros in the database (e.g., missing data versus no analyses undertaken), treatment of censored data (values less than detection), compatibility between datasets (leveling problems) and incomplete analyses.

First-order problems were not usually resolvable unless restrictive assumptions were made, and therefore these data were deleted. Additional analysis and adjustment using a GIS and the application of statistical methods accommodated the second-order problems (see Wilkinson et al, 1999), and thus these data were salvaged and included in the final geochemical database used in this paper.

⁵ Software available, free of charge, from the Geological Survey of Canada WWW site: <http://ntserv.gis.nrcan.gc.ca/wofe/project.htm>

5.3.3 *Identifying altered from un-altered samples*

In the Superior Province of Ontario, of which the SGB is part, mafic volcanic and intrusive rocks have often undergone regional low-grade metamorphism, resulting in the breakdown of pyroxene and olivine into hydrous minerals (i.e., amphibole, chlorite). Plagioclase typically breaks down into sausserite which incorporates Fe and Ca into the crystal structure of the epidote mineral group. Regionally metamorphosed felsic volcanics have frequently undergone feldspar destruction resulting in the loss of alkalis. Normative mineral calculations applied to metamorphosed and altered felsic volcanic rocks usually result in the presence of corundum. Carbonatization is often associated with both mafic and felsic volcanic rocks. The carbonate can take the form of pervasive in situ replacement or in veins, vugs and stringers which represent a flooding effect. In situ pervasive replacement typically replaces the feldspars in both mafic and felsic volcanic rocks (Grunsky et al. 1992; Gelinas et al. 1977).

Many methods exist for identifying altered samples (e.g., Madiesky and Stanley, 1993; Rollinson, 1993; Grunsky, 1986; Harris et al., 1999). In this study, the following methods were used to flag altered samples:

- excessive LOI (Loss on ignition > 8% for mafic rocks and > 4% for felsic rocks)
- excessive volatiles ($\text{CO}_2 + \text{H}_2\text{O}^+ + \text{H}_2\text{O}^-$) (> 3.8%)
- alteration indices (Hashimoto index > 49 and ACNK index > .72)
- atypical minerals based on normative mineral classification
- index of typicality (Grunsky, 1986)
- identification of anomalous trends on scatterplots

The thresholds for LOI were based on consultation with various exploration companies (Falconbridge Ltd., in particular) and a number of government field geologists (Ayer, pers. comm., 1997). Typically, regionally metamorphosed mafic volcanic rocks have higher LOI values due to their greater abundance of hydrous minerals (micas and

amphiboles) (Gelinas et al., 1977). Thresholds for total volatile content were set based on upper breakpoints observed on probability plots of the data.

The alteration indices were chosen in consultation with Falconbridge Ltd., who have used these indices for base metal and gold exploration in various greenstone belts throughout northern Ontario. The Hashimoto index is defined as follows:

$$((\text{MgO} + \text{K}_2\text{O}) / (\text{MgO} + \text{K}_2\text{O} + \text{CaO} + \text{Na}_2\text{O})) * 100$$

whereas the ACNK index is defined as:

$$\text{Al}_2\text{O}_3 / (\text{Na}_2\text{O} + \text{CaO} + \text{K}_2\text{O}).$$

The Hashimoto alteration index emphasizes MgO mobility over alkali depletion, and thus is useful for detecting alteration in mafic and ultramafic rocks. The ACNK index is useful for detecting Al_2O_3 mobility over alkali depletion, and is useful for detecting the alteration of feldspars, and thus is a more useful index for intermediate to felsic rocks. These alteration indices were computed using the raw weight percent oxides. Thresholds used to define anomalous concentrations were identified from normal probability plots of each alteration index (Hashimoto index > 49 and ACNK index > 0.72). In the case of ratios, there may be some difficulty associated with the interpretation due to the compositional nature of the data (Aitchison, 1986). This closure problem may create difficulty in interpreting ratio data (see Aitchison, 1986).

A normative mineral classification was undertaken using the major element oxide data. Altered samples were flagged if the following criterion was satisfied: presence of hematite or wollastonite or pervoskite or nepheline or leucite or kaliophilite or calcium silicate or acmite or sodium silicate or potassium silicate or corundum greater than 3%.

An alteration statistic based on the *index of typicality* (Grunsky, 1986, Grunsky et al., 1992; Grunsky, 1997) was also used. This index is a measure of how typical a sample is

with respect to a reference population of samples (i.e., calc-alkaline basalts, ultramafic komatiites) established by (Grunsky et al. 1992) for Archean volcanic rocks within the Abitibi greenstone belt. An index of typicality of 0.9 means a sample has a high probability of belonging to the specific reference population, whereas an index of 0 indicates that the sample under consideration does not belong to the group and perhaps represents an altered sample.

Altered samples can also be identified on scatterplots of major element data. Figure 5.3a shows scatterplots of Fe_2O_3 , Al_2O_3 , CaO and MgO concentration for all volcanic samples within the northern portion of the SGB. Unusual samples and data trends can be highlighted on these scatterplots (see samples in bold on Fig. 5.3a), and plotted on geologic maps (Fig. 5.3b).

The GIS was used to intersect each altered sample point, using a GIS *point-in-polygon* function, with the geology maps of the SGB (OGS, 1993; Ayer, 1995; Heather and Shore, 1999a-i), and a comparison between each method used to identify altered samples, and lithology, was made. Similarly, the altered samples were geochemically classified using a *Jensen cation classification*⁶ for Archean volcanic rocks (Jensen, 1976), and a comparison between each Jensen class (e.g., geochemical classification) and mapped lithology was undertaken. The results from these comparisons were used to determine the sensitivity of each method used to identify altered samples to lithology, either directly as mapped in the field and shown on geology maps, or indirectly through geochemical classification.

5.3.4 Visualization and processing of altered samples

The GIS can be used to visualize the geochemical data in different ways providing maps that facilitate the identification of altered and/or mineralized areas within the SGB. The

⁶ The Jensen classification (Jensen, 1976) is a ternary classification of Al_2O_3 , MgO and total $\text{Fe} + \text{TiO}_2$. It is based upon the proportions of cations ($\text{Fe}^{2+} + \text{Fe}^{3+} + \text{Ti}$), Al and Mg recalculated to 100%. The elements were selected for their variability in Archean volcanic rocks and their relative stability under low-grade metamorphic conditions.

first method for visualizing and processing the altered samples involved buffering each sample to a circle radius of 1km as discussed previously. This resulted in a set of binary maps, one for each of the methods used to detect altered samples (LOI, volatile concentration, atypical normative minerals etc. - see Fig. 5.2). Figure 5.4 shows the six binary alteration maps produced using this approach.

Figure 5.5a shows a simple bubble plot (proportional circles – expressed in percentiles) of LOI - one of the methods used to identify altered samples. Larger circles displayed in red reflect greater LOI values, perhaps indicating areas of more intense alteration. Figure 5.5b is a more complex bubble plot in which total volatile content, defined by summing total H_2O (H_2O^+ and H_2O^-) and CO_2 content for each sample, is presented. The contribution of CO_2 and H_2O^+ and H_2O^- to the total volatile content is proportional to the size of each wedge within each circle. H_2O^+ is a measure of the water content within the mineral lattice, and is released above 110°C , whereas H_2O^- represents water present as moisture in the rock powder, and driven off by heating up to 110°C (Rollinson, 1993).

Figure 5.6a and 5.6b are alternative methods for visualizing altered samples. These are RGB (red-green-blue) ternary maps showing alteration zones derived by combinations of the methods used for identifying altered samples. A maximum of 3 alteration maps can be combined in one image. The altered samples were converted to a continuous surface (raster) map by:

- converting each sample point to a raster (grid) cell using a *point-to-grid* conversion in the GIS (altered samples define a 100 by 100m grid cell with a value of one whereas cells not occupied by an altered sample point receives a value of zero, cells with more than one altered sample received a value of 2)
 - calculating the average density (count) of altered points for each grid cell using a mean 25 X 25 mean filter (~ 2.5 x 2.5 km filter size)
 - assignment of red, green and blue colours to any trio of gridded maps creating an RGB ternary map
-

In Figure 5.6a, altered zones derived from the index of typicality, LOI and alteration index have been displayed in red, green and blue colours, respectively. Figure 6b shows altered zones derived from atypical normative minerals, LOI and volatiles displayed in red, green and blue colours, respectively.

5.3.5 *Processing of major oxide data*

Variograms, are useful geostatistical tools for determining: (1) the spatial structure (association) between sample points, (2) the size of the search window to be used for interpolation, and (3) directional effects (spatial anisotropy) in the data. Furthermore, the kriging variance provides a measure of uncertainty due to interpolation. Thus, variograms were constructed for the major oxide data for each group of samples, and the variogram parameters were used to interpolate the data using kriging.

The geochemical data were normalized to take account of the effect of underlying lithology on major oxide concentration. (Harris et al. 1997, 1999). This involves calculating the median concentration for each oxide element for each lithologic unit and the following formula is then used to normalize element concentration for background lithology:

$$Z^* = (Z/M - 1) * 100$$

where, Z^* = normalized concentration value and

Z = oxide or trace element concentration (for all samples)

M = median value of the element for the lithologic unit

Values of Z^* less than or equal to zero represent background values (e.g., $\leq$ median value for each lithological unit), whereas values greater than zero may represent anomalous concentrations. The -1 term simply adjusts samples with values greater than the median value to positive numbers (e.g., possibly anomalous), whereas those samples with values less than the median are set to negative numbers (possible background).

The median value is used in the above equation rather than the mean as it is generally less sensitive to outliers, and thus is a more appropriate measure of background (e.g., Garrett, 1991, 1993). The equation is applied to all the samples as a reasonable estimation of regional background for each lithology is required. The assumptions are: (1) the geologic map is an accurate representation of lithologic variation, (2) the lithological background is constant for each lithologic unit, and (3) the geochemical sampling is unbiased and is spatially and statistically representative of each lithologic unit. The normalization equations represents an approximate correction for average values by lithology, but variability due to other factors (e.g., sampling pattern, alteration patterns) are still present in the data.

Five sets of interpolated maps (100m grids) were constructed for each oxide element (SiO_2 , Al_2O_3 , CaO , K_2O , Na_2O , MgO , FeO , Fe_2O_3) based on the following: *altered* samples, *un-altered* samples, *all* samples, *normalized* samples and *altered/un-altered* samples (ratios). Once the major oxide data were interpolated to continuous surface maps (grids), anomalous concentrations of each oxide for each group of samples were identified using three methods:

- identification of breakpoints on normal probability plots
- definition of statistical thresholds based on the WofE technique
- 95th percentile threshold.

Figure 5.7 shows examples of probability plots for CaO , K_2O and MgO (altered samples), in which significant upper breakpoints can be seen. Using these methods, binary anomaly maps were produced showing the distribution of anomalous concentrations of the major oxides. These maps were evaluated with respect to the distribution of known gold prospects (see next section).

5.3.6 *Evaluation of oxide and alteration maps with respect to known Au prospects*

The WofE technique, based on Bayesian probabilities (see Bonham-Carter, 1994 and Appendix C for a detailed description of this method), was used to compare the anomalous geochemical data in the form of binary anomaly maps, to known gold prospects. Gold favourability maps were produced for the major oxide data, based on *all*, *altered*, *normalized* and *ratioed* samples as mentioned previously. WofE was also used to assess which of the methods used to identify altered samples was best for predicting the known gold prospects. A gold favourability map was also produced by combining the binary alteration maps, and the resulting map was compared and contrasted to the favourability maps produced from the major oxide data.

Areas of uncertainty due to high variance in the weights and due to missing data have been masked out in the gold favourability maps. This was accomplished by creating uncertainty maps for each of the posterior probability maps, and excluding these areas on the final favourability maps (Agterberg et al., 1990).

5.4 Results

5.4.1 *Evaluation of altered versus un-altered samples*

Figure 5.8 shows the distribution of altered and un-altered samples identified using the methods outlined in Section 5.3.3. Table 5.1 summarizes the number of altered samples flagged by each method. Out of a total of 3395 samples, 1606 have been flagged as altered, representing approximately 47% of the total number of samples. The thresholds based on the atypical normative mineral classification and LOI were the most liberal (i.e., producing the groupings with the greatest number of altered samples), flagging 810, and 665 altered samples, respectively. The thresholds based on total volatile content and scatterplot analyses identified the fewest number of altered samples.

The spatial coincidence between the altered samples identified by each method can be seen in Figure 5.4. The areas of highest spatial coincidence between the methods occur in mafic volcanic rocks in the northern SGB (area A on Fig. 5.4), along the Old Women iron formation and footwall felsic rocks (area B on Fig. 5.4), and over a mixed package of felsic and mafic volcanic rocks in the western SGB (area G on Fig. 5.4).

Virtually all oxide element concentrations showed a significant difference between altered and un-altered populations, using a variety of exploratory analysis procedures (e.g., box-and-whisker plots), as well as various statistical tests (t-test, Mann Whitney test). SiO_2 , K_2O and MnO are significantly higher for altered samples, whereas CaO , FeO and TiO_2 are substantially lower. Although MgO concentration is lower in the altered samples, the altered population is characterized by a high percentage of outliers (> 13wt%). No discernible trend was evident for Al_2O_3 , one of the least mobile major elements.

Table 5.2 shows the lithological units that have the highest percentage of altered samples for each method used to identify alteration. Table 3 shows a breakdown of altered and un-altered samples by their Jensen cation classification (Jensen, 1976) and indicates that ultramafic, followed by felsic Jensen-classified samples have the highest percentage of altered samples, as indicated by the ratio of altered and un-altered samples. Table 2 shows that, with respect to the mapped geology, ultramafic and mafic lithologies have the highest percentage of altered samples. Furthermore the altered samples identified by excessive LOI values, scatterplot and alteration index methods are more numerous in ultramafic and mafic intrusive rocks, whereas those identified by the normative mineral method are more numerous in felsic rocks (felsic volcanic rocks, granitoids). As might be expected, the volatile method generates a relatively large number of altered samples in mafic volcanic rocks, granitoids and sedimentary rocks, all of which contain abundant hydrous minerals and therefore high volatile content.

5.4.2 *Evaluation of alteration maps*

The binary alteration maps (see Fig. 5.4), show areas where alteration is either present or absent, but give no indication of the degree of alteration. Area A (see Fig. 5.4a for location) is characterized by altered samples identified using excessive values for LOI and volatiles, whereas areas B and G are characterized by samples with excessive LOI values only. These differences are a reflection of the lithology sampled, as area A comprises mafic metavolcanic rocks that typically contain more hydrous and CaO-bearing minerals (amphiboles, micas, clinopyroxenes), and thus their volatile content would be expected to be higher. Area B comprises samples from an extensive iron formation (Old Women iron formation) and felsic volcanic rocks that form the footwall to the iron formation.

The proportional circle maps (Figs. 5.5a, b), produced using all the samples, show areas of alteration, and give an indication of alteration intensity as reflected by the size of each circle. Thus, areas A, B and G, discussed previously, are also interpreted as areas of intense alteration. Areas A and G, as well as a broad zone in the southeastern SGB, represent zones of possible intense carbonatization, as reflected by high CO₂ concentration.

The RGB ternary maps (Figs. 5.6a, b) are useful as they show areas of alteration, give an indication of intensity (by intensity of colours), and also show the spatial coincidence between the methods used to identify alteration (by additive mix of red, green and blue colours). For example, area B (Fig. 5.6b) is displayed in yellow, indicating that this alteration zone is characterized by a relatively high percentage of atypical normative minerals (red) as well as high LOI values (green). Areas in white are where all 3 methods used for identifying altered samples coincide. The areas of most intense alteration on the RGB ternary maps are similar to the distribution of altered samples (see Fig. 5.8), as both these maps reflect the co-incidence of samples classed as altered by different methods as a measure of alteration intensity.

5.4.3 Evaluation of interpolated major oxide maps

Figure 5.9 show examples of directional variograms for K_2O and CaO , for both altered and non-altered sample populations. Tables 5.4a and 5.4b summarize the salient aspects of the variograms for the oxide data. Variograms based on un-altered samples display more regular spatial structure, are less erratic and are characterized by larger range parameters than the variograms constructed from the altered samples, as might be expected (see Fig. 5.9 and Table 5.4). The variograms based on the altered samples are characterized by higher semi-variance values than the un-altered samples. Most of the oxides (altered and un-altered samples) are anisotropic with the greatest range in an approximate east-west direction (112°), reflecting the regional strike of lithology. These geostatistical observations indicate that oxide concentrations for the un-altered samples are more homogeneous than altered samples and are spatially autocorrelated, over a greater distance, reflecting regional lithological variations. The concentrations based on the altered samples are highly variable over space, reflecting rapid changes in alteration and mineralization characteristics across and along lithologic units.

CaO is used here as an example of the interpolated maps. Anomalous high concentrations of CaO may reflect carbonate alteration, known to be related to gold mineralization in the Swayze greenstone belt (Hodgson, 1993; Heather et al, 1995). Figure 10 shows interpolated CaO maps for *all*, *normalized*, *altered*, *non-altered* and *ratio* samples. An east-west trending felsic unit (Fig. 10a) can be seen to be relatively low in CaO in the maps of *all* samples, *un-altered* samples, and to a lesser degree, altered samples. However, the CaO maps based on the normalized samples and ratio of altered to un-altered samples show areas of relatively high CaO concentrations within this same felsic unit. Normalization has thus suppressed the effect of the naturally low background CaO concentration in felsic volcanic rocks and revealed a CaO enrichment in parts of the unit. The maps based on the altered and normalized samples also show anomalous zones of CaO concentration in the southern portion of the SGB, paralleling the Rideout deformation zone, and in the western portion of the belt, in the vicinity of the Wakami shear zone (see Fig. 5.1).

The effect of normalization is further illustrated by the following examples. Figure 5.11 shows plots of K_2O , CaO and MgO concentration for geochemical samples along a north-south profile (A-B) shown on Figures 5.8 and 5.10b. Mapped lithology from which each geochemical sample was taken is shown along the X axes of these plots. The profiles consist of raw oxide (wt %) and normalized values by lithology. Altered and un-altered samples are shown in different symbols along these profiles. Table 5.5, a summary of the raw and normalized values for these oxides partitioned into altered and un-altered samples and felsic and mafic volcanic lithologies, shows that MgO and CaO concentrations are lower for altered samples along the profile compared to un-altered samples, whereas SiO_2 , K_2O and Na_2O concentrations are higher. This general trend is the same for both raw and normalized values. However, the percentage of outliers (e.g. possibly anomalous samples) does change. For example, in the raw data, outliers are more frequent in the altered group of samples whereas they are more frequent in the un-altered samples for the normalized data. This can be seen in Figure 5.12 which shows box and whisker plots for MgO and CaO concentration for raw and normalized data partitioned into altered and un-altered samples.

With respect to the breakdown by lithology, MgO and CaO concentrations are higher in mafic volcanics along the profile and SiO_2 , Na_2O and K_2O in felsic rocks, as would be expected. However, the normalized values are opposite to the raw (wt %) values for each oxide partitioned into lithologic groups along the profile (see Table 5.5). Normalization suppresses the effect of oxides that are naturally higher in a given lithology and enhances the effect of oxides that are naturally lower. For example, the median raw value (wt %) for MgO is higher in mafic volcanic rocks than felsic (as expected) whereas the reverse is true for the normalized values (see Fig. 5.12). Thus, normalization is useful for more selectively identifying possible anomalous samples and reducing the effect of natural lithologic variation of oxide concentrations.

This effect can be clearly seen on the profiles shown on Figure 5.11. The highest normalized values for a given major oxide tend to occur in rocks in which natural

concentrations for that given element are low. For example, normalized MgO values are highest in felsic rocks, K₂O in mafic rocks and CaO in felsic rocks. Another interesting observation is that the highest normalized values, at least for MgO and CaO, are not altered samples but un-altered samples indicating that the normalization process is identifying unique samples from the other methods used to identify alteration.

Table 5.6 shows Pearson correlation coefficients for the CaO maps shown in Figure 5.10. The correlation is a measure of the global similarity between maps but may not reflect important local spatial variations. The maps based on the *un-altered* samples and *all* samples show a moderately strong positive correlation, indicating that lithological variations account for most of the variation in CaO concentrations. One would expect a lower correlation coefficient between the two if the altered samples were more influential. Altered and un-altered sample maps are only mildly correlated indicating that both groups of samples are reflecting different processes (e.g., lithologic variation and alteration/mineralization). In particular, the map of altered samples shows zones characterized by possible carbonate and/or epidote alteration. The normalized data are poorly correlated with the other datasets, suggesting that the data may be highlighting different alteration trends, or possibly effects of regional metamorphism (see previous discussion on the effects of normalization).

Of more importance for mineral exploration, are the local spatial variations within each map that may reflect alteration / mineralization processes. Figure 5.13 presents binary maps showing anomalous concentrations for the interpolated CaO maps (Figure 5.10). Table 5.7 shows the Yule coefficient (∞) (see Bonham-Carter, 1994 – Ch. 8) between the anomaly maps. The calculations are based on a series of 2 x 2 contingency tables showing the overlap between binary anomaly maps. The contingency tables contain the area of overlap between two maps, the area which is anomalous on one map but not on the other (and vice versa), as well as the area of no overlap. This coefficient ranges from -1 and +1 and can be interpreted like a correlation coefficient in that values close to 1 and -1 indicate strong positive and negative associations between methods used to identify alteration, respectively. The anomaly maps based on *all* samples and *altered*

sample groups and *altered* sample and *ratio* sample groups have the greatest overlap suggesting that the information contained in each member of these map pairs are similar.

Table 5.8 shows the Pearson correlations between the normalized maps for each major oxide element. Statistically, correlation between normalized grids circumvents the problems of closure (Aitchison, 1986) where compositional data, such as weight percentages reported for oxides, are typified by a closed number system (sum to 100%) and are therefore, not free to vary independently. This can result in false correlations between the major oxide data (Rollinson, 1993). Aitchison (1986) has developed a method for dealing with the closure problem of compositional data based on log-ratio transformations. However, the normalized data are in fact ratios typified by an open number system, as opposed to a closed number system (e.g., 0 – 100%) thus correlations between the oxides can be meaningfully interpreted. The highest correlation is between CaO and FeO, suggesting : (1) a moderate association between these elements in mafic volcanic rocks that are spatially the most extensive in the study area and, (2) an association between carbonatization and iron oxidization (ferric). Ankerite (Fe carbonate) is frequently associated with gold mineralization in quartz veins in Archean greenstone belts, and many examples of this alteration can be found in the field (Heather, pers. comm, 1997). The highest negative correlation is between SiO₂ and CaO. This may again reflect an expected antithetic relationship between these elements in mafic volcanic rocks. From an alteration perspective this is problematic to interpret as one might expect silicification (quartz veins) and carbonate alteration (but not necessarily epidotization) to be positively correlated.

Identification of anomalies vs. background oxide concentration: Table 5.9 summarizes significant thresholds based on inspection of upper breakpoints of probability plots, 95th percentile breakpoints, and breakpoints determined using the WofE method (breakpoints in contrast value – see Appendix A), for each of the groups of samples (*all*, *altered* and *un-altered* samples). Although data based on dimensionless numbers (e.g., normalized and ratio values) are not shown in Table 5.9, the breakpoints were calculated in the same way. Subsequent testing of the binary predictor maps, for each element, and for each

threshold with respect to the known gold prospects, indicated that in many instances the thresholds calculated from the probability plots, and in some situations, the 95th percentile limit, resulted in binary maps over which no gold prospects were found (i.e. the thresholds are too high). Thresholds calculated using the WofE method were generally lower (see Table 5.9), resulting in a higher coincidence between gold prospects and geochemical anomaly maps. Therefore, the WofE-identified thresholds were used for final comparison with the known gold prospects using the WofE technique. Note that the un-altered data were not subjected to WofE analysis, as these samples reflect primarily lithologic variations as opposed to alteration patterns. Figure 5.13 shows the binary anomaly maps for CaO, based on thresholds determined using WofE, for the interpolated maps shown in Figure 5.10 (un-altered sample map excluded).

5.4.4 *Evaluation of anomaly maps with respect to known gold prospects*

Alteration anomaly maps : Table 5.10 shows the statistics generated from WofE, for each binary alteration map (see Fig. 5.4 for examples). Although the differences in contrast (C) values (see Appendix C) are not great, indicating that all alteration maps are mildly to moderately strong predictors of the known gold prospects, the alteration map based on excessive volatile concentration is a slightly better predictor of known gold prospects (based on relatively high W+ and C values) than the others. The studentized values (C/SD – contrast / standard deviation of the contrast) indicates that all C values are significant as they are greater than 1.5 (see Bonham_Carter, 1994). The similarities in the C values, in part, reflects the fact that mafic volcanic units (characterized by a higher percentage of hydrous minerals) are dominant in the greenstone belt, and that a high percentage of the gold prospects occur in mafic volcanic rocks. The map based on atypical normative minerals is also a moderately strong predictor of known gold prospects.

Figure 14 shows a posterior probability (gold favourability map) produced using the WofE technique, based on the maps shown in Figure 5.4. It must be stressed that the posterior probabilities, used as a measure of favourability on this map, are severely

overestimated in some locations due to the failure of the tests for conditional independence between the input maps (an assumption made when combining several maps together using WofE). This is not surprising as the binary alteration maps shown in Figure 5.4 are produced from the same set of samples, and thus spatial overlap between maps would be expected. However, the weights shown in Table 5.10, are based on maps one at a time (no conditional independence assumption) and are therefore valuable as a measure of the predictive power of each alteration map. Furthermore, the relative favourability (ignoring the absolute probability values) provide a reliable picture of the spatial pattern of gold potential, given these geochemical predictors.

Oxide anomaly maps: Table 5.11 is a summary of the WofE results, for the binary anomaly maps produced from the oxide elements, (see Fig. 13 for example of CaO maps), for each interpolated group of samples. The statistics are based on all the known gold prospects, 155 (out of a total of 255) of which fell in volcanic and sedimentary rocks within the study area. The volcanic and sedimentary rocks formed the “basemap” for WofE analysis (see Appendix C) as the majority of gold prospects occur in these general rock types. A unit cell size of 200 m^2 was used for each gold prospect. Elements that show a strong spatial association with known gold prospects are characterized by relatively high W+ and C value, and a studentized value (C/SD) of greater than 1.5 (Bonham-Carter, 1994, p. 323). These elements include Al_2O_3 , Fe_2O_3 and FeO for the all sample group, Na_2O and CaO for the altered sample group, CaO, K_2O , FeO, and Al_2O_3 for the normalized sample group, and CaO and Fe_2O_3 , for the ratio sample group.

Figures 5.15A, B, C and D show posterior probability maps (e.g., gold favourability maps) calculated using all the major oxide elements (SiO_2 , Al_2O_3 , K_2O , MgO, Na_2O , FeO, Fe_2O_3 , TiO_2 , P_2O_5 , MnO) processed using *all* the samples, *normalized* samples, *altered* samples only and *ratios*, respectively. The posterior probability map calculated from the altered samples (Fig. 5.15c) was did not meet the conditional independence assumption (see previous discussion) between SiO_2 and K_2O binary anomaly maps. This is an interesting correlation as it indicates that silicification and potassic alteration are spatially coincident in the most altered samples. Therefore, a boolean “OR” operation

was performed on the SiO_2 and K_2O anomaly maps, creating one combined anomaly map for input to the WofE modeling. This eliminated some of the overall conditional dependence caused by the spatial correlation of these two maps. The “OR” operation was chosen as this will provide a more conservative map of spatially anomalies (i.e. larger area) than a boolean “AND” operation.

Table 5.12 shows Pearson correlation coefficients between the posterior probability maps shown in Figure 5.15. The correlation between the maps was calculated on a grid cell to grid cell basis (e.g., by area) and the calculated coefficient represents the overall correlation between maps. The correlation between the maps is generally low (although significant at the 95% confidence level) indicating that, statistically and spatially, the maps are dissimilar. The posterior probability maps based on the altered samples (after reducing the conditional independence), and ratioed data are the highest correlated (albeit mildly). This is not surprising given that the posterior probability map calculated from the ratio includes the altered samples in the numerator (e.g., altered/un-altered samples). The posterior probability map based on the normalized samples shows the lowest correlation with the other maps (except all samples).

Of greater interest for gold exploration is the similarity between the areas of highest posterior probability (e.g., highest gold favourability). Figure 5.16 shows binary maps of the highest posterior probability (approximately top 5% of area) for each map shown in Figure 15. It was not possible to threshold the maps so that the areas of highest probability were equal due to the data distribution of each map, thus the results presented below, although valid, should be treated as approximations. Table 5.13 is a matrix that summarizes the spatial overlap between the maps shown in Figure 5.16 using the Yule coefficient. Comparison of Tables 5.12 and 5.13 show that grid-to-grid correlation coefficients between each favourability map and spatial overlap of the binary maps showing the most favourable areas, are not always the same.

Maps that show the highest correlation coefficient do not necessarily show the greatest overlap between the areas of highest gold favourability (top 5%). For example, the

correlation coefficient between the posterior probability maps calculated from the normalized and ratioed samples is very low (.03), although the Yule coefficient is relatively high (.56) (see Table 5.13). The greatest spatial overlap occurs between the maps calculated from *all* samples and *altered* samples (.64). These results demonstrate that comparison of anomalous areas on maps (based on a binary threshold) may give different results from a comparison based on maps scaled over a complete range. Spatial coincidence of anomalies may be much more important for mineral exploration than spatial coincidence of areas with low to intermediate values of the mapped variable.

Table 5.14a summarizes the results of applying WofE process to the maps in Figure 5.16 that show only the areas of highest gold favourability. Maps produced using the normalized samples (Fig. 5.16b) and altered samples (Fig. 5.16c) are the best predictors of the known gold prospects, as posterior probabilities are generally higher for the maps produced from these datasets. Table 5.14b shows the results of WofE analysis applied to the binary anomaly maps shown on Figure 5.16. This table differs from Table 5.14a in that the results are normalized on the number of deposits (in this case ~ 12). As was the case in Table 5.14a, it was not possible to get the number of deposits for each map exactly equal due to the areal relationship between prospects and anomaly patterns, however the results are still valid for a generalized comparison. It can be seen that the geochemical anomalies based on the normalized data are the strongest predictors of known gold prospects as 12 prospects were found on the smallest area (69 km²) whereas much larger areas were required to encompass approximately the same number of gold prospects for the other maps.

Comparison of gold favourability maps: Comparison between the gold favourability map (Fig. 5.14) derived from the binary alteration maps (Fig. 5.4), and the gold favourability maps (Fig. 5.15) produced from the major oxide data (Fig. 5.13 for example), indicates that the favourability map produced from the oxide data using only the altered samples (Fig. 5.15c) is most similar, spatially, to the gold potential map produced from the alteration maps. This is not unexpected as both were created using

only the altered samples. The high potential areas (A, B, D, and F shown on Figs. 5.14 and 5.15c) are similar on both these maps.

Evaluation of high potential gold zones with respect to regional geology: Table 5.15 is a summary of the major altered zones (locations A-G) identified on Figures 5.4, 5.5, 5.6, 5.14 and 5.15. All zones of intense alteration are located in high strain zones mapped by Heather and Shore, (1999) in the southern and central portions of the belt, and by Ayer and Theriault (1993) in the northern area. Zones C and B coincide with areas known to be mineralized (Shunsby mine and Old Women iron formation, respectively) although the other zones do not. Area A is particularly interesting. Geologically, the area is underlain by a thick sequence of homogeneous tholeiitic basalt that lies in the core of a broad, southwesterly-trending anticline (antiform?), that is transected by a number of northeast-trending shear zones. These shears are smaller subsidiary splays off the Slate Rock deformation zone to the north, and the Deerfoot deformation zone to the south. The subsidiary deformation zones are 10-100 m wide, and are manifest as highly schistose, carbonatized, chloritized and locally sericitized mafic volcanics with cross-cutting quartz veins (Ayer, pers. comm., 1997; OGS, 1993).

5.5 Discussion

In this paper, the high density of sample points and the mild to strong spatial autocorrelation present in the major oxide data favoured the use of kriging as a method of interpolating the geochemical data. Kriging each of the major oxides independently may lead to values at a given location that do not sum to 100%. The effect of this has not been evaluated, but is not likely in the present study to change the principal results, because of the large number of samples. The decision to interpolate geochemical data is left to the individual geologist, however GIS (and associated geostatistical software) provide tools (e.g., variograms) which can assist in the decision making process.

The WofE method requires a priori knowledge (i.e., knowledge of existing mineral prospects) to define breakpoints or thresholds, whereas the other methods (percentile cutoffs, breakpoints on probability plots and log concentration versus log area plots – Cheng et al., 1996) do not require pre-existing knowledge of mineral prospects. The probability plots are the simplest method for determining thresholds above which the data may be considered anomalous, potentially reflecting alteration associated with mineralization. They are easy to calculate and understand and often show a number of breakpoints that may reflect mixtures of populations, produced by various geological processes, including alteration and /or mineralization

Analysis of scatterplots, although useful for detecting unusual groups of samples, should be treated with caution for identifying alteration. Harris et al. (1999) show that groups of outliers visually identified on scatterplots can sometimes represent geochemically unusual rocks such as komatiites as opposed to alteration trends. For example, the unusual trend seen in the scatterplots shown on Figure 5.3a comprises 31 samples, 29 of which plot as ultramafic komatiites (PK) on a Jensen ternary diagram (Jensen, 1976). The remaining 2 samples fall within units mapped as mafic intrusions. All these sample have been flagged as altered, using the methods discussed previously. These samples, although now classified as ultramafic komatiites (PK), are altered through MgO enrichment, and were probably once basaltic komatiites (BK) or mafic tholeiites with lower MgO concentrations.

Maps showing the presence or absence of alteration have been constructed using several methods. There is a high degree of coincidence between these maps (Fig. 5.4), as would be expected, since they were derived from the same group of altered samples. Generally the methods based on excessive volatiles and LOI concentrations and high alteration index values are best for identifying altered samples from ultramafic and mafic rocks, whereas the method based on atypical normative minerals is best for felsic rocks. The alteration map based on excessive total volatile concentrations was the best predictor of known gold prospects. This is not unexpected as mafic volcanic rocks were typified by the highest percentage of altered samples identified using excessive volatile

concentrations (see Table 5.2), and also the highest percentage of gold prospects. In general, with the exception of the altered samples identified from scatterplots, all methods for identifying altered samples resulted in maps that were mildly to moderately predictive of known gold prospects. This indicates that the presence of alteration, regardless of type and intensity, is an important indicator of gold mineralization within the SGB.

Table 5.14 shows weights of evidence statistics for the gold favourability maps, produced from the different groups of samples (e.g., *all* samples, *altered* samples, *normalized* samples, *ratio* samples). Relative rankings (based on contrast values) for the major oxides, for each group of samples, is also shown in this table. The difference in W+ and C values for each are generally small, but are nevertheless useful for relative comparisons between the oxides for each group of samples.

Al_2O_3 and ferrous and ferric iron were the strongest predictors of gold prospects for the posterior probability map based on all the samples (Fig. 5.15a). The spatial association between anomalous iron (all samples) and gold may relate more to lithology, in this case, as 60% of the gold occurrences are found in mafic volcanic rocks, which would have naturally higher iron content. Al_2O_3 , CaO, FeO and Na_2O anomalies are the strongest predictors of gold when considering only the altered samples (Fig. 5.15c). However, only Na_2O is important when considering the studentised value (C/SD). The relatively high weights (W+ and C) for CaO and Na_2O suggest that carbonatization and perhaps albitization are alteration trends spatially associated with gold mineralization. The strongest predictors of gold for the normalized data (Fig. 5.15b) are CaO, Al_2O_3 , K_2O and FeO, all of which are important, and Fe_2O_3 , which is less significant (lower C/SD value). The anomalous CaO and K_2O indicate that carbonatization and potassic alteration (K-metasomatism and sericitization) are spatially associated with gold mineralization. The presence of iron oxides, reflected by anomalous Fe_2O_3 concentrations, may indicate an association of Fe-carbonates (e.g., ankerite) with gold mineralization. This is a common association found in many Archean greenstone belts (Hodgson, 1993). The best predictors for the ratio (mass balance) (Fig. 15d) data are, once again, CaO and Fe_2O_3 .

Al_2O_3 , which is generally considered immobile in low- to medium-grade metamorphic conditions, is generally a good predictor of gold prospects especially for the posterior probability maps produced from all the samples, altered samples, and normalized samples. Areas of anomalously high Al_2O_3 concentrations correspond mildly with areas of anomalously low K_2O concentrations (but not Na_2O concentrations). This indicates that Al_2O_3 may be a strong predictor of gold, not necessarily due to significant enrichment of this element, but by associated alkali depletion (especially K_2O). This would result in a volume change, and not necessarily an overwhelming addition of Al_2O_3 . Thus, areas of K_2O depletion, as well as areas of potassic alteration, are mild predictors of gold prospects.

It is surprising that TiO_2 , usually a relatively immobile element that comprises late-fractionating restite accessory minerals, appears to be significantly lower in altered samples. Harris et al. (1999) present a more detailed interpretation of altered versus unaltered samples with respect to different lithologic units within the SGB.

Results of statistical analyses (e.g. calculation of correlation coefficients) applied to the major oxide data require further study with respect to the problem of closure (Aitchison, 1986). This work is ongoing and involves the statistical and spatial comparison of the major oxide data with the transformed oxide data (using a log-ratio transformation) for the delineation of geochemical anomalies.

5.6 Summary and Conclusions

A number of diverse geochemical databases have been compiled into one seamless database and the data have been divided into altered and un-altered populations using a number of univariate and multivariate techniques.

GIS can be used effectively to visualize geochemical data in a variety of ways ranging from traditional proportional-circle plots to interpolated maps and to combinations of the data in RGB ternary plots. Ternary maps are particularly useful as they not only show the presence or absence of alteration (or areas where no samples are present), but also give an indication of alteration intensity and the spatial association between different methods used to identify alteration. Furthermore, the ternary concept can be extended to include RGB images which show the spatial associations in terms of pattern and concentration, among major oxides or trace elements (Harris and Wilkinson, 1999). A number of areas of intense alteration have been identified on the various geochemical maps produced in this paper, many of which coincide with high strain zones (see Fig. 5.1 and Fig.5.6)

Atypical normative minerals and LOI methods identified the largest number of altered samples, and result in the highest correlation with altered samples identified by other criteria. Altered samples are characterized by higher SiO_2 , K_2O and MnO concentrations, and lower MgO and TiO_2 concentrations. Ultramafic rocks are characterized by the highest proportion of altered samples, identified best by the LOI, scatterplot and alteration index methods. The atypical normative mineral method is more sensitive to felsic rocks (felsic volcanic rocks, granitoids), whereas the volatile method is more sensitive to mafic volcanic rocks, granitoids and sedimentary rocks.

Normalization is effective for the suppression of the effects of lithologic geochemical variation, and also circumvents the problem of closure. Normalization of the data to account for lithological variations produced geochemical anomaly maps which were, in general, more predictive of known gold prospects than anomaly maps based on samples that were not normalized. Furthermore, the gold potential map produced from the normalized data predicted more of the known gold prospects than the maps based on the altered, ratioed and all sample groups. The high correlation between normalized CaO and FeO , suggests an association between carbonatization and iron oxidization (ferric), possibly ankerite (Fe carbonate).

The alteration map based on excessive volatiles is the best alteration map for predicting the known gold deposits.

CaO, Fe, K₂O and Al₂O₃ were the oxides found to be the best predictors of the known gold prospects. Anomalous concentrations of these oxides reflect carbonatization, Fe-carbonate alteration and potassic alteration trends and indicate that these alteration styles are spatially related to gold mineralization. Anomalous concentrations of Al₂O₃, an element generally considered to be immobile in Archean greenstone belts characterized by widespread greenschist metamorphic conditions, is also predictive of known Au prospects. This may be due in part to accompanying alkali depletion (K₂O especially) in certain areas. Thus, potassic alteration and depletion appears to be an important alteration characteristic of gold mineralization within the SGB.

The WofE method is a useful technique with which to evaluate the geochemical maps produced in this paper. Although other methods of evaluation could be envisaged, WofE is useful not only for comparing geochemical anomalies to the location of known gold prospects, but also for establishing the strength of association between anomalies and gold prospects using objectively generated weights and contrast values (e.g., W⁺, W⁻, C). Furthermore, the gold potential maps generated using WofE, not only highlight (or predict) known areas of gold mineralization but also identify high potential areas where no mineralization occurs. A number of areas within the SGB have been identified as having high gold potential on many of the geochemical maps produced in this paper. Several of these areas coincide with areas of known gold mineralization, whereas others are enigmatic and await follow-up exploration.

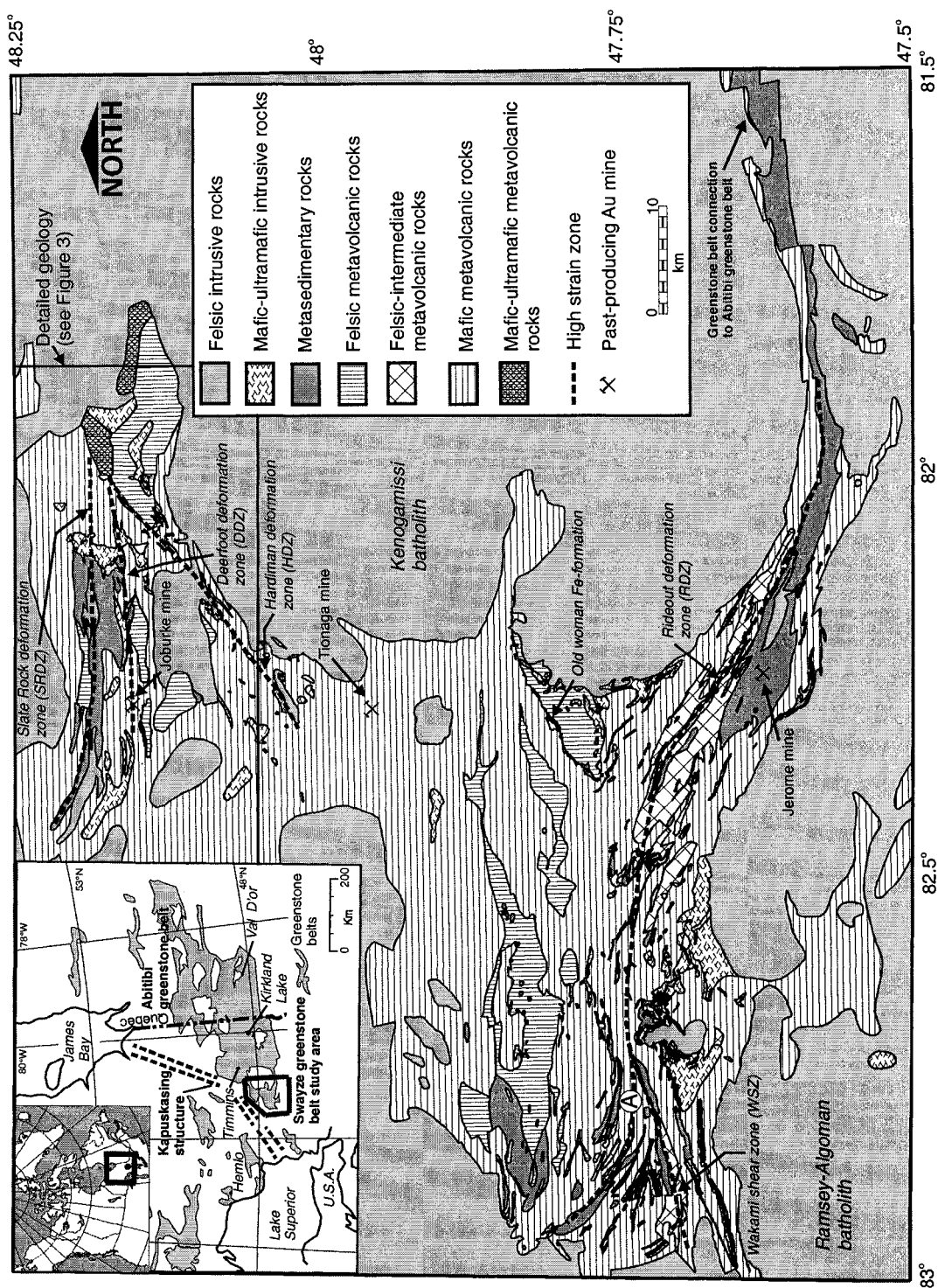


Figure 5.1 Location map and generalized geology of the Swayze greenstone belt study area (after Ayer, 1995a,b; Heather and Shore, 1999a-i; OGS, 1993)

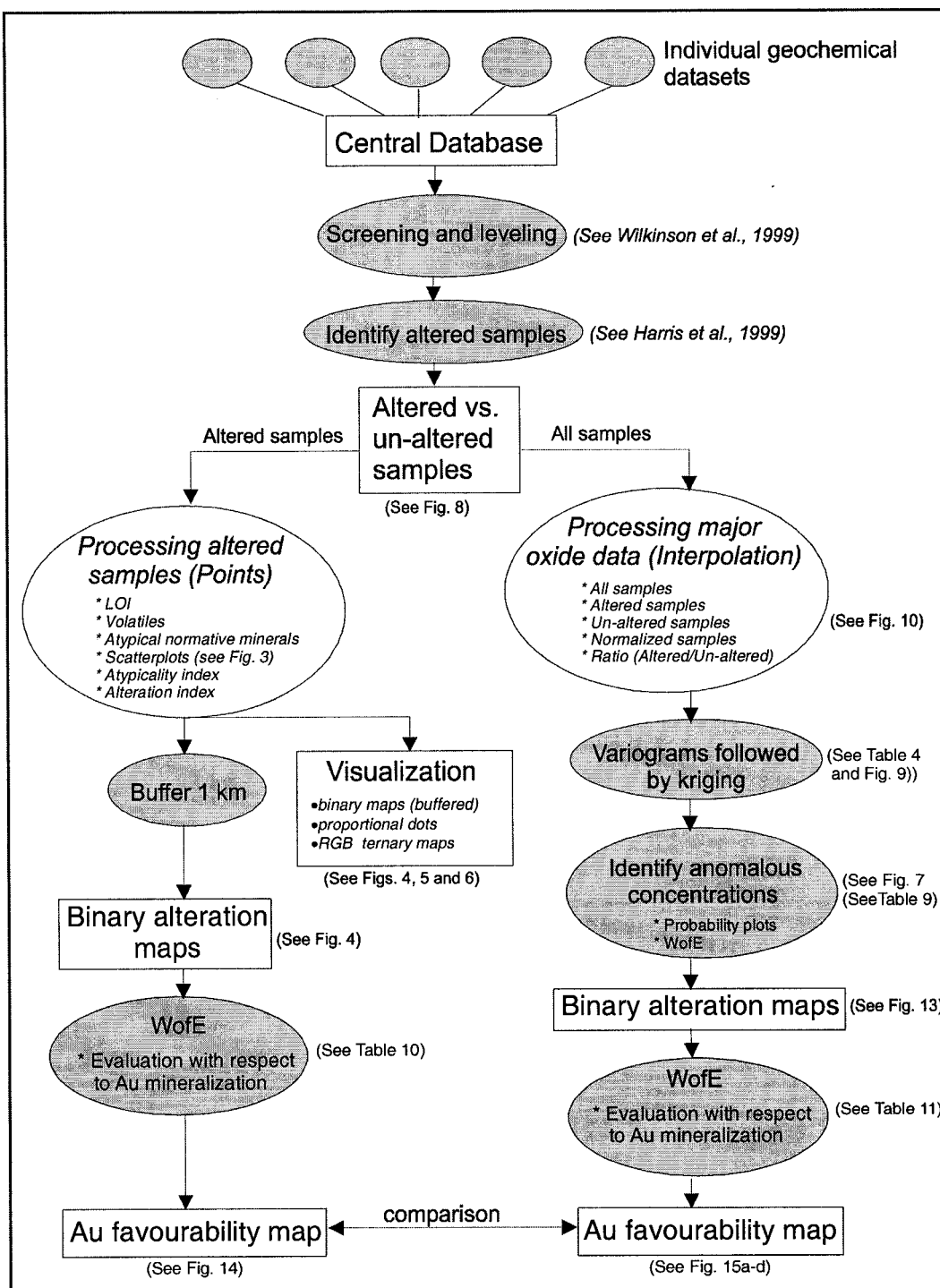


Figure 5.2 Summary of the data processing methodology used in this study

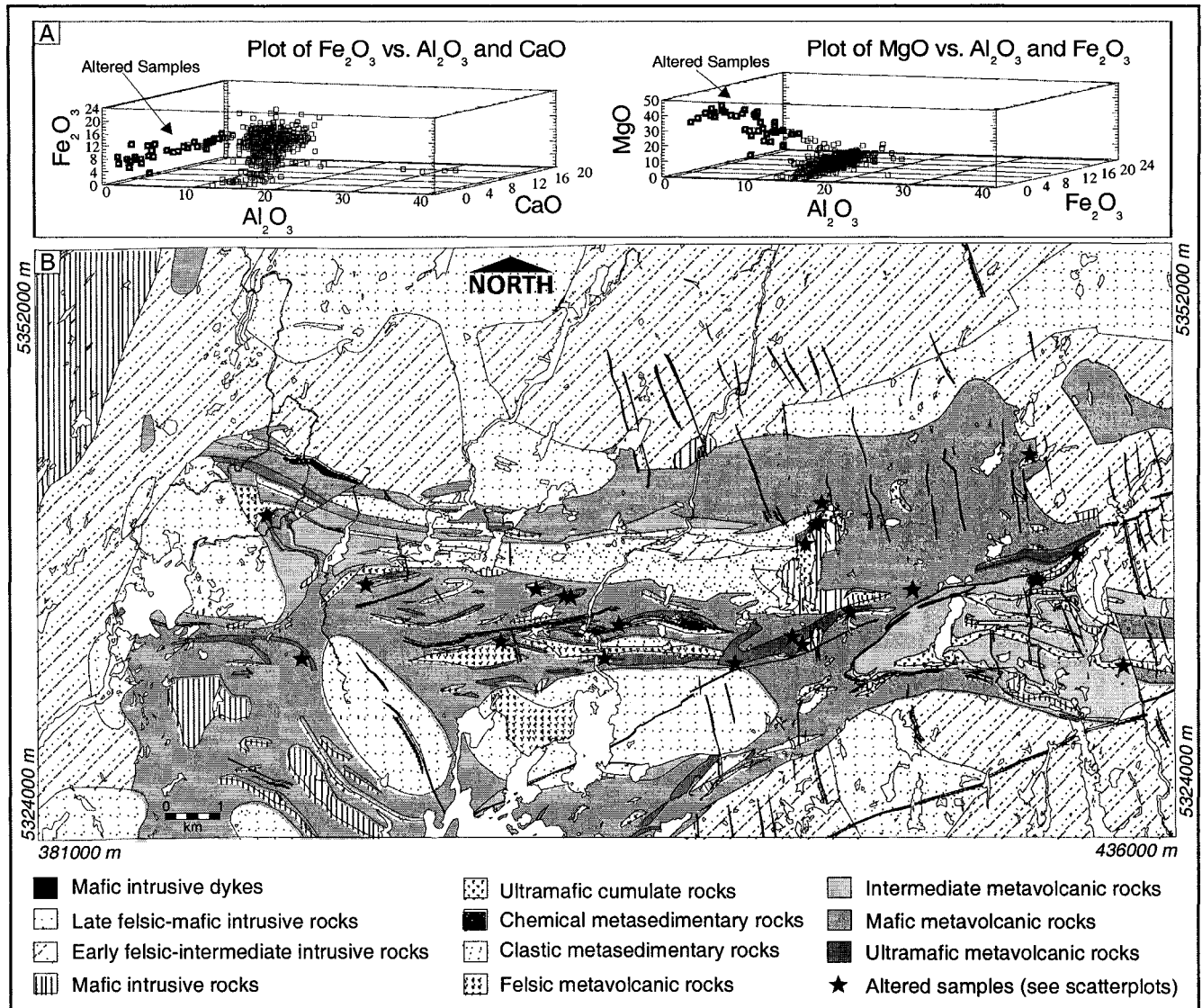


Figure 5.3 Scatterplots of Fe_2O_3 , Al_2O_3 , CaO and MgO concentration for all volcanic samples within the northern portion of the SGB (see Figure 5.1 for location of detailed geology within SGB). Unusual samples and data trends are indicated on the scatterplots (A), and plotted on the accompanying geologic map (B) (geology from Ayer, 1995a,b)

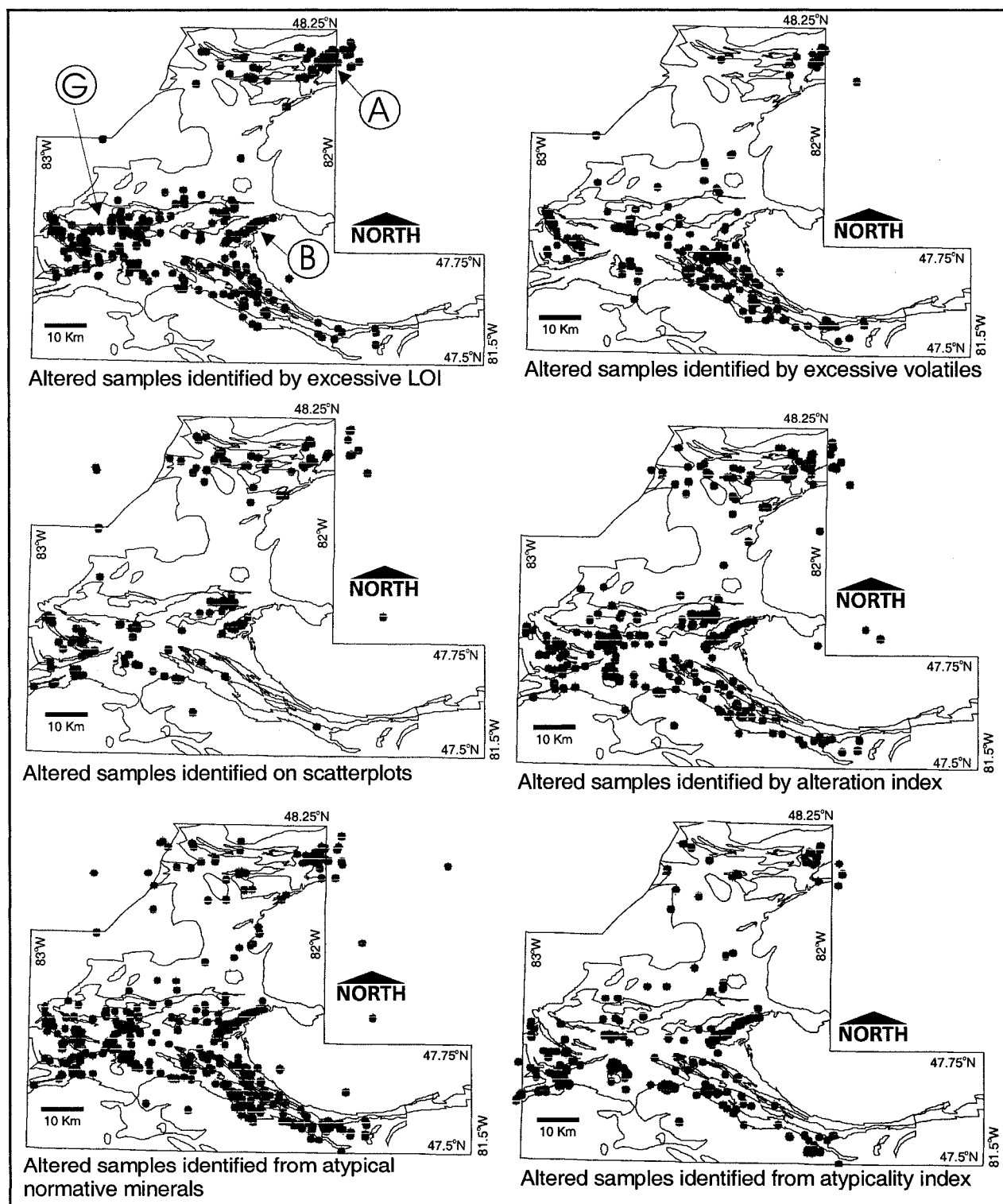


Figure 5.4 Binary alteration maps produced by “dilating” (buffering) the location of each altered sample (identified by the various alteration methods) to a distance of 1 km. Areas in black thus represent 1 km buffers around altered samples

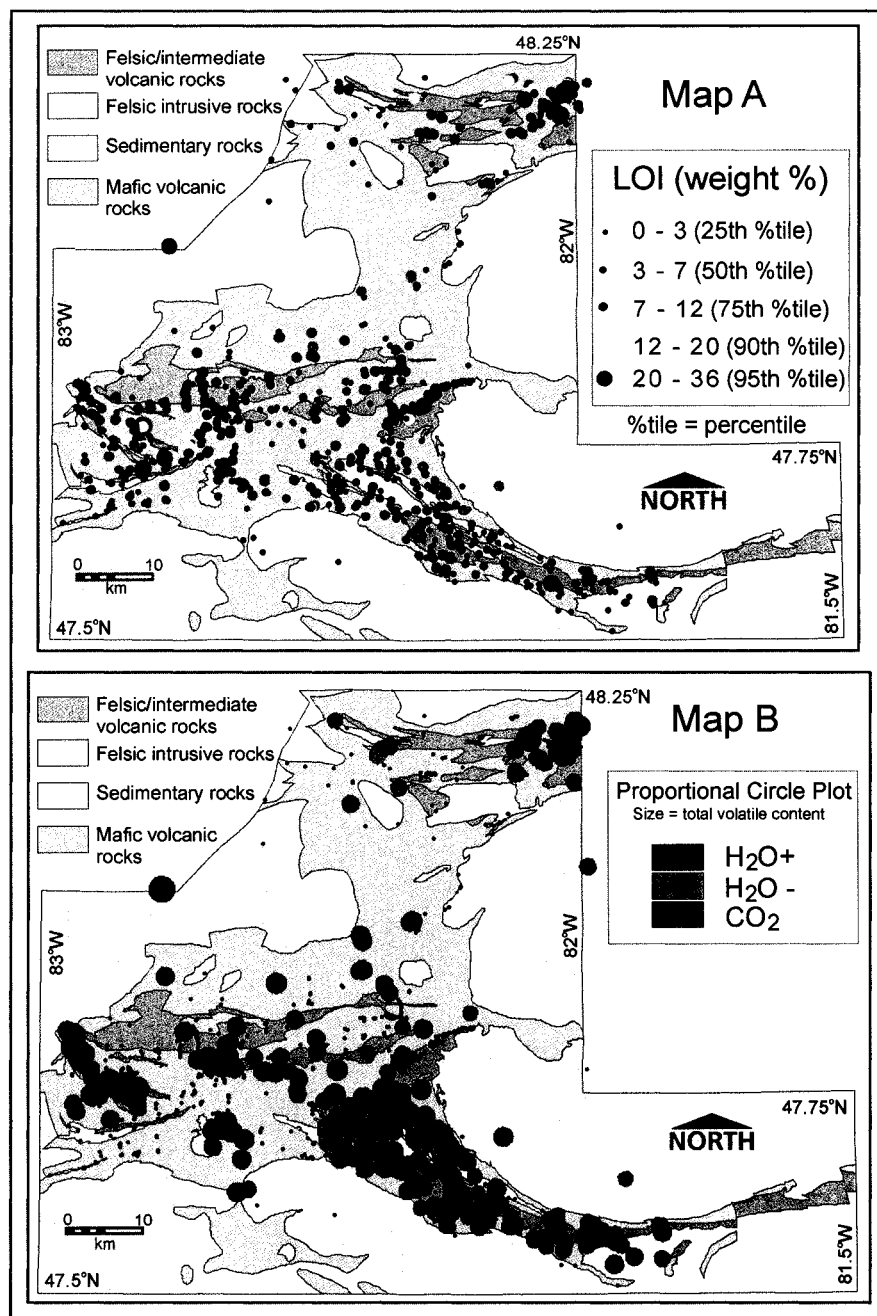


Figure 5.5 Bubble (proportional circle) plots. Map A shows proportional circles based on percentiles of LOI. Larger circles are displayed in red, and reflect higher LOI values. Map B shows proportional circles based on total volatile content, defined by the sum of H_2O (H_2O^+ and H_2O^-) and CO_2 content for each sample. The contribution of CO_2 and H_2O^+ and H_2O^- to the total volatile content is proportional to the size of each wedge within each circle

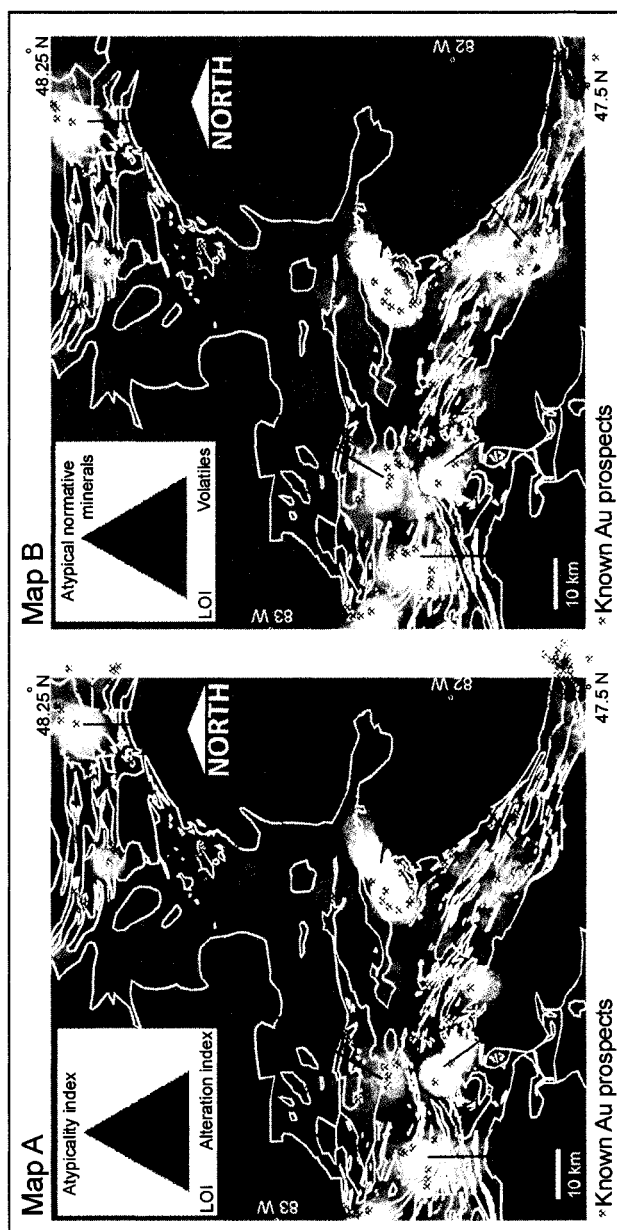


Figure 5.6 RGB (red-green-blue) ternary maps showing alteration zones defined by the overlap of anomalous areas delineated by the various methods for identifying altered samples. Map A combines anomalous areas identified by the index of typicality, LOI and alteration index, whereas Map B combines anomalous areas identified by atypical normative minerals, LOI and volatiles

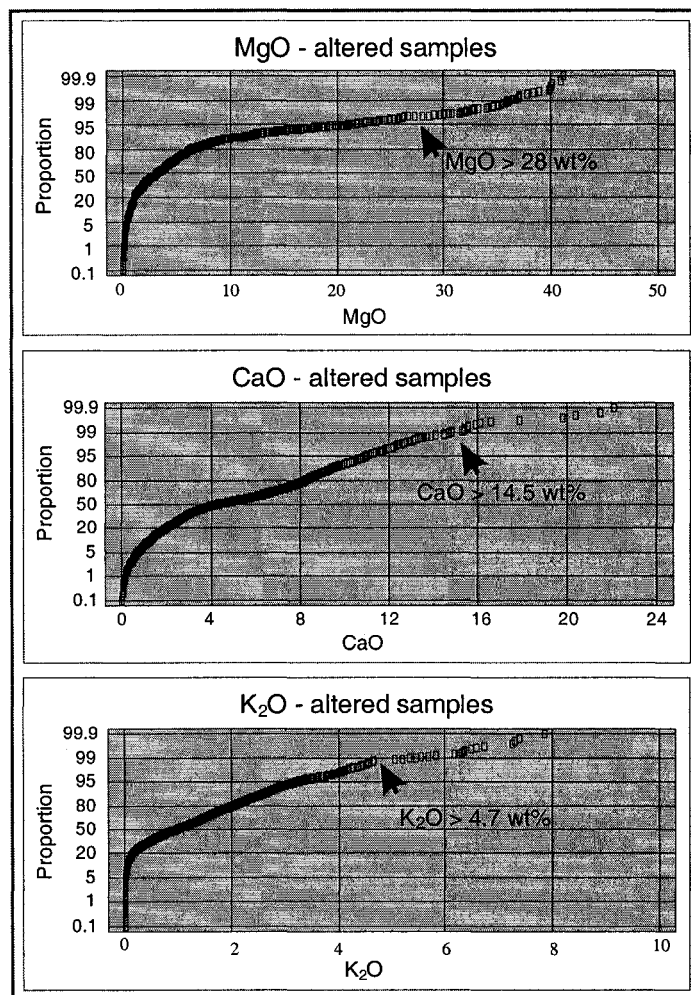


Figure 5.7 Examples of probability plots for CaO, K₂O and MgO (altered samples), in which significant upper breakpoints are identified

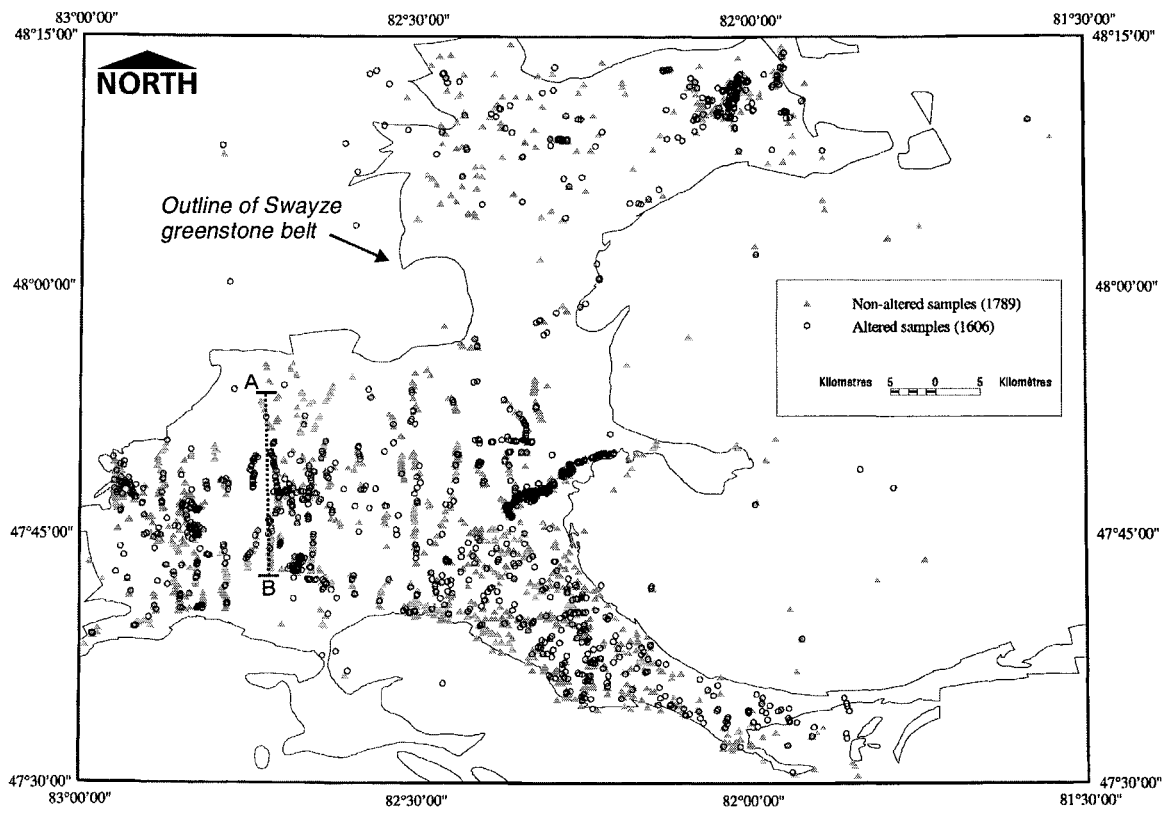


Figure 5.8 Distribution of altered and un-altered samples over the Swayze greenstone belt

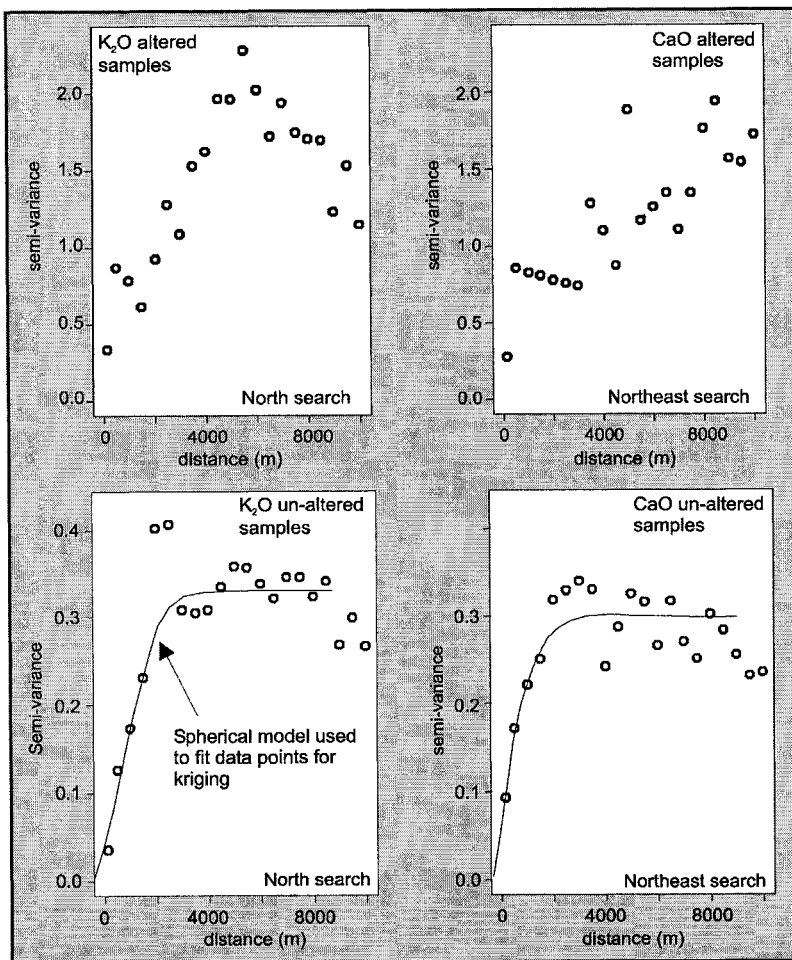


Figure 5.9 Examples of directional variograms for K₂O and CaO, based on altered and un-altered samples

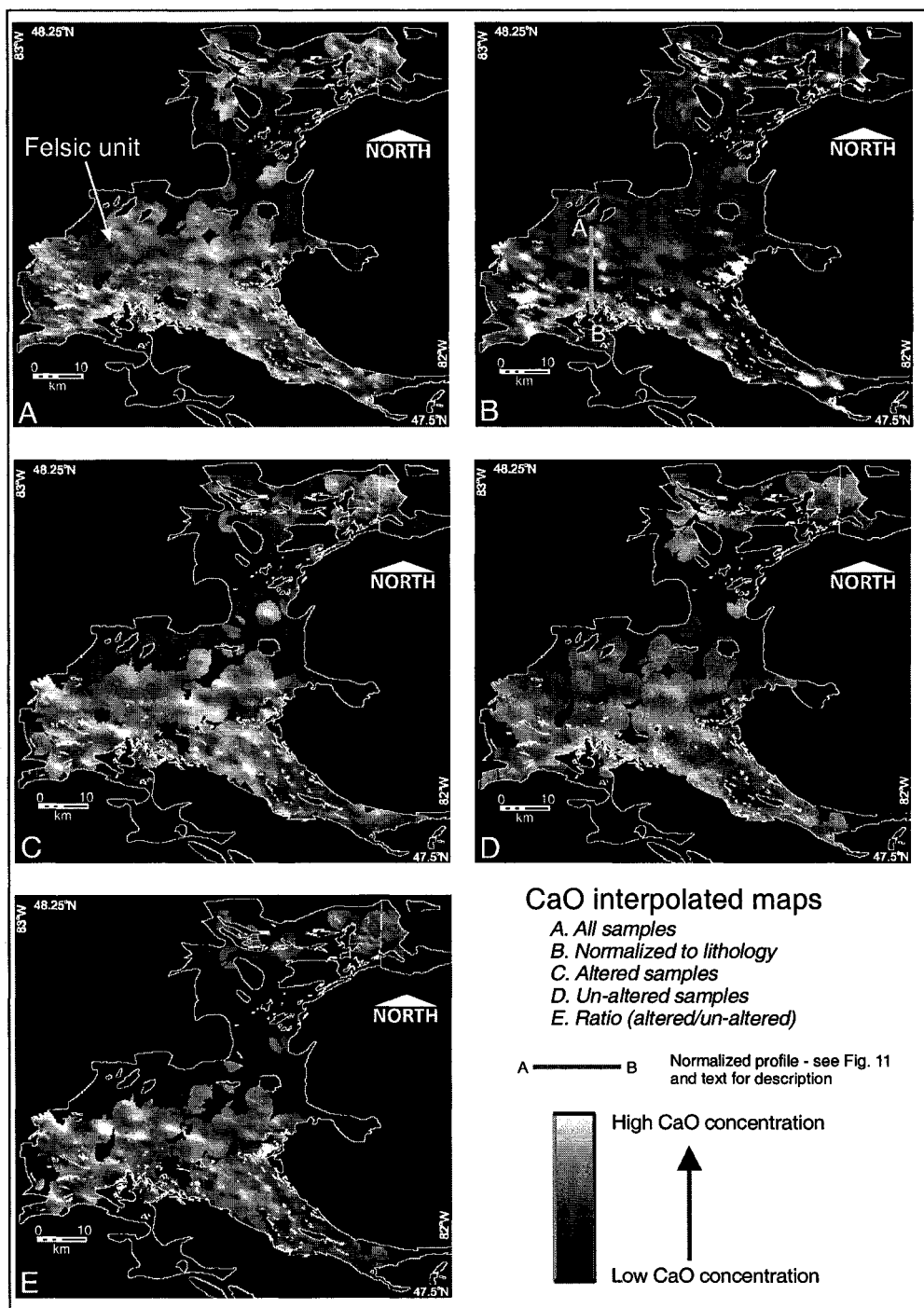


Figure 5.10 Interpolated (kriged) maps of CaO using all samples, samples normalized to lithology, altered samples, un-altered samples, and ratios (altered/un-altered). Higher concentrations of CaO are shown in the brighter grays and white

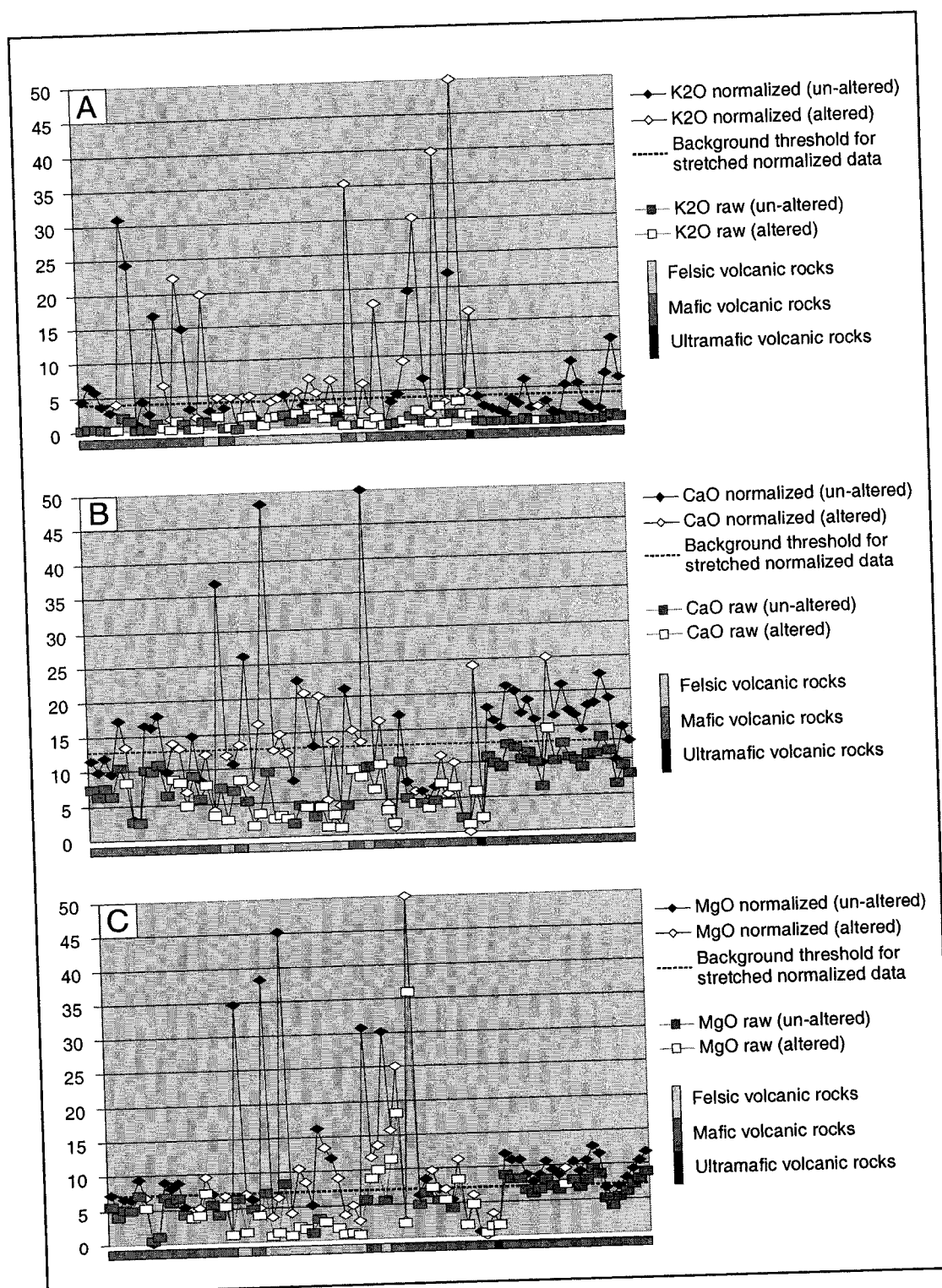


Figure 5.11 Plot of MgO and CaO (raw and normalized values) along profile A-B shown on Figure 5.8

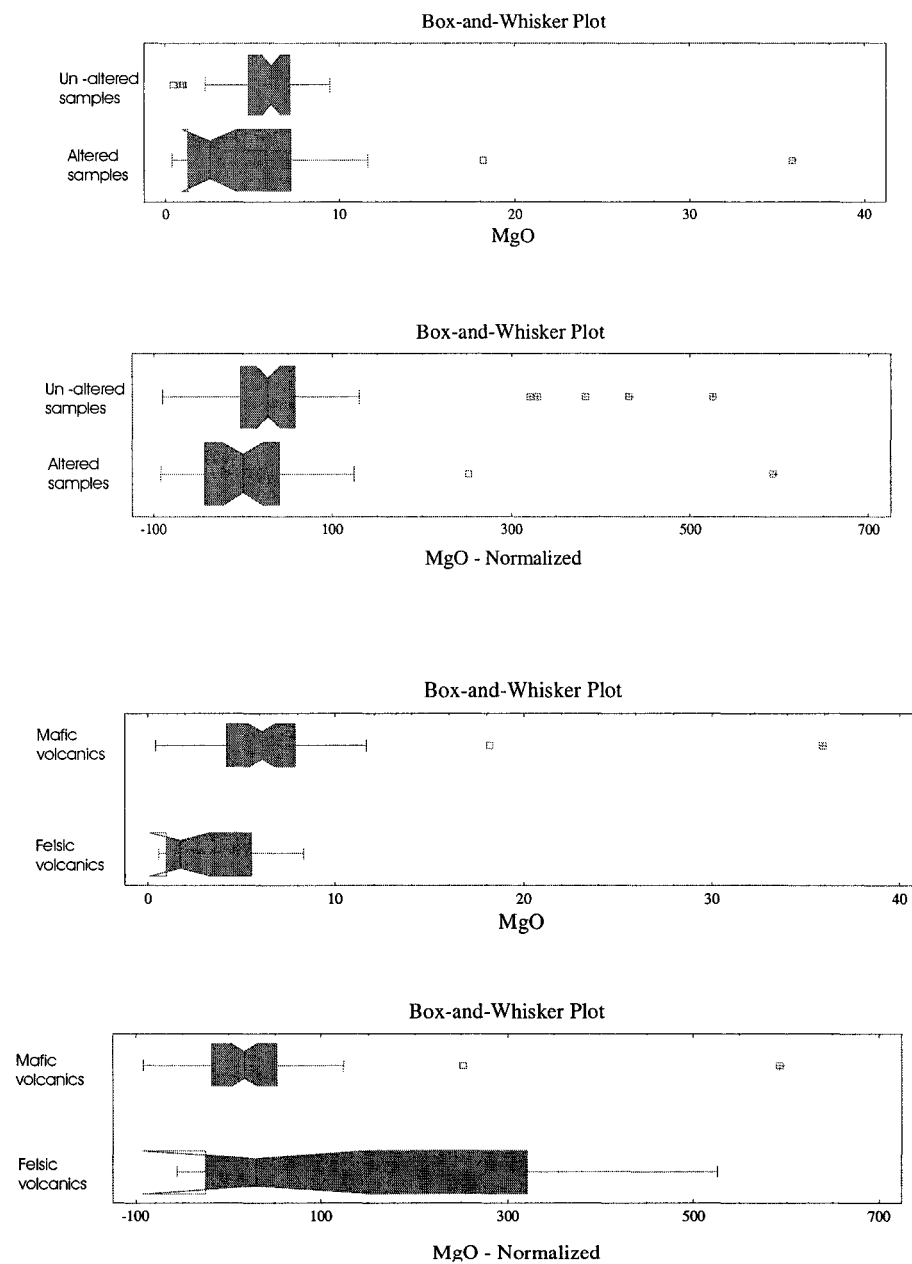


Figure 5.12 Box and whisker plots of MgO (raw and normalized values) for altered and un-altered samples and mafic and felsic volcanic lithologies

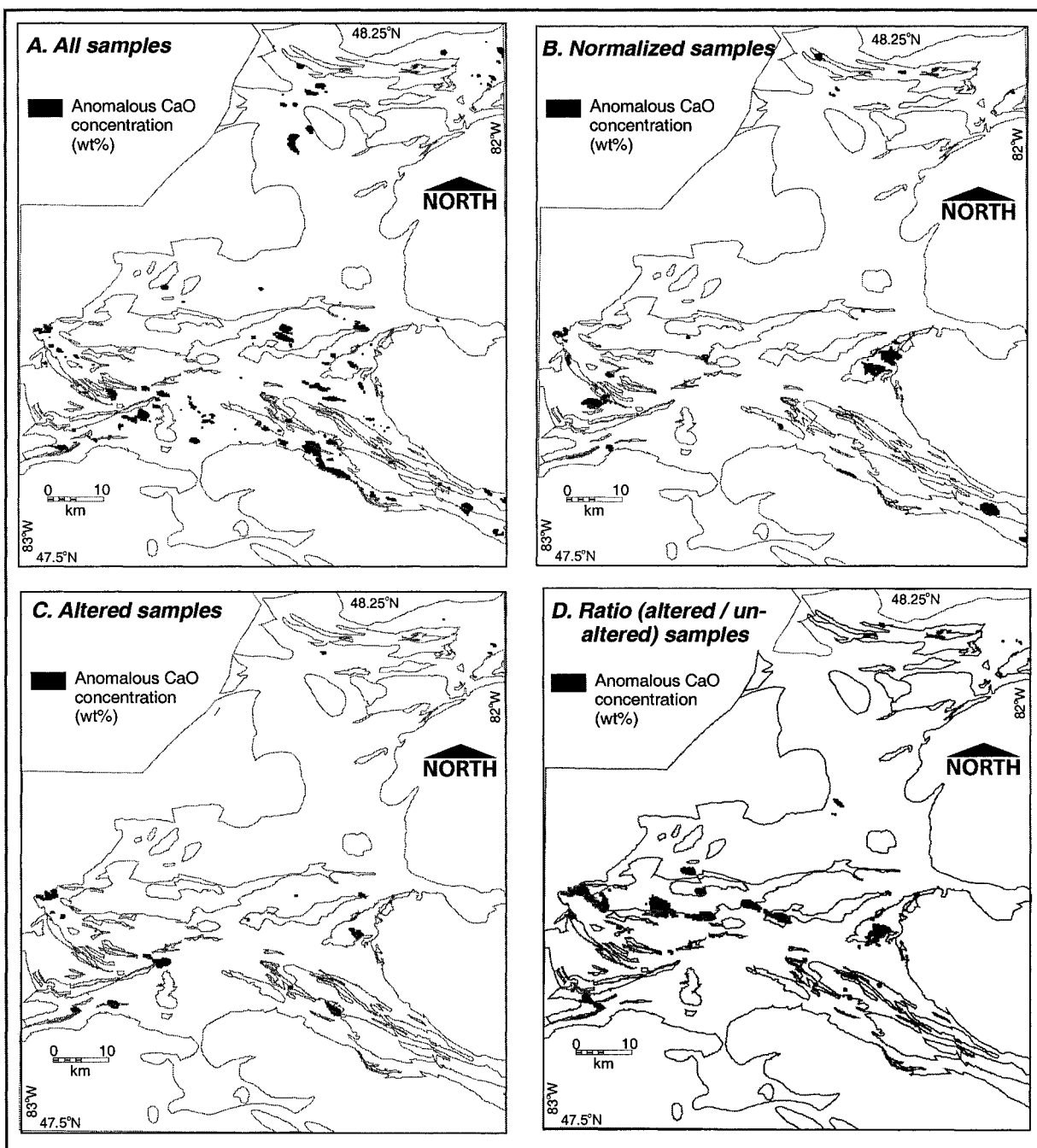


Figure 5.13 Binary anomaly maps derived by thresholding the interpolated CaO maps. Anomalous areas of CaO (above selected threshold) are shown in black, for all samples, normalized samples, altered samples, and ratios (altered/unaltered samples)

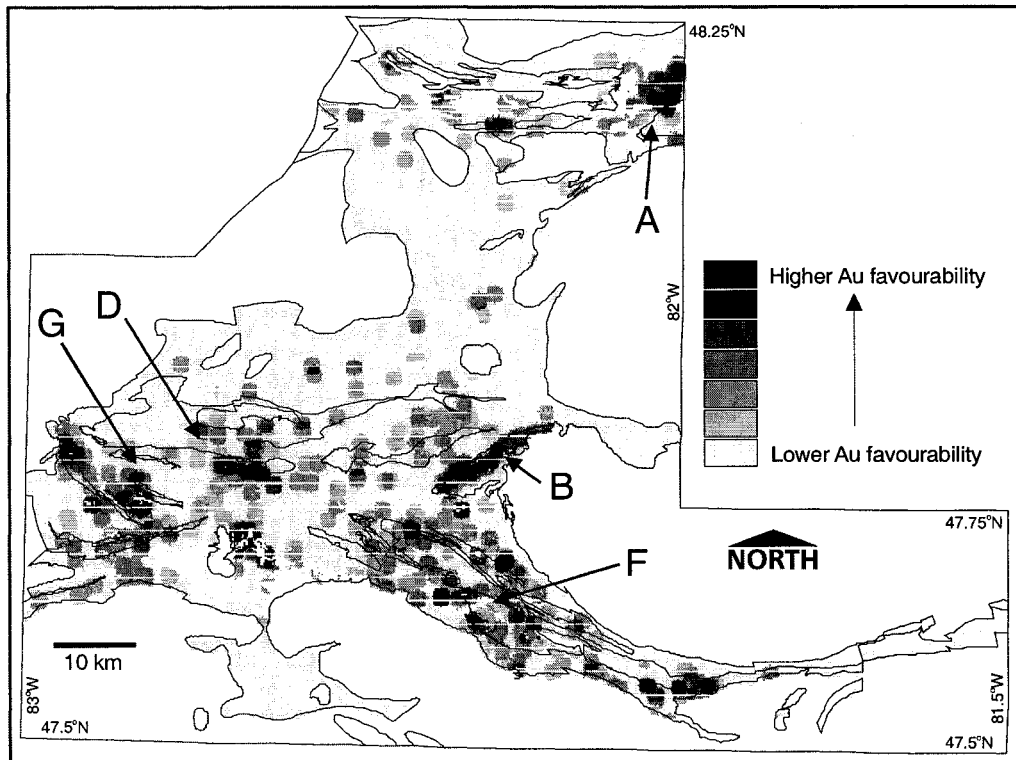


Figure 5.14 Posterior probability (gold favourability map) produced using *WofE*, and based on the alteration binary anomaly maps (see Figure 5.4). Areas with the highest favourability for Au are shown in black on this map

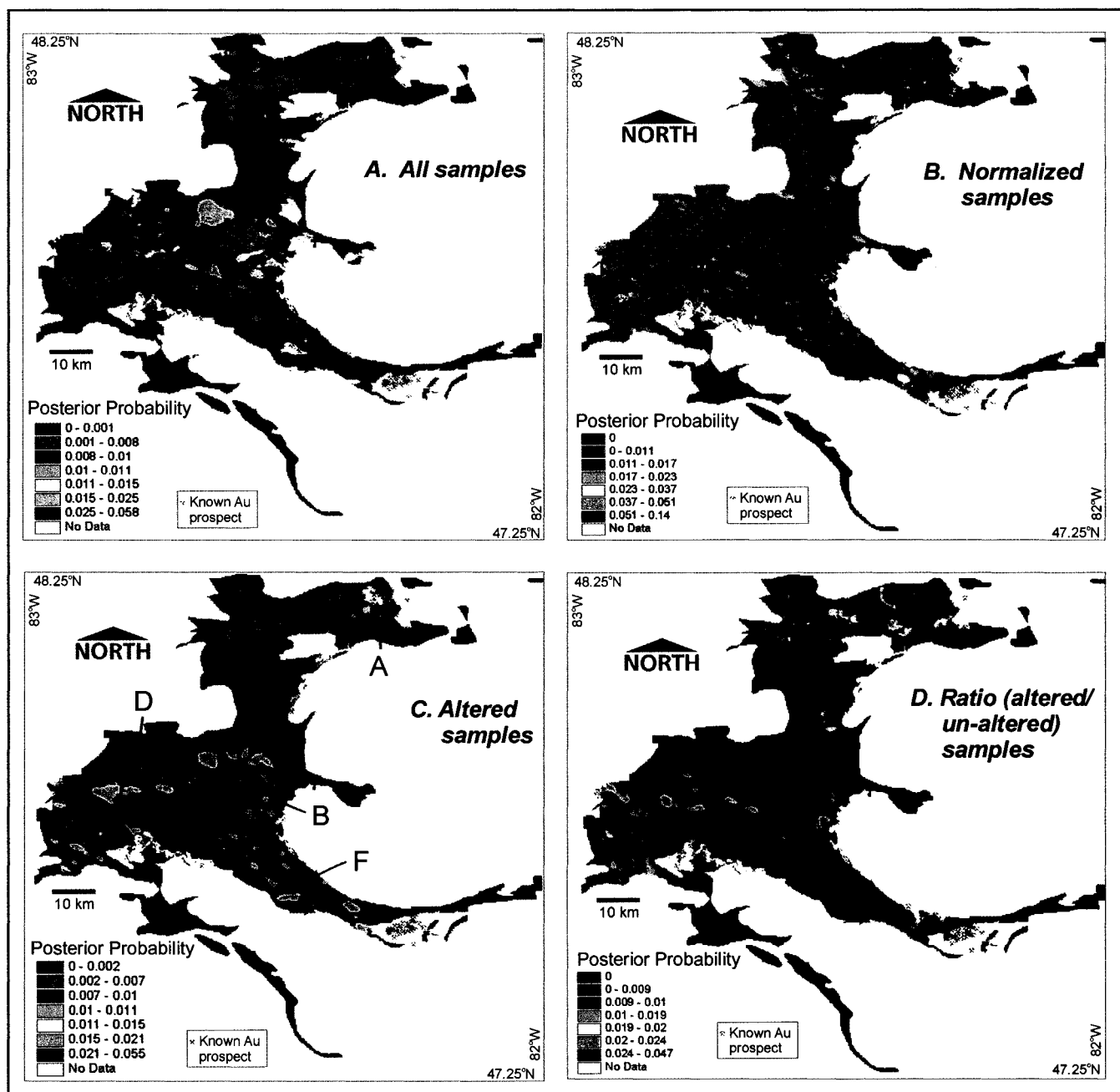


Figure 5.15 Posterior probability maps calculated from the interpolated and thresholded oxide binary maps. Map A displays results for all samples, Map B for normalized samples, Map C for altered samples, and Map D for ratio (altered/un-altered) samples

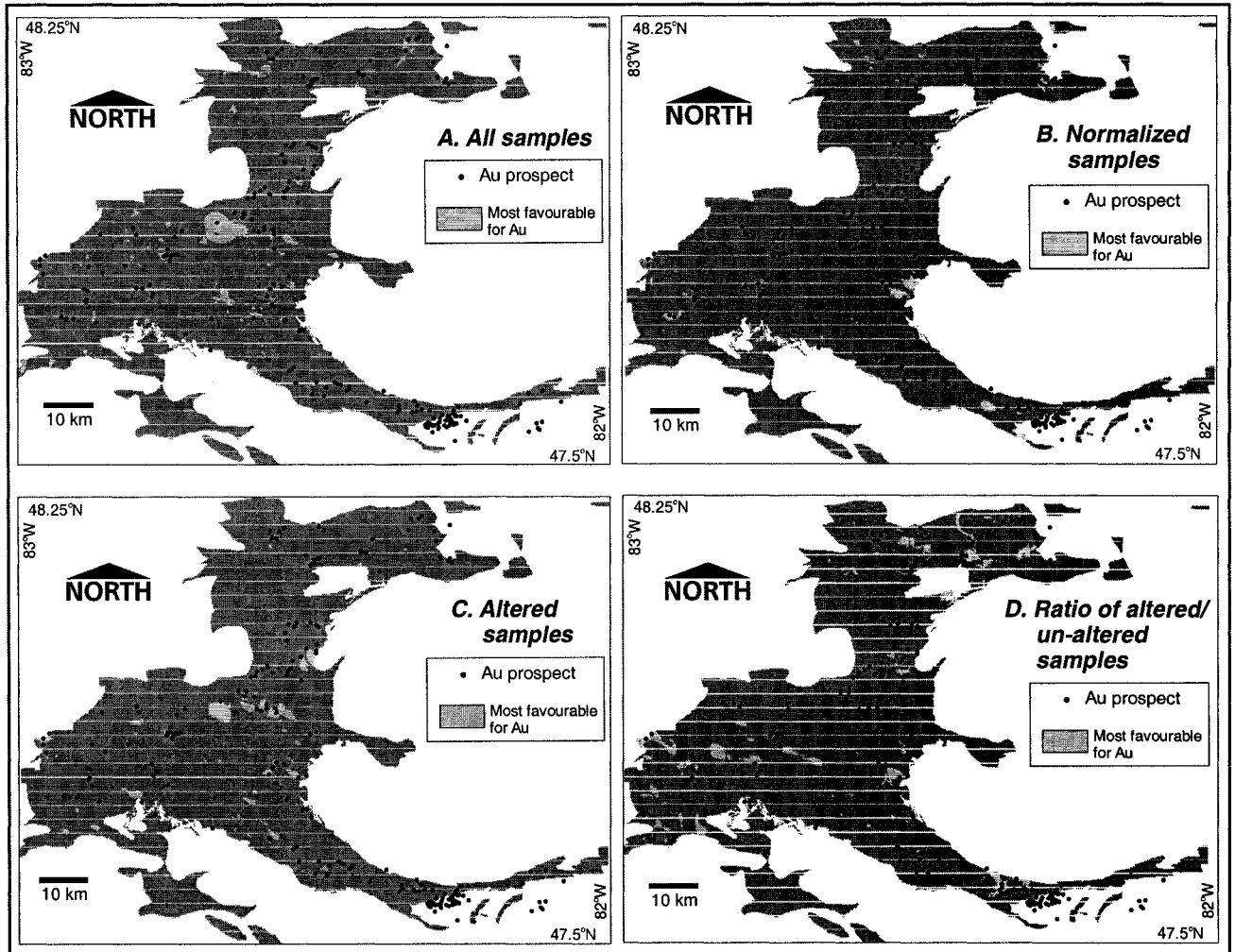


Figure 5.16 Binary maps of the highest gold potential based on posterior probabilities (approximately top 5% of area) for each of the oxide favourability maps shown in Fig. 5.15

<i>Alteration flag method</i>	<i>Number of samples</i>	<i>% of total samples</i>
Atypical normative minerals	810	23.8%
LOI	665	19.6%
Volatiles	260	7.6%
Alteration index	432	12.7%
Index of typicality	413	12.2%
Scatterplots	209	6.1%

Table 5.1 Number of altered samples identified by each alteration method

<i>Method (used to identify altered samples)</i>	<i>Lithology with highest percentage of altered samples</i>	<i>Lithology with second highest percentage of altered samples</i>
Atypical normative minerals	Felsic volcanic rocks (76%)	Granitoids (69%), Sulphidic sedimentary rocks (67%)
LOI	Ultramafic rocks (73%)	Mafic intrusive rocks (71%), Mafic volcanic rocks (50%)
Volatiles	Mafic volcanic rocks, Granitoids, Sedimentary rocks (all 19%)	
Alteration index	Ultramafic rocks (68%)	
Index of typicality	Sulphidic sedimentary rocks (47%)	Mafic intrusive rocks (40%)
Scatterplots	Ultramafic rocks (100%)	Mafic intrusive rocks (30%)

Table 5.2 Summary of cross tabulation results between altered samples identified by each method and mapped lithology

	<i>Felsic</i>	<i>Intermediate</i>	<i>Mafic</i>	<i>Ultramafic</i>
Jensen class	CR, TR	CA, CD, TA, TD	HFT, HMT, CB	BK, PK ^a
Number of un-altered samples	121	366	1003	19
Number of altered samples	229	273	356	121
Ratio (altered/non-altered)	1.89	0.74	0.35	6.36

^a Jensen cation classification. BK = basaltic komatiite; PK = picritic komatiite; CA = calc-alkaline andesite; CB = calc-alkaline basalt; CD = calc-alkaline dacite; CR = calc-alkaline rhyolite; HFT = high Fe tholeiite; HMT = highMg tholeiite; TA = tholeiitic andesite; TD = tholeiitic dacite; TR = tholeiitic rhyolite.

Table 5.3 Breakdown of altered and unaltered samples by Jensen geochemical classification (Jensen, 1976)

<i>Oxide</i>	<i>Options</i>				
	Range ^a	Scale ^b	Nugget ^c	Ratio ^d	Azimuth ^e
<i>Table 4A: Altered data</i>					
SiO₂	2000	40	10	0.5	75
Al₂O₃	5000	10	0	0.5	45
CaO	3000	10	2.5	0.5	112
Na₂O	3000	3.2	0.3	0.5	112
K₂O	4000	0.95	0.1	0.3	112
MgO	4000	40	0.18	0	112
<i>Table 4B: Un-altered data</i>					
SiO₂	5000	30	10	0.5	112
Al₂O₃	5000	1.8	0.6	0.5	0
Fe₂O₃	6000	10	0	0.5	15
FeO	4000	4.5	0	0.5	112
CaO	4000	8	1	0.5	112
Na₂O	5000	1.4	0.5	0.5	112
K₂O	5000	0.18	0.1	0.5	0
MgO	4000	4.82	0.18	0.5	112

^a Range refers to the distance at which the semi-variance becomes constant (read from the x-axis of the variogram - see Figure 9).

^b Scale is used to define the sill for the variogram, where the sill is a point at which the variance stabilizes and no longer increases or decreases (read from the y-axis - see Figure 9). The sill equals the scale plus the nugget.

^c The nugget is a reflection of variability between sample points at small distances. It is often caused by small-scale geologic and surficial controls.

^d Ratio values define the shape of the ellipse, and allow for modeling anisotropic relationships in the data due to stratigraphy. For example, a ratio of 0 defines a circle, whereas values less than 0 define an elongated ellipse.

^e Azimuth defines the orientation of the ellipse in degree units, where a value of 0 represents north. It defines the directional anisotropy present in the data (due to orientation (strike) of lithology).

Table 5.4 Variogram results of oxide data for altered (A) and unaltered (B) samples

	Altered		Un-altered		Mafic		Felsic	
	Raw (wt%)	Normalized	Raw (wt%)	Normalized	Raw (wt%)	Normalized	Raw (wt%)	Normalized
MgO	2.5	.5	6.1	28.0	6.1	17.7	1.7	30.8
SiO ₂	59.6	-6.4	49.1	-3.7	48.4	-6.0 (-.99)	62.0	-7.0 (-7.7)
K ₂ O	1.2	14.8	0.29	-16.58	0.29	7.4	1.5	-4.4
CaO	4.1	-11.9	9.0	22.1	8.3	4.3	3.1	13.5
Na ₂ O	3.1	7.5	2.4	-11.8	2.4	1.2	4.1	4.5

Table 5.5 Summary of oxide concentrations (raw and normalized) for altered and unaltered samples, and felsic and mafic volcanic rocks along profile A-B (see Fig. 5.11)

	<i>All</i>	<i>Altered</i>	<i>Un-altered</i>	<i>Normalized</i>	<i>Ratio</i>
<i>All</i>		0.59	0.78	0.36	0.11
<i>Altered</i>			0.44	0.28	0.65
<i>Un-altered</i>				0.23	-0.07
<i>Normalized</i>					0.19
<i>Ratio</i>					

Table 5.6 Pearson correlation coefficients for CaO interpolated maps (Fig. 5.10), based on all, altered, unaltered, normalized and ratio sample groups (all correlations significant at the 95% confidence limit)

	<i>CaO</i> - All samples (Fig. 13a)	<i>CaO</i> - altered samples (Fig. 13c)	<i>CaO</i> - normalized samples (Fig. 13b)	<i>CaO</i> - ratio (altered/ un-altered) (Fig. 13d)
<i>CaO</i> - all samples		0.74	0.53	-0.27
<i>CaO</i> - altered samples			0.65	0.69
<i>CaO</i> - normalized samples				0.55
<i>CaO</i> -ratio				

Table 5.7 Yule correlation coefficients between CaO anomaly maps shown in Fig. 5.13

	<i>CaO</i>	<i>K₂O</i>	<i>Na₂O</i>	<i>FeO</i>	<i>Fe₂O₃</i>	<i>Al₂O₃</i>	<i>MgO</i>	<i>SiO₂</i>
<i>CaO</i>		-0.25	-0.2	0.46	0.26	0.06	0.24	-0.48
<i>K₂O</i>			0.12	-0.15	-0.08	0.10	-0.1	0.10
<i>Na₂O</i>				-0.24	-0.08	0.36	-0.02	0.18
<i>FeO</i>					0.09	-0.06	0.16	-0.34
<i>Fe₂O₃</i>						-0.14	0.32	-0.33
<i>Al₂O₃</i>							-0.34	0.01
<i>MgO</i>								-0.36
<i>SiO₂</i>								

Table 5.8 Correlations between normalized oxide interpolated maps (all significant at the 95% confidence limit). The strongest correlations (> .4 or < -.4) are shown in bold

	<i>All samples</i>			<i>Altered samples</i>			<i>Un-altered samples</i>	
	95th percentile	PP ^a	WofE ^b	95th percentile	PP	WofE	95th percentile	PP
K₂O	3	5	2.3 (90%)	3.4	5	2.7 (90%)	2	2.9
CaO	11.5	14	11 (90%)	12	13	11 (90%)	12	13.8
MgO	9	25	8.3 (90%)	10	26	24 (90%)	8	9.5
Na₂O	5.5	6	5.5 (95%)	4.7	5.2	4.3 (80%)	5.5	6.2
Al₂O₃	17	19	17 (19%)	18.8	19.8	19.7 (99%)	15	30
Fe₂O₃	14	18	12.8 (90%)	13	16	13.7 (95%)	14	18
FeO	9	12	9 (95%)	8	12	8 (95%)	10	12
SiO₂	72	76	70 (90%)	74	77	72.1 (90%)	70	74

^a PP = probability plot^b WofE = Weights of evidence. For the WofE results, the corresponding percentile value is shown in brackets.

Table 5.9 Comparison of methods for identifying thresholds and defining anomalous concentrations of major oxides

<i>Method</i>	<i>Area (km²)</i>	<i>No. of Au prospects</i>	<i>W+</i>	<i>W-</i>	<i>C^a</i>	<i>C/SD</i>	<i>Rank</i>
Atypical normative minerals	645	61	0.68	-0.31	0.99	5.80	2
LOI	525	46	0.60	-0.19	0.79	4.42	4
Volatiles	365	43	0.90	-0.22	1.13	6.10	1
Alteration index	498	43	0.58	-0.17	0.76	4.16	5
Index of typicality	390	40	0.76	-0.18	0.95	5.00	3
Scatterplots	253	19	0.40	-0.05	0.49	2.00	6

^a Contrast values are highlighted, and are used to determine the rankings of the map.

Table 5.10 WofE statistics for binary alteration maps (shown in Fig. 5.4)
All C values are significant as $C/CD > 1.5$ (see Bonham-Carter, 1994)

	CaO	K ₂ O	Na ₂ O	FeO	Fe ₂ O ₃	Al ₂ O ₃	MgO	SiO ₂
All samples								
Area (km ²)	88			56	12	6		59
No. of Au prospects	6			6	2	2		5
W+	0.21			0.63	1.18	1.85		0.34
C ^a	0.22			0.65	1.19	1.86		0.35
C/SD	0.52			1.50	1.60	2.50		0.77
Rank ^b	(5)			3	2	1		(4)
Altered samples								
Area (km ²)	15	64	75	135	25	6.5		
No. of Au prospects	2	6	8	4	2	1		
W+	0.78	0.39	0.53	0.58	0.24	0.98		
C ^a	0.79	0.40	0.56	0.60	0.25	0.99		
C/SD	1.10	0.96	1.50	1.17	0.34	0.97		
Rank ^b	(2)	(5)	4	(3)	(6)	(1)		
Normalized samples (all samples used)								
Area (km ²)	32	31		101	8	48	96	10
No. of Au prospects	6	4		9	1	6	7	1
W+	1.20	0.85		0.45	0.83	0.80	0.32	0.43
C ^a	1.24	0.86		0.48	0.83	0.83	0.33	0.44
C/SD	2.90	1.69		1.50	0.82	1.90	0.87	0.43
Rank ^b	1	2		5	(4)	3	(7)	(6)
Ratio								
Area (km ²)	40				65			
No. of Au prospects	6				8			
W+	0.90				0.68			
C ^a	0.94				0.72			
C/SD	2.20				1.90			
Rank	1				2			

^a Contrast values are highlighted, and are used to determine the rankings of the maps.

^b Ranks shown in brackets indicate poor confidence due to low values (<1.5) for C/SD. Note: the differences in C values are small (rankings are therefore used for relative comparisons only)

Table 5.11 WofE statistics for oxide element, binary alteration maps, for all samples, altered samples, normalized samples, and ratios. Columns with no values indicate elements that were not predictive (C is negative or very low W+)

	All samples (Fig. 15a)	Altered samples (Fig. 15c)	Normalized samples (Fig. 15b)	Ratio (altered/ un-altered) (Fig. 15d)
All samples		0.25	0.28	0.26
Altered samples			0.02	0.36
Normalized samples				0.03
Ratio				

Table 5.12 Correlation between posterior probability maps shown in Fig. 5.15 (all significant at the 95% confidence limit)

	All samples (Fig. 16a)	Altered samples (Fig. 16c)	Normalized samples (Fig. 16b)	Ratio (altered/ un-altered) (Fig. 16d)
All samples		.64	.63	-.36
Altered samples			-.21	.23
Normalized samples				.56
Ratio				

Table 5.13 Spatial overlap (reflected by Yule coefficient; see text for description of calculation) between highest posterior probabilities (top 5% by area) for each map shown in Fig. 5.16

Table 14a - normalized to area (~ top 5% of area)

Method	Area (km ²)	No. of Au prospects	W+	W-	C ^a	C/SD	Rank
All samples	72	8	.85	-0.03	.88	2.40	3
Normalized samples	68	12	1.29	-0.05	1.35	4.41	1
Altered samples	60	8	1.00	-0.03	1.03	2.80	2
Ratio	56	5	.63	-0.01	.65	1.4	4

^a Contrast values are highlighted, and are used to determine the rankings of the maps.

Table 14b- normalized to approximately same number of gold prospects (see text for discussion)

Method	Area (km ²)	No. of Au prospects	W+	W-	C ^a	C/SD	Rank
All samples	131	11	.65	-0.04	.70	2.40	3
Normalized samples	68	12	1.29	-0.05	1.35	4.41	1
Altered samples	131	14	1.00	-0.03	1.03	2.80	2
Ratio	104	11	.8	-0.04	.85	1.4	4

^a Contrast values are highlighted, and are used to determine the rankings of the maps.

Table 5.14 WofE statistics for areas of highest gold potential, as identified by the binary maps of all samples, normalized samples, altered samples, and ratios

<i>Zone</i>	<i>Lithology</i>	<i>Alteration</i>	<i>Structure</i>
A. Northeastern Swayze	Mafic metavolcanic rocks	LOI, volatiles, atypical normative minerals, alteration index, atypicality index	Intersection of 2 high strain zones as mapped by Ayer (1995)
B. Old Woman iron formation	Oxide to sulphide facies iron formation	LOI, volatiles, atypical normative minerals, alteration index, atypicality index	Highly strained limb of large anticline
C. Shunsby iron formation	Oxide to sulphide facies iron formation	LOI, volatiles, atypical normative minerals, alteration index, atypicality index	
D. Western Swayze	Mafic metavolcanic rocks	LOI, volatiles, atypical normative minerals, alteration index, atypicality index	High strain zone (continuation of Cadillac-Larder Lake "break")
E. Central Swayze	Felsic metavolcanic rocks	LOI, volatiles	Northern limb of Brett Synform mapped by Heather et al. (1995).
F. Southern Swayze		Atypical normative minerals	High strain corridor (continuation of Cadillac-Larder lake "break")
G. Western Swayze	Mafic/intermediate metavolcanic rocks	Atypical normative minerals, atypicality index	Wakami high strain zone

Table 5.15 Summary of the lithology, alteration characteristics, and structure of the major alteration zones (locations A-G identified in Figs 5.4 , 5.14, and 5.15)

CHAPTER VI

Surficial Geochemical Data – Processing, Visualization and Modelling

6.1 Introduction

Geographic Information Systems (GIS) provide the geologist with a powerful tool, when used in concert with statistical and geostatistical analysis, for archiving, manipulating, analysing and visualizing geochemical data. This paper uses geochemical (Zn, Cu) data obtained from various media (rock, lake sediments, till, soil and humus) over the Swayze greenstone belt in northern Ontario, to explore methods for analysing and visualizing geochemical data with a focus to mineral exploration applications.

The behaviour of Zn and Cu in both bedrock and the surficial environment is studied using statistical and geostatistical techniques. Interpretation and uses of traditional statistics and dot plots are contrasted with interpolated geochemical maps as well as red-green-blue (RGB) ternary maps. Techniques for multimedia comparison and geochemical anomaly detection and screening are presented. The processing methods presented in this paper can be utilized and adapted by other geologists for exploring their own geochemical data. Many of the algorithms presented here are available within standard GIS software packages, or can be written easily using a GIS macro language.

The traditional approach to the analysis of geochemical data involves the use of spreadsheets and/or statistical software packages. Often the results are plotted using proportional symbol plots, where the size of each dot is proportional to the concentration of a given element, usually ranked by percentiles. A Geographic Information System (GIS) can offer the geologist significant advantages over traditional approaches to archiving, visualizing, manipulating, analysing, integrating and presenting geochemical data. GIS is now a firmly established technology that many mining companies are adding to their arsenal of exploration tools. These systems can and should be used by the exploration geochemical community to facilitate the storage and display of

geochemical data. Furthermore, the GIS facilitates the spatial analysis and comparison of large volumes of geochemical data.

As with a Computer Aided Design System (CAD), a GIS employs graphic primitives (points, lines and polygons) which are the building blocks for constructing digital maps. These form the basis of the vector model which the GIS uses to store and view spatial data. The GIS also uses the raster model in which spatial information is divided into grid cells (pixels) containing a number (referred to as a digital number or DN) that has some user or data- defined meaning. Unlike a CAD system, the GIS utilizes a database which contains descriptive information (attributes) for each point, line or polygon. Thus, a geochemical sample point has a specific location, as well as a number of attributes that describe the sample, stored in an internal or external database. The data can be displayed and queried, by any attribute or combination of attributes in the database, using a database query language (e.g. SQL - Structured Query Language) or the proprietary query language of that particular GIS software. Although the GIS can be used as a cartographic tool for producing traditional geochemical maps (proportional symbols), it also provides spatial analysis and visualization tools that can be used to analyse the statistical and spatial characteristics of geochemical data. At the present stage of GIS development, other software packages (statistical and geostatistical) are still required by the geologist in addition to the GIS, to thoroughly analyse geochemical data, both statistically and spatially. However, this is beginning to change as many GIS vendors are now integrating more geostatistical and statistical tools into the GIS environment.

In this paper the GIS, in concert with statistical and geostatistical analysis software, is used to demonstrate techniques for:

- Separating geochemical concentrations into anomalous and background populations;
- Visualizing geochemical data;
- Identifying lithologic signatures in surficial media (till, soil, humus);
- Comparing geochemical responses in different geochemical sample media;

- Screening surficial geochemical data (soil) for false anomalies (e.g. anomalies not due to alteration or mineralization).

6.2 Study Area

The Swayze greenstone belt (SGB) (Fig. 6.1) is the westernmost extension of the mineral-rich Abitibi greenstone belt (AGB), and has recently been re-mapped by both the OGS (Ayer 1995 *a, b*), and the GSC (Heather & Shore 1999). Like the AGB, the SGB contains a number of fold-repeated 2730-2680 Ma mafic-felsic metavolcanic packages, which are unconformably overlain by Timiskaming-type metasedimentary rocks and cut by high strain zones thought to be extensions of the major *breaks* (Destor-Porcupine and Cadillac-Larder Lake faults) found in the AGB (Heather 1993; Ayer & Theriault 1993; Heather & van Breeman 1994; Heather *et al.* 1995, 1996). These high strain zones are the hosts of several large Au deposits in the Timmins and Kirkland Lake areas.

The SGB shares many features in common with the mineral-rich AGB to the east, but lacks any significant mineral production. A detailed mineral occurrence database has been completed for the belt (Fumerton & Houle 1993; Fumerton *et al.* 1993). The two principal commodity types found within the current map area are base metals and Au.

The surficial geology of the study area (Fig. 6.2) is dominated by thin, sandy till mapped as bedrock-drift complex (Bernier & Goff 1993; Bernier 1994; Bernier *et al.* 1996). Glaciofluvial outwash and other glacial and post-glacial sediments occur throughout the study area, as well as several large esker complexes orientated approximately N-S to NNE-SSW. Relief is generally low except in the southern portion where rolling topography reflects underlying granitoid rocks. The EW-trending Chapleau Moraine forms a dominant topographic feature.

6.3 Geochemical Data

A total of 845 geochemical samples were collected concurrently from humus, B-horizon soil and C-horizon till over the SGB, by the OGS from 1993 to 1995 (Bernier & Goff 1993; Bernier 1994; Bernier & Kaszycki 1995; Bernier et al. 1996). Table 6.1 is a summary of the survey methodology and Table 2 presents a summary of the analytical methods. Figure 6.2 shows the location of each humus, soil and till geochemical sample site within the study area. The Shunsby and Kenty mine areas (Figs. 6.1 & 6.2) were sampled in more detail to characterize the behaviour of metals in the locally sampled media with respect to glacial dispersion (i.e. orientation surveys).

The lake sediment geochemical data (Fig. 6.3), consisting of over 350 samples, were collected as part of the National Geochemical Reconnaissance (NGR) program undertaken by the GSC (GSC 1987, 1988).

Approximately 4500 whole rock samples over the SGB were acquired from four principal sources: GSC, OGS, Falconbridge Ltd. and provincial assessment files (Table 6.3). Wilkinson et al. (1999) provide a summary on the compilation and levelling of this dataset. Harris et al. (1999a) have divided the database into altered and unaltered samples, using a variety of statistical methods.

The trace elements, Cu and Zn, were chosen as the focus of this paper due to their relevance in regional base metal exploration, their chemical similarity (transition elements), and their differences with respect to mobility in the surficial environment. Thus, different responses with respect to various analysis techniques applied to the data, and behaviour in different sampling media, would be expected.

The surficial geochemical data (humus, soil, till) were evaluated for quality using split and field duplicate analyses. Approximately 1 in 15 samples were split for duplicate analyses and 1 field duplicate was collected for every 20 samples. Zinc and Cu results were evaluated for quality control using Thompson-Howarth precision control plots

(Thompson & Howarth 1976, 1978): both elements in all media were found to be within 10% precision levels. The lake sediment geochemical data were subjected to strict quality control measures under the NGR program (see Friske et al. 1988). Wilkinson et al. (1999) review the quality control procedures applied to the lithogeochemical data used in this paper.

6.4 Data analysis

The following section describes GIS techniques used in concert with statistical and geostatistical methods for visualizing, manipulating and analyzing Zn and Cu sampled from various media.

6.4.1 *Characterizing geochemical distributions*

Before applying map visualization procedures, geochemical data should be evaluated to characterize statistical distributions. Howarth (1983), Garrett (1991) and Grunsky (1986, 1997) provide thorough reviews of techniques used to characterize frequency distributions as well as exploratory data analysis (EDA) techniques for geochemical data. These techniques form the basis for further analysis, which includes methods for separating anomalous geochemical concentrations from background and methods for visualizing the spatial characteristics of the data.

Descriptive statistics such as histograms, normal probability plots and box and whisker plots provide insights into the statistical distribution of geochemical data. GIS complements statistical analysis by providing many methods with which to visualize the spatial characteristics (distributions) of the data. Table 6.4 is a summary of descriptive statistics for Zn and Cu from the various media sampled for this study. Log-transformation of the geochemical data produces distributions that are close to normal allowing for parametric statistical testing. Box and whisker plots (Tukey 1977) are useful for characterizing and comparing geochemical distributions and for assessing the

shape of distributions (e.g. positively or negatively skewed). Figure 6.4 present box and whisker plots of log-transformed Zn and Cu concentrations in all media sampled for the entire study area without regard to lithological or surficial divisions. A box and whisker plot encloses the middle 50% of a data distribution by a box where the median value is represented by a line and the notch represents the 95% confidence interval around the median value. The lines (whiskers) are drawn from the lower and upper quartiles to the smallest and largest point within 1.5 interquartile ranges, respectively. Outliers beyond these ranges are displayed as points. The mean value is plotted as a point within the box. Distributions in which the notches overlap are not significantly different.

In this study the distributions for Zn and Cu are log normal or close to log normal. Copper concentration is highest in rock and lowest in soil whereas Zn concentration is highest in lake sediments and also lowest in soil. Copper concentrations amongst all media are significantly different as notches in the box and whisker plots do not overlap. The median value for Zn in lake sediments is significantly different from the median in the other media, although there is not a significant difference between soil and till nor between rock and humus. These differences between media may reflect differences in the behaviour of Cu and Zn in the surficial environment as well as variations due to bedrock and surficial geology. These variations will be investigated with the aid of statistical and GIS analysis techniques in the following sections.

An important goal for mineral exploration, with respect to the statistical and spatial analysis of geochemical data, is the detection of zones of elevated concentrations of major or trace elements that may reflect the presence of alteration and/or mineralization. A geochemical anomaly represents an area of elevated concentrations of a single element or group of elements that exceed the threshold expected for regional background (Howarth, 1983; Garrett 1991). Many statistical and geostatistical techniques have been used to highlight or enhance trends or patterns in geochemical data. These anomalous populations, particularly in lithogeochemical data, may reflect specific geologic processes, such as fractionation, regional alteration, hydrothermal alteration and metasomatism. Grunsky (1997), Grunsky *et al.* (1992) and Harris *et al.* (1999a) provide

comprehensive reviews of univariate and multivariate techniques used to identify anomalous geochemical populations.

Many univariate methods exist for determining thresholds for identifying anomalous geochemical populations. A threshold, in this paper, follows the reasoning of Garrett (1991) and is defined as the outer (upper and/or lower) limit of local background variation. Methods used for determining anomalous populations include: exploration knowledge applied as *a rule of thumb* (e.g. it is known that within a given area rocks with > 1000 ppm Cu are anomalous); arbitrary methods using percentile or standard deviation values; visual inspection of probability plots (Stanley 1987; Grunsky 1997; Harris *et al.* 1997); visual inspection of area versus concentration plots (Cheng *et al.* 1994), and weights of evidence (WofE) (Bonham-Carter 1994). The WofE method requires knowledge of existing mineral prospects, whereas the other methods do not. The method presented by Cheng *et al.* (1994) requires geochemical data to be interpolated to a continuous surface map so that areas enclosed by different contour levels can be calculated.

Normal probability plots are arguably the most practical univariate method for determining thresholds, as they are easy to calculate and simple to interpret. Although percentile ranges are often used to divide and display geochemical data distributions, percentile divisions (e.g. 50-75, 75-80, 80-90, 90-95) do not always correspond to breakpoints present on probability plots. Ideally, natural breakpoints divide geochemical data into separate populations that may reflect different geologic or surficial processes (Grunsky 1997). Furthermore, upper or lower breakpoints on a probability plot may separate anomalous samples that may reflect mineralization.

Figure 6.5a shows normal probability plots for Cu and Zn concentrations in rock, for all samples within the SGB. Figure 6.5b shows a map (generated using the GIS) of anomalous samples (Cu, Zn) derived from selecting samples above the upper thresholds interpreted on the probability plots, overlaid on a shaded relief magnetic image. Elevated Cu and Zn concentrations characterize the Shunsby area (A), and an area in the

south along the contact between mafic volcanic and granitoid rocks (B). Anomalous Zn and Cu concentrations characterize the southeastern and western portions of the SGB (C and D). Most of these anomalies fall on linear magnetic highs many of which are Fe formations, either contiguous (Old Woman Fe Formation (E)), or fragmented and broken up by later faulting (Rideout high strain zone – see Fig. 1) in the Shunsby area (A), and in the southeast portion of the study area (C).

One of the advantages of GIS is the ability to divide geochemical data into separate populations on the basis of map-based spatial divisions. A *point-in-polygon* operation (a common GIS function) can be invoked that will intersect each geochemical sample point, over a polygon map. Thus, the geochemical samples can be grouped into different populations and analysed separately. This is particularly useful for: (1) evaluating geochemical data by lithologic or surficial units; (2) normalizing lithogeochemical data to take account of lithological variations; and, (3) identifying geochemical anomalies that are proximal to mineralization. Therefore, probability plots were calculated for Zn and Cu for each mapped lithologic unit (see Fig. 6.1) and thresholds were selectively identified (*selective query* in GIS terminology) dividing the geochemical samples into background and anomalous. This has the effect of normalizing concentrations to lithology, thus accounting for variations in concentration as a function of rock type. Harris *et al.* (1999a, 2000) provide more details on normalization applied to rock samples in the SGB. The GIS database was exported to a statistical analysis package to perform statistical analysis and generate probability plots. Figures 6.5c and 6.5d show Cu and Zn anomalies in rock based on this selective querying (normalizing) process by rock type. Comparison between Zn and Cu anomalies calculated from the entire study area (Fig. 6.5b) and anomalies based on selective querying (Fig. 6.5c, d), indicates that many more Cu and Zn anomalies are identified using selective querying. In particular, many more Cu anomalies in rock are found along the felsic volcanics that form the footwall to the overlying Old Woman Fe formation (E), as well as in the central portion of the SGB along the length of the Brett River Synform (F) which comprises a package of ultramafic, mafic and intermediate volcanic rocks. Many more anomalous Zn samples

occur in the southeastern portion of the belt within the Rideout high strain zone (Fig. 6.5c - C) than on Fig. 6.5a.

Figure 6.6a shows Cu anomalies in surficial media (humus, soil, till), calculated from thresholds on probability plots based on all the data irrespective of lithological unit whereas Fig. 6.6b show Cu anomalies based on selective querying by rock unit. Comparison of Figs. 6.6a and b reveals the presence of many more Cu anomalies on the image showing selective Cu anomalies, especially in the south over granitoid rocks (G) and in the southeast over volcanic and sedimentary rocks (C).

Summary: Box and whisker plots are useful for characterizing and comparing geochemical distributions either between different elements or the same element in different media.

The major strength of the GIS is that the results of statistical analysis can be displayed spatially assisting in revealing patterns that may reflect lithological, surficial and mineralization processes. Furthermore, geochemical data can be broken into separate populations based on user-defined groupings (e.g. lithology, surficial unit, topography etc.) for detailed statistical and geostatistical analysis. Simple to complex queries can be undertaken by spatial unit, thus assisting to reveal geochemical anomalies that may be suppressed or entirely hidden when considering the entire geochemical population.

6.4.2 Visualization

Once geochemical distributions have been characterized, allowing appropriate methods to be selected with which to divide the data into meaningful intervals (e.g. percentiles or breakpoints on probability plots) and separating anomalous concentrations from background, the data may be displayed in a variety of ways. Most GIS provide the geologist with a wide range of software tools with which to visualize geochemical data. The process of visualization (see Harris *et al.* 1999b, for a detailed study) involves

displaying and combining geochemical with other geoscience data for the purpose of exploratory data analysis. This is important in that non-traditional geochemical maps and images can assist the geologist in identifying spatial patterns that may be important for regional mineral exploration.

Traditional dot plots, in which the size of the symbol is proportional to element concentration, are straightforward to interpret and are effective for showing the spatial variation in concentration of elements. Figure 6.7 shows proportional dot plots of Cu concentration in humus, soil, and till. Figure 6.8 is a variation of Fig. 6.7, in that the size of the pie reflects the total Cu content in all three media (humus, soil and till), while the shading of the wedges comprising the pie reflects the proportion of the total Cu content by medium.

Areas of elevated concentration in all media, can be seen in the vicinity of the Shunsby base metal prospect (Fig. 6.7, A). Another area of elevated Cu concentration in especially humus and soil (but not till) is found within the area of granitoid rocks in the southwest portion of the study area (G). Figure 6.8 shows that the area of anomalous Cu concentration in the granitoids (G) occurs dominantly in humus, whereas in the Shunsby area (A) till values are the highest, perhaps indicating different processes taking place. For example, scavenging of Cu by organics (humus) over the granitoids may have led to Cu enrichment in this area whereas mechanical breakdown of Cu-bearing minerals and dispersion in the clay+silt portion of glacial till predominates in the Shunsby area.

Interpolation: Establishing a zone of influence around a geochemical sample point, whether by artificial constructs or by interpolation, is often advantageous for visualization and modeling purposes within the GIS. A zone of influence around a geochemical sample can be as simple as setting a buffer zone of a given distance around each point. This distance can be determined based on exploration knowledge (i.e. alteration around a rock sample can be seen to extend for a radial distance of 50 m), or on geostatistical reasoning using variograms. Conversely, a natural zone of influence, such

as a drainage basin, can be established around a lake or stream sediment sample point (see Bonham-Carter et al. 1987).

Geochemical data can be interpolated producing continuous surface maps if certain criteria are met:

- (a) does the point data behave as a continuous random variable where the mean value is stationary over the entire area of interest;
- (b) does the data behave isotropically or anisotropically;
- (c) is the point sampling dense enough to warrant meaningful interpolation?

The particular medium sampled for geochemistry often controls the first two factors. Spatially, lithogeochemical data differ from other geochemical media, such as till and lake sediments, in that rocks are a site-specific medium with a zone of spatial influence very close to the sample site. Geochemical data sampled from till and lake sediments reflect a much broader area (a drainage basin in the case of lake sediment data, and often a broad dispersal train in the case of till data), and therefore the concentration at a specific sample point represents an average of a much broader area than does a lithogeochemical sample. This has important implications for sampling strategies and for methods of data analysis and visualization.

Spatial behaviour of the data can be determined through analysis of a variogram. Experimental variograms can be calculated for all directions (omni-directional) or for any given direction (directional). Thus, directional effects, such as down-ice dispersion of metals in till, may be identified and accounted for in the interpolation process. Variograms are extremely useful, providing information such as maximum radius of influence around each point (range), which can be used to set the search radius (zone of influence) for various interpolation algorithms, as well as directional biases which can be used to set the shape and orientation of the search. If the variogram displays no spatial structure (i.e. pure nugget effect), then one should not interpolate the data or at best use an exact and simple interpolation algorithm (e.g. Delauney triangulation) that makes

fewer spatial assumptions. Alternatively, one could choose a different method to present and visualize the data (proportional symbols), or choose a natural zone of influence around each sample point (e.g. drainage basin for a lake sediment sample).

Many different interpolation algorithms exist, such as kriging, minimum distance curvature and inverse-distance-weighted (IDW) interpolators. In this paper, kriging, using parameters derived from variograms, was used to interpolate the geochemical data. Further details on interpolation methods can be found in Davis (1986), and Issacks & Srivastava (1989). The advantages of interpolating geochemical data are that it: (1) facilitates overlay analysis within the GIS; (2) highlights regional geochemical patterns that may not be obvious when the data are displayed as points; and, (3) facilitates the comparison of geochemical data from different media that are not collected at the same geographic location.

Figure 6.9 shows variograms calculated for log Cu in till and log Zn in humus. These orientations represent the *best* variograms (i.e. display the most coherent spatial structure between points), for each element in each medium. Better variograms were produced using log-transformed data, rather than raw data, as the transformed data were closer to a normal distribution, and the effects of outliers were thereby reduced. The associated kriged (interpolated) data are also shown on Figure 6.9. The variograms of Zn and Cu in rock have the smallest ranges, whereas the lake sediment, soil and humus data show larger ranges. This is reasonable given the effects of glacial transport and averaging over broad drainage basins. The best variogram for Cu was calculated from till (Fig. 6.9a) and consisted of a NE-SW anisotropy, reflecting the dominant, although not the youngest, direction of glacial transport (see Fig. 6.2). Range (length) of approximately 8 km potentially indicates the maximum detectable down-ice dispersion of Cu-bearing minerals above background. However, other factors such as variation in surficial and bedrock geology are important when interpreting information from variograms. The variogram for Zn in humus is spatially the most coherent, with a range of approximately 4.5 km (Fig. 6.9b). Generally, the poorest variograms were produced from Cu, in all media. The variograms for Cu were characterized by large nugget effects and large

semivariance in the first lag (first distance interval used for calculation of semivariance) suggesting extreme variability between sample points at short distances.

Figure 6.9a shows high concentrations of Cu in till in an elongated zone centered over the Shunsby base-metal prospect (A) and a zone to the west at the intersection of the Wakami shear and Ridout high strain zones (H). Figure 6.9b shows a N-S trending zone (I) that is elevated in Zn in humus extending from the north of the SGB and terminating over the granitoid rocks in the south. The southern portion of this anomalous zone is centered on an area of organic and glaciolacustrine surficial deposits and the northern and central portions are roughly centered on N-S trending esker and glaciofluvial ice-contact deposits (see Fig. 6.2). This suggests that the anomaly may be surficial in origin, as opposed to reflecting bedrock. The area of apparent low concentration in both Cu in till and Zn (J on Figs. 6.9a & 6.9b) reflects an area of low sample density over a wide area of thick glaciolacustrine deposits. This area was not extensively sampled as the samples would not provide a representative picture of anomalies in the underlying bedrock (glaciolacustrine deposits would mask the geochemistry of the underlying bedrock).

Ternary images: Red-Green-Blue (RGB) ternary images (Broome *et al.* 1987; Harris *et al.* 1990), often used in the display of remotely sensed data, are also effective for visualizing interpolated geochemical data. These maps or images are constructed by taking three continuous surface (interpolated) geochemical maps, and displaying one in a blue, one in a green and the other in a red colour. The additive mixes of the primary colours, which results in a wide range of hues, can be interpreted with respect to the varying concentrations of each geochemical element, allowing the spatial associations between geochemical elements to be visually assessed.

Figures 6.10a and 6.10b show RGB ternary maps for total Zn and Cu concentration in till, soil and humus, respectively. Proportional circles (dots) in which the size of the circle reflects total base metal content and the wedges, the contribution of each medium to the total content (see Fig. 6.8), have been overlaid to facilitate comparison between the geochemical data visualized as points and the underlying interpolations. With respect to

the Zn ternary image (Fig. 6.10a), it can be seen that humus is the dominant medium, as reflected by wide spatial variations in red hues. This is also verified by the box and whisker plot of Zn concentrations by medium (Fig. 6.4b). The Shunsby area (A) is elevated in Zn, in all media, as reflected by the white hue. Copper (Fig. 6.10b) shows much more variability in the different media, as shown by more variability in hue. The eastern portion of the study area is dominated by a NNW-SSE trending zone of yellow and green hues reflecting a predominance of Cu in soil and humus, whereas the western portion of the study area has a higher proportion of green hues, reflecting higher concentrations in soil, and blue hues reflecting higher Cu concentrations in till. The central portion of the SGB over the Shunsby area (A) is dominated by elevated concentrations of Cu in till, as reflected by the bluish hue. Copper concentration is also relatively high in humus over granitoid rocks in the southwest portion of the study area (G) as reflected by red hues.

Figure 6.10c is a ternary image that shows total base metal content ($\text{Cu} + \text{Zn} + \text{Pb}$) in humus. Total base metal content in humus over the study area is variable, reflected by a wide variation in hue. The northwestern portion of the study area is dominated by higher concentrations in Zn (green areas), whereas the eastern portion of the study area is dominated by higher concentrations in Pb and Cu, as indicated by a magenta hue (red + blue). Local areas of elevated Cu concentration throughout the belt are reflected by a red hue. The black areas in Fig. 6.10 reflect low element concentration and/or low sample density. Areas of low sample density can be masked out as demonstrated by Harris *et al.* (2000), resulting in an RGB ternary image in which areas of low sample density are not confused with areas of low element concentration.

Integrated images: The dispersion of elements in the surficial environment is often affected by topography (e.g. elevation, slope, and aspect). Figure 6.11 shows an RGB ternary image in which log-transformed Cu concentrations in humus, soil and till are displayed in red, green and blue hues respectively. This RGB ternary image uses the same data used in Figure 6.10b; however, the hues appear different due to the effect of a different contrast stretch algorithm applied to the data. This results in a different

distribution of values, which in turn affects the overall distribution of hues. The RGB ternary image was then combined with a DEM (digital elevation model) to reveal possible associations between topographic and geochemical patterns. An IHS (intensity-hue-saturation) transform, available on most GIS, was used to combine the data (see Harris *et al.* 1990 and Harris *et al.* 1999b for a detailed description of the IHS transform).

The combined image (Fig 6.11) shows that a N-S trending linear zone of Cu anomalies in humus and soil (greenish-yellow) is coincident with a N-S trending drainage channel in the eastern portion of the study area (see E) and that an area with high concentrations of Cu in humus is coincident with a zone of high relief over an area of granitoid rocks in the south (G).

2.5 dimensional images: The GIS can also make use of relief to portray geochemical data to advantage (Grunsky & Smee 1999). Figure 6.12a shows the RGB ternary map shown in Fig. 6.11, painted over a 2.5 dimensional surface (artificial relief) representing Cu concentration in lake sediments. Anomalous Cu concentrations in rock are overlaid as red dots. The relationship between Cu in five media can therefore be seen on this one image. The areas of high relief representing anomalous Cu concentration in lake sediments are coincident with high concentrations of Cu in till, soil and humus (white hue) over the Shunsby area (A) and with high Cu concentrations in humus over granitoid rocks in the south (G). Elevated Cu concentration in lake sediments is focused in two N-S trending linear zones. The eastern zone (K) corresponds with anomalous concentrations in humus and soil (yellow hues) whereas the central linear zone (I) corresponds with high Cu in till in the north, all media in the central (white) and humus in the south (red) hues. These linear zones may reflect N-S glacial transport of Cu-rich debris as these zones crosscut regional stratigraphy. The Shunsby area (A) is also characterized by high Cu concentrations in rock.

Figure 6.12b is a similar image except that relief is represented by true topographic relief. The areas of elevated Cu in humus can be seen clearly to be coincident with an area of high topographic relief (G). The two distinct large N-S drainage channels are easily

recognizable, the western-most (K) coincident with Cu anomalies in humus and soil, as previously mentioned.

Summary: Proportional dot and pie maps are simple to construct in a GIS and, since the points are not interpolated, no potential artifacts or generalizations due to the interpolation process are produced. However, only one element can be shown at a time (unless pie plots are used), and often percentile divisions, which is the most popular method of ranking and displaying the data, may not be sensitive to natural population breaks (thresholds) in the data. Furthermore, it is difficult to compare different elements both statistically and spatially.

Variograms provide information on spatial structure enabling the modeling of anisotropies such as glacial dispersion. Kriging generates an interpolated geochemical map that emphasizes regional geochemical patterns and also provides a measure of uncertainty in the interpolation process. This allows areas of high uncertainty in the kriging process to be excluded from the final interpolated map. Furthermore, producing a sample density map using the GIS can also identify areas of low sample density and these areas can also be excluded in the final map. Interpolated geochemical data often reveal both regional and subtle geochemical patterns to a greater extent than dot maps.

Using variations in the additive mixture of colours, RGB ternary images are useful for the multivariate comparison of geochemical patterns, either between different elements or between the same element sampled from different media. This not only highlights areas of anomalous concentrations but also the patterns identified and the resulting colours may shed light on surficial processes at work over a given geographic area (e.g. processes of glacial dispersion, scavenging). Thus, RGB ternary images are not only useful for identifying anomalous concentrations of elements, but also for qualitatively identifying spatial correlations between three (or more) elements.

Combinations of geochemical data with other geoscience data such as topographic information using GIS technology (IHS transform) can reveal associations between

geochemical data and other surficial factors that may be important for mineral exploration. Adding the third dimension allows for the comparison of at least four variables in one image, facilitating the comparison between elements or media. These images can assist in revealing spatial associations between different elements and/or between elements and topography.

6.4.3 *Lithologic signatures in geochemical data sampled from surficial media*

Relevant questions for mineral exploration when analysing geochemical data sampled from surficial media include:

- (a) do element concentrations in surficial media vary over mapped surficial units;
- (b) is there a bedrock signature in the geochemical data sampled from surficial media;
- (c) do variations in element concentration in surficial media (till, humus, soil) reflect the concentration in the bedrock spatially and statistically;
- (d) is there a spatial relationship between geochemical anomalies in bedrock and surficial media?

The GIS can be effectively utilized to help answer these questions by employing the *point-in-polygon* procedure, to partition the geochemical data into separate groups based on mapped lithological and surficial units. A number of techniques can also be employed to assess the spatial relationships between geochemical signatures in different media. Examples of GIS analysis techniques used in concert with statistical analysis methods which address the questions listed above are illustrated in the following sections.

Statistical analysis of Zn and Cu by lithological and surficial units: Figures 6.13a and 6.13b are box and whisker plots showing log-transformed Cu and Zn concentrations in rock by mapped lithology (units shown on Fig. 6.1) ranked by concentration from highest on the left to lowest on the right. Outliers from each geochemical dataset have been removed (trimmed at approximately the 96th percentile for each data distribution) since, in this analysis, a mean signature for each lithological unit is required. Outliers

may represent mineralization signatures as opposed to lithologic signatures. Zinc concentration in rock is on average 50% higher than Cu, irrespective of lithological unit. Copper concentration is generally more variable between lithologic units than Zn concentrations. This observation is also supported by generally more erratic variograms for Cu than Zn in the various media. Differences between Cu populations are also more significant than Zn populations between lithologic units, as indicated by more variation in median values with less overlap between 95% confidence notches in the box and whisker plots. Copper is highest in ultramafic and mafic volcanic rocks and lowest in felsic volcanic rocks whereas Zn is highest in intermediate and mafic volcanic rocks and also lowest in felsic volcanic rocks.

Figures 6.14a and 6.14b are plots of mean values for log Cu and log Zn, respectively, for each surficial unit shown on the regional surficial geology map (Fig. 6.2). Once again the data have been trimmed. Error bars are not shown on these plots for the sake of clarity. However, both median and mean values were tested for significance using a Mann-Whitney test and t-test, respectively. Significant differences between median values were also assessed by using box and whisker plots (not shown). Both differences between mean values between log Cu and log Zn by medium (vertical direction on mean plots) and between values for each media with respect to different surficial units (horizontal direction on mean plots) were assessed for significance.

Many of the same trends seen on Fig. 6.13 are also evident on Fig. 6.14. Zinc concentration is appreciably higher than Cu in soil, by a factor of two and is approximately 50% higher in humus. The concentrations of Cu and Zn in till are approximately the same. Zinc in lake sediments is greater than Cu in lake sediments by a factor of one. The higher levels of Zn is not surprising as Zn in rock is roughly 50% higher than Cu (see above). Zinc is highest in lake sediments and rock whereas Cu is highest in lake sediments over all surficial units except for lacustrine deposits.

The majority of differences between mean (also median) concentrations in each medium between surficial units are significantly different for Cu (Fig. 6.14a - compare means

between media in a vertical direction on plot). With respect to Zn concentrations, the differences are significant between only the two obvious groupings seen on Fig. 6.14b, indicating that between surficial units, lake sediments and humus have similar Zn concentrations, whereas till and soil have similar concentrations but are appreciably lower than the other media. Although there are differences between mean (and median) values in each medium between surficial units, many are not significant. Copper concentration is more variable than Zn concentration between surficial units as was the case for lithologic units (Fig. 6.13). In general, Cu and Zn concentrations in lake sediments are highest in areas of till (which is generally thin in most parts of the SGB) and over areas of bedrock where weathering products of Cu- and Zn-bearing minerals would be deposited and dispersed locally within drainage basins. Most of the significant differences between populations for the surficial media across surficial units are between till, bedrock and glaciolacustrine deposits. Zinc and Cu concentrations are relatively high in glaciolacustrine deposits which may be acting as a *sink* for Cu and Zn through effects such as scavenging by Mn and Fe oxides.

The next problem is to determine whether the variability in Cu (and to a lesser extent Zn) concentrations between lithologic and surficial units can be detected in the geochemical data obtained from surficial media. Figures 6.15a and 6.15b show log Zn and log Cu concentrations in rock and surficial media over each lithologic unit. Ultramafic units are not shown due to a lack of geochemical samples. Again, error bars are not shown, but as before, differences between median and mean values were tested for significance using tests mentioned previously. Two groups are once again evident for Zn concentration (Fig. 6.15a): Zn is at higher concentrations in rock, lake sediments and humus (Group 1) and lower concentrations in till and soil (Group 2). The differences in means values for Zn in each media between the two groups are significant statistically (t-tests). A number of differences between media in the first group (rock, lake sediments, humus) are significant; however, there are no significant differences between lithology except between felsic volcanic rocks and other lithologic units. The variation in mean (and median) Zn concentrations between lithology are similar for rock, lake sediment and humus except over felsic rocks where concentration is low in rock but relatively high in

humus and lake sediments. This indicates that lake sediments and humus are varying sympathetically with bedrock and thus reflect bedrock signatures. Zinc in till and soil also vary sympathetically but at much lower concentrations. This divergence over felsic rocks may result from the geometry of the felsic units with respect to the dominant glacial dispersion direction. The felsic units trend generally in an E-W direction (see Fig. 6.1), perpendicular to the N-S glacial flow and are generally thin. Thus the relatively high Zn concentrations in surficial sediments may reflect the presence of mafic volcanic rocks north of each narrow felsic unit.

Copper concentrations (Fig 6.15b) between media for each lithology are significantly different except for till and lake sediments. Copper concentrations between lithologic units are more variable and the differences more significant than Zn concentrations, except for humus. Copper in till varies more sympathetically with rock than does Cu in soil and humus, except for felsic volcanic rocks for reasons discussed previously. A strong trend in decreasing Cu concentrations in rock can be seen across mafic rocks starting from ultramafic rocks, through mafic, intermediate and felsic rocks. This trend parallels a trend in Mg concentration in rock (Fig. 6.15c) and may reflect a fractionation trend as shown by a moderately strong Spearman rank correlation coefficient (0.5) between MgO and Cu in rock.

Figure 16 shows plots of mean and median values for log Zn (Fig. 6.16a) and Cu (Fig. 6.16b) concentrations in rock by lithology and a plot of the ratio between the median and mean values for Zn and Cu in rock by lithology (Fig. 6.16c). The data were not trimmed, as these plots can be used not only to assess the normality of each population but also as a mineralization indicator for each lithology. Larger ratio values (Fig. 6.16c) indicate median values greater than mean values reflecting a positively skewed distribution with the presence of many outliers (e.g. anomalously high values) possibly reflecting mineralization. Thus, with respect to Zn, although concentrations are not particularly high over felsic volcanic rocks (see Fig. 6.16a), the large ratio values for felsic volcanic rocks (Fig. 6.16c) indicate a higher percentage of outliers and therefore a higher prospectivity for Zn. Ultramafic and sedimentary rocks are also characterized by larger

ratios. With respect to Cu concentrations, granitoid, mafic and ultramafic rocks have the largest ratios but not necessarily highest Cu concentrations (Fig. 6.16b). Opposite concentration trends for Cu and Zn are evident on Figs. 6.16a and 6.16b for ultramafic, mafic and intermediate volcanic rocks: Zn concentration increases whereas Cu concentration decreases.

Summary: The point-in-polygon technique automates the process of determining the map unit (e.g. lithology) in which a point (e.g. geochemical sample) occurs making it possible to analyse and compare geochemical populations by surficial or lithologic units. This can result in more meaningful interpretation than when comparing total populations.

Copper and to a lesser extent Zn, show larger variations in concentration between media for each lithologic unit than within each medium over the various lithologies. Copper concentration is generally more variable between lithologic units than is Zn. Distinctive Zn and Cu signatures are evident in surficial media, but are suppressed with respect to the signatures in rock due to the homogenizing effect of weathering and erosion processes. The similarity in Zn and Cu concentrations in rock and lake sediments indicates that geochemical signatures in lake sediments (at least for Zn and Cu) reflect local bedrock concentrations. Till, soil and humus, with the exception of Zn concentrations in humus, do not appear to reflect bedrock signatures as closely.

6.4.4 The effect of glacial dispersion on Zn and Cu concentrations in till and soil

One concern for exploration is whether elevated levels of Cu and Zn in rock are related, statistically and spatially, to elevated levels in surficial media. To address this issue, a nearest-point search algorithm (available on many GIS) was employed. The advantage of the nearest-point method is that it takes into account spatial variations in Cu and Zn concentration over distance and direction within the study area. Thus, assessment of varying patterns by direction and distance is possible, as opposed to a strictly global statistical measure which correlation coefficients provide.

Table 6.5 presents global correlation coefficients (i.e. coefficients between the total data population over the entire study area) between Zn and Cu in rock, till, humus, soil, and lake sediments. The correlations are based on spatially interpolated (gridded) data as the surficial media were sampled at different geographic locations than rock and lake sediment samples, making point-to-point comparisons impossible. The highest correlations are shown by: (1) Zn in soil and till, (2) Cu in soil and till, (3) Zn in till and lake sediments and, (4) Cu in soil and humus and, (5) Cu in soil and lake sediment. The results for both Zn and Cu suggest that soil is directly derived from the underlying thin till over much of the belt. The correlation between Zn in till and lake sediments is reasonable, as both lake sediments and till would present an average signature of Zn over broad zones (i.e. drainage basin and glacial dispersion area). In addition, given the greater mobility of Zn in the surficial environment and the higher background Zn levels (in a range of rock-forming minerals), this is not an unexpected result. The moderately strong correlation between Cu in soil and humus is also not unexpected given the well-known ability of organic matter to scavenge Cu.

There is little correlation between Zn and Cu concentrations in rock with other media. This is not entirely unexpected, as correlation coefficients are global in nature, and do not account for spatial factors such as glacial dispersion and variations due to lithology. Furthermore, the zone of influence for a rock sample is small, whereas the zone of influence for till, lake sediments, and to a lesser extent soil and humus, are broader.

With respect to the nearest-point search process, the data distributions for Cu and Zn concentrations in rock were divided into separate percentile rankings ($> 95^{\text{th}}$ and $> 75^{\text{th}}$ percentiles), and the samples above these percentiles were used as a basis for comparison with Zn and Cu in surficial media. The identified Zn and Cu samples in rock can be regarded as anomalous ($> 95\%$) and possibly anomalous ($> 75\%$). The nearest-point method involves searching from each rock sample with anomalous Zn and Cu concentration to the closest Zn and Cu anomaly in the another media (till, soil, humus) out to a maximum distance of 3 km in all directions, or optionally in specific directions chosen by the geologist. The mean and median concentration of Zn and Cu are then

plotted against distance. Figure 6.17 is a cartoon example illustrating how the nearest-point algorithm searches by distance and direction or by a combination of the two (i.e. search by distance intervals in a specific direction).

Figures 6.18 and 6.19 shows cumulative plots of median and mean concentration of log Zn and log Cu values in till and soil plotted by distance (using an omni-directional search) to the nearest Zn and Cu anomaly in rock, for rock samples above the 95th percentile. The same plots were produced for rocks samples above the 75th percentile (graphs not shown). Generally, Cu and Zn concentrations, for the 95th percentile ranking, in till and soil decrease with distance from an anomaly in rock suggesting that Zn and Cu anomalies in till reflect anomalies in bedrock within a distance of 1 km. The plots for humus and soil (not shown) were more variable, and did not show a clear trend of decreasing concentrations of Zn and Cu concentration with distance from a anomalous rock sample. Box and whisker plots are also included in Figs. 6.18 and 6.19 to determine whether concentrations are statistically different with distance. Differences in Zn and Cu median values in till and soil, between the closest distance to a rock anomaly (0 - 0.5 km) and other distances (e.g > 0.5 km), are significant (median notches do not overlap). The exception is for Cu concentration in soil (see Fig 6.19). A significant difference was also noted between Zn concentrations in both till and soil with distance from a Zn sample in rock (>75%) (graph not shown). However no difference in Cu concentration at the 75th percentile was evident.

The search was then divided by direction (four cardinal directions) with a 40° tolerance (see Fig. 6.17). Only the south and east searches resulted in the trends seen in Fig. 20. The decrease (albeit weak) in Cu and Zn concentration in till in a southerly direction suggests that this may be a down-ice dispersion effect, whereas the easterly trend may reflect the east-west strike of bedrock lithologic units. It is interesting to note that concentration levels (as indicated by mean values) are higher in an easterly search than a southerly search direction, again reflecting the general E-W strike of lithologic units.

Summary: The GIS can be used to compare the spatial relationship between geochemical anomalies in rock and anomalies in surficial media by using a nearest-point search algorithm which can be programmed to search by distance and any given direction. This can direct an explorationist's search from a given element anomaly in rock in a direction in which the concentration of the same element in surficial media is the highest. From a process point of view this type of analysis can detect down-ice dispersal patterns in till in the absence of an orientation survey or detailed mapping, and also identify the effects of lithology on geochemical trends and patterns that may be present in surficial media. Zinc and to a lesser extent Cu concentration in till is related to Zn and Cu concentration in bedrock within distances of approximately 1 km. An E-W and N-S directional bias in the data can be detected using the nearest-point technique. The E-W bias can be attributed to the general E-W strike of stratigraphy whereas the N-S bias is a reflection of down-ice glacial dispersion of Zn- and Cu- bearing minerals.

6.4.5 Identifying geochemical anomalies due to mineralization

GIS/statistical methods can be used to screen or filter out anomalies in soil, humus or lake sediment data that may be due to factors not related to mineralization such as lithological variations and/or metal scavenging due to organic matter and Fe and Mn oxides. Many methods for screening geochemical data for scavenging effects exist. Four related methods that are easily implemented in a GIS are reviewed in this section: (a) selective query; (b) linear regression, (c) ratios and, (d) RGB ternary maps. These methods can be applied to multimedia data from the same geographic location or to data sampled from different geographic locations. The former involves processing the data as discrete points whereas the latter necessitates interpolating the data to produce continuous surface maps. Copper concentration in soil is used as an example to demonstrate the advantages and disadvantages of each method.

The selective query method involves inspecting normal probability plots of Cu, Mn, Fe and LOI (as a measure of organic matter) and selecting upper breakpoints that divide the

geochemical population into background and anomalous groups. The GIS is then used to select anomalous Cu samples that are not coincident with anomalous Fe, Mn or LOI concentrations. This can be done using a SQL statement as follows:

Select (Cu >= 80 ppm) AND (Mn < 40 ppm) AND (Fe < 30 ppm) AND (LOI < 5 %)

Figure 6.21a shows the results of the selective query process in which anomalous Cu concentrations has been screened for Mn scavenging using the following query:

Select (Cu > 50 ppm) AND (Mn < 340 ppm)

Conversely, Cu may be regressed against Fe, Mn or LOI as explanatory variables and only the residual values (i.e. values that do not fit the linear model within a certain prediction interval) selected. Residuals represent samples where there is little correlation between the elements (Cu vs. Fe, Mn, and LOI) under study. The regression may be univariate, taking one explanatory variable at a time, or multivariate where all three explanatory variables are used simultaneously.

Figure 6.22 is a scatterplot of Mn and Cu concentrations in soil; a moderate correlation of 0.54 exists. The best fit line, as determined by linear regression, and lines showing the predicted limits are included on this plot. The lines showing the prediction limits represent the limits for the forecast of the fitted value (Cu) associated with a given value of the independent variable (Mn). The positive residuals that are elevated in Cu (above predicted line) and also low in Mn (< 340 ppm), but also greater than the predicted line, are highlighted as square and circle symbols on the plot. These are the samples shown in Fig. 6.21b.

Ratios, where Cu is divided by Fe, Mn or LOI can be used as a method to correct for scavenging effects. Ratios can be calculated within the GIS (or statistical package) and since only high ratio values (e.g. high Cu and low Mn for example) are important, a probability plot of the ratio values can be constructed and anomalous upper thresholds can be selected which presumably reflect samples free from scavenging effects. Figure 6.21c shows samples with high ratios (> .35) between Cu and Mn. High ratio values

were determined by identifying an upper break (threshold) on a normal probability plot of the ratio values.

Figure 6.22 indicates that all three methods are similar, differing only slightly on how the samples with elevated Cu and low Mn are identified. Over a 75% overlap in samples identified by all three methods exists, although there are some unique combinations of samples identified by only one or two methods. The selective query method is simple and straightforward as samples which fall above 50 ppm Cu and below 340 ppm Mn (threshold not shown on Fig. 6.22) are selected. With respect to the regression method, samples above the predicted line are selected (Fig. 6.22) and for the ratio method, samples above a ratio threshold (≥ 0.35) are highlighted. The selective query method resulted in 16 samples high in Cu and low to moderately low in Mn. The regression method has identified 12 samples whereas the ratio method has identified 14 samples.

Figure 6.23 presents a RGB ternary map, which is another method of visually screening anomalies due to scavenging. This map shows concentrations of Cu, Mn and Fe in lake sediments as red, blue and green colours, respectively. Thus, intense red anomalies represent elevated Cu concentrations whereas intense yellow hues represent coincident Cu and Mn anomalies, magenta hues represent coincident Cu and Fe anomalies and white represent coincident Cu, Mn and Fe anomalies. Thus, anomalies displayed in yellow, magenta and white might be considered as lower priority, as they may represent Cu anomalies due to scavenging. One must be cautious when visually interpreting the colours in Fig. 23 as the white area, which reflects coincident Cu, Mn and Fe anomalies is also coincident with mineralized Fe formations and therefore may be more a reflection of the underlying geology as opposed to scavenging processes.

Summary: All methods reviewed for screening for the effects of scavenging yield similar results. The selective query technique is perhaps the simplest and most effective method, as it can be applied directly in the GIS using simple query statements. Caution must be used when using the ratio method as high ratio values can result from Cu

concentrations that are not necessarily anomalous and are below upper thresholds present on probability plots.

6.5 Discussion and Conclusions

Zinc and Cu concentrations (based on mean values) in the various media are summarized from Figure 6.4 as follows:

- (a) Zn --- lake sediments > (humus > rock) > (till > soil)
- (b) Cu --- rock > lake sediments > till > humus > soil

The media enclosed in brackets above do not have significantly different concentrations of Zn. Zn concentrations in all media are higher than Cu. This may be due to generally higher background concentrations as a function of the predominance of mafic and intermediate volcanic rocks and greater mobility. Concentrations of Cu and Zn in till are similar. The greatest amount of mixing would occur in till thus averaging out total concentration (similar to the effect of lake sediments) resulting in similar Zn and Cu concentrations at least in the clay+silt fraction of glacial till. Concentration of Zn and Cu in lake sediments and rock are the highest and typified by the highest contrast anomalies for both Zn and Cu. Soil and to a lesser extent, till (especially for Zn) have the lowest concentrations of Zn and Cu as well as lowest contrast between anomalies and background.

The highest concentration for Zn is found in lake sediments. This is not unexpected given the relative mobility of Zn and the large catchment areas involved in lake sediment sampling. In addition, mafic volcanic rocks dominate the study area and in these rocks Zn can readily substitute in mafic-forming minerals resulting in higher background levels. The relatively high Zn concentration in humus is somewhat anomalous. The following factors may be important in accounting for this observation: (1) scavenging of Zn by organic matter and colloidal Fe and Mn oxides still present in the humus; (2)

vegetation tapping mineralized bedrock directly (in thin soil/till conditions) resulting in higher concentrations in humus than in soil or till; and (3) higher background levels of Zn (see above) combined with preferential uptake of Zn by vegetation and subsequent recycling in humus. It is also noteworthy that Zn concentration in humus resulted in the best-structured variogram. This is also somewhat surprising, given that humus is generally considered to reflect element concentrations local to the sample point (i.e. small zone of influence). This result may suggest that humus has a homogenizing effect (e.g. scavenging) on more mobile elements such as Zn, thus averaging out concentrations over space, or that vegetation (from which the humus is derived) are efficient in gathering Zn over broad areas.

The concentration of Zn in rocks is generally less variable than Cu. Zinc exhibits both chalcophile and lithophile characteristics and can substitute readily in major-rock forming silicate minerals such as biotite, pyroxene and amphiboles; oxide minerals such as magnetite; and in sulphides (sphalerite). Copper displays chalcophile characteristics and prefers sulphides to silicates or oxide minerals. Thus, Cu will be found predominately in sulphides (e.g. chalcopyrite, covellite) whereas Zn can be found both in sulphides, and in common rock-forming silicate minerals. Therefore, high Cu concentrations may reflect primarily sulphide mineralization whereas high Zn concentrations may represent both sulphide mineralization and lithologic variations. The more homogeneous distribution of Zn between lithological units suggests that Zn concentration is more a reflection of lithologic variations (e.g. more Zn occurring ubiquitously as a substitute mineral in mafic-forming minerals). This may reflect a general trend (or difference) between lithophile and chalcophile elements.

Copper concentration is highest in rock and given that most Cu will be found in sulphides, anomalies in Cu are more likely to reflect mineralization or extensive weathering of sulphides. High concentrations in lake sediment again may represent a mineralization signature rather than primarily a lithologic signature, as in the case for Zn. This illustrates the importance of accounting for lithologic variations using normalization techniques. Copper concentration in humus is lower than Zn in humus.

Global correlation of Cu and Zn in the various media is highest between soil and till, suggesting that in the generally thin till conditions across the belt, soil is derived directly from the till, and that the till is for the most part residual (traveled short distances generally ≤ 3 km). This suggests that either till or soil can be used as an effective medium for exploration purposes in Archean greenstone belts covered by a thin veneer of till.

With respect to Zn concentration between lithologic units, rock, lake sediments and humus have higher Zn concentrations than soil and till. Zinc concentration in humus varies sympathetically with lake sediments across lithology as does soil and till. Humus is similar to rock except over felsic volcanic rocks. With respect to Cu concentrations between lithologic units, all media vary sympathetically with lithology across ultramafic, mafic and intermediate rocks and to a lesser extent over felsic, granitoid and sedimentary rocks. Copper concentrations in lake sediments and till are similar and vary sympathetically over all rock units. These results suggest that lake sediments and humus (at least in thin till conditions) are good media for sampling for base metal exploration as they reflect a broad geochemical signature that is reflective of bedrock variations.

Copper and even more so Zn concentrations in till (and to a lesser extent soil) are related to anomalous concentrations in rock within a distance of 1 km. This, again, may reflect a stronger bedrock signature for Zn than Cu concentration in till. The GIS, using a nearest-point algorithm, can be used to identify directional anisotropies in geochemical data sampled from till, thus assisting in geographically narrowing down prospective targets. This is especially important for exploration in areas that are not well mapped (e.g. in areas where information on surficial units and glacial movement direction is lacking).

With regard to visualizing geochemical data, RGB ternary images are effective in presenting interpolated geochemical data. However, continuous surface (interpolated) geochemical maps can only be generated if certain criteria, discussed in this paper, are

met (e.g. sufficient sample density, well-behaved variograms). Otherwise, the data should be visualized and analysed as discrete points or with a natural zone of influence (e.g. drainage basin for lake sediment data) or using small zones of influence (e.g. buffers). Variogram analysis in conjunction with kriging is the most powerful method of interpolating geochemical data. Variograms provide critical information on spatial associations between points, directional biases and spatial structure. The degree of smoothing desired in the interpolation process obviously depends on what the data will be used for. If the goal is to preserve all high frequency variability, which may be important for regional mineral exploration, then less smoothing, as obtained from the IDW interpolations, is desirable. However, if the goal is to produce a geochemical map useful for characterizing surficial or lithologic patterns then a certain degree of smoothing is warranted.

The hue variations in RGB ternary images can not only indicate anomalous areas (both in concentration and spatial pattern) worthy of exploration follow-up, but also suggest differences in surficial/glacial processes operating between different elements in the different media. For example, the dominance of Zn in the humus (Fig. 6.10a) may reflect a direct bedrock signature, greater mobility of Zn, greater scavenging of Zn by organic matter, preferential uptake of Zn by vegetation and subsequent recycling in humus and the relative homogenizing influence of humus with respect to Zn especially over a N-S linear trending zone in the central portion of the belt. Copper concentration is much more variable in the different media (Fig. 6.10b) reflecting more heterogeneous concentrations in bedrock and variability in surficial processes ranging from scavenging by humus in the southern granitoid rocks, mechanical distribution of Cu-bearing minerals in the central portions of the study area and a combination of scavenging and chemical breakdown of Cu-bearing minerals in soil and humus over primarily granitoid rocks in the eastern portion of the study area.

In processing geochemical data, normalization (e.g. selective query) to lithology is important for especially for lithogeochemical data (also see Harris *et al.* 1999a, b). The selective query process can identify anomalous elemental concentrations by lithology.

Thus, a sample that may fall between the 70th and 80th percentile for the total population of samples (and not considered anomalous), may fall above the 95th percentile range for a specific lithology and thus would be selected as anomalous. The success of the normalization process in identifying anomalies depends on the element, and in this case, because Zn concentration is both reflective of lithologic variations as well as mineralization, selective querying by rock unit may be too liberal in that anomalies due to lithologic variations are also being identified. The majority of Cu anomalies reflect mineralization.

Correcting (screening) geochemical data (soil, humus, lake sediments) for extraneous effects such as scavenging is important to help identify anomalies more likely due to mineralization. Providing the geochemical data pertain to the same geographic location, the selective query method presented in this paper is the simplest and most straightforward method for screening scavenging effects. An RGB ternary map showing the concentration of a given element (Cu, Zn) and elements that may be responsible for scavenging (Fe, Mn) assists in identifying areas where anomalies may be due to strong scavenging processes rather than mineralization. However, consideration of the underlying geology is crucial in the interpretation process.

In conclusion, the GIS offers geologists a powerful tool with which to manage, evaluate, analyse and visualize geochemical data sampled from a variety of media. GIS, in concert with statistical analysis and geostatistical analysis packages, can be used to fully assess the statistical and spatial characteristics of geochemical data using techniques ranging from simple SQL queries to more complex multivariate methods. Furthermore, analysis of geochemical data using a GIS can be conducted in a timely fashion which is an important factor when working under exploration deadlines. The GIS, in conjunction with other software tools, assists the geologist in extracting the most information from their data. More time can be spent on the analysis and visualization of the data rather than the laborious task of overlaying maps manually. Analysis of geochemical data using a GIS, in addition to providing information on geochemical anomalies, can often reveal subtle associations between different geochemical elements and/or different media

through the integration and overlay of multiple layers of geochemical data. Lastly, but not of insignificance, the GIS provides an organized and geo-referenced archive for large volumes of geochemical data that can be accessed and updated quickly and efficiently.

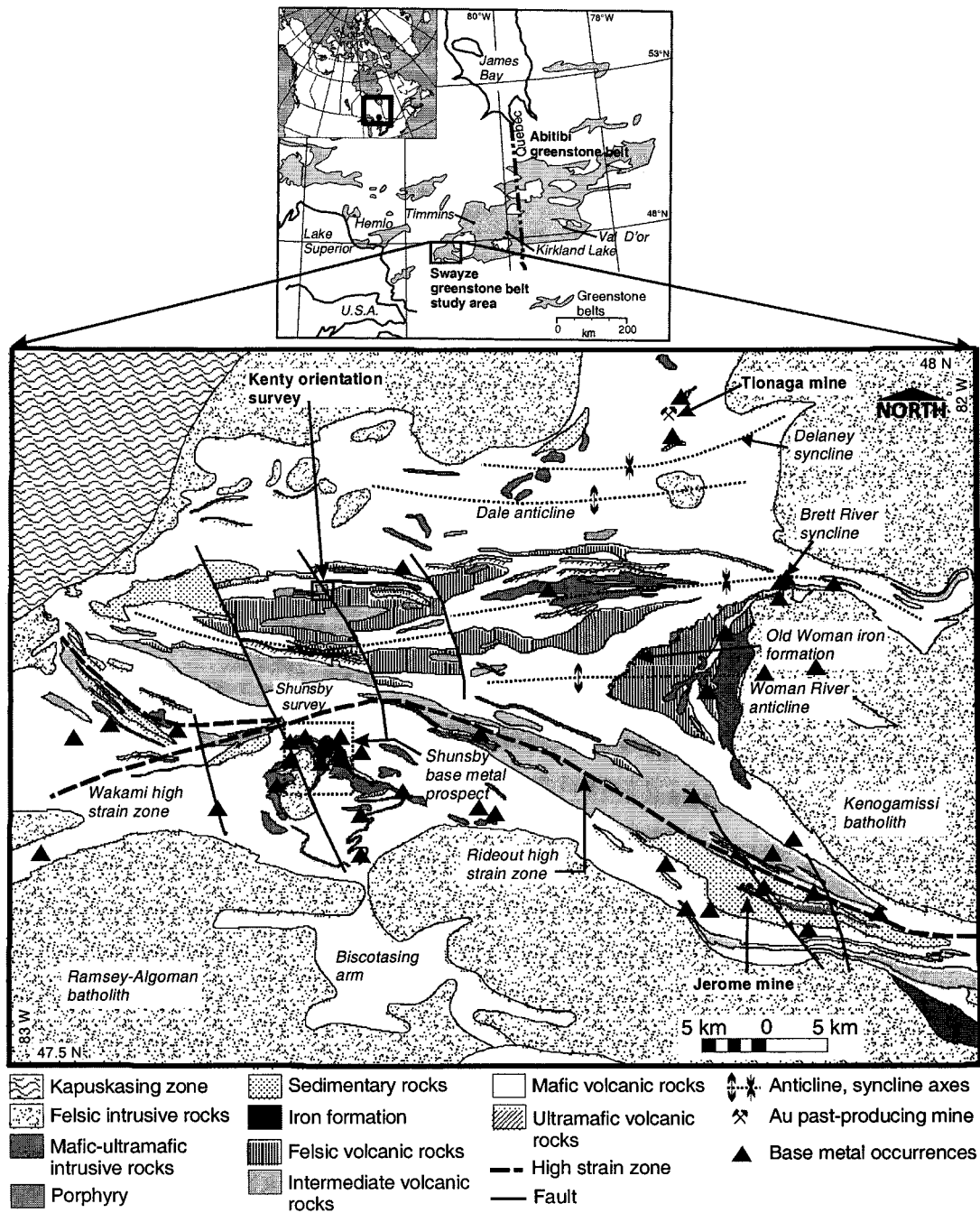


Figure 6.1 Study area – generalized geology (Heather and Shore, 1999).

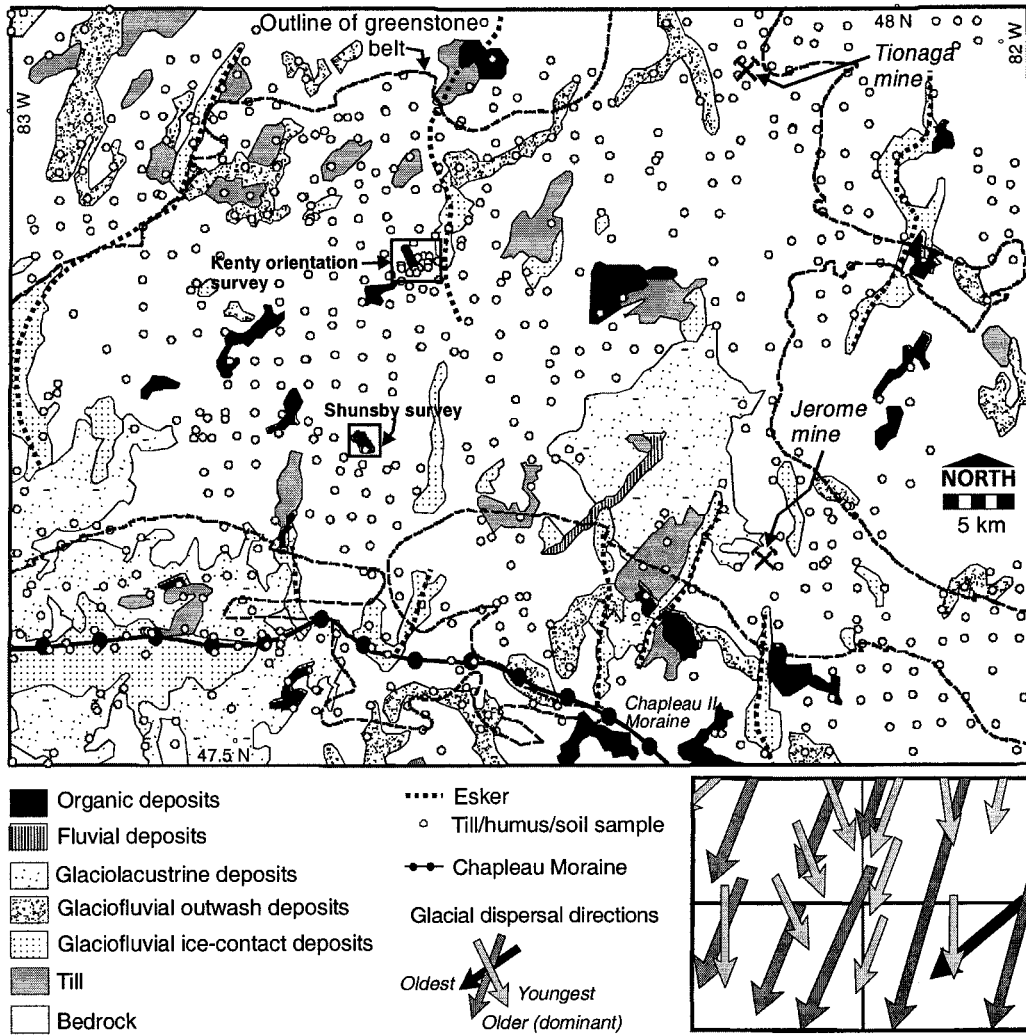


Figure 6.2 Study area – generalized surficial geology (Bernier, 1994) and geochemical sample points (till, humus and soil)

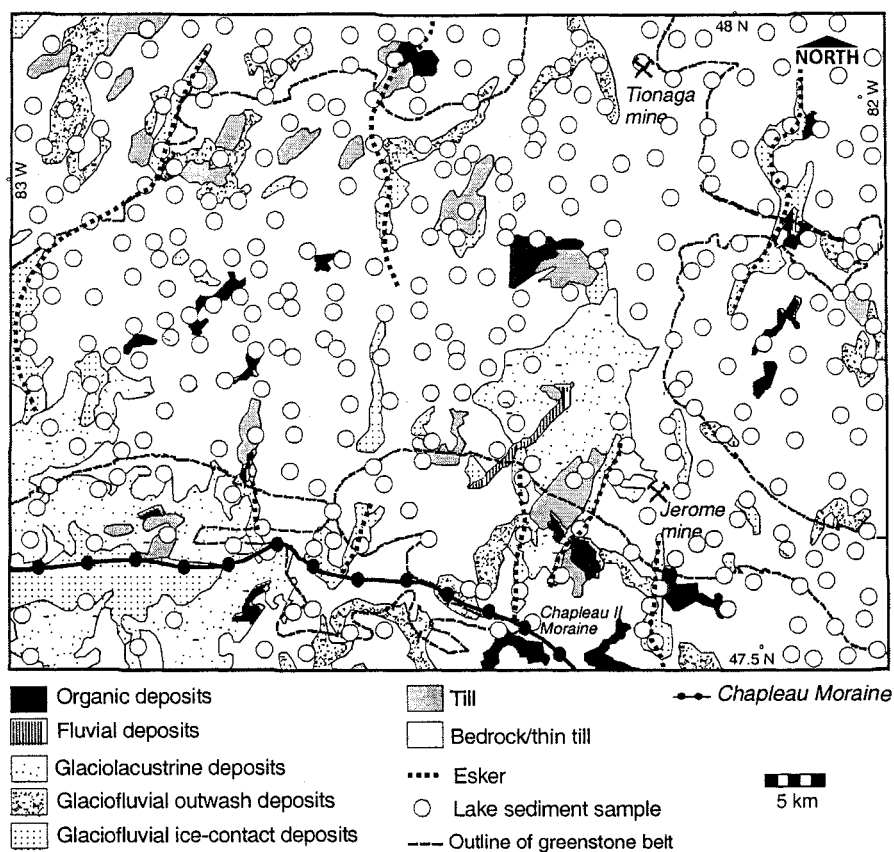


Figure 6.3 Location of lake sediment samples

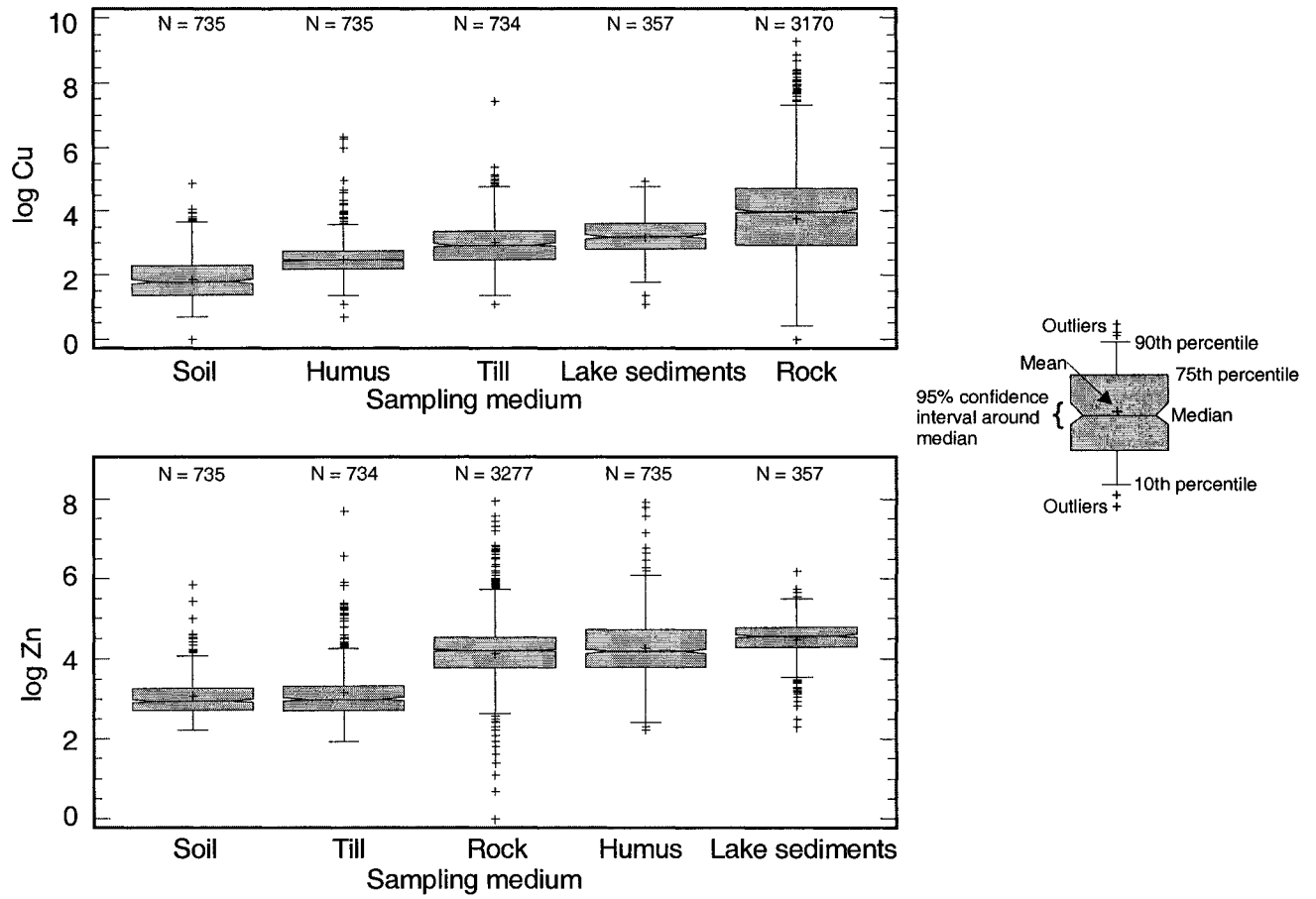


Figure 6.4 Box and whisker plots of Zn and Cu concentration by media (rock, till, soil, humus, lake sediments)

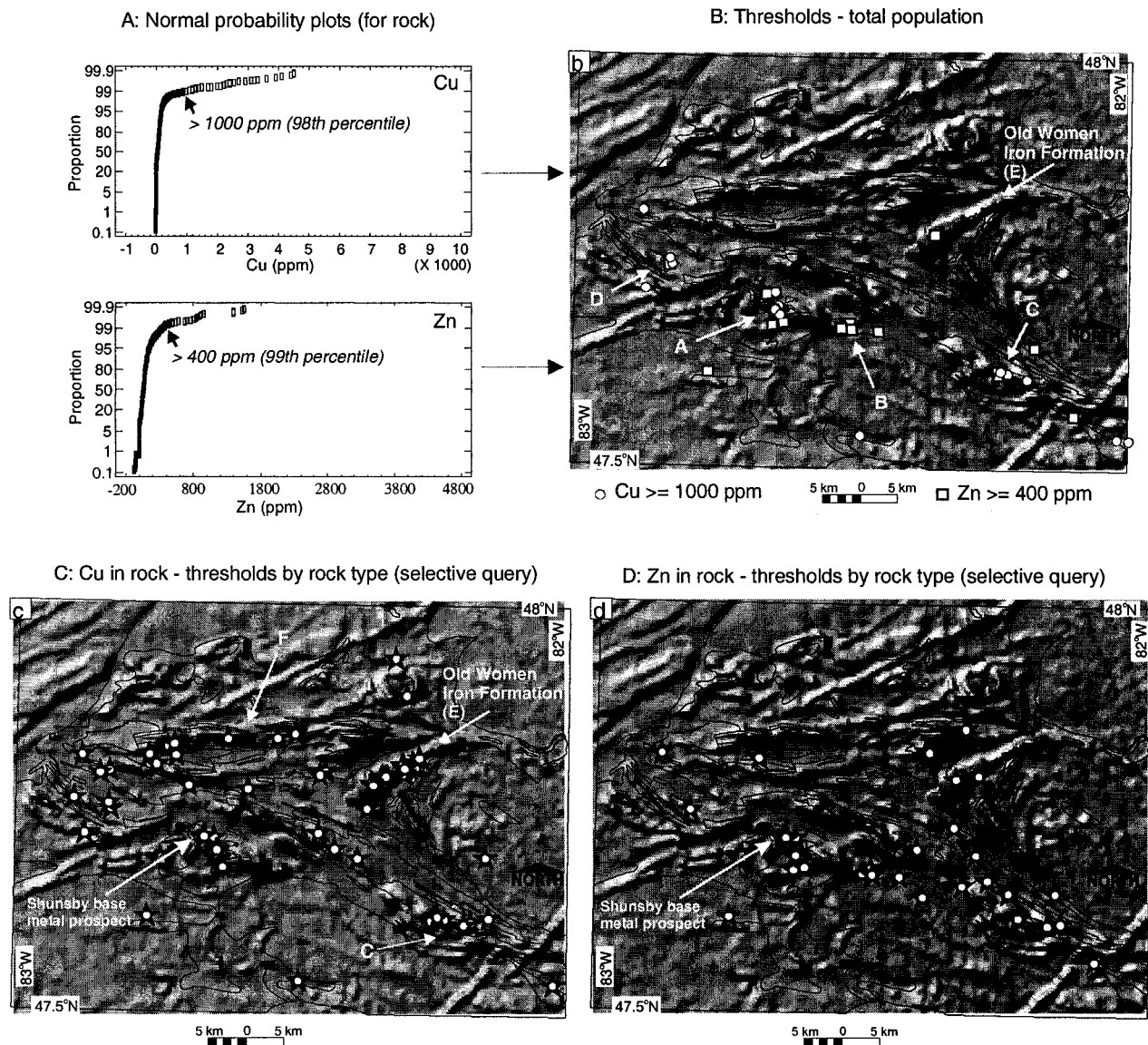
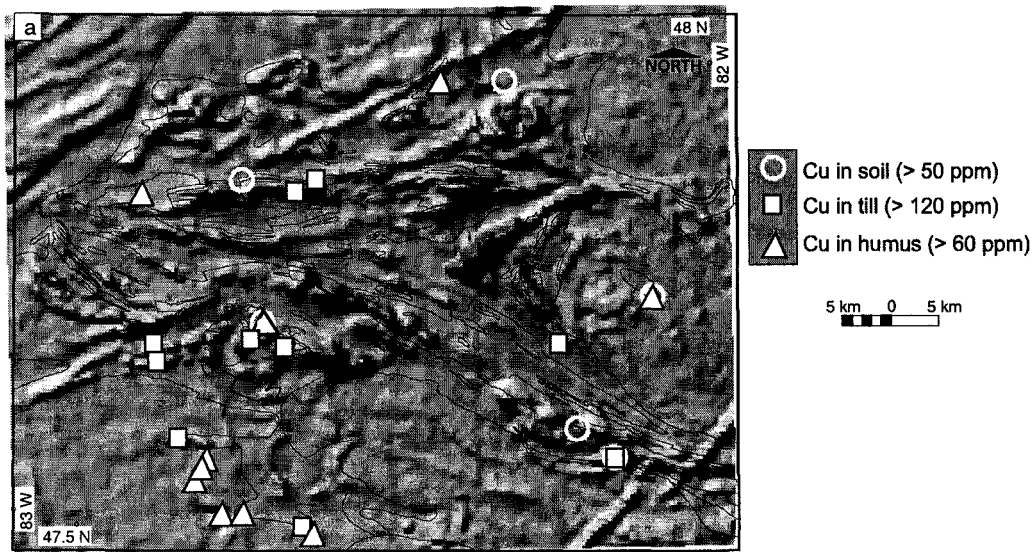


Figure 6.5 Cu and Zn anomalies in rock, (a) normal probability plots of Cu and Zn in rock, (b) map of Cu and Zn anomalies irrespective of lithology, (c) Cu anomalies determined from selective query, (d) Zn anomalies determined from selective query

Cu anomalies in soil, till and humus based on the total population



Cu anomalies in till, soil and humus - selective query by rock type

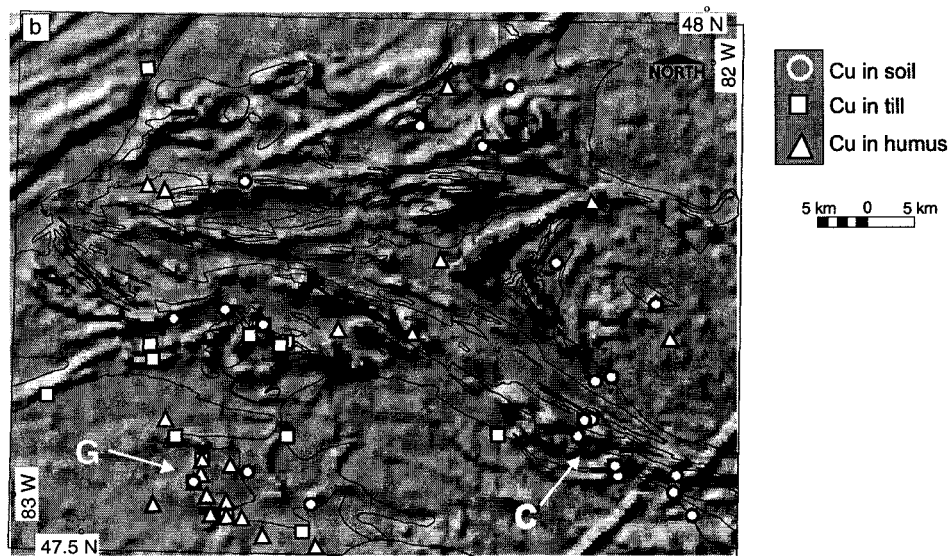


Figure 6.6 Cu anomalies in surficial media, (a) based on total population irrespective of lithology, (b) based on selective query

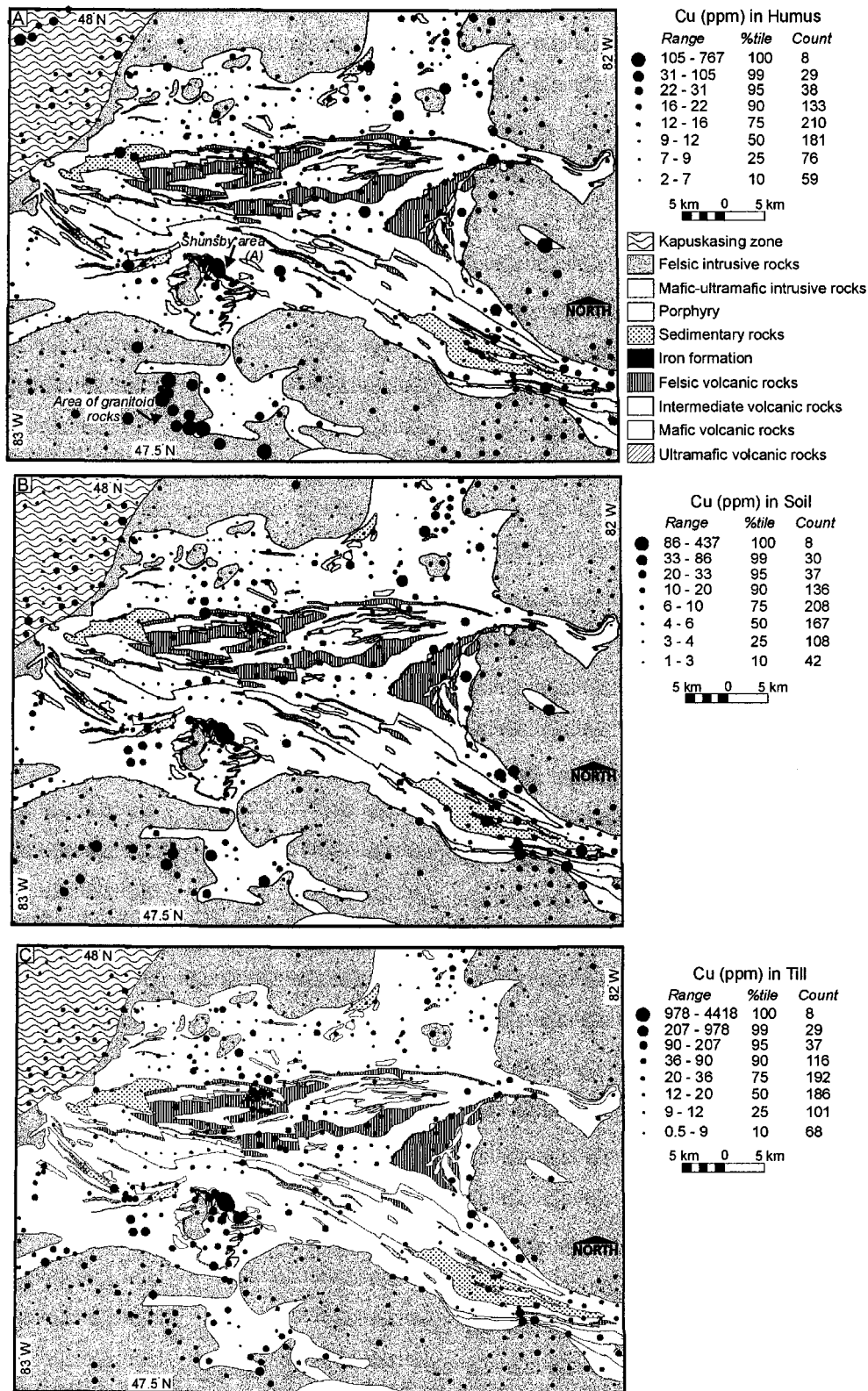


Figure 6.7 Proportional symbol (dot) maps. (a) Cu concentration in humus, (b) Cu concentration in soil, (c) Cu concentration in till

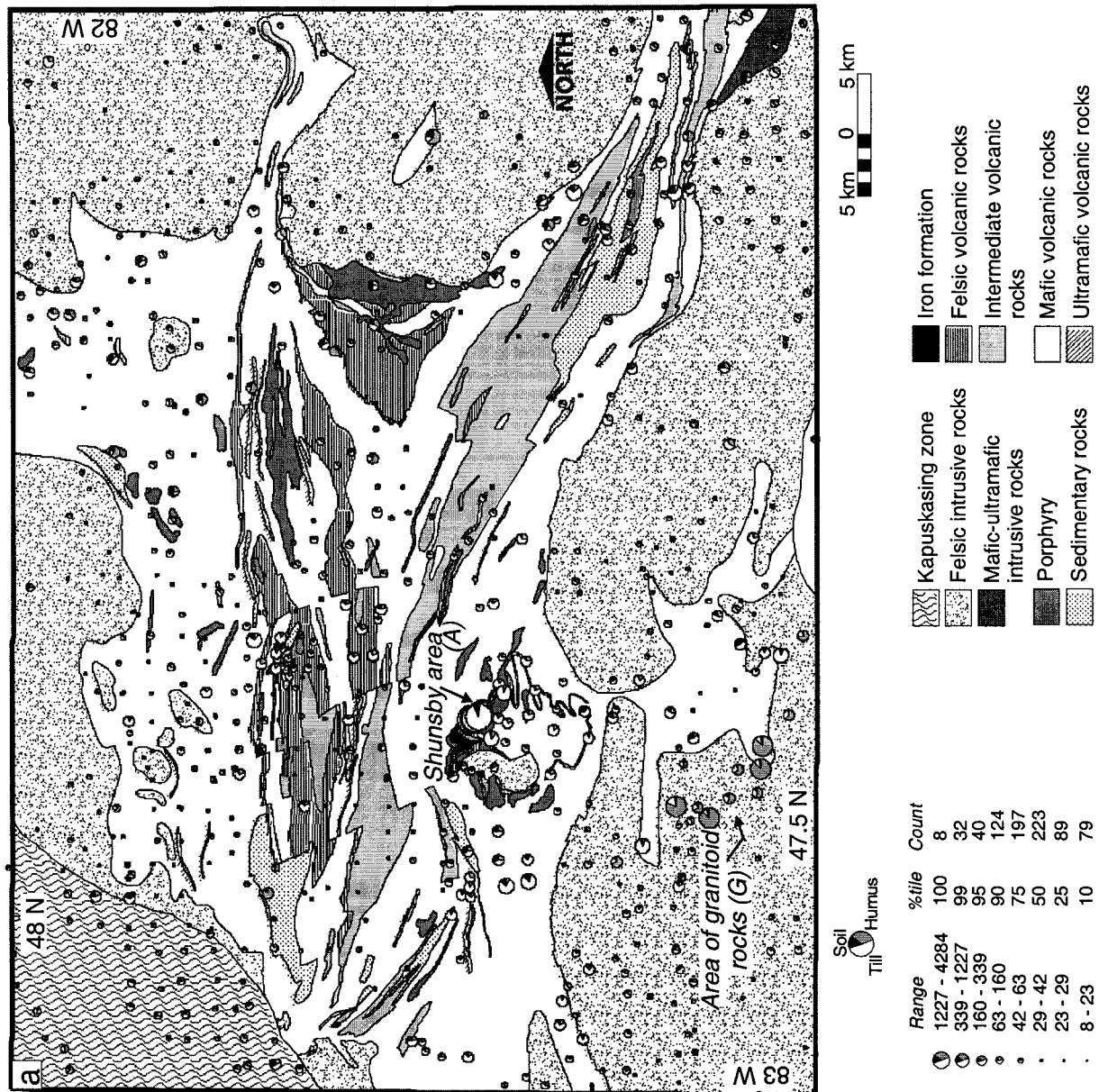


Figure 6.8 Proportional symbol (pie) plot showing Cu concentration in soil, till and humus

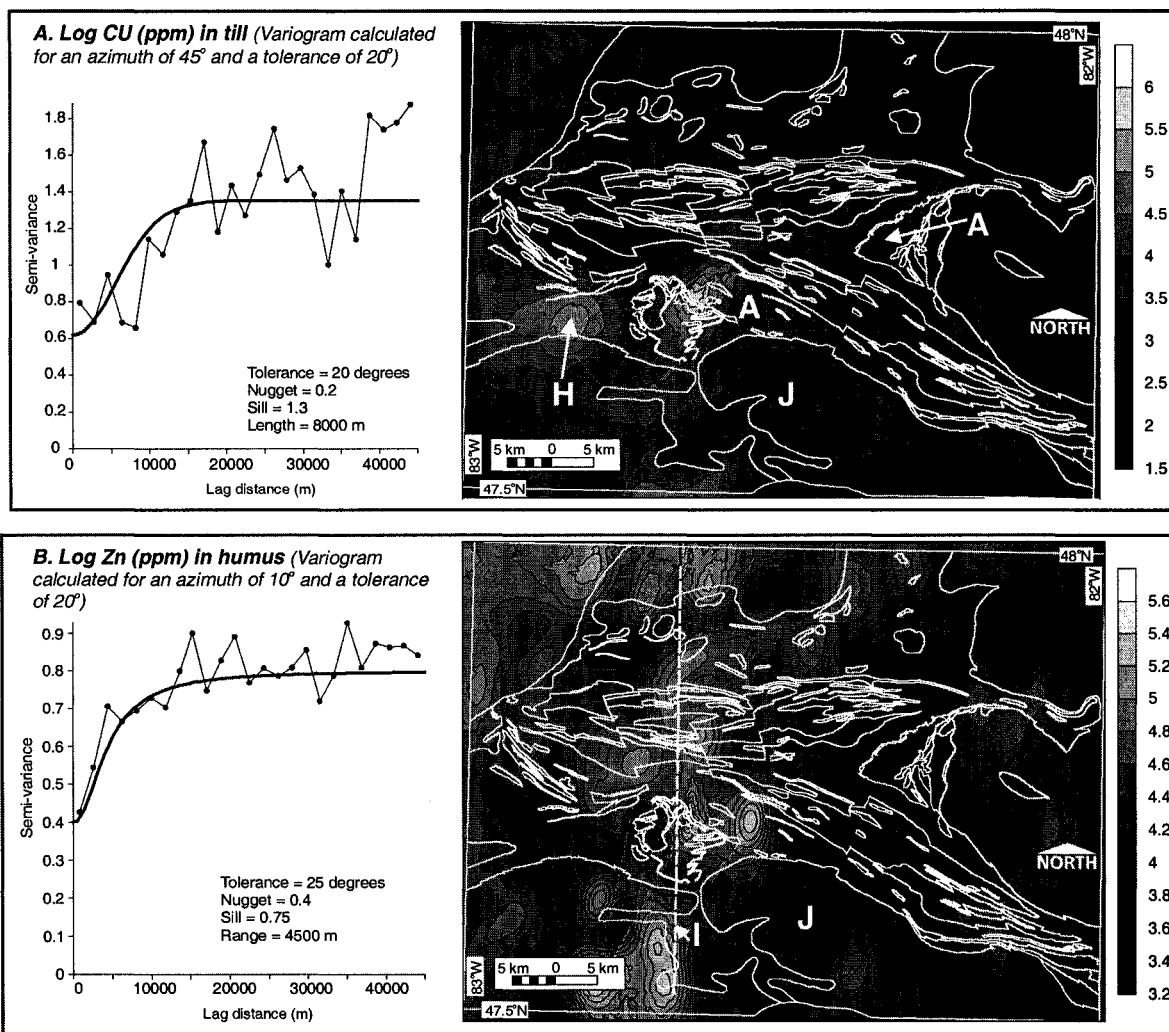


Figure 6.9 Variograms and associated interpolated maps (kriged) of Cu and Zn data, (a) log Cu in till, (b) log Zn in humus

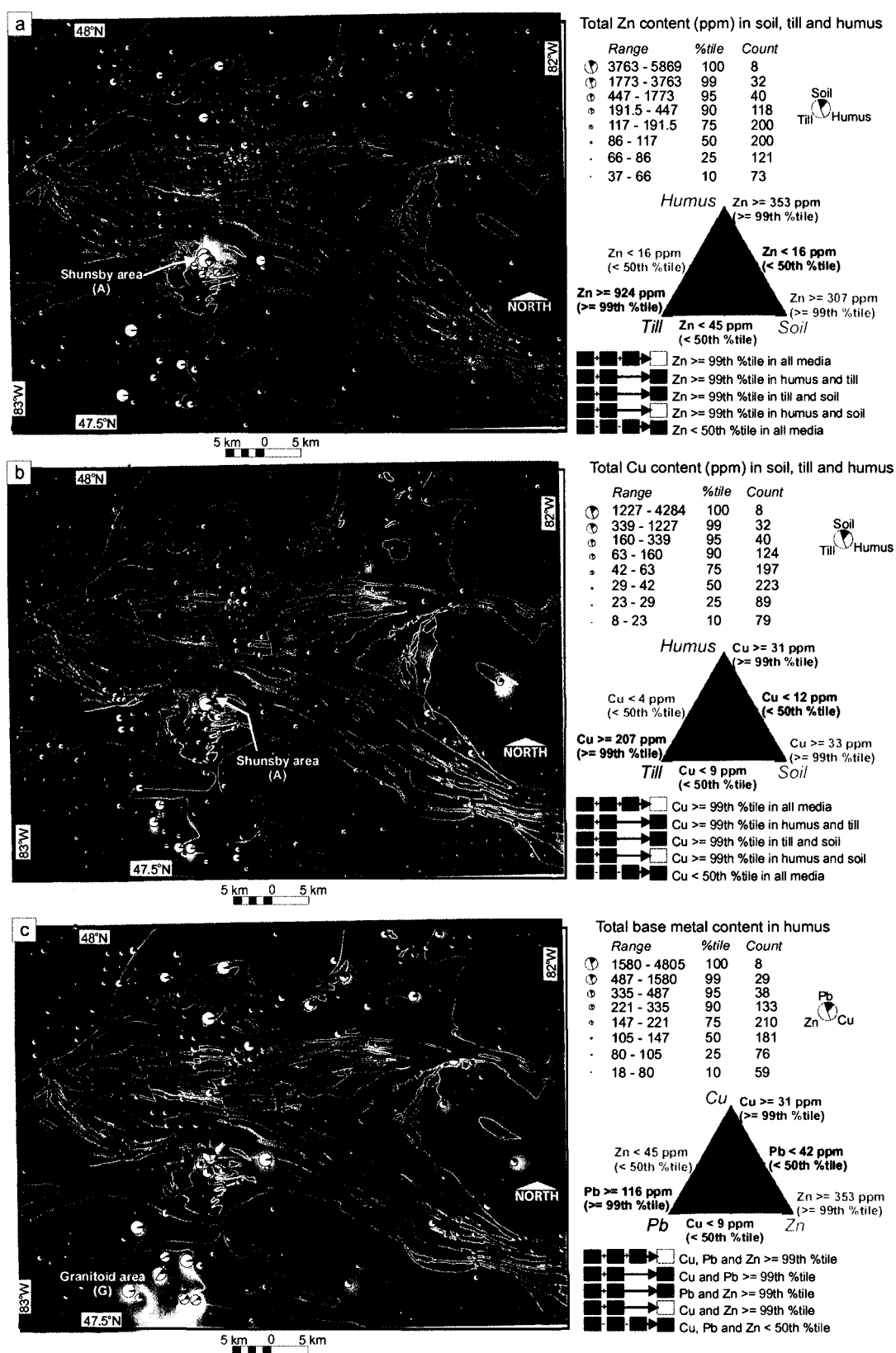


Figure 6.10 RGB (red-green-blue) ternary maps, (a) Zn concentration in till, soil, humus, (b) Cu concentration in till, soil and humus, (c) total base metal content in humus

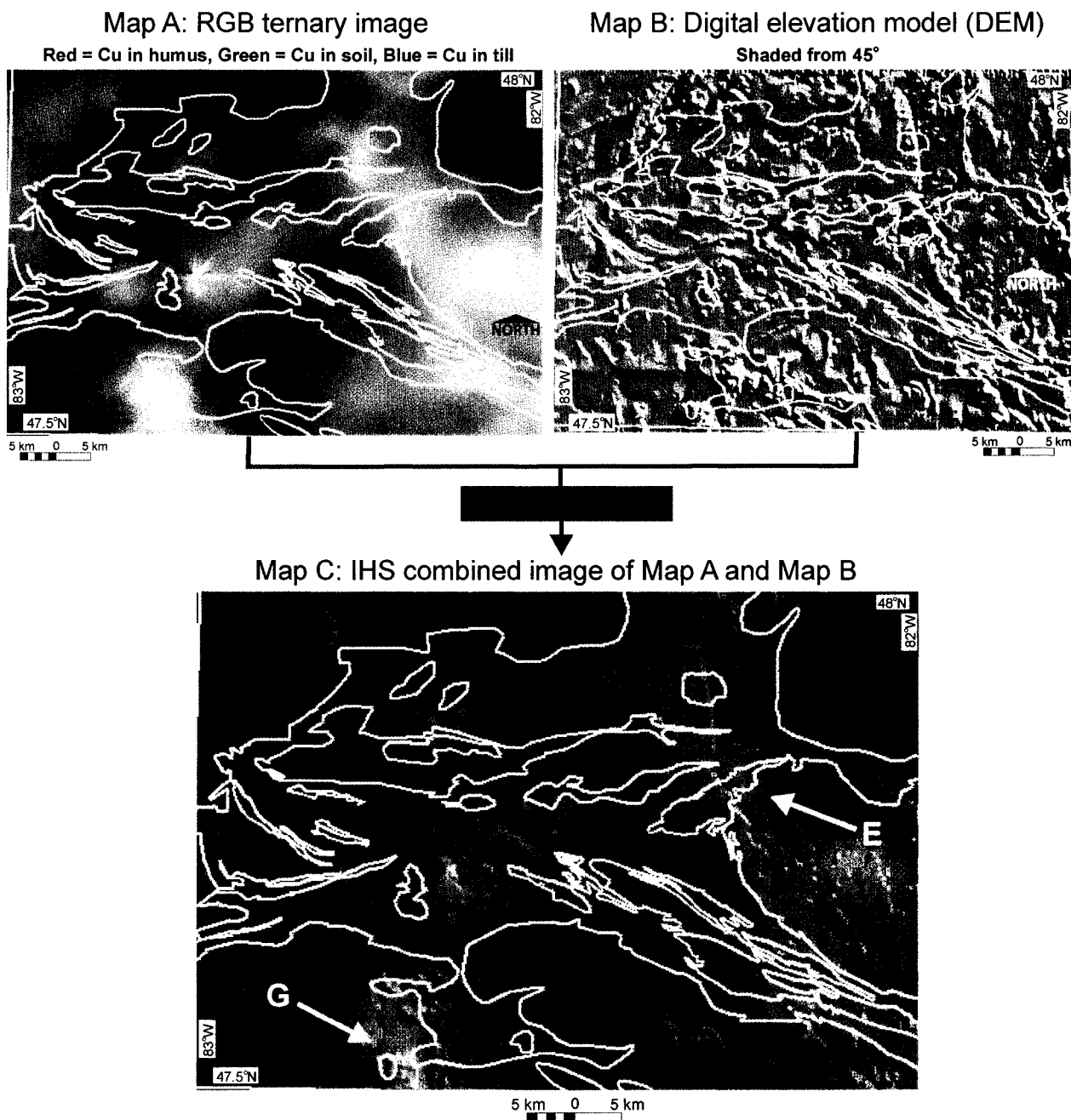


Figure 6.11 Integrated geochemical image-maps. (a) RGB ternary map where red is Cu in humus; green is Cu in soil; blue is Cu in till. (b) Digital elevation data (DEM) – artificial shading from 45°. (c) Ternary map shown in (a) and DEM shown in (b) combined using an IHS (intensity-hue-saturation) transform

Map A: Cu in humus, soil, and till draped on lake sediment
 Red = Cu in humus, Green = Cu in soil, and Blue = Cu in till, relief = lake sediment

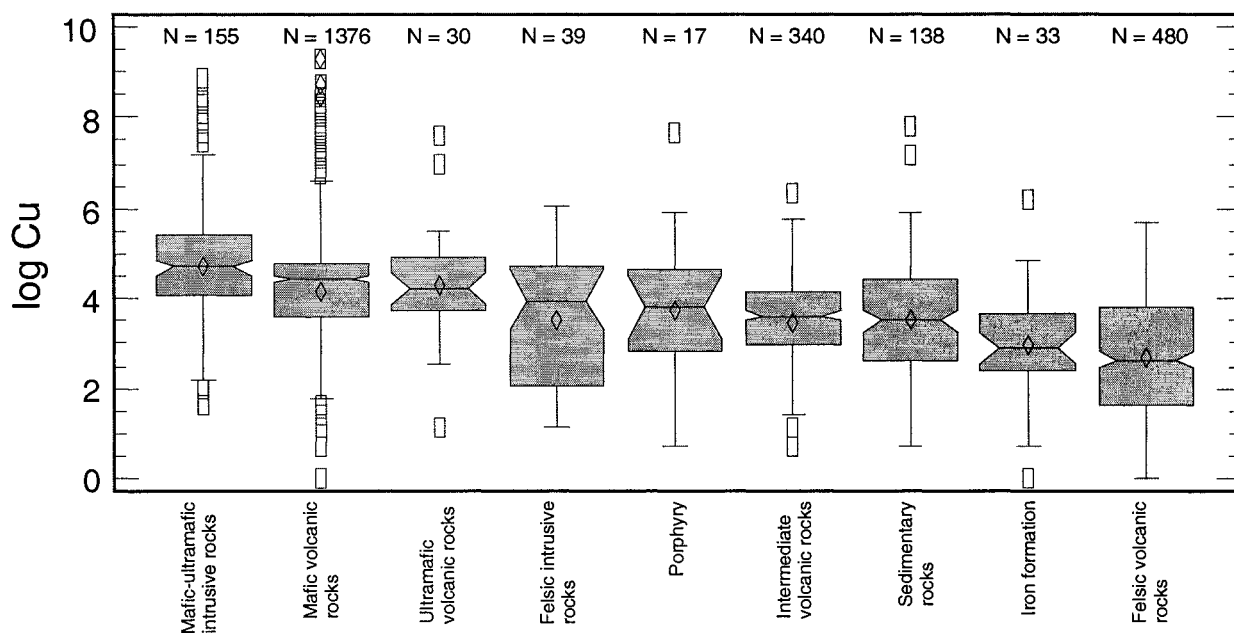


Map B: Cu in humus, soil, and till draped on topography (vertically exaggerated)
 Red = Cu in humus, Green = Cu in soil, and Blue = Cu in till, relief = topography



Figure 6.12 2.5 dimensional image maps, (a) RGB ternary image showing Cu concentration in humus, soil and till (same as Fig. 6.11a) draped over a relief image representing Cu in lake sediments – Cu anomalies in rock have been overlayed as red dots, (b) RGB ternary image (as above) draped over topographical relief derived from a DEM

A. log Cu (ppm) in rock by lithology



B. log Zn (ppm) in rock by lithology

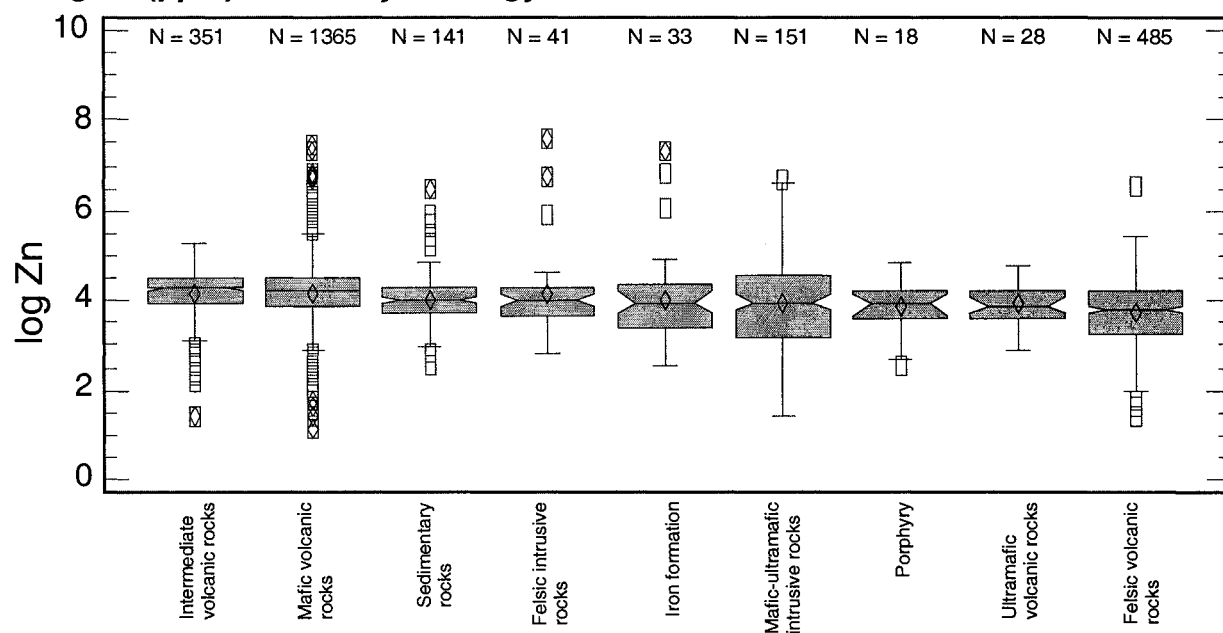


Figure 6.13 Box and whisker plots showing log Cu and log Zn concentration by lithological unit, (a) log Cu from highest to lowest concentration, (b) log Zn from highest to lowest concentration, N, number of samples

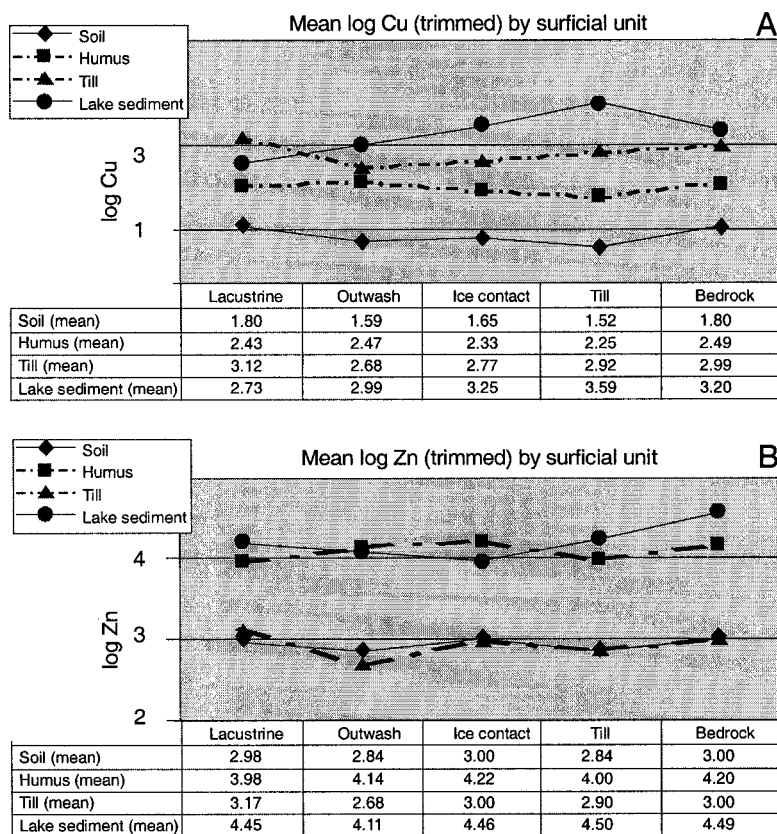


Figure 6.14 Plots showing log Zn and log Cu concentration (mean values) in till, humus, soil and lake sediments by surficial unit (see Fig. 6.3), (a) log Cu by surficial unit, (b) log Zn by surficial unit (error bars based on standard deviations not shown for sake of clarity – see text for discussion of significance)

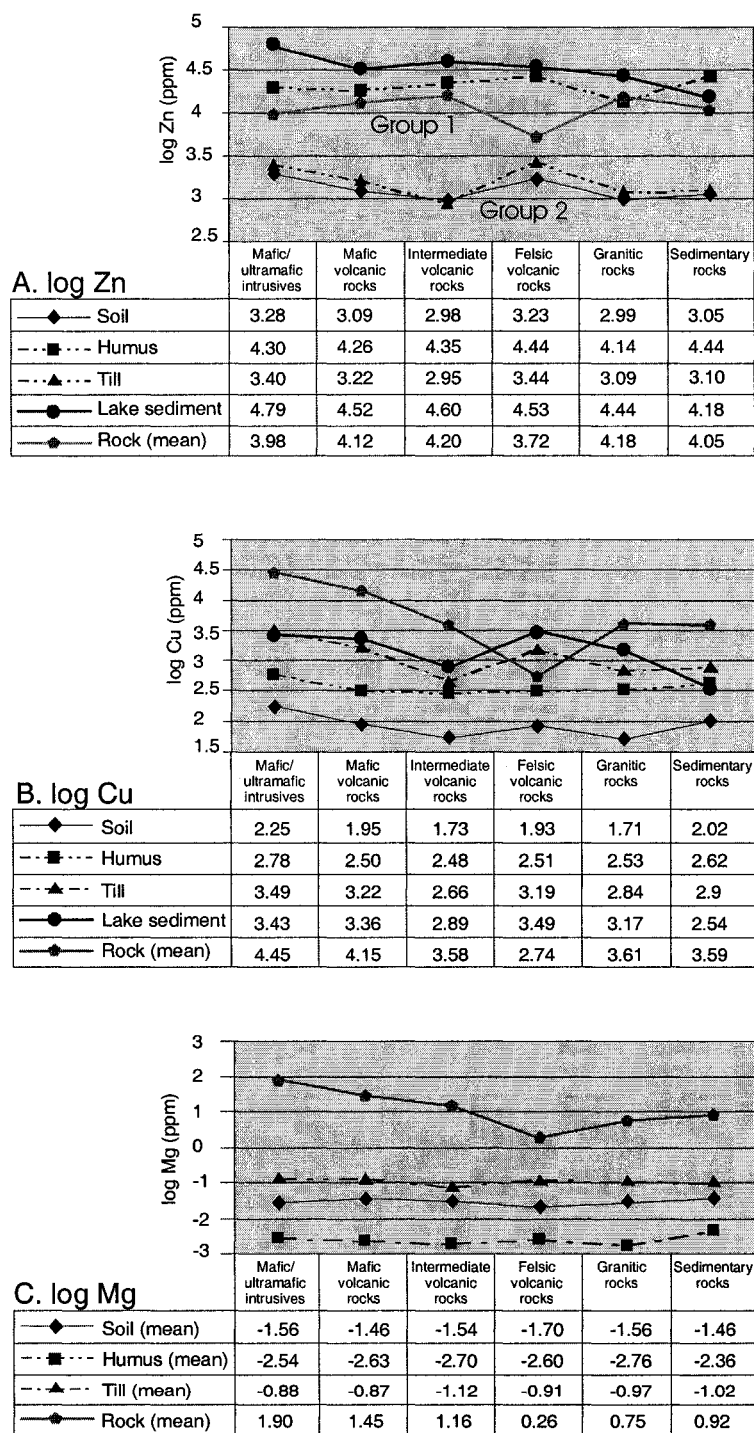


Figure 6.15 Plots of mean values for log Zn, Cu, and Mg by lithological unit, (a) Zn in soil, humus, till, lake sediments and rock, (b) Cu in soil, humus, till, lake sediments and rock, (c) Mg in soil, humus, till, lake sediments and rock (error bars based on standard deviations not shown for sake of clarity – see text for discussion of significance)

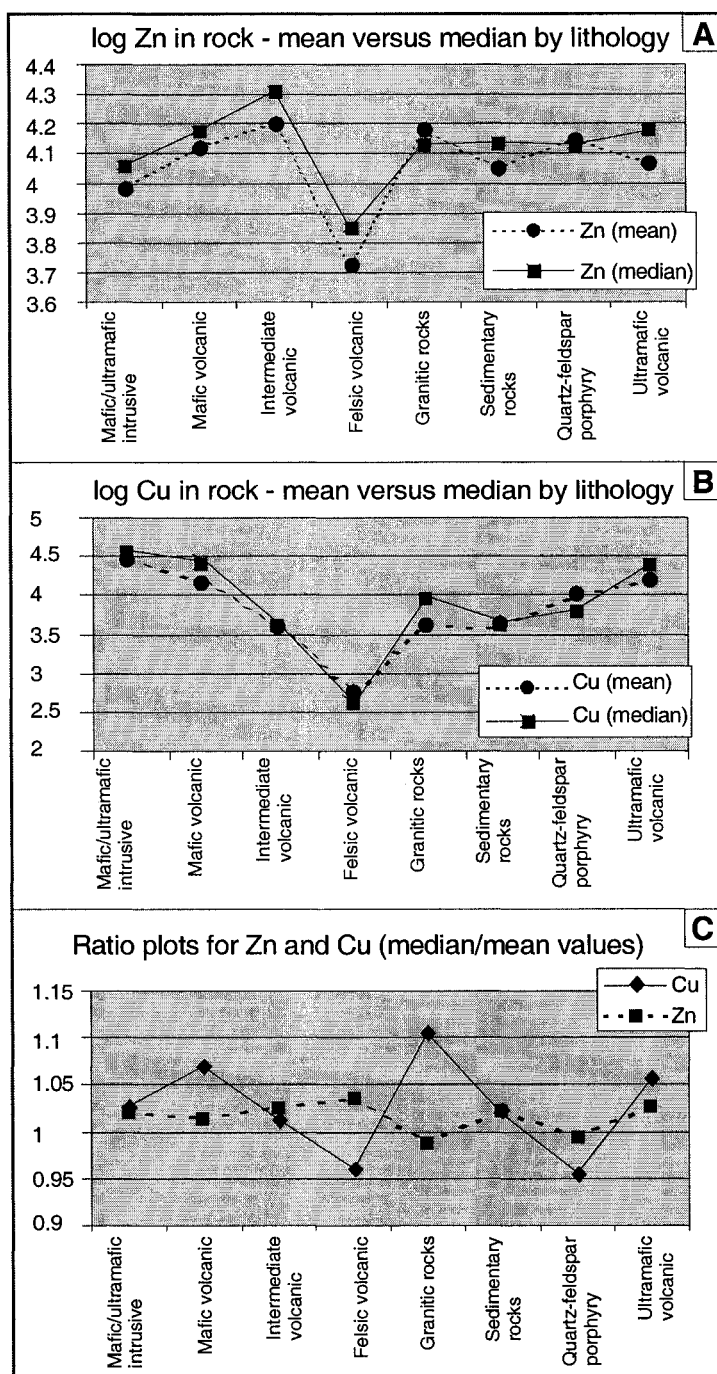


Figure 6.16 Plots of the mean and median values and ratio between mean and median values for lithological units, (a) log Zn by lithology, (b) log Cu by lithology, (c) ratio of mean and median values for log Zn and log Cu by lithology (error bars based on standard deviations not shown for sake of clarity – see text for discussion of significance)

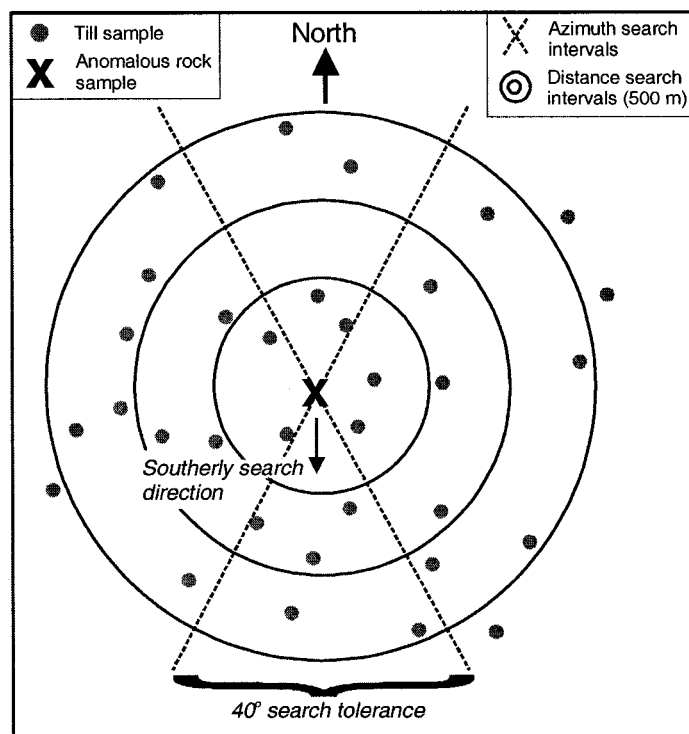
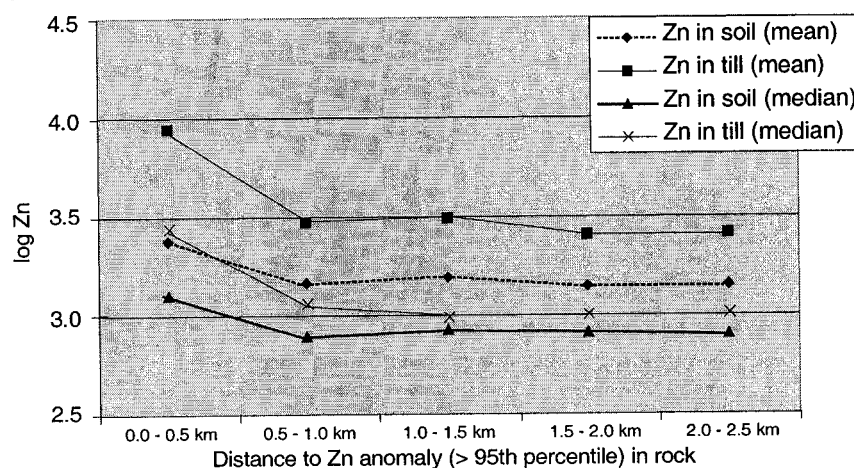
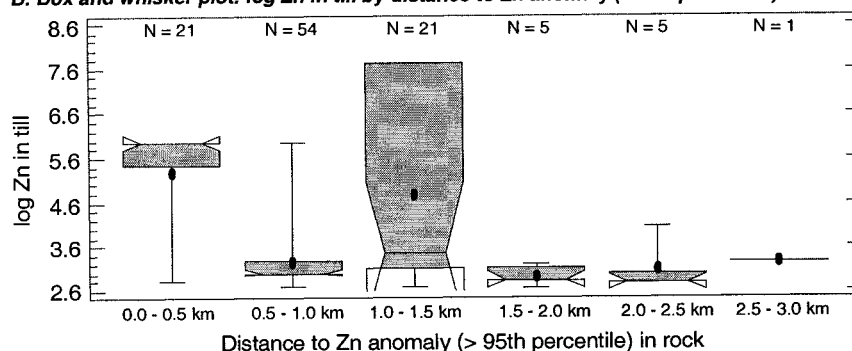


Figure 6.17 Cartoon diagram of nearest-point search strategy showing distance radii and directional search wedges

A. Distance/concentration plot: log Zn in till and soil versus Zn anomaly (>95th percentile) in rock



B. Box and whisker plot: log Zn in till by distance to Zn anomaly (>95th percentile) in rock



C. Box and whisker plot: log Zn in soil by distance to Zn anomaly (>95th percentile) in rock

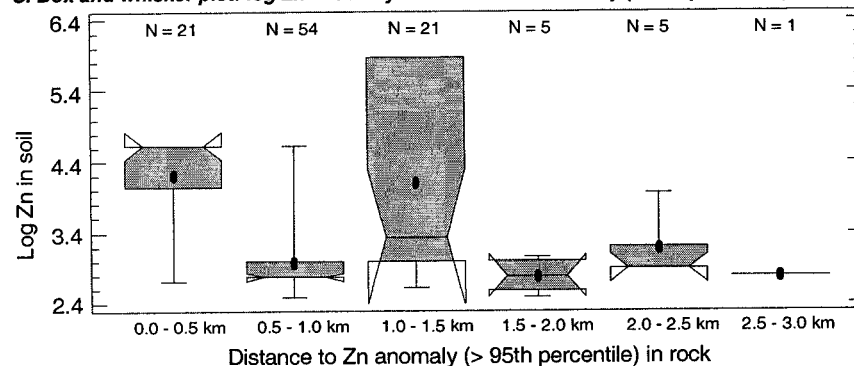
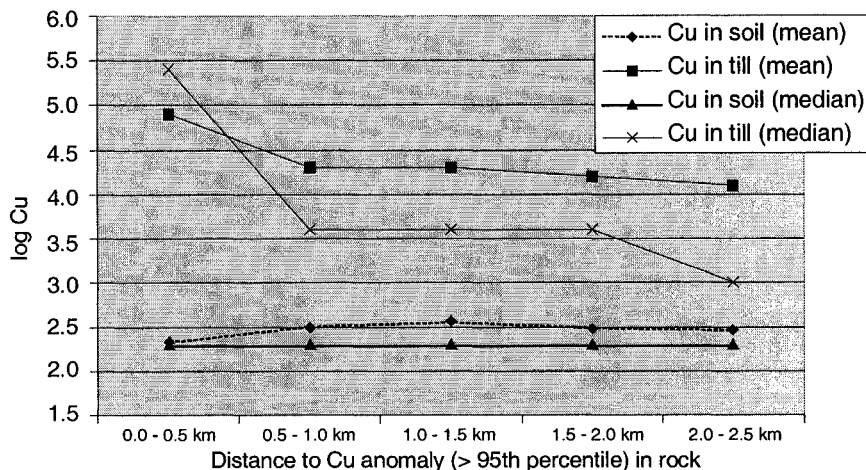
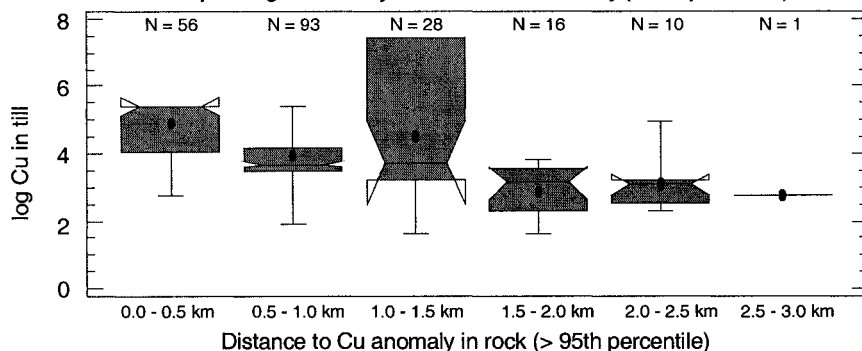


Figure 6.18 (a) Cumulative plot of log Zn concentration (mean and median values) in till and soil by distance to nearest anomalous rock sample (values for rock are above the 95th percentile), (b) Box and whisker plot (not cumulative by distance) of log Zn in till by distance to Zn anomaly in rock, (c) Box and whisker plot (not cumulative by distance) of log Zn in soil by distance to Zn anomaly in rock

A. Distance/concentration plot: log Cu in till and soil versus Cu anomaly (>95th percentile) in rock



B. Box and whisker plot: log Cu in till by distance to Cu anomaly (>95th percentile) in rock



C. Box and whisker plot: log Cu in soil by distance to Cu anomaly (>95th percentile) in rock

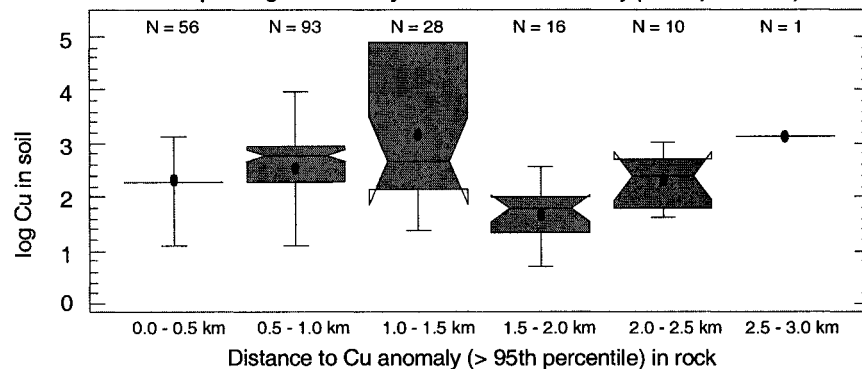


Figure 6.19 (a) Cumulative plot of log Cu concentration in till and soil (mean and median) by distance to nearest anomalous rock sample (values for rock are above the 95th percentile), (b) Box and whisker plot (not cumulative by distance) of log Cu in till by distance to Cu anomaly in rock, (c) Box and whisker plot (not cumulative by distance) of log Cu in soil by distance to Cu anomaly in rock

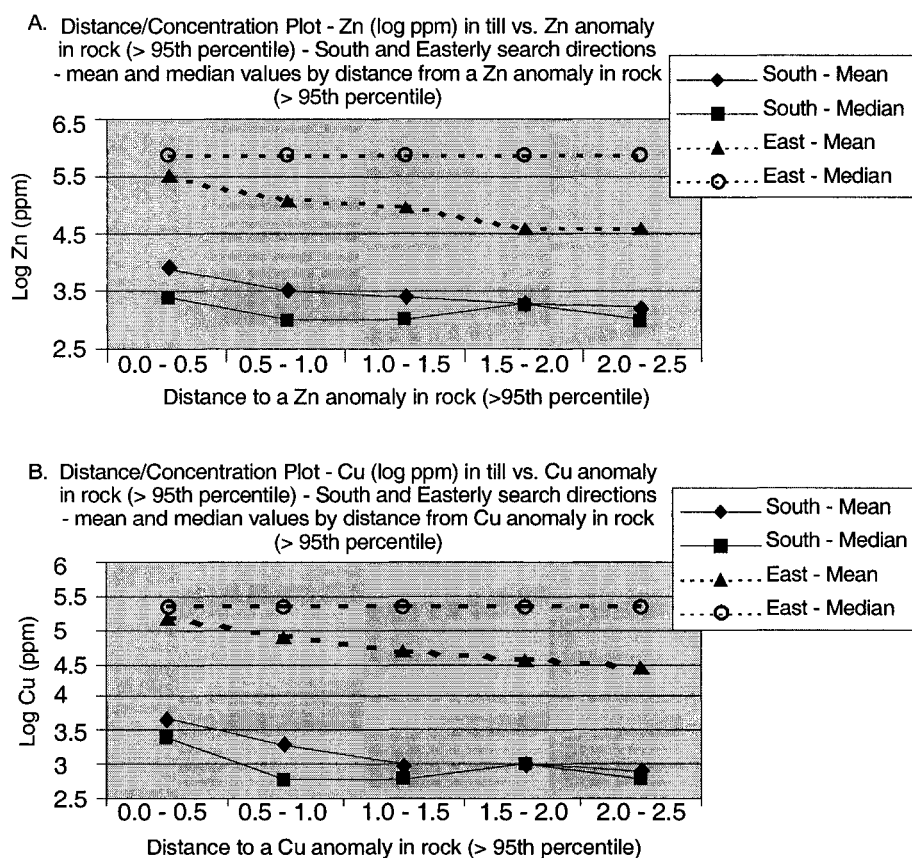


Figure 6.20 (a) Cumulative plot of log Zn concentration in till (mean and median) by distance to nearest anomalous rock sample (values for rock are above the 95th percentile) – southerly and easterly search directions, (b) Cumulative plot of log Cu concentration (mean and median) in till by distance to nearest rock sample (values for rock are above the 95th percentile) – southerly and easterly search directions

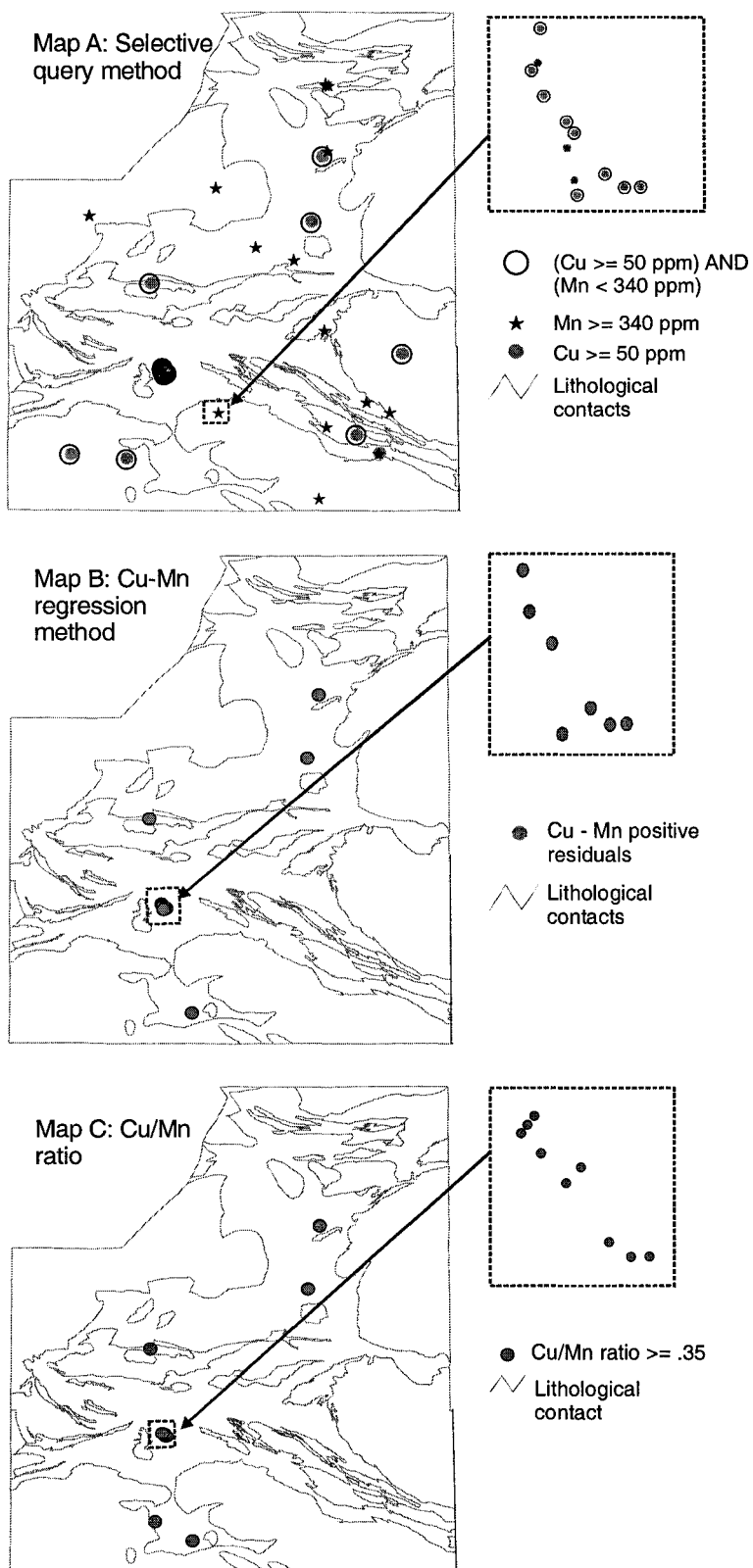


Figure 6.21 Maps of Cu samples from soil screened for Mn scavenging, (a) selective query, (b) regression – Cu vs. Mn, (c) Cu:Mn ratio

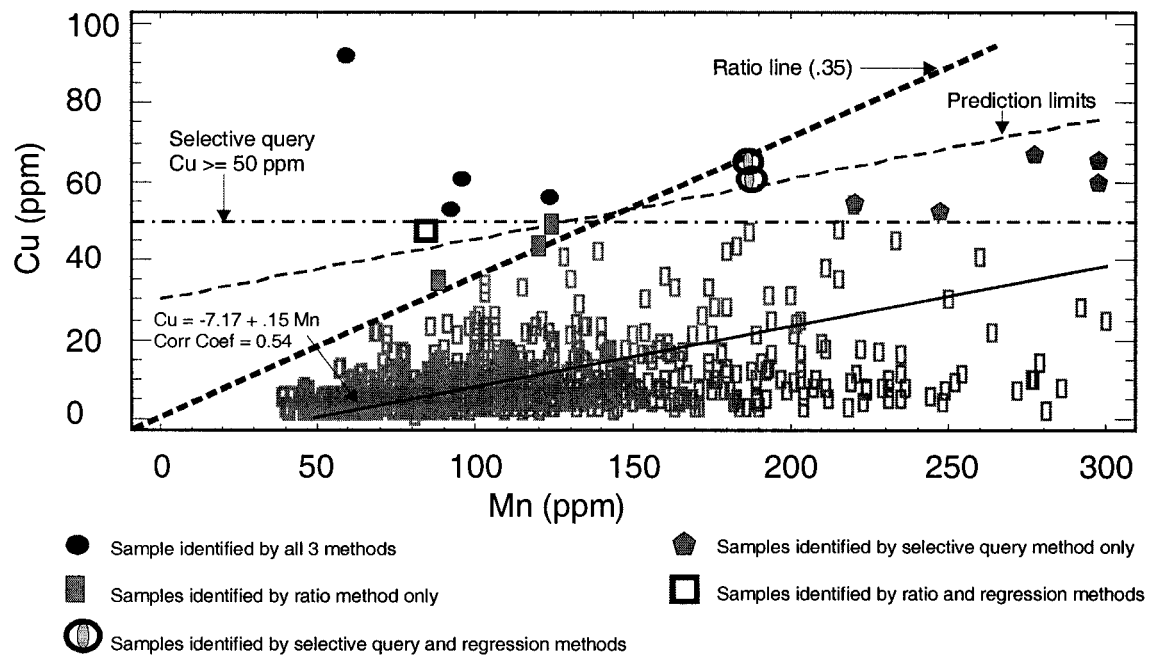


Figure 6.22 Scatterplot between Cu and Mn in soil showing linear regression line and predicted limits, Cu/Mn ratio (threshold line – 0.35) and selective query threshold

RGB Ternary Image

Red = Cu in lake sediments, Green = Mn in lake sediments, Blue = Fe in lake sediments



Figure 6.23 RGB (red-green-blue) ternary map where R is Cu concentration in soil, G is Mn concentration in soil and B is Fe concentration in soil

Scale	Density	Media	Objectives
Regional	1 sample/4-7 km ²	C-horizon till B-horizon soil Humus	Identify variations related to: <i>Changes in lithology</i> <i>Mineralization</i> <i>Changes in drift composition</i> Evaluate mineral potential and outline new exploration targets
Local (Orientation)	50-200 m spacing	C-horizon till B-horizon soil Humus	Characterize signatures of various types of mineralization Identify pathfinder components Map scale and form of dispersal
Site specific (Vertical profiling)	25-50 cm intervals (Systematic)	A ₀ -A ₂ and B- horizon soils C-horizon tills	Identify surface weathering trends, in-situ variability, and variations in composition related to stratigraphy

Table 6.1 Survey methodology, Swayze greenstone belt NODA geochemical program

Medium	Size fraction	Analysis method *	Elements
Humus	-80 mesh (<177µm)	INAA	Au, As, Ba, Sb, Bi, Cr, REEs, Th, U, Rb, Sc
		ICP-ES (AR)	Base metals, Ag, As, Co Ba, Mo, V, Mn
B-Horizon soil	-230 mesh (<63µm)	ICP-ES (HF)	Majors, base metals, Cr, Li, Ba, Co, Nb, Mo, V
C-Horizon till	-230 mesh (<63µm) (silt+clay)	CV-AAS	Hg
		Carbonate analysis	% calcite, % dolomite, % total carbonate
C-Horizon till	-10 mesh (<2 mm) (sand+silt+clay)	Heavy mineral separation (> 3.2 specific gravity), mineralogical studies	Gold grains; kimberlite indicator minerals; total ferromagnetic and non-ferromagnetic heavy mineral abundance

* INAA - Instrumental neutron activation analysis, ICP-ES - Inductively coupled plasma emission spectrometry,
AR - aqua regia, HF - Hydrofluoric acid , CV-AAS - Cold vapour atomic absorption spectrometry

Table 6.2 Analytical methods, Swayze greenstone belt NODA geochemical program

Dataset	No. of samples	Years collected	Analytical methods*	Source†
J. Ayer (JA)	136	1991-1993	91-XRF/ICP-MS/ICP-ES/ CV-AAS 92-XRF/ICP-ES/ICP-MS	OGS
K. Heather (KH)	157	1993-1995	XRF/ICP-MS/CV-AAS/ DIONEX	GSC
PETROCH (PT)	646	1976-1993		OGS
S. Fumerton (SF)	1304	?	XRF/ICP-MS/CV-AAS/FA	Assessment files
Falconbridge (FA)	1425	1978-1979	XRF	Falconbridge Ltd.
Texas Gulf (TG)	943	?	XRF/ICP-ES	Falconbridge Ltd.

* XRF = X-ray fluorescence, ICP-MS - Inductively coupled plasma mass spectrometry, ICP-ES - Inductively coupled plasma emission spectrometry, CV-AAS - Cold vapour atomic absorption spectrometry, FA - fire assay

† OGS = Ontario Geological Survey, GSC = Geological Survey of Canada

Table 6.3 Lithogeochemistry data sources

Element	No. of samples	Mean (ppm)	Median (ppm)	Min (ppm)	Max (ppm)
Cu					
Rock	4195	75.3	60.0	0	4500
Humus	734	114.0	66.0	9	4616
Soil	734	26.0	19.0	9	351
Till	734	38.2	20.0	7	2258
Lake sediment	357	100.8	87.0	10	500
Zn					
Rock	2733	116.0	55.0	2	25100
Humus	734	16.7	12.5	2	562
Soil	734	9.3	6.0	1	132
Till	734	33.5	19.0	3	1704
Lake sediment	357	30.4	25.0	3	140

Table 6.4 Descriptive statistics for Cu and Zn populations in all sampling media

	Humus	Soil	Till	Rock	Lake sediment
Humus		0.15 (0.52)*	0.04 (0.22)	-0.04 (0.01)	-0.01 (0.33)
Soil			0.68 (0.52)	-0.02 (0.03)	0.18 (0.41)
Till				-0.01 (0.06)	0.41 (0.30)
Rock					0.07 (0.01)
Lake sediment					

* Number in brackets is correlation for Cu, non-bracketed correlation is for Zn

Table 6.5 Correlation of Zn, in various media, and Cu in various media, based on interpolated geochemical maps (significant at the 95% confidence limit). Bold numbers show stronger correlations (i.e. > .4)

CHAPTER VII

Down Ice Effects in Till Data : Identification of Glacial Dispersal Trains

7.1 Introduction

Collection and analysis of till is an important part of regional mineral exploration programs in glaciated terrains (Coker, 1991; McClenaghan, 1992; Shilts, 1995; Bajc, 1996; McClenaghan et al., 1997; Klassen, 1997). Glacial till (drift) comprises an unsorted mixture of rocks, clay, silt and sand derived from bedrock and mechanically modified by the physical processes of glacial erosion, transport and deposition (Shilts, 1991, 1996). Other glacial sediments such as outwash and glaciolacustrine sediments are derived deposits having been further transported and modified by glacial processes.

Because till is deposited by a moving ice-sheet a spatial dislocation often exists between a till geochemical anomaly and the mineralized bedrock source up-ice. This dislocation can be relatively small (< 1 km) or much larger (> 100 s km) depending on the glacial dynamics and composition of the underlying bedrock and can impart a directional bias on the spatial patterns of geochemical values in till reflecting one or more periods of glacial ice movement. Mathematical models of glacial dispersal have been developed (Gillberg, 1965, 1967a,b; Shilts, 1976; Salonen, 1986; Salonen and Palmu, 1989; Dilabio, 1981, 1991, 1995; Finck and Stea, 1995, Klassen, 1999) and consist of a negative exponential distribution in which concentration in till decreases with distance down-ice from a bedrock source (Fig. 7.1) (Shilts, 1976). Ideally, the dispersal train consists of a *head* that is close to the bedrock source and a tail that represents the decreasing geochemical concentration down-ice from the source. Dispersal trains are variable in length although many studies have shown the bulk of till deposits have undergone limited transport on the order of hundreds of meters to several kilometers (Clarke, 1987). The shape and length of a dispersal train is also variable and is affected by ice-flow dynamics and bedrock topography (Klassen, 1997). Klassen (1997) has divided dispersal trains into three basic shapes or patterns in map view; ribbon, fan and amoeboid. Ribbon trains are generally

narrow and formed by a single ice flow event; fan-shaped trains are often the product of two different ice-flow directions and are dispersed outwards from a bedrock source in a wedge shape in which the apex points up-ice. Amoeboid-shaped trains result from the interaction of a number of ice-flow directions outward from a central source. The thickness of till and the depth of the mineral deposit responsible for the geochemical anomaly in bedrock also affect the displacement of the dispersal train from the mineral source.

Thus the major concerns for mineral exploration when utilizing till geochemistry data is: (1) whether dispersal trains can be identified, (2) whether the concentration in the tail can be distinguished from regional background and, (3) whether the up-ice source of a geochemical anomaly can be located. Detailed mapping and an orientation survey, conducted before regional sampling begins, are usually undertaken to gather information on till type and thickness, the distance of maximum down-ice dispersal, the direction(s) of glacial transport, the optimum size fraction of till for geochemical analysis and the nature and spatial characteristics of dispersal trains. However, in some exploration programs, time and cost do not permit detailed mapping or conducting an orientation survey.

Geographic Information Systems (GIS) in concert with spatial and non-spatial analysis, can greatly facilitate the interpretation of till geochemical surveys for mineral exploration. Visualization techniques such as plotting the data as dot maps in which the size of the dot is proportional to element concentration or by interpolating the data are useful for identifying patterns in the data that may reflect dispersal trains. Methods such as variogram analysis (Harris et al., 2000, 2001a) contouring and mathematical derivative surfaces (slope, aspect etc.) can also be used to identify anisotropic patterns in geochemical data that may be due to glacial dispersal or to contrasting geochemical concentrations between various underlying bedrock lithologies.

This paper addresses the issue of identifying glacial dispersal trains (items 1 and 2 above), and presents an objective technique for use with till geochemical data from

regional scale surveys. The algorithm is named the Dispersal Train Identification Algorithm (*DTIA*), and is applied in this paper to simulated data as well as to till data from southeastern Cape Breton Island, Nova Scotia where documented dispersal trains exist, and to data from the Swayze Greenstone belt in Ontario where no documented dispersal trains are known. Work presented here builds on analysis of geochemical data from this area by Harris et al. (2001a) and Harris and Wilkinson (1998, 1999).

7.2 Study Areas

The Cape Breton study area is located in the Mira-Framboise area on the southeastern side of Cape Breton Island, 5 km south of Sydney (Fig. 7.2). The bedrock geology consists of northeast-southwest striking metavolcanic and metasedimentary rocks of the Precambrian Fourchu Group (Weeks, 1954) that are separated by late Precambrian to early Carboniferous clastic and sedimentary units of the Windsor group (Barr et al., 1992). A number of plutons intrude the Fourchu Group. Details of the surficial geology can be found in Grant (1988) and McClenaghan and DiLabio (1993). Most of the area is covered by sandy till. Orientations of glacial landforms and striations indicate that the area was affected by three major ice flow events (Fig. 7.2), an oldest easterly flow, a younger flow to the northeast and a youngest flow to the southeast (McClenaghan and DiLabio, 1993). Well-documented dispersal trains exist in the central part of the study area, near Yava (McClenaghan and DiLabio, 1993, 1996) and are shown on Figure 7.2.

Two abandoned mines occur in the study area; the Zn-Pb-Cu massive sulphide Mindamar deposit at Stirling and the sandstone hosted Pb-Zn deposit at Yava. Several small base metal occurrences occur within Devonian plutons or metamorphosed contact aureoles (Deep Cove, Blue Mountain, Gillis Mountain and Copper Shaft). The locations of these mines and occurrences are shown on Figure 7.2.

The Swayze greenstone belt (SGB) (Fig. 7.3) is the westernmost part of the mineral-rich Abitibi greenstone belt (AGB), and the bedrock geology of the belt has been recently been mapped by the Ontario Geological Survey (OGS) (Ayer, 1995a,b), and the

Geological Survey of Canada (GSC) (Heather and Shore, 1999). The surficial geology of the study area is dominated by thin sandy till. (Fig. 7.3; Bernier and Goff, 1993; Bernier, 1994; Bernier et al., 1996). Glaciofluvial outwash and other glacial and post-glacial sediments occur throughout the study area, as well as several large N-S-trending eskers. Relief is generally low except in the south where rolling topography reflects granitoid rocks. The E-W-trending Chapleau Moraine forms a dominant topographic feature. The primary ice-flow directions (Fig. 7.3), are an older SSW and southwards trend, and a younger SSE and SE trend. Although the SGB shares many geologic features with the mineral-rich AGB, it lacks any significant mineral production (Fumerton and Houle, 1993; Fumerton et al., 1993). The two principal commodity types found within the area are base metals and gold.

7.3 Geochemical data

7.3.1 Cape Breton

A total of 324 till samples were collected from the C-horizon of the soil profile in hand-dug pits surface pits (0.5 –1.0m deep) with an average spacing of 3 –5 km (McClenaghan and DiLabio, 1993). An additional 166 samples were collected around the abandoned Mindamar mine and two mineralized bedrock occurrences (Deep Cove and Blue Mountain) to document the nature of glacial dispersal in the region. More details on this survey can be found in McClenaghan and DiLabio (1993,1996). Figure 2 shows the location of the geochemical sample points, mineralized areas and abandoned mines. In this study geochemical data for the uppermost till sample were used at sites where pits were vertically sampled.

McClenaghan and DiLabio (1993) provide details on the geochemical analysis. The clay+silt (<0.063 mm) fraction was analysed by Inductively Coupled Plasma Emission Spectroscopy (ICP-ES) following a partial digestion in HCl and HNO₃ (3: 1). McClenaghan and Dilabio (1993) also present proportional symbol maps of the data as well as univariate statistics.

7.3.2 *Swayze greenstone belt*

A total of 845 geochemical samples were collected concurrently from humus, B-horizon soil and C-horizon till over the SGB at an average density of 1.5 km² (Bernier and Kaszyki, 1995; Bernier and Gof, 1993; Bernier, 1994; Bernier et al., 1996). The Shunsby and Kenty mine areas (Fig. 7.3) were sampled in more detail to characterize the distribution of metals in the locally sampled media with respect to glacial dispersal (i.e., orientation survey). However, these detailed surveys were not included in the regional analysis of the data to prevent biasing the results statistically and spatially.

Copper and gold grain counts, are the focus of this study. The samples were totally digested using hydrofluoric acid, and the clay+silt fraction were analysed using ICP-ES.

Till data were evaluated for quality using split and field duplicates. Approximately 1 in 15 samples were split for duplicate analyses and 1 field duplicate was collected for every 20 samples. Cu and Au grain analyses were evaluated for quality control using Thompson-Howarth precision control plots (Thompson and Howarth 1976, 1978) and were found to be within 10% precision levels.

7.4 **Dispersal Train Identification Algorithm (DTIA)**

A glacial dispersal train is characterized by a down-ice concentration of a given element that can be modeled by a negative exponential function of concentration versus distance (Fig.7.1). The algorithm developed in this paper, hereafter referred to as the dispersal train identification algorithm (*DTIA*), fits an exponential model to concentration-distance data for a succession of search directions, for any number of search points. It is currently programmed in FORTRAN, and searches from a set of search points, one at a time, in a user-specified direction using a wedge of a specified length and angle. The parameters used in the algorithm can be controlled and used to model various aspects of glacial dispersal trains.

Consider a geochemical variable, $z(x,y)$, measured at n sampling points where x and y are the coordinate locations over a region of interest. For example, z could be the concentration of Zn in till, and x and y the eastings and northings, respectively, of sample sites. The sample points are usually not on a regular grid, although this is not critical for the method. The objective is to search the sample points systematically for patterns that might indicate the presence of a dispersal train.

A set of search points is defined that is used to test for a dispersal train pattern. Search points may be at the same locations as the till sample points, or may be a grid of points defined independently. They could also be another set of points, such as the locations of known mineral occurrences or anomalous geochemical concentrations in bedrock. The following steps are repeated for each search point, and the process is illustrated in Figure 7.4.

1. For the j -th search point, identify the subset of sampling points that occur within distance L —i.e. the subset $K(1,2,\dots,k)$ sampling points for which *distance (search point to sampling point) is less than L metres*. L is known as the wedge length, and is typically a few thousand metres.
2. Compute the mean (or optionally the median) value of z in subset K , $kmed$. This is the local average of points that are within distance L from (but may in any direction of) the search point.
3. Determine a subset $P(1,2,\dots,p)$ of points from K that satisfy *direction (search point to sampling point) is in the interval $(\sigma + \theta/2, \sigma - \theta/2)$ degrees*, where θ is the wedge angle, and σ is the search direction (azimuth from north in degrees). This is the group of points within the search wedge for testing as representing a dispersal train by fitting a local exponential model and summarizing other characteristics.
4. Compute projected distance r of each point in P in direction σ from the search point. Then the concentration value z_i and distance r_i is known for each of the $i=1,2,\dots,p$ points in P . The projected distance r is the down-ice distance.

5. Compute the mean (or optionally the median) value of z in P , $pmed$, and determine the difference $diff = pmed - kmed$. This difference provides a measure of whether the average value of points within the wedge is greater than the local average, where 'local' is defined to be those points within distance L of the search point. Take the natural logarithms of z , and fit a straight line to the points in P (if $p > 3$), $\ln z (\hat{)} = a + br$, where a is the intercept and b is the slope to be estimated by least squares and $\ln z (\hat{)}$ indicates predicted value. Compute the standard error of b , denoted by se , and the test statistic $ts = b/se$. This statistic is the 'studentized' slope, and like a student t-test is a measure to evaluate whether the slope values are significantly different from zero. If the assumptions for a t-test are satisfied, a ts value less than -1.96 indicates that the slope in question would occur at random in only 5 cases out of 100. Even in situations where the formal assumptions for a t-test (normal distribution, independent random samples) are not strictly satisfied, ts values less than -2 provide an informal test of significance for a negative slope.
6. Save $i, L, \sigma, \theta, p, a, b, ts, pmed, diff$.
7. Repeat steps 3-7 for each search direction.
8. Repeat steps 1-8 for each search point.

The search radius (wedge length), L , is fixed for a given run of the program. A general guideline for the value of L may be obtained from an orientation survey, by visually inspecting proportional dot plots of the data or by estimating the range in a variogram of z . Search directions can be changed, but are generally set to be a series of azimuths from 0° to 360° in increments of 10° . The incremental change in the sequence of directions is not dependent on the wedge angle.

An important criterion to consider arises from the situation where a search wedge contains sufficient sample points for fitting the exponential function, but the sample points are unevenly distributed in distance from the search point. If there are no sample points 'close' to the search point, for example, the search point should be discarded. For example, with a wedge length L equal to 6 km, wedges where the nearest sample point is

greater than 1 km from the search point should be discarded. The radial distance to the closest point is denoted by *rmin*.

If the search points are on a regular grid, any of the output values such as θ , *b*, *ts*, *pmed*, *diff* or *rmin* can be displayed as images to facilitate interpretation. In addition, selection of search points can be carried out using thresholds and logical intersection to find those search points where more than one criterion is satisfied (see Fig.4).

An ideal dispersal train is expected to have a negative slope, with a small standard error and a value of *ts* less than -2. Ideally the length of the train will be within some optimal range, the average value of points in the wedge, *pmed*, will be relatively large, and the difference between the average concentration of points within the wedge will be significantly greater than those in the local search circle, as given by *diff*. The output from *DTIA* consists of a set of search points that can be mapped and displayed in various ways. Search points can be screened by selecting only those points that satisfy various criteria, defined with respect to thresholds. Typically, the points that satisfy the chosen thresholds can be displayed as maps, and a listing of best *points* that show the locations of potential dispersal trains (see Fig. 7.4). The points themselves may represent the head of a potential dispersal train (see Fig. 7.1) or in the case of surface mineralization, a possible bedrock /mineralized source zone of the dispersal train.

With experimentation, the most critical output parameters from *DTIA* are *b*, *ts*, *pmed* and *diff*. In the next section, some examples of testing the algorithm on artificial data and application to field data are described.

7.5 Results

During the algorithm development, *DTIA* was tested on simulated datasets to help constrain the best parameters to use and evaluate the algorithm performance. The rationale for using simulated data is that an artificial dispersal train can be produced with consistent (known) characteristics and controlled a spatial pattern (i.e., direction, size, length etc). The train can also be embedded in background noise (simulating geochemical

background) in a fully controlled manner. The Cape Breton dataset is one step removed from a fully controlled test of *DTIA* but does offer the advantages of the presence of documented glacial dispersal trains, well-known ice-flow directions and known mineralized bedrock source zones. The Swayze dataset represents a more difficult test for *DTIA*, as no documented dispersal trains are known; however, the ice-flow directions are well mapped.

7.5.1 *Summary of Simulations*

Appendix A-4 provides details on the various experiments performed using simulations of both ribbon- and fan-shaped dispersal trains embedded in varying levels of background noise. The simulations were useful as a ‘controlled lab environment’ in which *DTIA* could be systematically evaluated with respect to the effect of various parameters and search strategies on the identification of dispersal trains.

The simulations indicated that, (1) *ts* (and a negative slope) are the most diagnostic *DTIA* parameters and, (2) as background noise increases to approximately > than 1 standard deviation from the mean value of the train, spurious points begin to appear. However, the correct point can still be identified using *ts*, in combination with *pmed* and *diff*. Only when the noise (background) level is equal to the maximum value of the train, is the dispersal train impossible to identify using *DTIA*. This situation would not be common in nature.

Fan-shaped (distributed) dispersal trains are more difficult to identify especially in high background noise levels than ribbon-shaped dispersal trains. When the maximum background value approximates the mean value of the dispersal train, *DTIA* although identifying the true location of the dispersal train, also identified spurious points. Denser search grids are best for identifying the true location of the dispersal train in low to moderate background noise. *Pmed* and *diff* values must be increased when using dense search grids and datasets with high background noise to screen out spurious points.

7.5.2 Cape Breton Island

Nature of documented dispersal trains: Figure 7.2 shows the locations of documented dispersal trains from McClenaghan and DiLabio (1993,1996). The Yava deposit is characterized by a NE trending, 7 –15 km long ribbon-shaped dispersal train with anomalous levels of Zn and Pb in till. The dispersal train is derived from several low grade Pb-Zn showings SW and NE of the Yava mine which have been transported down the Salmon River valley to the NE by the second (youngest) glacial event (see Fig. 7.2). The Deep Cove, Cu-As dispersal train trends eastward to a maximum distance of 1 km and reflects the oldest glacial ice flow direction. Less developed dispersal patterns of Zn and Pb have also been noted. Due to the apparent short glacial transport distance, the identification of the Deep Cove dispersal train using this regional dataset (3-5 km density) is problematic. Till samples in the vicinity of the Blue Mountain, Copper Shaft and Gillis Mountain showings contain elevated concentrations of Cu, As, Zn and Pb and associated fan-shaped dispersal trains trend toward the NE paralleling the second youngest ice direction. The Stirling area is characterized by only slightly elevated levels in Pb and Au; the poor geochemical response may be masked by an exotic red till covering the surface of the area (McClenaghan and Dilabio, 1993). Visually there appears to be an eastward trend in the data in this vicinity perhaps representing dispersal by the oldest ice trend.

McClenaghan and Dilabio (1993) have found tills containing up to 10% rhyolite clasts derived from the Salmon River Porphyry up to 7 km down ice (NE). At 15 km the percentage decreases to 1%. Therefore search lengths ranging from 0 to 15 km may be appropriate.

Variogram analysis: Directional variograms were produced for the elements that are involved in documented dispersal trains (Zn, Pb) in the Cape Breton study area to determine whether a directional anisotropy that matches the known glacial dispersal directions, as evidenced by documented dispersal trains, exists in the till data. Table 7.1 presents the results.

Zn and Pb show variograms in which directional anisotropy can be identified, with orientations that correlate with known glacial dispersion directions. The anisotropic variogram *ranges* vary from 5 to approximately 8 km, which are consistent with the distance of documented glacial dispersal (McClenaghan and DiLabio, 1993,1996).

Experiment 1 – The effects of varying length, angle and direction (Pb, Zn): The documented Yava (Pb, Zn) dispersal train, trending NE down the Salmon River valley (Fig.7.5) was used to determine the sensitivity of *DTIA* output to changes in length (*L*), angle (α) and direction (θ) of the search wedge. Each of these three parameters was changed systematically and the resulting values of *pmed*, *diff*, and *ts* were plotted. These experiments indicated that although *pmed* and *diff* are crucial for identifying anomalous concentrations, thus identifying where element values are locally above background, the *ts* value is the most diagnostic parameter for identifying potential dispersal trains.

Figure 7. 6 shows for Pb how *ts* responds to changes in direction (Fig. 7.6a), wedge angle (Fig. 7.6b) and wedge direction (Fig. 7.6c), using the Yava deposit as the search point (see Fig. 7.5). In these calculations, two of the three parameters were held constant, using the best values determined from the previous search results, and the sensitivity of *ts* with incremental changes in the third parameter was evaluated. For example, Figure 7.6a indicates that *ts* is the greatest in 45° and 50° directions, which approximately matches the known NE direction of glacial dispersal. Figure 7.6b indicates that *ts* is insensitive to changes in angles greater than 35° . This is reasonable given the sampling pattern (see Fig. 7.5) which is restricted along a line (the till on the valley sides was not sampled). This paucity of sample points off the main axis means that an increase in wedge angle greater than 35° captures few additional sample points. Figure 7.6c shows *ts* values for various search lengths using the best angle and direction shown in Figures 7.6a and b. The best length of 6 km is generally consistent with documented field observations (McClenaghan and Dilabio, 1993) and the *range* parameter obtained from variograms of the Pb data (see Table 7.1). Figure 6d shows the best-fit line using an exponential model of glacial dispersion derived from a 6km search length using a 35° angle in a 48° direction

indicating that *DTIA* has successfully captured the dispersal train. Figure 7.7 shows the optimum wedge direction, length and angle, using the *ts* criterion, superimposed diagrammatically on a dot plot of the Pb values.

Figure 7.8 shows similar plots to Figure 7.6 except that the searches were conducted from the Blue Mountain Zn (Fig.7.2) using Zn data. Visual inspection of the Zn data in this vicinity indicates that potential dispersal trains in this area trend in a north to northeast direction and are broader (fan-shaped) than the Yava train. This presents a greater challenge to *DTIA* to identify broad dispersal patterns, as also indicated in the studies conducted on simulated data (Appendix A). The best parameters, determined from Figures 7.8a, b, and c are a 7 km length, 50° angle and 30° (NE) direction. Figure 7.8d shows the best-fit exponential model, for the optimum wedge. Figure 7.9 shows the optimum wedge superimposed on a dot plot of the Zn values.

Experiment 2 – Using search points on a grid: Unlike the previous experiment in which searches were conducted from known mines or prospects, searches were conducted from a regular grid of points to determine how well *DTIA* performs in the situation where no mineralization is known beforehand. Searching from a regular grid of search points has the advantage of identifying potential dispersal trains over the entire area of study, given that the density of till samples is sufficient to resolve regional or local dispersal trains. However, not only is the density of the sample data crucial, but also the density of search points must be on a sufficiently small interval to identify dispersal trains effectively.

A series of searches were conducting using the best parameters for Pb determined from experiment 1 (length of 6 km, angle of 35° and direction of 48° – NE), from 3 search grids over the entire study area at densities of 3, 1 and 0.5 km², respectively (see Fig. 7.10). The mode of calculation is different when using a search grid. Instead of focusing on the results from a single search point, a large point attribute table is generated, one row per search point, with values of wedge parameters and fit parameters as columns. The resulting table is imported into a GIS, where the grid points can be selected,

symbolized and plotted along with other data, such as dot plots of the geochemical values, for interpretation.

In order to evaluate the best grid density, a complete grid of search points was first evaluated without applying thresholds to weed out unlikely candidates. The exception was for wedges containing fewer than 3 sample points, because of the lack of reliability of the resulting statistics. A large table of points and their attributes was generated from the program for each grid resolution, and imported into a GIS for further analysis and display. In each case, thresholds were applied of 6.6, 2.0 and -2.0 were used for *pmed*, *diff* and *ts*, respectively. (Note that the *pmed* and *diff* calculations were applied to natural logarithms of ppm value, so these correspond to concentration values of $pmed=735$ ppm and $diff=7.4$ ppm.).

No candidate points were found using the 3 km^2 search grid, 5 were found using the 1 km^2 search grid and 6 points were found using the 0.5 km^2 search grid. Figure 7.11a shows the points, displayed as dots proportional to *ts*, for the 1 km search and Figure 7.11b shows the points identified using the 0.5 km^2 search grid. All candidate points, for both the 1 and 0.5 km^2 searches are found close to the Yava mine, on the southwest side. The point with the largest negative *ts* value (i.e. the wedge in which the exponential model line has the most significant negative slope) for the 0.5 km^2 grid is located less than 1 km SW of the Yava mine and represents the best candidate point for the location of the Yava dispersal train (Point 1 on Fig. 7.11b).

There is no doubt that by increasing the grid density, the optimum search point can be determined with greater reliability. The 3 km^2 grid clearly was inadequate, and the 1 and 0.5 km^2 grids were better. The actual resolution needed will depend on the scale of the dispersal trains and average density of the sampling points. Ideally, a search strategy that determines the location of search points by an automatic optimization approach (rather than an exhaustive grid search) would be ideal, but was beyond the scope of this study.

The selected search points for Pb using the 0.5 km^2 grid were superimposed on a

contoured surface of *ts* values in Figure 7.11. This plot illustrates that the *ts* value is insufficient on its own to determine the optimum points; the values of *pmed* and *diff* play an important role in restricting the candidate wedges to those that have elevated geochemical concentrations that are greater than the local neighbourhood.

Experiment 3 – Significant search directions: An experiment was devised which conducted searches in all directions from the 0.5 km² search grid for both Pb and Zn. The best angles and lengths were used as determined from experiment 1, discussed previously (6 km and 35° for Pb and 7km and 50° for Zn).

For each search point, a range of wedge directions was tried, starting from 0° to 360° in 15° increments, and computing *ts*, *pmed*, *diff*, *rmin* etc in each case. This produced a larger point attribute table, with 24 records per grid point for display and analysis in the GIS environment. Points were then systematically screened on the values for DTIA parameters (*pmed*, *diff*, *ts* as well as the *rmin* distance from the search point to the first sample point) until only a few candidate points remained as potential candidates as the head zones of dispersal trains.

Figure 7.12 shows the results of this screening process for Pb. The following values for screening candidate points were used (note thresholds for *pmed* and *diff* are in log units):

- all points where (*pmed* > 0) AND (*diff* > -10) AND (*ts* < 0) and the minimum number of points in the wedge = 4 (Fig. 7.12a) – Screen1 (not shown)
- Distance between the search point and first sample point (*rmin* () <= 2 km) (Fig 12a)- Screen 2
- AND (*Diff* > .5) (Fig. 7.12b) – Screen 3
- AND (*Pmed* > 5.0) (Fig. 7.12c) – Screen 4
- AND (*ts* <= -2.0) (Fig. 7.12d) – Screen 5

Note that the step from screen 2 to screen 3 (Fig. 7.12b to 7.12c) weeds out a great many points, using the criterion (*diff* > 0.5), ensuring that only wedges that enclose points that

are on average substantially greater than the local average, are retained. Finally, the points shown in Figure 7.12d are further reduced by requiring that the fitted slope as shown by ts is significantly less than zero.

In Fig 7.13a, the candidate points have been further reduced by requiring that ($rmin < 1$ km), and then classified (coloured) by wedge direction. Notice that although the principal dispersal trains are selected this way, in some cases the algorithm picks a direction 180° from the expected one. For example, the majority of the points in the Yava district indicate a north to northeast vector of glacial transport, agreeing with the known dispersal direction. However, a much greater spread of directions is found over the Blue Mountain area, some of which correlated with known dispersal directions (northwards to NE and eastward and southward), while others do not. This indicates that *DTIA* has found good fits irrespective of the known dispersal directions. Thus the geologist must visually screen these points based on field knowledge. It should be noted that a visual assessment of the Pb data displayed as proportional dots does not necessarily give the best picture of directions of glacial transport.

Figure 7.13b shows the final map of the screened points derived from the Zn till data. The same steps for screening the data, presented previously for Pb, were used except that the $pmcd$ thresholds was set to 6.0. The intermediate maps are not shown for space reasons. Again the points have been colour coded by *best directions*. Note that the two best points with a direction of 30° (NE) have been selected close to the Yava mine. However, two points have also been selected at the NE end of the Yava train with good fits in a SW direction. This indicates that results from *DTIA* must also been screened using reliable field knowledge as this technique is purely based on statistical analysis and pattern fitting.

7.5.3 Swayze greenstone belt data

Copper sampled from the clay+silt fraction of till, and gold grain counts in the heavy mineral fraction of till were used to test *DTIA*. Gold grains in till which are the product of

mechanical dispersal rather than chemical dispersion, make them ideal for testing this approach although the well-known *nugget effect* may result in local variability. Threshold levels for *DTIA* parameters (*pmed*, *diff*) were determined from probability plots for separating background and anomalous populations.

Orientation survey and striae directions: An orientation survey conducted over the Kenty Au district by Bernier (1994) revealed that the maximum glacial dispersal down-ice in till is approximately 3 km—as seen in gold counts and other elements. The orientation survey was carried over an area of well-exposed felsic volcanic bedrock that form topographic ridges, with ice flow directions perpendicular to the lithologic strike, and a well-exposed and broad zone of mineralization.

Fig 7.14a is a contour map showing the orientation of striae over the Swayze greenstone belt. Individual striae orientations, as measured in the field have been overlaid. Fig. 7.14b shows a histogram of striae orientations and Fig 7.14c shows a map of correlogram values for lag shifts in both eastings and northings constructed from the map of striae orientations shown on Figure 7.14a. A correlogram (Davis, 1986) is similar to a variogram for characterizing spatial autocorrelation, except that the correlation coefficient is used instead of the semi-variance. Fig. 7.14c clearly shows a strong SSW preferred orientation. Figures 7.14a, b and c (as well as Fig. 7.3) show that a strong southward-tending component is evident in the movement of glacial ice over the study area, regardless of age. The dominant orientation of striae (median value) is 190° (SSW). Other prominent orientations occur in S, SW, SSE and SE directions. The SE and SSE orientations are prevalent in the central part of the study area.

Gold grain counts: Directional variogram analysis at intervals of 20° of the gold grain data revealed that three orientations were prominent, possibly caused by glacial transport in these directions (Table 2). The most spatially coherent variograms were obtained for the NW-SE, N-S and NNE-SSW directions, results that are consistent with the dominant striae orientations (Fig. 7.14).

Visual inspection of wireframe and contour maps of Au data (Fig. 7.15) suggest that potential dispersal trains occur at locations A, B, C and D. The linear N-S feature at C is more than 25 km long. It may represent a series of dispersal trains, oriented in a north-south direction. This linear zone also parallels a linear zone of Au prospects.

A wedge length $L=5$ km and a direction (σ) = 40° was chosen based on the directional variogram results, and visual inspection of the maps shown in Fig 7.15. A grid of search points, 1.0 km^2 in spacing was used. The threshold approach for screening points based on the values of the output parameters was applied.

Figure 7.16 shows the final stage of the screening process using the same thresholds used for the Cape Breton data except for *pmed* which set to ≥ 5 (counts in log units).

Mapped striae directions and dots proportional to the Au grain counts have also been included. Figure 7.16a show the candidate points colour coded by best direction and Figure 7.16b shows the same points as square symbols that are proportional to *ts* values.

The 8 selected points are clustered around the known Kenty Au district (see Fig. 7.3).

DTIA has found directions with good fits that do not apparently correlate with known glacial dispersion directions indicating a potential limitation with *DTIA* (Fig. 7.16a).

However, the *best point* characterized by a best fit line (highest *ts* value - see Fig. 7.16b – Point 1) in a SSW direction (210°) does match the known glacial dispersion direction (see Fig. 7.14 as well as striae on Fig. 7.16b). Again this illustrates that *DTIA* is useful for narrowing down potential candidates for dispersal train locations but geological knowledge must be used in concert with the algorithm to make a final selection of candidate points.

The apparent very long dispersal train as indicated on Figure 7.15 (location C) was not identified due to insufficient search resolution (search length). The only potential glacial dispersal train identified by *DTIA* and visual analysis of the gold grain data as dot plots and interpolated maps, was location A (Kenty Au district – Fig.7.15 and Fig. 7.3).

Cu: Directional variograms (Table 7.3) show that the NE-SW and NW-SE directions correlate with the known glacial dispersal directions, whereas the E-W direction is

probably a reflection of the E-W trending lithology which dominates the study area (see Fig. 7.3).

Figure 7.17 shows an interpolated map and wireframe perspective presentation of the Cu data. Potential dispersal trains identified through visual analysis of the data have been marked on the figure. Based on visual analysis of Figure 7.17 and variogram analysis, a wedge length of 6 km and a wedge angle of 40° was chosen for conducting *DTIA* analysis.

The same screening process applied to the Au grain data was applied to the Cu data using the same thresholds except for *pmed* which was set to > 4 (ppm log units). Figure 7.18 shows the results of the last screening process ($ts < -2.0$), followed by colour coding the *best points* by direction. Fig 7.18a shows the *best points* as squares proportional to *ts* and Figure 7.18b shows the points colour coded to represent the directions of the best fit line. The *best points* cluster around the Shunsby base metal prospect (see Fig. 7.3) and in the southeastern portion of the study area. The point with the highest *ts* value (Point 1 on Fig. 7.18a *ts* of -4.2) indicates a best fit line trending towards the SW (210°) which generally match the mapped striae directions. This point lies over mafic volcanic rocks and may represent a mineralized bedrock source zone. Comparison to Cu values from rock, using the GIS, indicated elevated levels of Cu in this area. The two *best points* identified by *DTIA* in the southeastern portion of the study area have best fit lines trending in an easterly direction. These points are more a reflection of the ESE trending lithology in this area rather than dispersal trains. Figure 7.19a shows the best point (Point 1 on Fig. 7.18a) and the optimum wedge. Figure 7.19b shows the best fit line for this point.

The only potential glacial dispersal train identified by *DTIA* and visual analysis of the Cu data as dot plots and interpolated maps, was location A (Shunsby base metal district – Fig.7.17 and Fig. 7.3).

7.6 Discussion

Geochemical maps based on till data must contend with the problem of displaced anomalies due to ice movement. The ideal tool for analysis and interpretation of such

data would be a method that would somehow recognize the direction and distance of transport as a transport vector field, and restore the observations to their pre-transport positions. This paper represents a small step towards this goal, in proposing an automatic tool for detecting dispersal trains in geochemical data. Even this seemingly modest task is difficult, however, for several reasons, of which two predominate.

- (1) Because there is only a general idea of what a real dispersal train looks like in geochemical survey data, the notion of applying a template matching approach—iteratively comparing the local form of the geochemical surface to an idealized 2.5 D shape—is inevitably an uncertain process. We do not know the length or width of the train, or its direction. We do not know how much local relief there will be in the geochemical surface in relation to the local background. Real dispersal trains may be subject to more than one direction of ice movement, and other factors affect geochemical values besides the effect of transport and dilution by ice, such as effects of weathering and erosion, variation in geochemical background and uncertainty about the nature of the chemistry of the mineralized source.
- (2) Even if idealized trains were well enough defined to allow detection by template matching, spatial resolution of till samples may be inadequate to allow train recognition. In order to recognize a dispersal train that is, say, 5 km long and up to 2 km wide, it may be necessary to have till samples spaced not more than 0.5 km apart, so that on average the train would consist of about 10 samples. Even this sample density may be insufficient unless the geochemical relief and shape of the feature is clear.

The approach described here is therefore best regarded as an exploratory spatial data analysis tool, and the results must be carefully reviewed in light of what is known about the local glacial history from other evidence.

The only other quantitative approach to the problem of which the authors are aware is the use of directional variograms. Directional variograms provide a measure of spatial

autocorrelation the data, broken down by orientation. The results of directional variograms can show which orientations have the greatest spatial autocorrelation, as expressed by the sill and range values. Directional variograms are, however, based on all the data from the study area at once (in theory it is possible to examine local variograms, but in practice there are usually too few sample points, particularly for directional variograms, for reliable results). And directional variograms can only give an orientation, such as E-W, and there is no information about the sense of direction--it could be towards the E or towards the W. In the work of Herzfeld and Higginson (1996) local variograms were calculated on images of seafloor elevation, and parameters fitted to the variograms to characterize their shape were themselves imaged producing new measures of geometric features on the seafloor--but in that situation the data volume was large, the data value being derived from scanning instruments. The spatial density of till geochemical measurements is totally inadequate to support such an approach in a mineral exploration environment.

The *DTIA* approach, however, is defined to be local, and examines a spatial data field for particular instances of a certain pattern. Further, it is specifically directional, searching for a shape in a particular direction. The philosophy of *DTIA* is therefore totally different than directional variography, although the information obtained from data may be complementary.

7.7 Summary and Conclusions

Results from this paper indicate that *DTIA* can be useful for automatically identifying potential dispersal trains in regional till data. It has been shown that the algorithm works satisfactorily on simulated data, and on data from an area in Cape Breton with known geochemical dispersal trains. When it was applied to data from the Swayze greenstone belt, with no previously identified dispersal trains, *DTIA* recognized a number of candidate trains whose directions agree with directions determined from glacial striae. The user has control of a number of algorithm parameters that can be used to model dispersal train patterns, such as wedge length and angle. The user also has the option of

searching in any given direction to look for patterns in the data that may be related to glacial dispersion.

The experiments using simulated data (Appendix A) show that the search algorithm is quite robust as it can identify dispersal trains even in moderate to high levels of background noise. Ribbon trains are easier to identify than fan-shaped trains due to their more compact and continuous pattern. Fan-shaped trains are difficult to identify in situations with relatively high background levels.

DTIA is, however, not a *black box* that can be applied without careful selection of various thresholds for parameters, and the results treated with caution and evaluated against geological knowledge of an area and its glacial history. The geologist must carefully screen each candidate point found by *DTIA* using the following criteria:

- *pmed* and *diff* must be high, demonstrating that the average value of points occurring inside the candidate wedge are generally high, and anomalous with respect to local background
- The value of *ts*, a statistic to test that the slope of the line fitted to points within the wedge is significant, should be less than about -2.0
- Search wedges that are significant in other ways must be checked to see whether the sampling point closest to the apex (at distance *rmin*) is no further than some threshold, in most instances less than 1 km. Otherwise the fit may be good, but the wedge apex may be an inappropriate candidate as the head of a dispersal train.
- Visual analysis of the values of sample points inside the wedge versus distance from the apex to evaluate the character of the dispersal pattern, and how well the fitted exponential model (and 95% confidence limit) accounts for the data points.

Besides examining the candidate points, and their associated wedges, the geologist should assess whether the direction is consistent with known glacial dispersion directions

(if known). Results of the *DTIA* analysis should be evaluated with respect to supporting geoscience data (topography etc), and this step is most conveniently carried out in a GIS.

Potential dispersal trains can be identified based on individual parameters or all the calculated parameters using a logical AND operations. Maps of *ts*, *pmed* and *diff* can be produced using a GIS. Selection and display of candidate points on the basis of logical combinations of criteria facilitate the interpretation of the results. The *ts* value in concert with a negative slope (*b*) appears to be the most diagnostic parameter for identifying potential dispersal trains. However *ts* should be used in combination with high values for *pmed* and *diff* to locate dispersal trains that are characterized by good exponential fits but also anomalous concentrations of an element (*pmed*) as well as a large *diff* value indicating that locally an anomalous concentration of the element does exist.

The final following observations can be made:

- It is important to match the *DTIA* parameters with dispersal train dimensions as too large a wedge angle or an overly long wedge length may cause identification of spurious points. An iterative approach may be needed to achieve this, because there is usually insufficient data about glacial dispersion *a priori* to set angle and length values.
- With respect to the density of search points, using a high-density grid of search points is best to resolve potential dispersal trains, especially with respect to dispersal directions. The search grid should be ideally be of a greater spatial density than the average density of the till data points. In this case the average density of the till data was one point per 3-5 km² for the Cape Breton data and the best results were achieved using a one point per 0.5 km² grid, as compared to lower density grids.

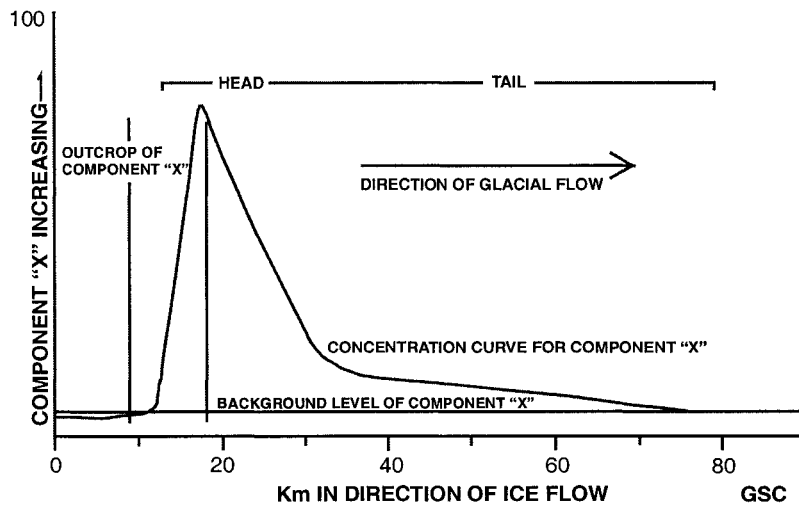


Figure 7.1 Theoretical model of glacial dispersal train

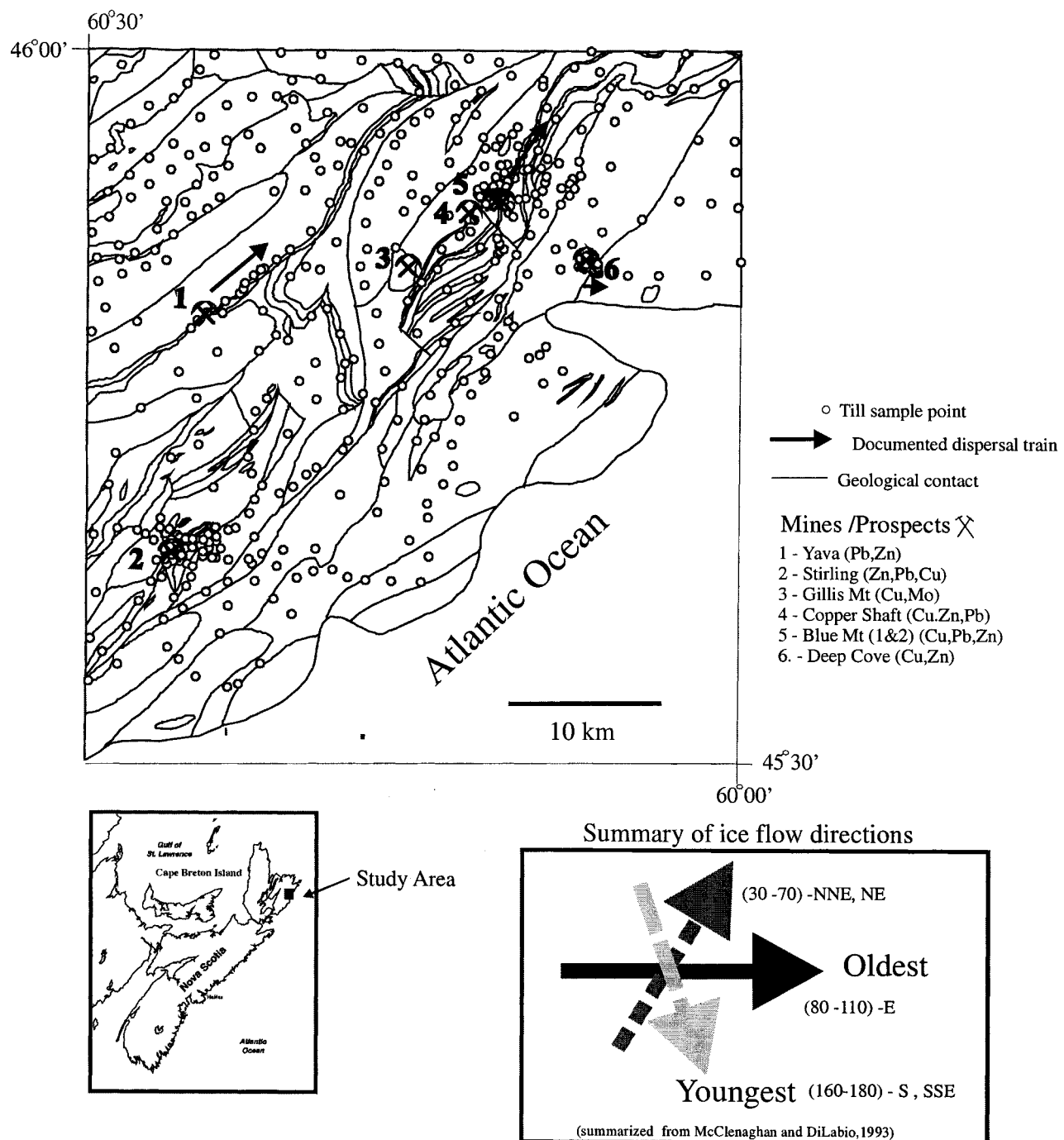


Figure 7.2 Cape Breton study area

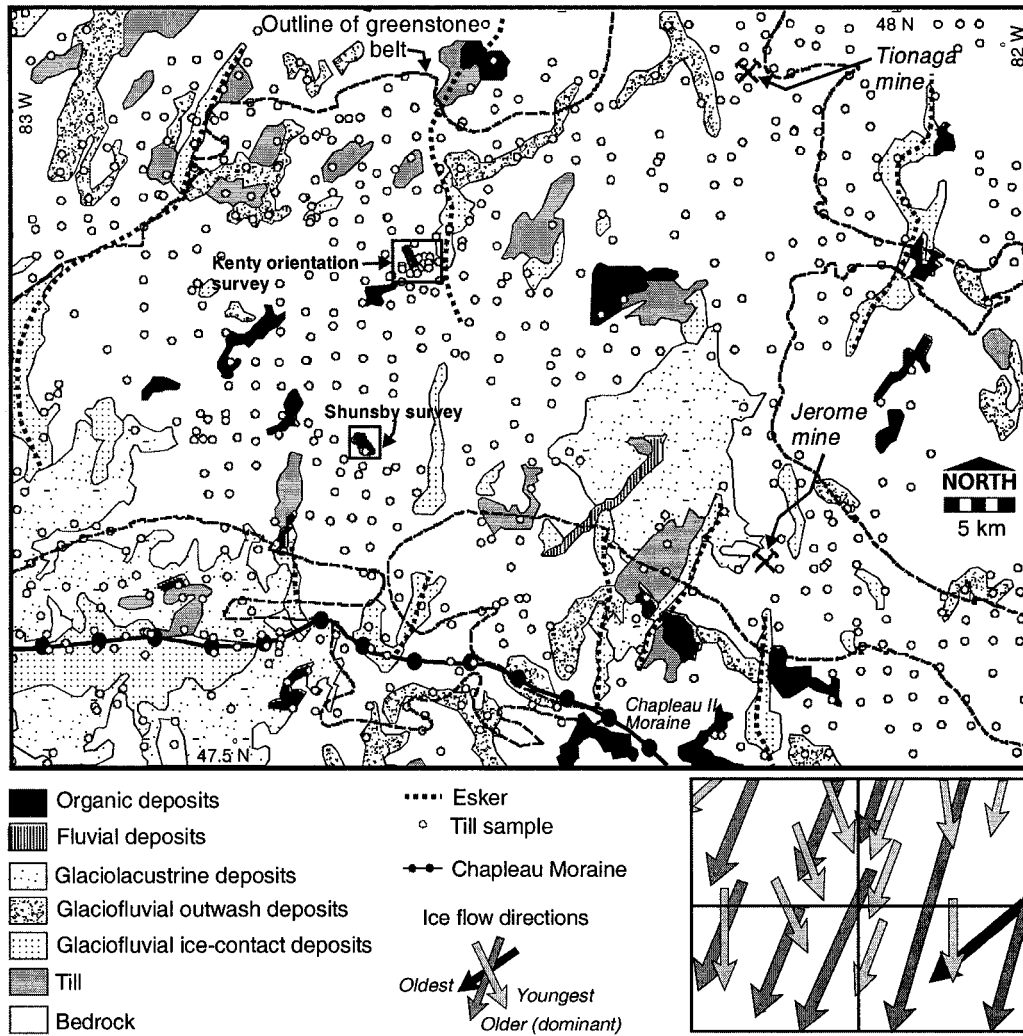


Figure 7.3 Swayze greenstone belt study area

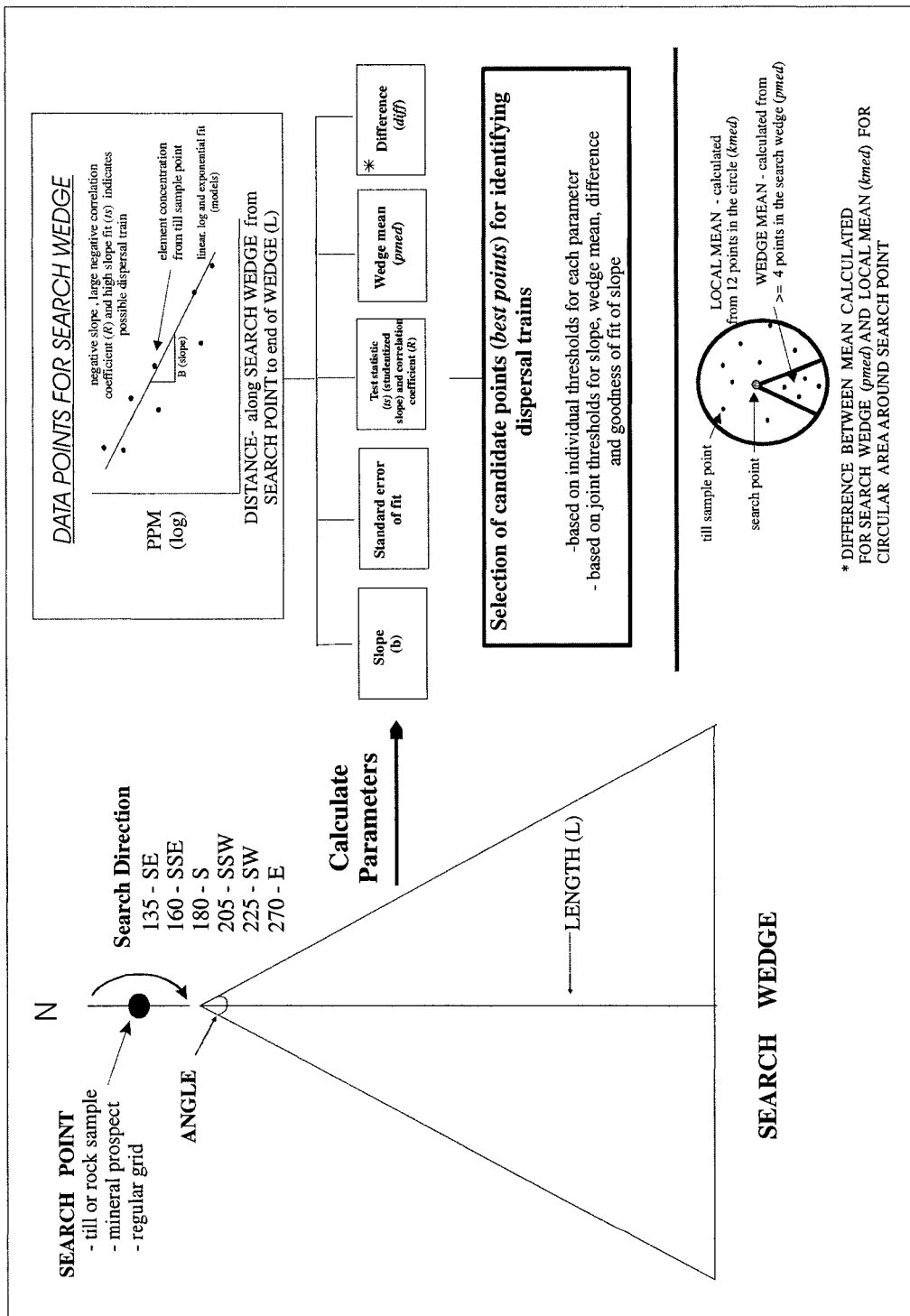


Figure 7.4 Dispersal train identification algorithm (DTIA) – summary

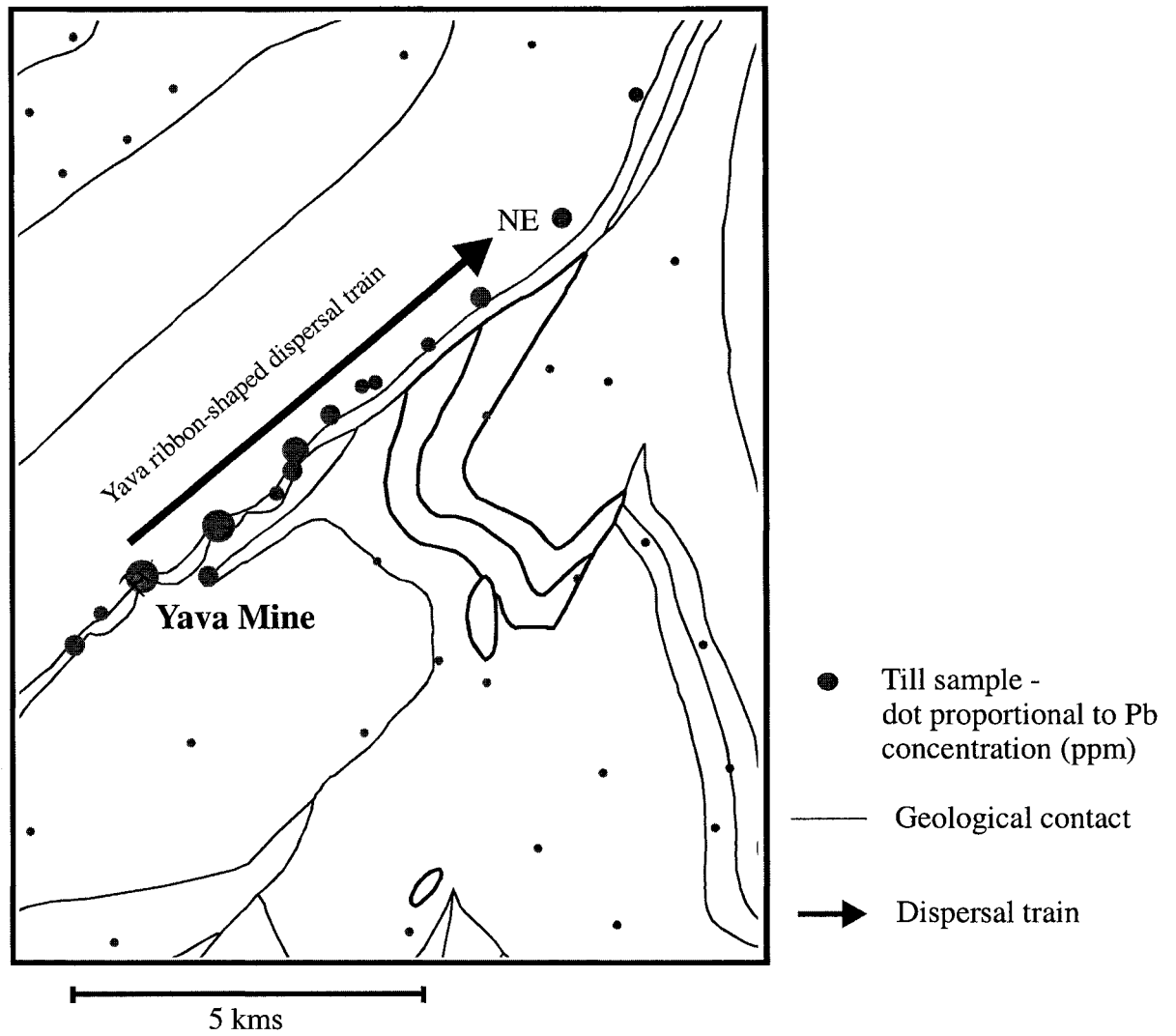
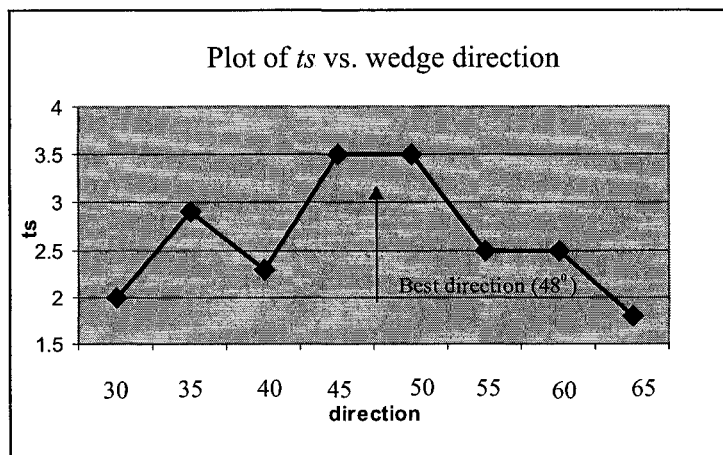
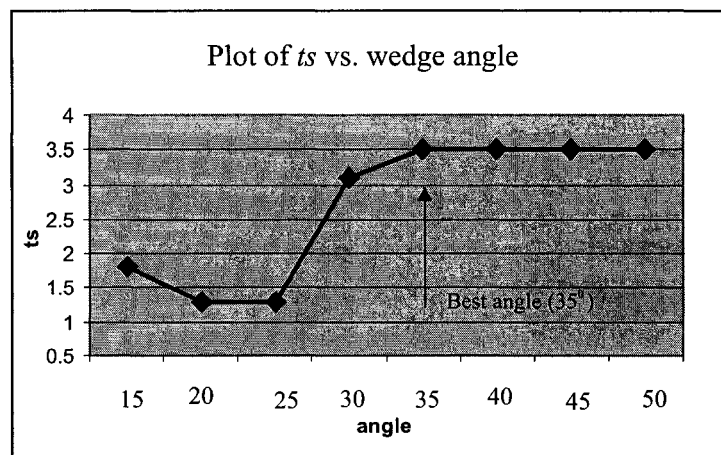


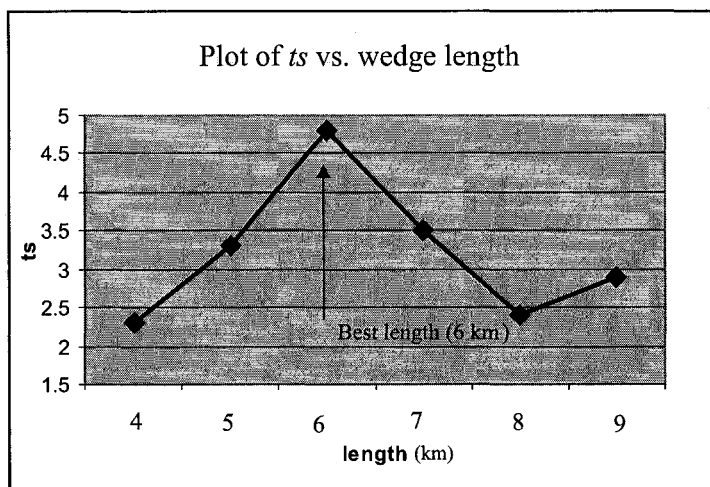
Figure 7.5 Yava Pb dispersal train – southeastern Nova Scotia



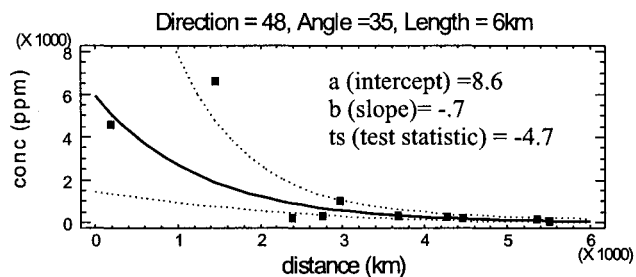
A - wedge angle = 35° and length = 6 km - using Pb



B - wedge direction = 48° (NE) and length = 6 km - using Pb



C - wedge direction = 48° (NE) and wedge angle = 35° - using Pb



D - best fit line (negative exponential model) for Yava Pb, ribbon-shaped dispersal train, using a 6 km search length, 48° direction (NE) and 35° wedge angle (these *best parameters* are based on the highest *ts* values derived from the plots A, B and C)

Figure 7.6 Plots of *ts* vs. (a) wedge direction, (b) wedge angle, (c) wedge length – for Pb in till – Cape Breton till dataset, (d) best fit line (negative exponential model) – search conducted from Yava mine

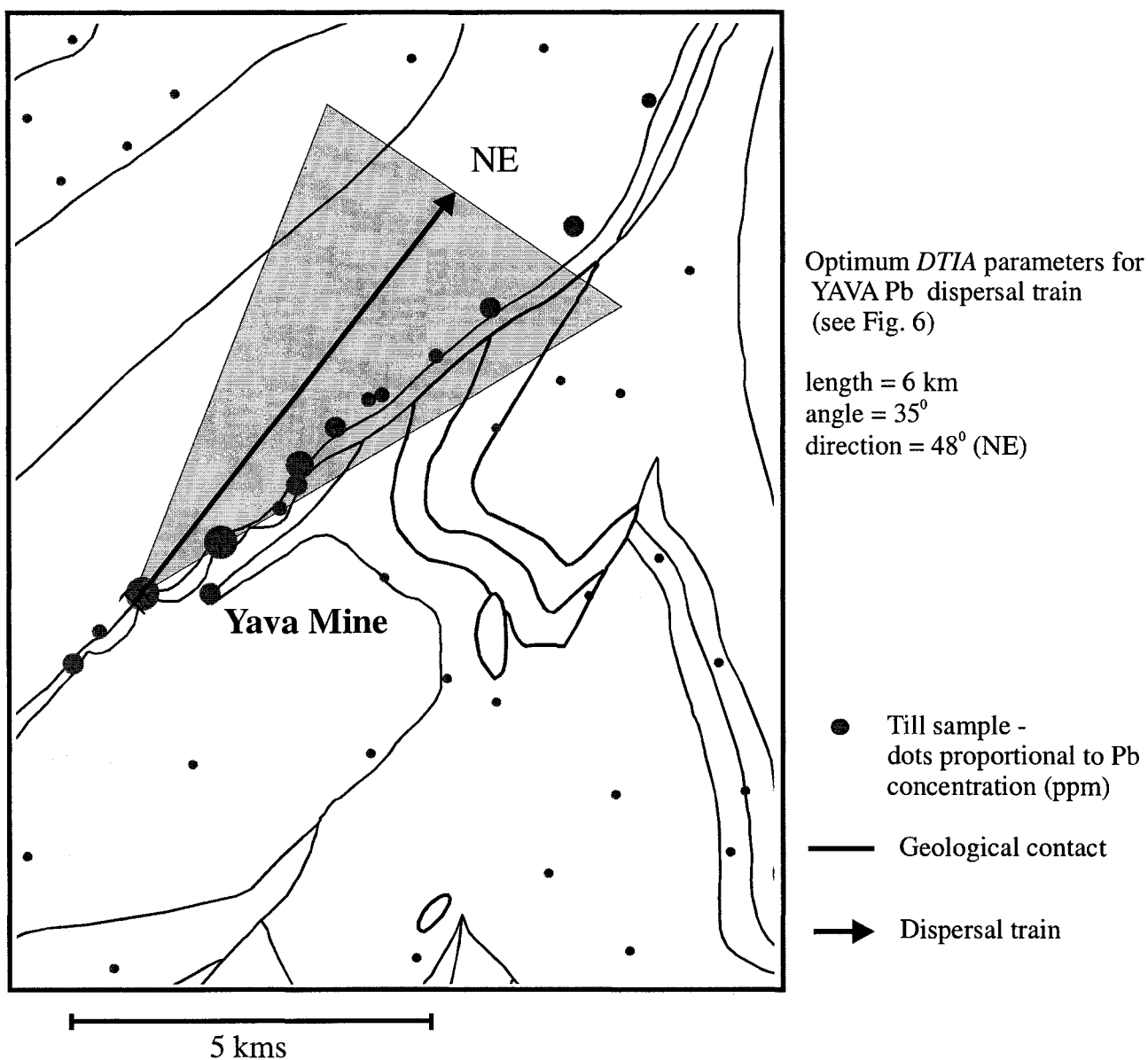
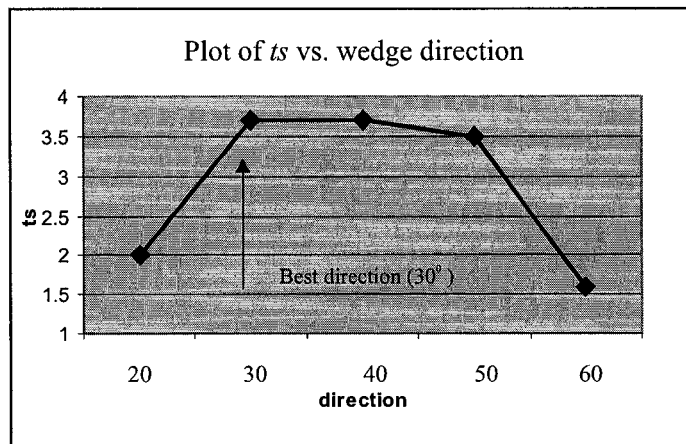
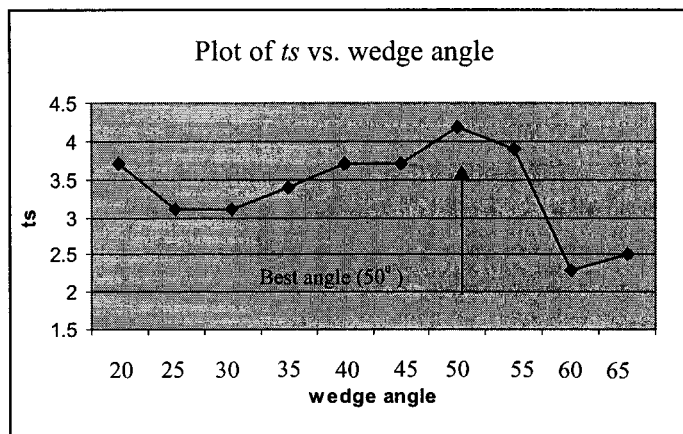


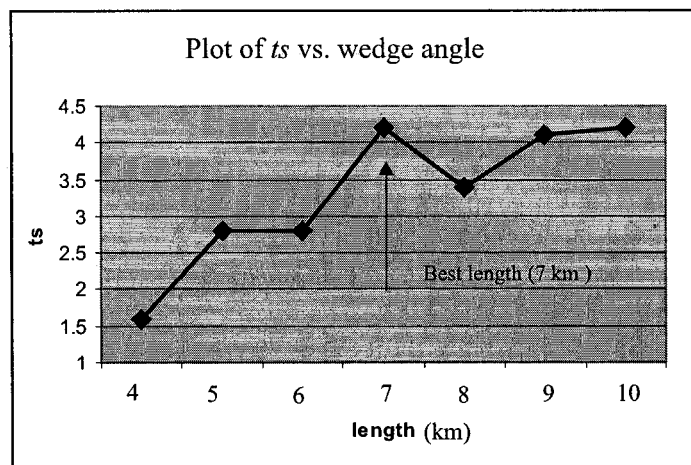
Figure 7.7 Optimum *DTIA* parameters for Yava, Pb glacial dispersion train (wedge length, angle and direction of 6 km, 35° and 48° (NE), respectively)



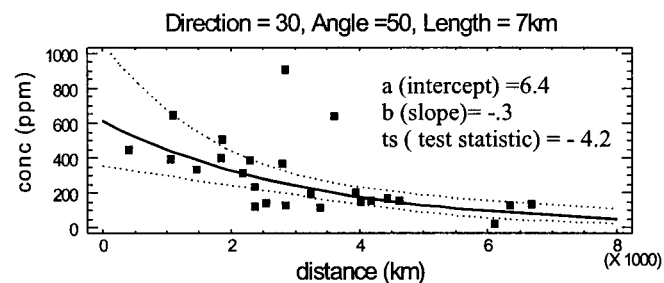
A - wedge angle = 40° and length = 7 km - using Zn



B - direction = 30° (NE) and length = 7 km - using Zn



B - direction = 30° (NE) and wedge angle = 40° - using Zn



D- best fit line (negative exponential model) for Blue Mountain Zn, fan-shaped dispersal train using a 7 km search length, 30° direction (NE) and 50° wedge angle (these *best parameters* are based on the highest *ts* values derived from the plots A, B and C)

Figure 7.8 Plots of *ts* vs. (a) wedge direction, (b) wedge angle, (c) wedge length – for Zn in till – Cape Breton till dataset, (d) best fit line (negative exponential model) – search conducted from Blue Mountain Zn prospect

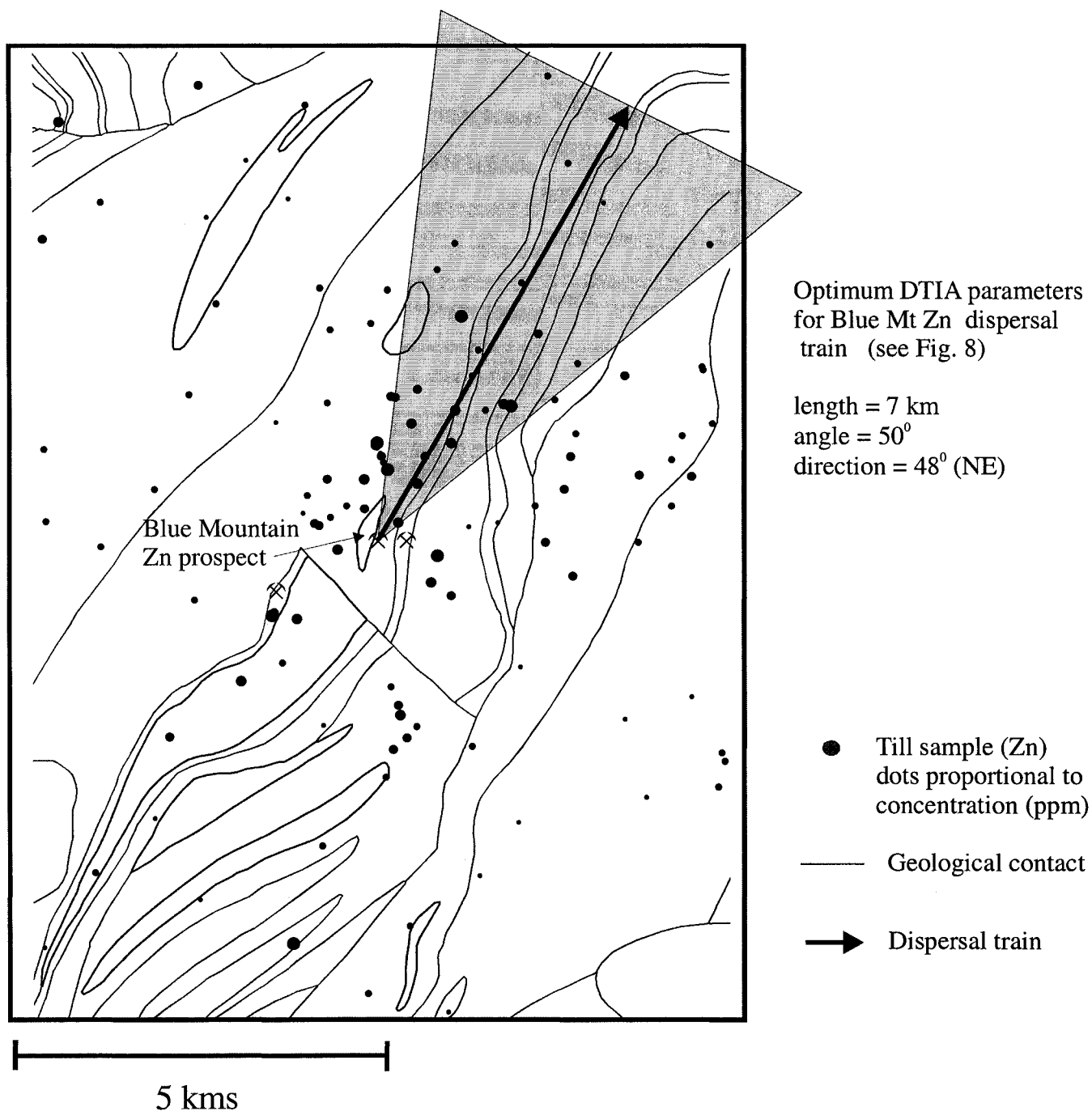
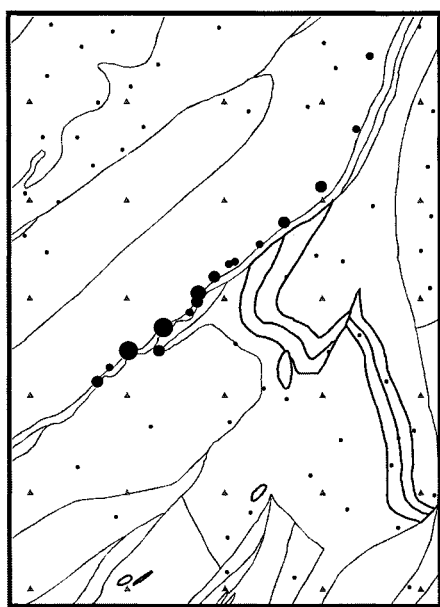
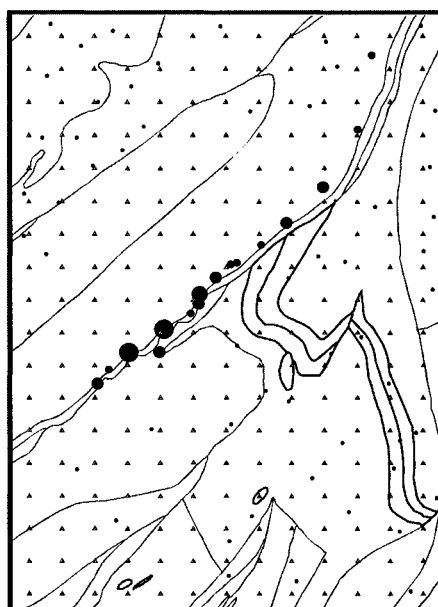


Figure 7.9 Optimum *DTIA* parameters for Blue Mountain, Zn glacial dispersion train (wedge length, angle and direction of 7 km, 50° and 30° (NE), respectively)

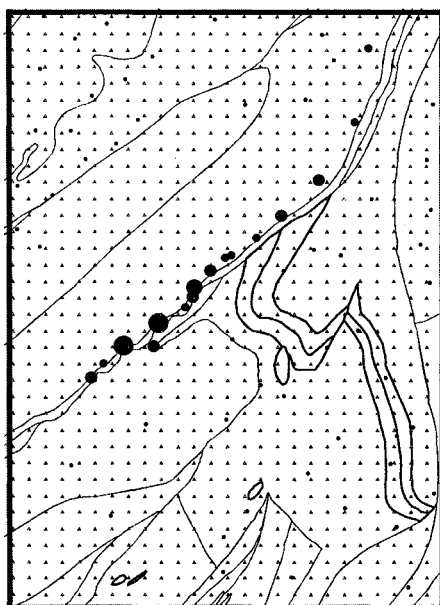


Low density point search grid - 3 km^2



Moderate density point search grid - 1 km^2

3 km

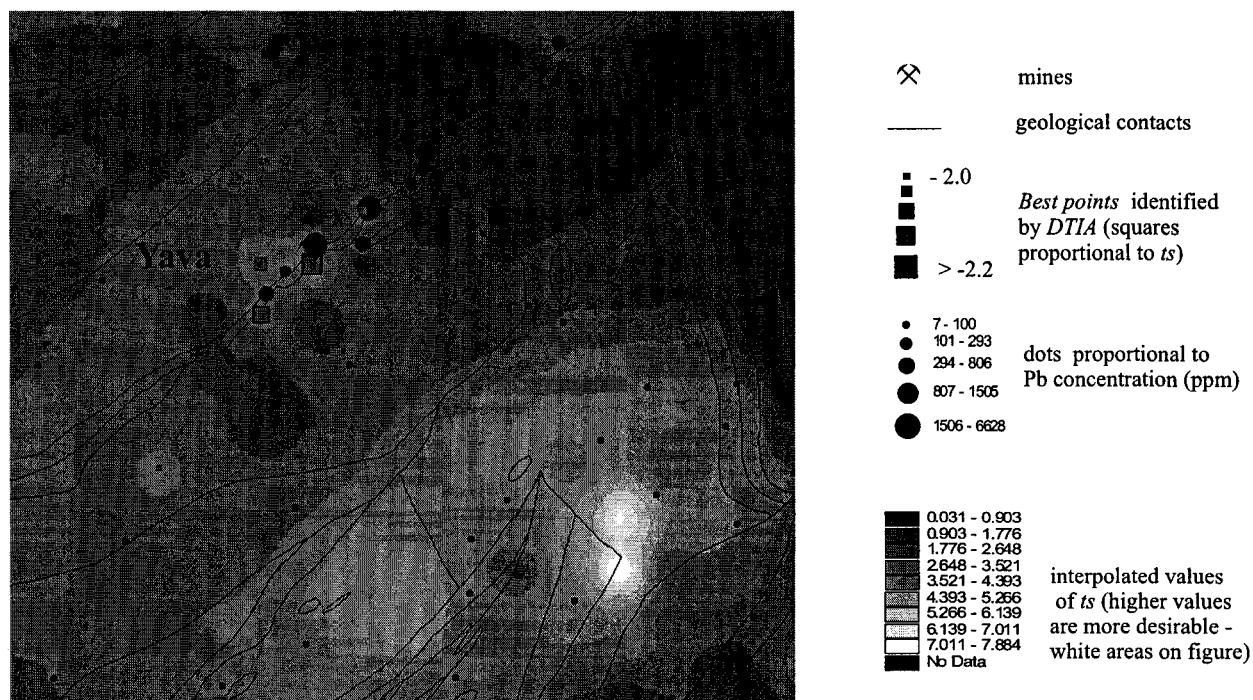


High density point search grid - 0.5 km^2

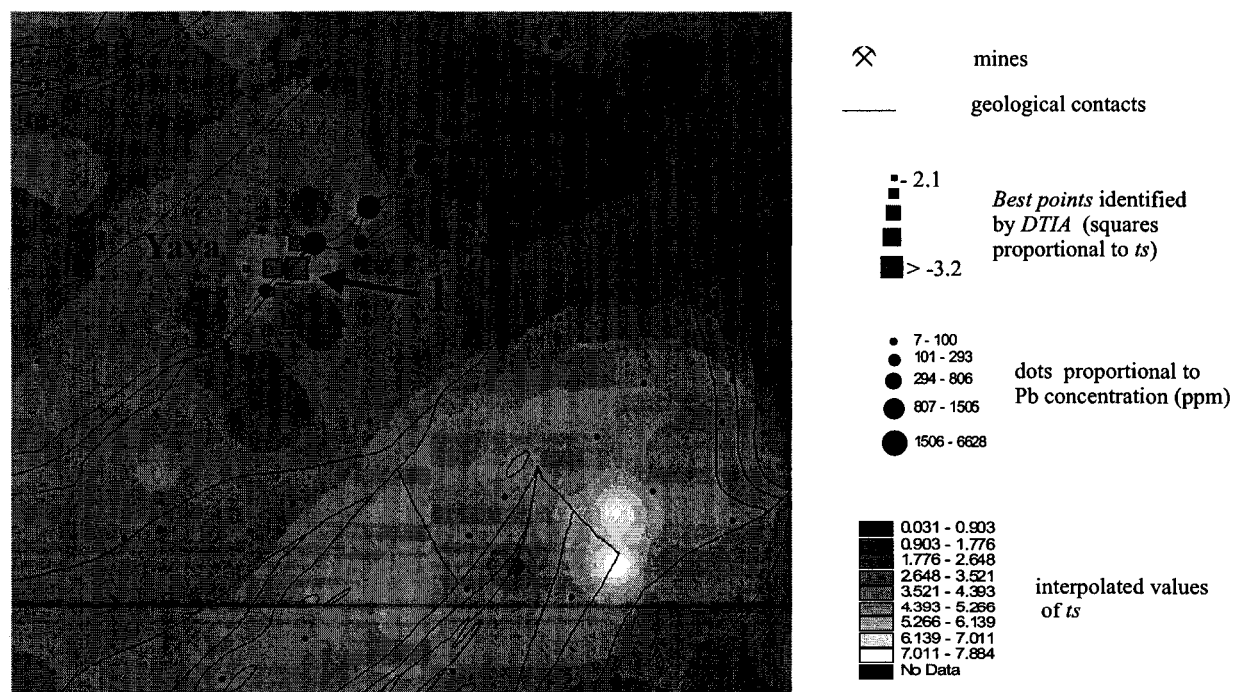
- Till sample site - dots proportional to Pb concentration (ppm)
- ▲ Search points
- Lithological contacts

Search grids used for Pb
dispersal train search over Yava mine area

Figure 7.10 Varying search grids for Yava dispersal train (a) – 3 km^2 point density, (b) 1 km^2 point density, (c) 0.5 km^2 point density



A - best points derived from a 1 km² search grid of points (see Fig. 10) - Pb - length = 6 km, angle = 35°, direction = 48°



B - best points derived from a 0.5 km² search grid of points (see Fig. 10) - Pb - length = 6 km, angle = 35°, direction = 48°

Figure 7.11 Best points identified by DTIA conducted using Pb data for the Yava area, using search length, angle and direction of 6 km, 35° and 48° (NE), respectively, (a) search conducted using a 1 km² search grid, (b) search conducted using 0.5 km² search grid

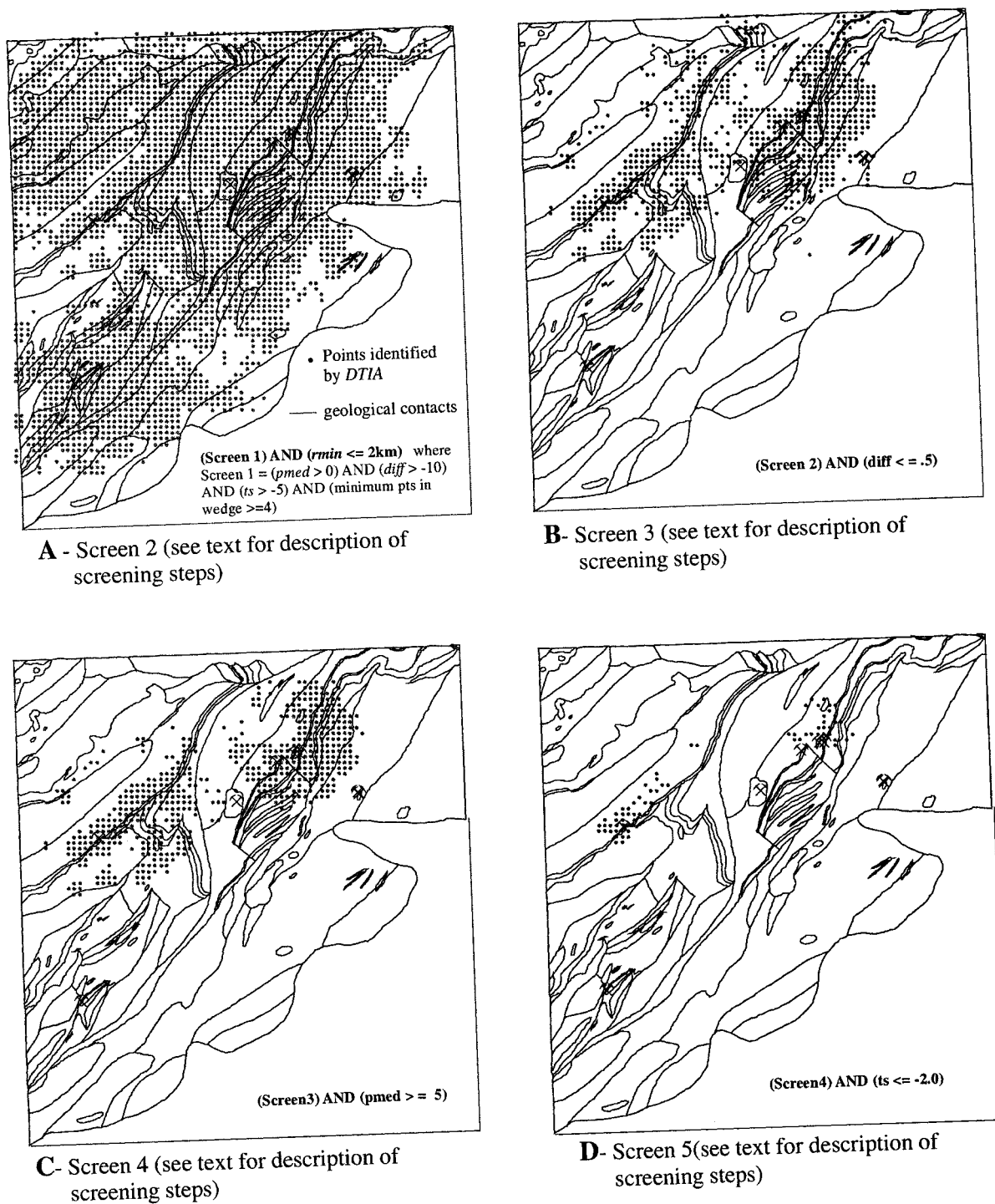
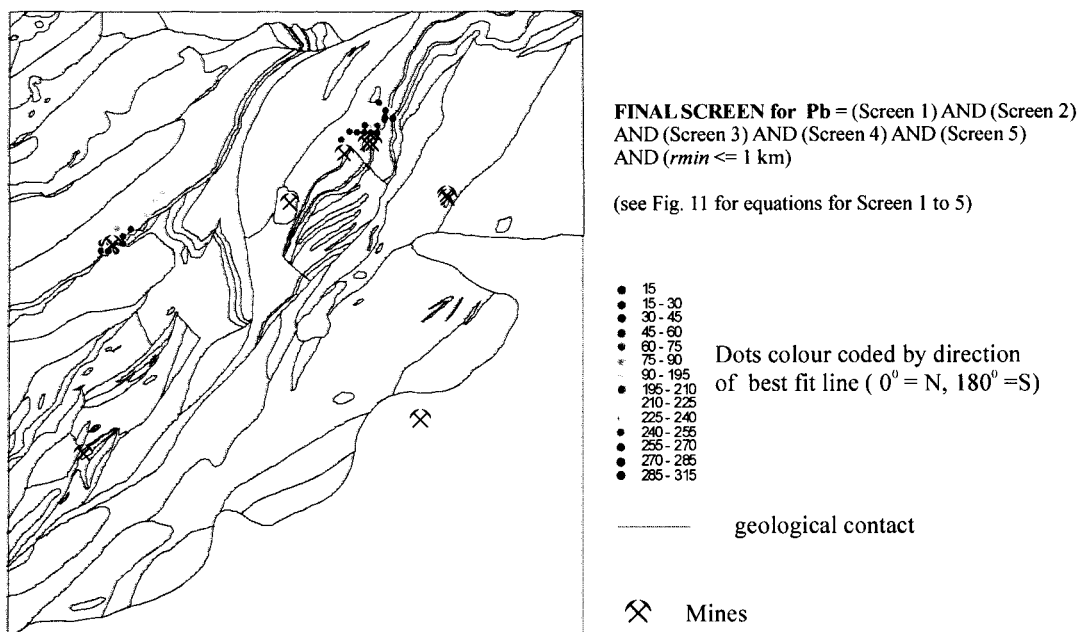
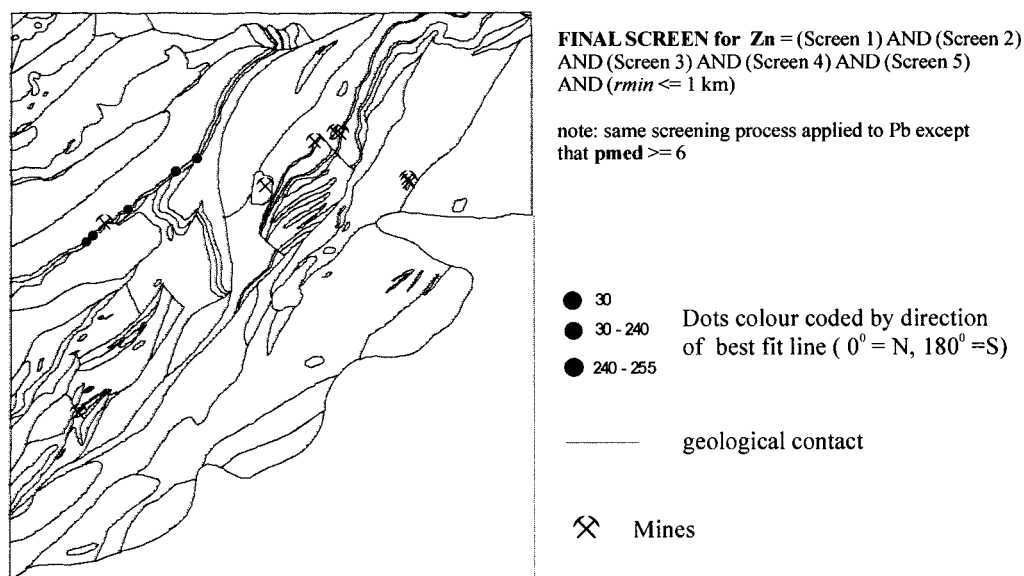


Figure 7.12 Screening steps applied to Pb data using search using 0.5 km^2 point grid wedge length of 6 km , wedge angle of 35° and multiple directions ($0 - 360^\circ$ in 15° increments), (a) results of Screen 1 AND ($r_{min} \leq 2\text{km}$), (b) results of Screen 2 AND ($diff \leq 0.5$), (c) results of Screen 3 AND ($p_{med} \geq 5$), (d) results of Screen 4 AND ($ts \leq -2.0$) – see text for description of screening process and screening equations



A - results of final screen on Pb using a 0.5 km^2 point grid search using best DTIA parameters (length = 6 km, angle = 35° , multiple directions (see text))



B- results of final screen on Zn using a 0.5 km^2 point grid search using best DTIA parameters (length = 7 km, angle = 50° , multiple directions (see text))

Figure 7.13 Results of final screen on Pb data – *Best points* (showing potential locations of glacial dispersal trains) identified by DTIA using Pb, 0.5 km^2 search grid, 6 km wedge length, 35° wedge angle and multiple directions, (a) best points colour coded by direction of best fit line, (b) best points proportional to t_s

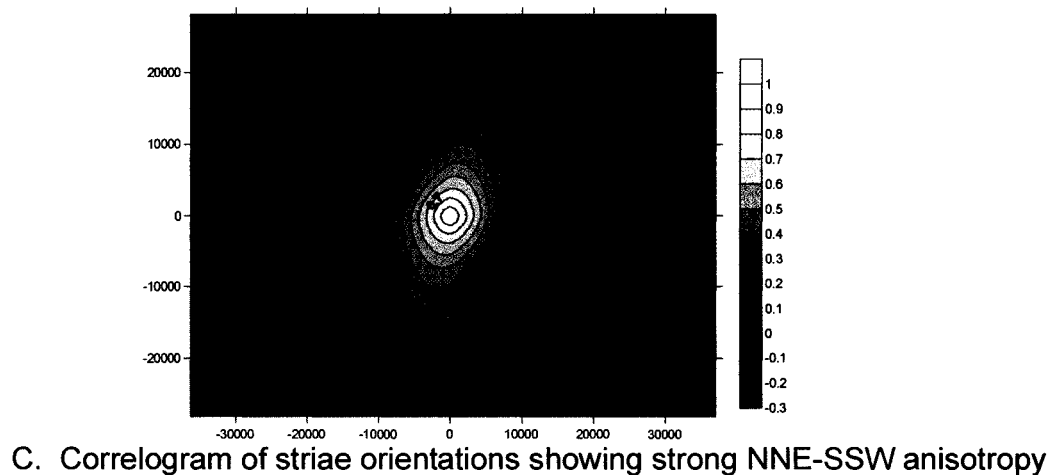
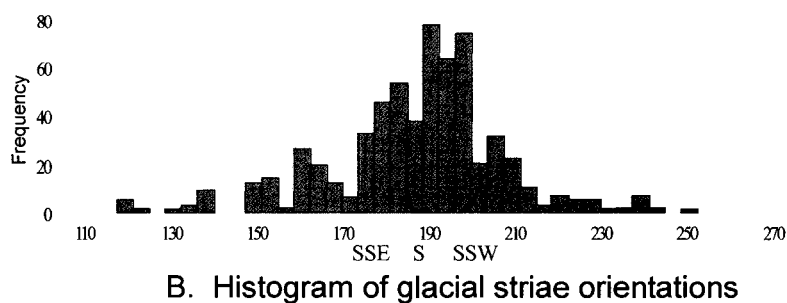
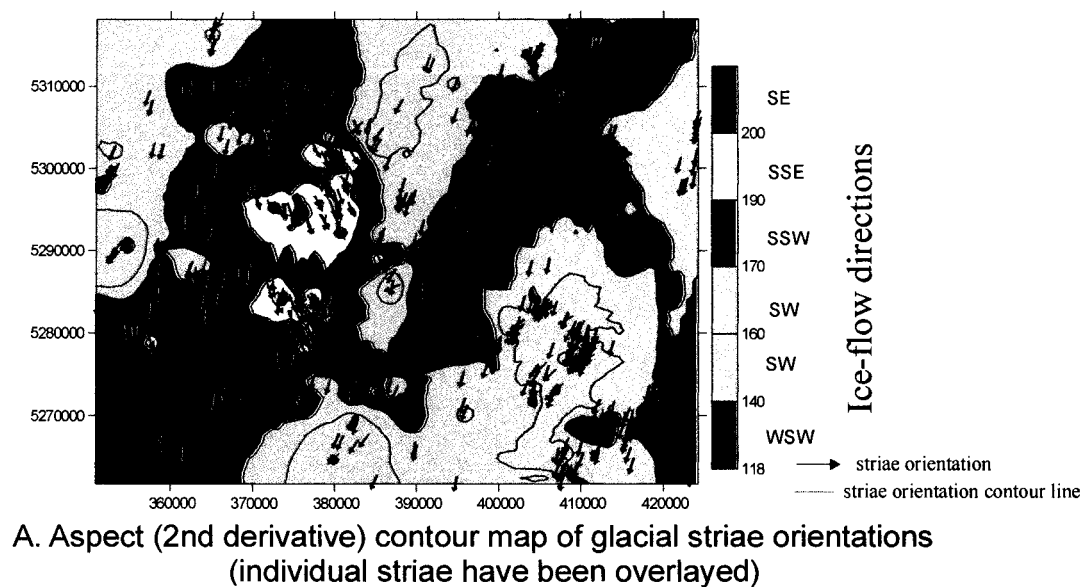


Figure 7.14 Summary of ice-flow directions – Swayze greenstone belt (a) aspect (2nd derivative) contour map of glacial striae orientation, (b) histogram of glacial striae, (c) correlogram of striae orientations

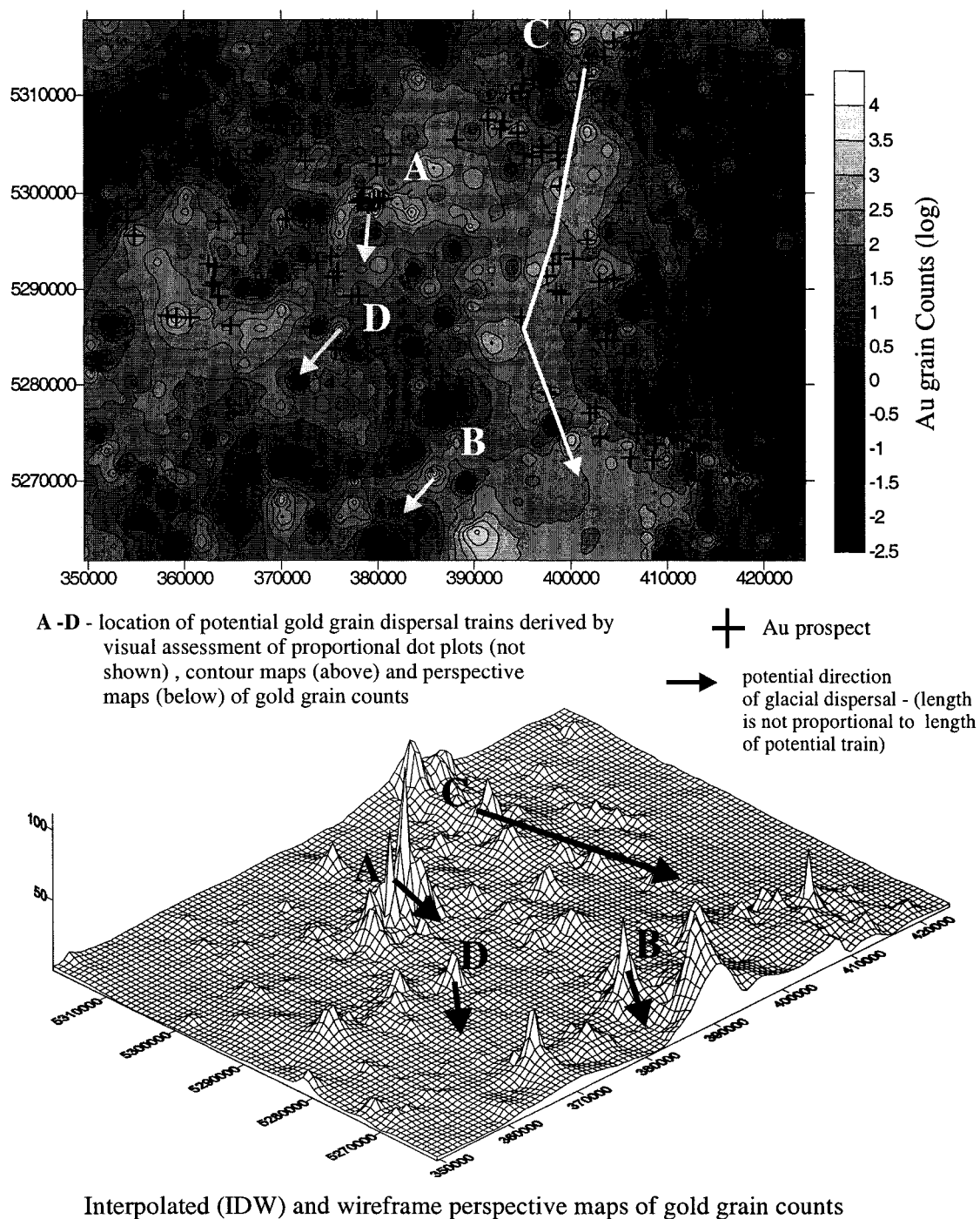
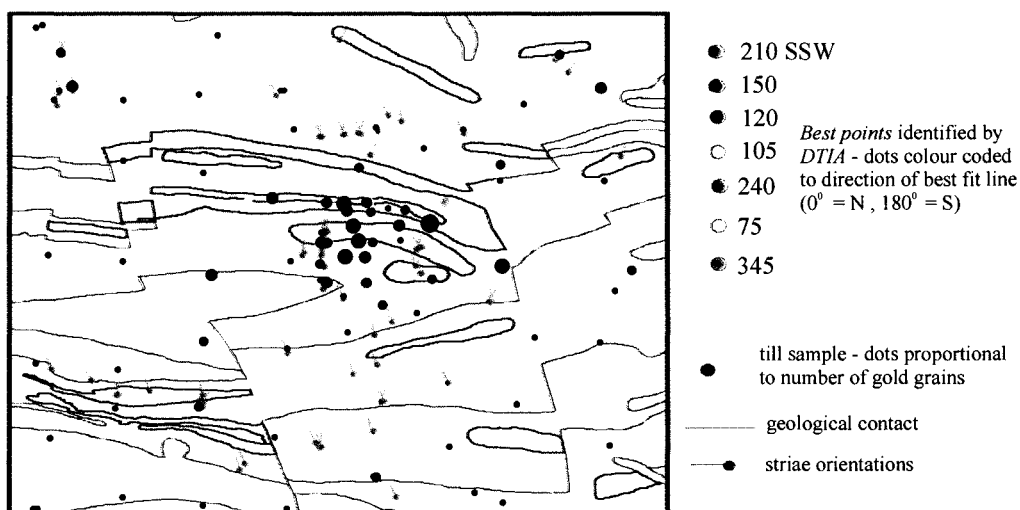
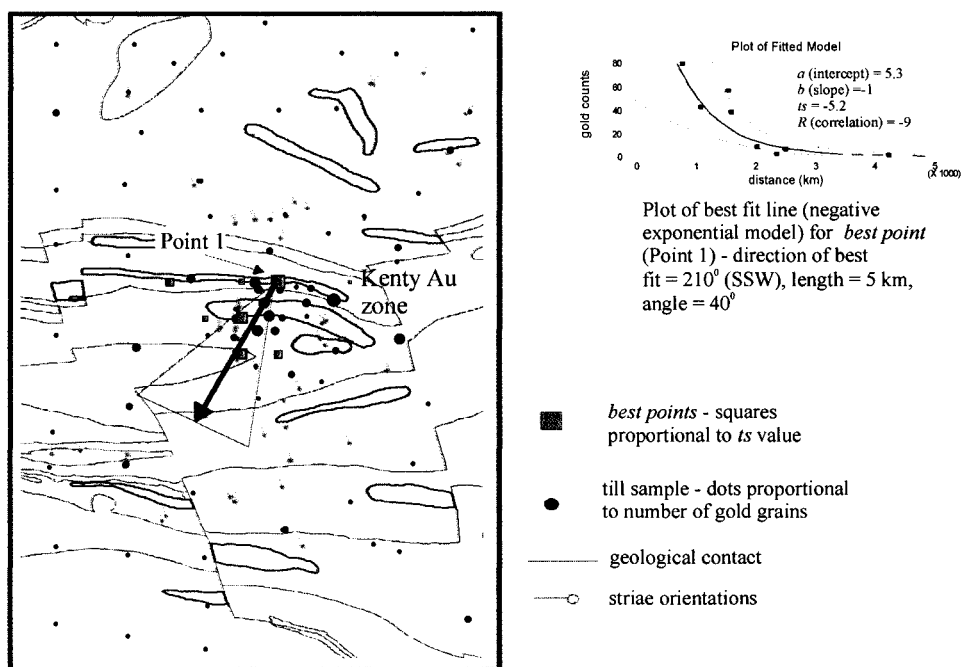


Figure 7.15 Interpolated and wireframe maps showing gold grain counts in till – gold grain counts have been log-transformed – arrows indicated location and direction of potential dispersal trains identified through visual interpretation of displayed maps

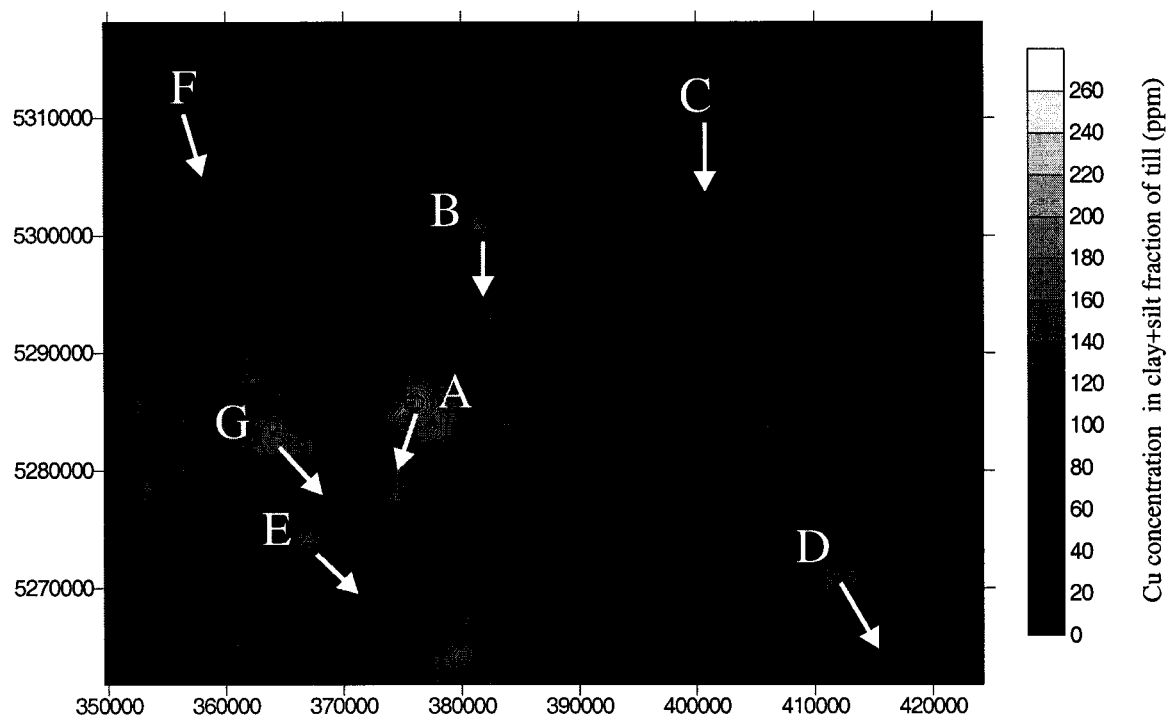


A Best points identified by DTIA using a 1.5 km^2 search grid of points - these represent candidates for the heads of potential dispersal trains or up-ice mineralized source zones - dots have been colour coded to direction of best fit line (negative exponential model)



B Best points identified by DTIA using a 1 km^2 search grid of points - squares are proportional to ts values (larger squares represent larger negative ts values)

Figure 7.16 Best points representing locations of potential glacial dispersal trains (gold grains) identified by DTIA – using 1.5 km^2 point search grid, wedge length – 5 km, wedge angle – 40° and multiple directions ($0-360^\circ$ in 15° increments), (a) best points colour coded by direction of best fit line, (b) best points proportional to ts – also shows plot of best fit line for Point # 1



A - G - location of potential Cu dispersal trains derived by visual assessment of proportional dot plots (not shown), contour maps (above) and perspective maps (below) of Cu concentration in till

→ Possible glacial dispersion direction - length not proportional to length of potential dispersal train

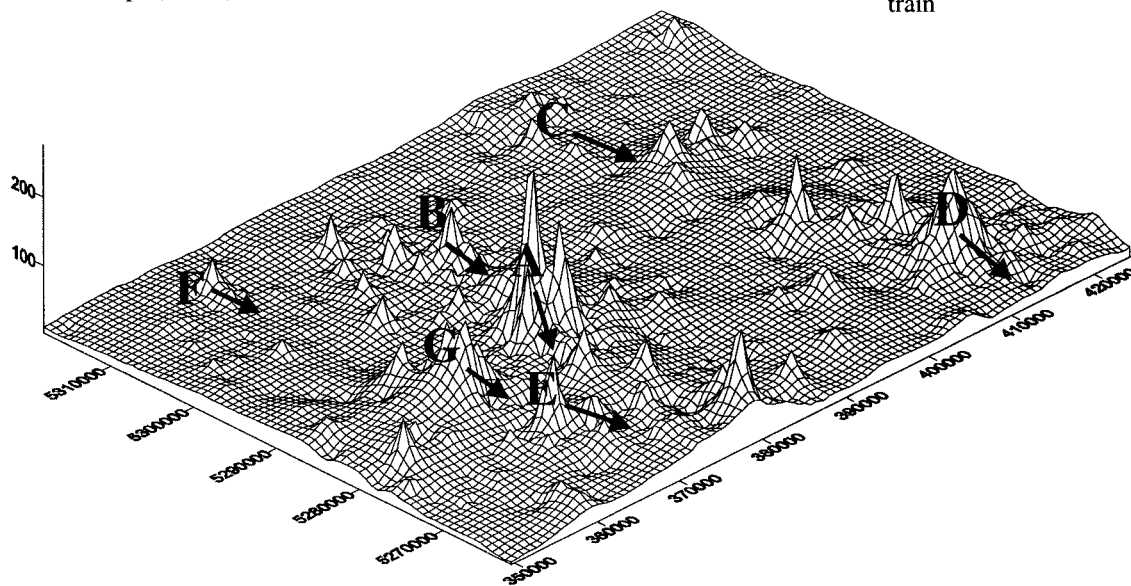
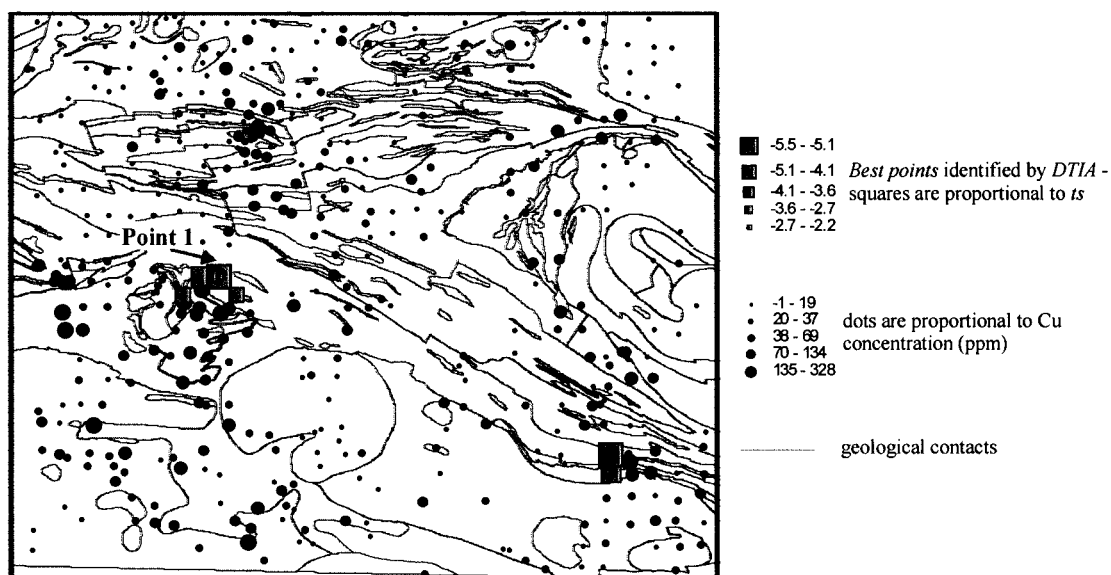
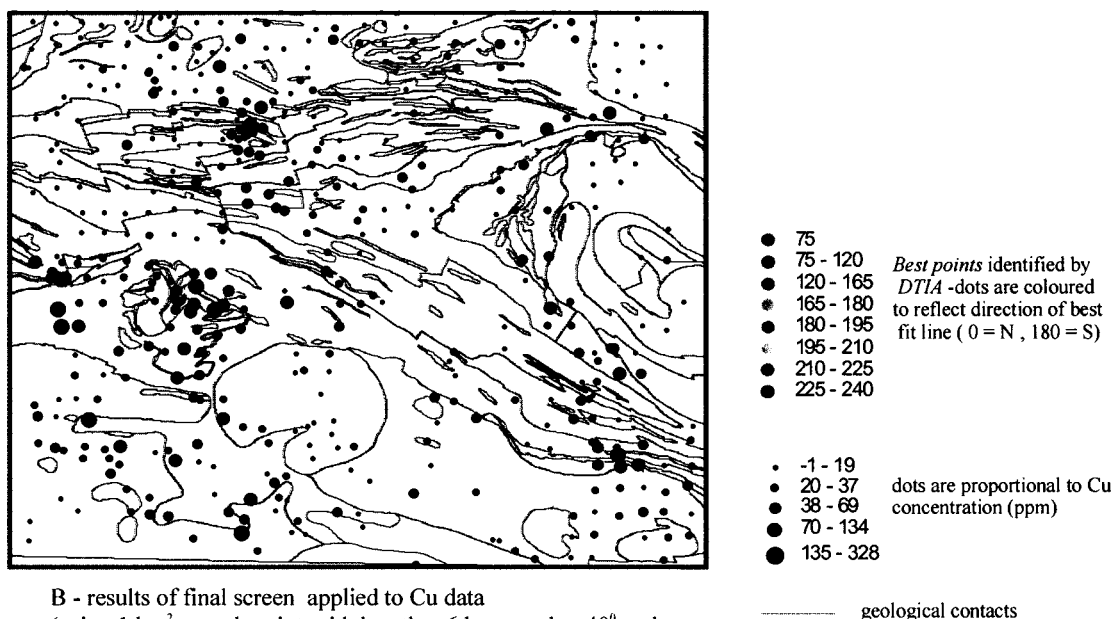


Figure 7.17 Interpolated and wireframe maps showing Cu concentration in till – Cu concentration in ppm – arrows indicated location and direction of potential dispersal trains identified through visual interpretation of displayed maps

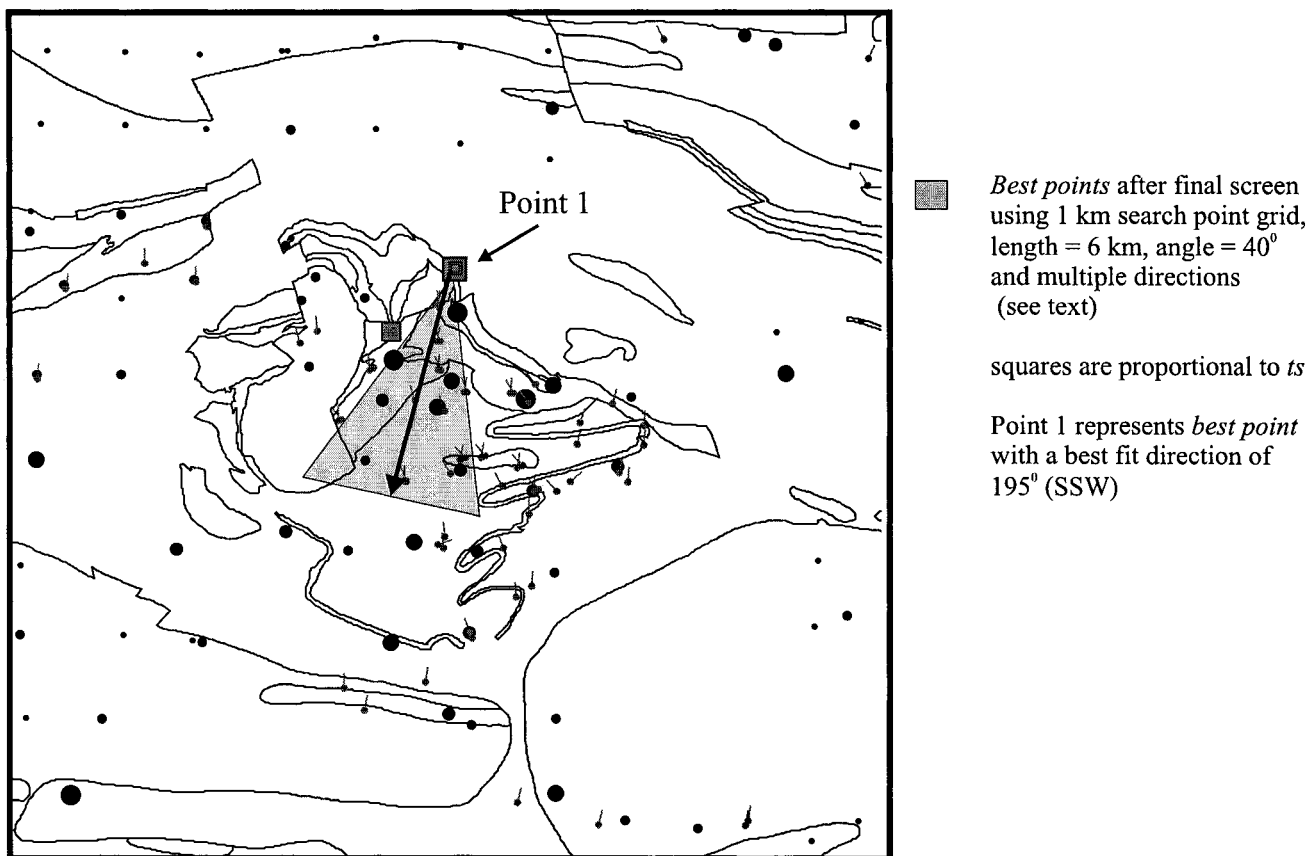


A - results of final screen applied to Cu data
 (using 1 km^2 search point grid, length = 5 km, angle = 40° and
 multiple search directions ($0-360^\circ$) - showing *best points* by t_s

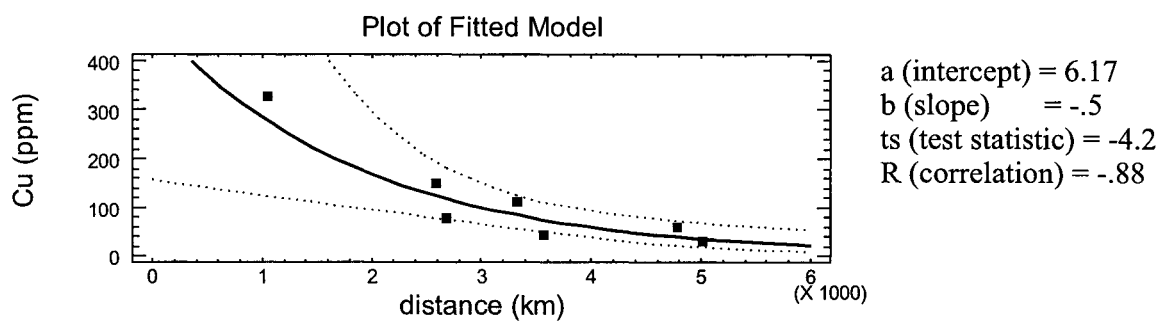


B - results of final screen applied to Cu data
 (using 1 km^2 search point grid, length = 6 km, angle = 40° and
 multiple search directions ($0-360^\circ$) - showing *best points* by direction
 of best fit line

Figure 7.18 *Best points* representing locations of potential glacial dispersal trains (Cu) identified by DTIA – using 1.5 km^2 point search grid, wedge length – 5 km, wedge angle - 40° and multiple directions ($0-360^\circ$ in 15° increments), (a) best points proportional to t_s , (b) best points colour coded by direction of best fit line



A - best points identified by *DTIA* after final screen



B - best fit line for Point # 1 (seen in A above)

Figure 7.19 (a) Optimum search wedge parameters for Point #1 (shown on Figure 7.18),
 (b) plot of best-fit line for Point #1

Element	Orientations and Ranges (from variogram)	Known glacial dispersion directions (see Fig 2)
Pb	SW-NE (7 km)	matches intermediate direction (towards NE) and matches oldest direction (towards E)
	W-E (7km)	approximately matches oldest direction (~towards E)
	WNW-ESE (8 km)	approximately matches oldest direction (~towards E)
Zn	WSW-ENE (5 km)	approximately matches oldest direction (towards E)
	W-E (7 km)	matches oldest direction (towards E)

Table 7.1 – Results of directional variogram analysis showing orientations and associated ranges, matched with known glacial dispersion directions from (McClenaghan & DiLabio, 1993,1996).

Direction	Range (of variogram)	Sill (of variogram)	Nugget (of variogram)
NW-SE	~ 3 to 6 km	2.4 counts	1.5 counts
N-S	5 km	2.4 counts	1.75 counts
NNE-SSW	~ 4 to 5 km	2.4 counts	1.75 counts

Table 7.2. Directional variogram results for gold count data. The range parameter indicates the extent of spatial autocorrelation, a possible indication of distance of transport.

Direction	Range (of variogram)	Sill (of variogram)	Nugget (of variogram)
NE-SW	~ 7 km	.5 ppm (log)	.1 ppm (log)
E-W	~ 4- 5 km	.51 ppm (log)	.1 ppm (log)
NW-SE	~ 6 km	.53 ppm (log)	.1 ppm (log)

Table 7.3. Directional variogram results produced from the log-transformed Cu data, Swayze dataset.

CHAPTER VIII

Geoscience Data – Processing, Integration and Modelling

8.1 Introduction

Exploration for gold within the Canadian landmass over the last century has been a major focus of mineral exploration companies. This has involved exploring for epithermal gold deposits, primarily in British Columbia, and mesothermal gold deposits in Archean volcanic greenstone belts in the Superior and Slave Provinces (Colvine, 1983; Colvine et al., 1988; Poulson, 1986; Robert, 1990, 1991; Hodgson, 1993; Franklin, 1997). However economic gold deposits are becoming increasingly difficult to find for a variety of political, economic, environmental and geologic reasons. Thus, new tools are required for archiving, managing, manipulating, integrating and visualizing the large volumes of geoscience data collected by industry, government and educational institutions. Geographic Information Systems (GIS) offer potential as a tool for accomplishing this task.

One of the major strengths of a GIS is the ability to integrate and combine multiple layers of geoscience data into mineral prospectivity maps showing areas favourable for mineral exploration (e.g., Chung and Agterberg, 1980; Bonham-Carter et al., 1988; Harris, 1989; Bonham-Carter, 1994; Rencz et al., 1994; Harris et al., 1995; Wright and Bonham-Carter, 1996; Harris et al., 2000; Wilkinson et al., 1999a; Raines, 1999). It is these capabilities that make GIS an extremely useful tool for mineral exploration. Production of a mineral prospectivity map using a GIS involves a number of steps. Firstly, data must be collected and compiled into a digital format acceptable for input to the GIS. Secondly the data must be properly geo-referenced which involves selection of an appropriate datum and map projection for presentation of the data. The database building process can be laborious but is a crucial one as the data must be error free, both spatially and statistically, for meaningful analysis to be undertaken and reliable results to be achieved. As an example

of the data building process, Wilkinson et al., (1999b) describes how the lithogeochemical example data used in this paper were compiled and screened for errors.

The geologist has many options for processing geoscience data for input to GIS modelling procedures. This paper presents two methods for processing geochemical data: processing as discrete (buffered) points and as continuous surface maps. Consideration of these two different processing methods is necessary, as often geochemical data will not be of sufficient density to warrant interpolation. The effect of using the two different processing methods on the final gold prospectivity maps, is also assessed. In some cases, the same data were not used for each rendition of the gold prospectivity maps due to data processing limitations. For example, the field observations of rock alteration were not interpolated due to too few samples and, more importantly, interpolating this data is not justified as observations on alteration would not be expected to vary continuously over space. Different data and processing methods were purposely used to compare the difference in spatial patterns on the resulting gold prospectivity maps.

Once the data have been properly prepared the GIS, in concert with other statistical and geostatistical software packages, can be used to manipulate and visualize the data in order to produce a mineral prospectivity map. Many spatial modelling techniques can be employed to produce such a map. However, these methods can be divided into two basic categories; knowledge- and data-driven techniques. Table 1 presents a summary of data-driven and knowledge-driven modelling methods and excellent reviews of the various modelling methods can be found in Bonham-Carter (1994) and Wright and Bonham-Carter (1996).

Data-driven approaches require that "a prior" knowledge (expressed in terms of a prior probability) exists in the form of known mineral deposits or occurrences (e.g., prospects) for the study area. Spatial relationships between the input data (evidence maps) and the spatial location of the mineral prospects are used to establish the importance (weight) of each evidence map. In other data-driven approaches, training areas can be established over each mineral deposit from which diagnostic signatures of mineralization can be

calculated from the various data (e.g., geochemistry, geophysics etc.) used in the modelling process. Methods such as logistic regression (Chung and Agterberg, 1980), weights of evidence (WofE) (Bonham-Carter, 1994), decision tree analysis (Reddy and Bonham-Carter, 1991) and neural networks (Singer and Kouda, 1996, 1999; Harris and Pan, 1999; Brown et al., 2000) are examples of data-driven approaches.

Knowledge-driven approaches rely on the geologist's input to weight the importance of each data layer (evidence map) as they relate to the particular exploration model being used. This approach is more subjective but has the advantage of incorporating the knowledge and expertise of the geologist in the modelling process. Examples of knowledge-driven approaches include boolean logic, index overlays (Harris, 1989), analytical hierarchy process (AHP) (Harris et al., 1995; Harris et al., 2000) and fuzzy logic (An et al., 1991).

Wright (1996) presents results on a study comparing different data- and knowledge-driven GIS modelling methods for producing mineral prospectivity maps and Singer and Kouda (1999) have compared data-driven techniques (WofE vs. neural networks). In this study both data-driven methods including weights of evidence (WofE) and logistic regression and knowledge-driven methods including index and boolean overlays are used to produce gold prospectivity maps. However in this paper the objective is not so much to compare data- and knowledge-driven modelling methods on an absolute basis (or to determine which method is superior), as the methods do not use identical datasets thus making a direct comparison impossible. The aim here is to demonstrate different methods for processing the data and different methodologies for producing a mineral prospectivity map. This is important as each modelling method has advantages and disadvantages and one or the other may be more appropriate given certain geologic environments and exploration scenarios. However, the gold prospectivity maps are compared in a general sense by evaluating how well each map has predicted the known gold prospects.

The GIS used in this paper is Arc/Info™ and ArcView™ with Spatial Analyst™, all ESRI (Environmental Research Institute) products. In addition, the weights of evidence (WofE)

(Kemp et al., 1999) and Spatial Data Modeller (ArcSDM) (Kemp et al., 2001) add-ons to ArcView™ (developed by the Geological Survey of Canada and United States Geological Survey supported by funding from the mining industry) were used for modelling of the data. WofE is available for free from the website listed in the references (Kemp et al., 1999).

8.2 Study Area – Swayze Greenstone Belt

The Swayze greenstone belt (SGB) is the southwestern extension of the Abitibi greenstone belt (AGB) being connected to the latter by a narrow band of volcanic-sedimentary rocks that wrap around the north and south margins of the Kenogamissi granitoid complex (Fig. 8.1). The belt has recently been re-mapped by Heather and Shore (1999) and Ayer (1995). Figure 1 is a generalized map of a regional geological compilation of the southern SGB by Heather and Shore (1999). The southern SGB is the focus of this paper as more geoscience datasets are available for this portion of the belt than the northern SGB.

Figure 8.1 also shows major high strain zones, faults and fold axes throughout the southern and central portions of the SGB. The Rideout high strain zone (RDZ) is a major high-strain zone that runs the length of the southern SGB and is interpreted to be the western extension of the Larder Lake-Kirkland Lake-Matachewan structure in the Abitibi (Heather et al., 1995), a structural feature that is a locus of many gold deposits. A major, NE striking structure, referred to here as the Wakami high strain zone (hereafter referred to as WKZ) (Fig. 8.1), sinistrally displaces both regional aeromagnetic anomalies and the RDZ.

Alteration in the SGB is typical of many Archean greenstone belts and varies from synvolcanic through syntectonic to late-tectonic in timing. Common alteration minerals consist of epidote, chlorite, sericite, Fe-carbonate, calcite, pyrite, tourmaline, garnet, hematite, magnetite and silicification. The RDZ is characterized by strong carbonate

(calcite and Fe-carbonate), chlorite, sericite and silica alteration. The WKZ is variably altered and overprints the RDZ, however the alteration within the zone has a restricted distribution due to its more brittle to brittle-ductile deformation style.

The SGB shares many features in common with the mineral-rich Abitibi greenstone belt to the east, but lacks any significant mineral production. A detailed mineral occurrence database has been completed for the Swayze belt (Fumerton and Houle, 1993; Fumerton et al., 1993). The two principal commodity types found within the current map area are base metals and gold. This paper focuses on the gold potential within the southern SGB. Figure 1 shows the location of gold prospects (compiled from Fumerton and Houle, 1993) divided into past-producers, deposits and occurrences. All of the past producing mines and the majority of the prospects are associated with quartz veins within high strain zones (i.e., shear zones). The RDZ hosts the past producing Jerome Mine (Fig. 1). Gold mineralization is hosted by a wide variety of rock types. Both the RDZ and WKZ localize felsic intrusive rocks (i.e., quartz-feldspar porphyries- QFPs) which may be associated with gold mineralization (e.g. Rideout porphyry – see Fig. 8.1).

8.3 Mesothermal Gold Exploration Criteria

Hodgson (1993) has divided mesothermal gold deposits into two broad categories based on the host rock: (1) those found in volcanic greenstone belts, typical of the Archean age rocks in the SGB and (2) those found primarily in sedimentary rocks. Type I deposits are the focus of this paper. Typically in Type 1 deposits, gold is found in quartz veins that occur within or in close proximity to major shear zones. Both high strain zones and later brittle-ductile faults may act as conduits for hydrothermal fluids and subsequent gold mineralization (Hodgson, 1993). Dimroth et al., (1983a,b) and Robert (1990, 1991) found that within the Abitibi greenstone belt gold is localized along faults that form low angle splays to the major shear zones or breaks (e.g., Destor-Porcupine and Cadillac-Larder Lake faults). Movement along these major faults is variable ranging from oblique strike-slip to vertical.

The host rocks for Type 1 deposits occur in three rock assemblages (Hodgson and MacGeehan, 1982; Nesbitt et al., 1986; Hodgson, 1993): (1) mafic to ultramafic rocks (e.g. komatiites) high in MgO, (2) fluvial sedimentary rocks and, (3) felsic intrusions (quartz-feldspar porphyries). Felsic intrusions (QFPs), many of which occur along major fault zones, are thought to have acted as heat engines driving the associated gold-bearing fluids derived from the surrounding host rocks. However, recent high precision data in the Abitibi greenstone belt indicates that some gold mineralization may be 50 to 100 my. younger than the felsic intrusions (Hanes et al., 1987; Anglin, 1991) suggesting multiple periods of gold deposition or late stage introduction of gold-bearing fluids.

Carbonatization of the host rocks, caused by deeply derived, CO₂ rich gold-bearing fluids, is the most common alteration style. Silicification, and potassic and sodium metasomatism are also typical alteration styles.

These exploration criteria, that have been derived from exploration knowledge and exploration experience in Archean greenstone belts by various mining companies, are used in this paper to extract relevant data (e.g., evidence maps) from the extensive geoscience database compiled over the SGB (Harris et al., 1999a) to produce gold prospectivity maps. Table 8.2 is a summary of mesothermal Au exploration criteria derived from Colvine (1983) and Colvine et al., (1988), Hodgson (1993) and Robert (1990, 1991).

8.4 Methodology

Figure 8.2 is a flowchart summarizing the modelling methodology invoked in this paper. This methodology involves selection of an exploration model, selection and preparation of evidence maps and integration of evidence maps creating a gold prospectivity map using data- or knowledge-driven modelling techniques. Data-driven techniques used in this study include weights of evidence (WofE) and logistic regression and knowledge-driven techniques include boolean and index overlay.

8.4.1 GIS Modelling techniques

Weights of evidence (WofE): In the WofE approach, developed by (Spiegelhalter, 1986) and applied to mineral exploration by Bonham-Carter et al. (1988), Harris et al., (1995), Wright et al., (1996) and Raines (1999), a series of evidence maps derived from the geochemical, geophysical and geologic data are combined to produce a mineral prospectivity map, using Bayesian statistics. The spatial association of each evidence map is assessed with respect to the location of known gold prospects. A pair of weights, W^+ and W^- , determined from the degree of overlap between the known gold prospects and the binary evidence map, are calculated for each binary evidence map. If there is no spatial association between the gold prospect and the binary evidence map, then $W^+ = W^- = 0$. A positive W^+ value indicates a positive association between gold prospects and the evidence map. The contrast value (C) (where $C = W^+ - W^-$) also reflects the degree of spatial association between the evidence map and prospects. A larger C value indicates a stronger association between gold prospects and the evidence map. An abrupt change (breakpoint) in a plot of the contrast (C) can also be used to identify a significant threshold dividing a data population into anomalous and background.

One limitation with WofE is that it assumes conditional independence between the data (evidence maps) (e.g., an elevated concentration in Cu is independent of an elevated concentration in Zn with respect to the location of known Au prospects). This assumption is often violated when producing a prospectivity map based on posterior probabilities. Bonham-Carter (1994) presents techniques for dealing with evidence maps that violate conditional dependence assumptions. In addition, methods of dealing with this problem are also presented later in this paper.

Bonham-Carter (1994), Raines (1999), Singer and Kouba (1999) and Harris et al., (2000) provide more detailed discussions of the WofE method and how the weights are calculated. In this paper each known gold prospect was set to a unit area of 200m². The study area, which comprises only volcanic rocks within the southern and central SGB, contains 155 known gold prospects.

Logistic regression: Regression methods are an important data analysis tool for describing the relationship between a response variable and one or more explanatory variables. In the case of logistic regression, in this study, the response variable is binary and represents the presence or absence of a mineral prospect (represented by a one or zero, respectively) and the explanatory variables are the binary evidence maps. The coefficients determined from the model are equivalent to a weight, signifying the importance of each evidence map in the regression process. An advantage of logistic regression over the weights of evidence method is that no assumptions of conditional independence between evidence maps are made. Further information on logistic regression can be found in Hosmer and Lemeshow (1989) and Harris and Pan (1999).

Index overlay: This knowledge-driven technique is a common GIS method for combining a series of evidence maps. It differs from WofE and logistic regression in that the geologist assigns each evidence map a weight reflecting their opinion on the importance of each evidence map in the modelling process as opposed to calculation of a statistical weight based on the spatial association between known gold prospects and evidence maps. The binary evidence maps in this paper were divided into a series of geologic themes (e.g. structure, lithology etc.) and each theme was assigned a weight reflecting its particular importance in the overall modelling procedure.

Boolean overlay: The boolean, know-ledge driven modelling method involves summing each binary evidence map producing a prospectivity map that shows the number of co-occurrences between evidence maps. The binary evidence maps are not weighted by importance (all have a weight of 1), as they are in the index overlay process. Thus, the highest gold potential is represented by areas that are typified by the highest number of coincidences between evidence maps.

8.4.2 *Creation of evidence maps*

Integral to the modelling process is the preparation of the various types of data comprising geologic maps, geophysical images, geochemical data and remotely sensed data, to create evidence maps for input to modelling. Evidence maps can be binary, multi-class or continuous in form. Multi-class maps, for example often are divided into quantile or percentile ranges, whereas continuous class (surface) maps are scaled within a user-defined range (see Harris et al., 1995 for examples). Normally the higher class values (i.e., > 95 percentile) will have more influence or weight when combined with other data in the modelling process. In this paper binary evidence maps are used in which values of 1 represent areas that are anomalous (with respect to geochemical concentration, geophysical signature, key lithologic unit etc.) and values of 0 which represent non-anomalous areas.

A critical or anomalous threshold value is usually determined from the data when producing a binary map. Many methods exist for determining thresholds for anomalous populations (Grunsky, 1986, 1997; Harris et al., 1999b, 2000; Cheng et al., 1994; Stanley, 1987; Garrett, 1991). In this paper upper breakpoints on probability plots and WofE analysis (peaks in contrast (C) value) are used for identifying anomalous geochemical populations.

Geochemical data are sampled at discrete points and depending on the sample density and pattern as well as the particular media sampled (e.g., rock, lake sediments, surficial sediments), it may or may not be appropriate to interpolate the data. Thus this paper treats the geochemical data as discrete points and as continuous surface (interpolated) maps. In either case, anomalous thresholds, interpreted to possibly reflect gold mineralization, must be determined in order to produce binary evidence maps.

Vector data, such as faults and lithological contacts, are often transformed to continuous surface maps by employing GIS analysis techniques such as buffering, a technique that defines distance zones around a particular vector object (e.g., zone of influence). Polygon

data representing lithological or Quaternary maps are thematic in nature and thus vary spatially in a discrete as opposed to a continuous sense.

General geochemical processing issues: Often the geologist will have to decide whether to interpolate lithogeochemical data or leave the data as discrete points. Interpolation can be succinctly defined as the process of predicting the value of a given variable at an unknown location from values of the same variable at surrounding, known locations. Many different interpolation algorithms exist including kriging, minimum distance curvature and inverse-distance-weighted interpolators. Kriging (Isaaks and Srivastava, 1989) is perhaps the most robust technique and is based on a generalized linear regression technique for minimizing an estimation of variance defined from the spatial properties of nearby samples (i.e., co-variance). Harris et al., (2000, 2001) present a discussion of the interpolation process and provide rules for the interpolation of geochemical data.

Normalization can be defined as a processing method by which the effects of non-mineralization and/or non-alteration factors on geochemical concentrations are reduced. For example, normalization in this paper involves processing lithogeochemical data to de-emphasize the effects of lithology, resulting in element anomalies that are more likely related to alteration/mineralization processes (see Harris et al., 1997, 1999b, 2000). This is more important for geochemical data sampled from rocks and lake sediments, as geochemical samples from these media have a stronger bedrock signature than samples from other media. One method to accomplish this is by calculating the median concentration for each oxide element for each lithologic unit after performing a “point-in-polygon” operation, whereby each geochemical sample point is intersected with an associated lithological map (Harris et al., 1999b). Another method involves analyzing the geochemical data by lithologic unit and identifying anomalous samples based on geochemical distributions for each lithology (e.g., selective query process – Harris et al., 1999b).

The effects of Fe, Mn and organic scavenging of metals, a common process in the surficial environment (Rose et al., 1979), were accounted for in the geochemical data

sampled from soil, humus and lake sediments. This was accomplished using a selective query process whereby anomalous concentrations of specific elements were accepted only when they did not co-occur with anomalous concentrations of Fe, Mn or excessive LOI (as a measure of organic content) values. Geochemical anomalies in these media that are coincident with Fe, Mn and LOI anomalies have a higher probability of representing a false anomaly due to scavenging by these oxides and organic matter. Harris et al., (2001) provide examples of how this screening process can be implemented.

8.4.3 *Geoscience data*

Table 8.3 lists the geoscience data used in this study. The data were selected based on the relevance with respect to mesothermal exploration criteria as discussed previously.

Airborne magnetic data (total field and vertical gradient) were used to identify linear magnetic anomalies representing geological features such as iron formations, magnetite bearing mafic and ultramafic lithologies, ductile high strain zones, dykes and faults. Airborne electromagnetic data were also used to identify linear anomalies, the majority which are faults, and/or conductive bodies (sulphide facies iron formations).

A LANDSAT Thematic Mapper image acquired during the fall (Oct. 1986) was used to identify dykes, brittle faults and high strain (shear) zones. A fall scene was chosen because at this time of year geologic structures are best identified in northern Archean greenstone terranes due to the spectral difference between coniferous and deciduous vegetation patterns which often reflect linear features. In addition, a lower sun angle during this time of year can enhance topographic patterns (see Harris and Slaney, 1982; Harris et al., 1992).

A number of geologic maps of varying scales were used in this study, including a recent compilation of the southern and central SGB by Heather and Shore (1999) (see Fig. 1), a less detailed regional compilation of the entire SGB (OGS, unpublished) and a detailed compilation of the northern SGB (Ayer, 1995).

A large lithogeochemical database comprising major oxides and trace elements, derived from a number of proprietary and non-proprietary sources, was used. Wilkinson et al., (1999b) give a detailed account on the problems and solutions involved in compiling this database from a number of disparate geochemical surveys. Harris et al., (1999b) and Harris et al., (2000) provide details on how this database was analysed for regional gold and base metal exploration applications.

A number of alteration indices useful for gold exploration were derived from the lithogeochemical data. Table 8.4 presents a list of these indices, their relevance to mesothermal gold exploration and associated references. Field measurements of alteration intensity and style and geologic structure by Heather and Shore (1999) were also used.

A geochemical survey of till, B-horizon soil, humus and gold grain counts by the Ontario Geological Survey (Bernier, 1995; Bernier and Kaszycki, 1995;) was used. An average density of 1 sample/4-7 km² characterized this regional survey. The -80 (<177µm) mesh fraction of humus was sampled and analyzed for a variety of trace elements using INAA and ICP-OES (aqua-regia digestion). The -230 mesh (< 63 µm) fraction of soil and till was analyzed using ICP-OES (aqua-regia digestion). More details on this survey can be found in Bernier (1994) and Bernier and Goff (1993). Harris et al., (2001) provide examples of how this dataset can be visualized and analyzed for mineral exploration applications.

Data from a lake sediment geochemical survey conducted under the National Geochemical Reconnaissance Program (NGR) by the Geological Survey of Canada (GSC 1987, 1988) were used. Only the central and southern portion of the SGB was covered by these surveys which sampled relatively large and deep lakes at an average density of 1 sample per 13 km².

8.4.4 *Preparation of Data (Evidence Maps) for Modelling*

Lithogeochemical data: Figure 8.3 presents a flow chart of the processing steps applied to the lithogeochemical data for interpolation purposes. Firstly the major oxides were normalized to lithology. Alteration indices, useful for identifying alteration patterns that may reflect gold mineralization, were also calculated (see Table 8.4). These alteration indices were also normalized to take account of overall lithologic variations. The trace data were not normalized as variations in the trace elements analyzed were generally thought to be more reflective of alteration and possible mineralization as opposed to lithologic variations.

Directional variograms were constructed for the log-transformed and normalized major oxides, trace elements and calculated alteration indices to determine the best parameters for interpolation. In this study it was found that the log-transformation of the data resulted in close to normal (gaussian) distributions which produced variograms with better spatial structure, especially for the trace elements. The “best” variogram structures for the lithogeochemical data were obtained using an elliptical search in which the long axis was oriented parallel to the strike of regional stratigraphy (112°). This was expected since greater spatial variations usually occur across lithology as opposed to along lithological units. The parameters (range, sill) based on the variograms were used to krig the data using a spherical model. An uncertainty map was produced by interpolating the residual values from the kriged model and the areas of highest uncertainty were identified (e.g., residuals below or above 3 standard deviations of the mean residual value). These areas of uncertain interpolation were then identified and eliminated from the interpolated geochemical maps using a masking procedure in the GIS.

Probability plots of the data were then examined for upper or lower thresholds above or below which geochemical concentrations were considered anomalous. These thresholds were used to create individual binary geochemical maps for each major oxide, alteration index and pathfinder trace element that were input to the knowledge base modelling procedure. An example of a probability plot can be seen on Figure 3.

Figure 8.4 is a flowchart showing how the lithogeochemical data were processed as discrete points. The major oxide data were divided into altered and un-altered samples as discussed in Harris et al., (1999b) and only the altered samples were considered for further processing, as it was felt that altered samples would provide more information on rock alteration patterns that may be related to mineralization. Alteration indices, also calculated from only the altered samples, were used (see Fig. 8.4 and Table 8.4) to identify alteration patterns that may reflect possible gold mineralization. The trace elements were not normalized to lithology for reasons discussed previously.

Anomalous concentrations of selected trace elements and anomalous alteration index values were identified using upper breakpoints on normal probability plots of the data. A selective query process (Harris et al. 1999b) was used to normalize and select anomalous thresholds from the major oxide data with respect to varying lithology as opposed to the equation method (see Fig. 8.3) which was used for normalization in the knowledge-driven modelling.

The anomalous geochemical sample points (oxides, trace elements, calculated alteration indices) were then dilated (buffered in GIS terminology) to a distance of 1 km representing a zone of influence around each sample point. This distance (1 km) was felt to be a reasonable choice as results from the variogram analysis indicated that the range parameter, indicating the distance at which sample points are no longer associated, was generally less than 5 km for most oxides.

One map of anomalous samples was produced for each oxide element (normalized as discussed above), trace element and alteration index. These anomaly maps were then simply overlaid (summed) producing a multi-class map showing the co-occurrences between anomalous samples for each element analyzed from the major oxides, derived alteration indices and selected trace elements (see Fig. 8.4). WofE was used to determine whether these summed anomaly maps were spatially associated with known gold prospects. In addition, WofE was also used to determine significant thresholds on these summed maps, based on the contrast value (C), to create binary evidence maps (see

Bonham-Carter, 1994). One might intuitively expect that areas that are characterized by multi-element anomalies may be better predictors of known gold prospects. The three resulting binary anomaly maps based on summed trace element anomalies, summed oxide anomalies and summed alteration index anomalies (see Fig. 8.4) were then input to the data-driven modelling process.

Surficial geochemical data (till, soil and humus, gold grain counts): Figure 8.5 summarizes the processing steps for the Quaternary geochemical data sampled from till, B-horizon soil and humus as well as gold grain counts.

The point processing of the geochemical data (Fig. 8.5a) involved selecting thresholds determined from probability plots. The effects of Fe, Mn and organic scavenging of metals were accounted for by a selective query process (discussed previously) which involved deleting sample points which were high in iron or manganese and other pathfinder trace elements (e.g., Zn, Cu, Au, As etc.). Each anomalous geochemical sample point was then buffered to a distance of 3 km for till samples and gold grain counts and 1 km for soil and humus samples. These distances were selected based on an orientation survey undertaken by the OGS (Bernier, 1994) over the Kenty gold property in the central SGB (see Fig. 8.1 for location). This survey indicated that the maximum down-ice dispersion of indicator minerals was approximately 3 km and 1 km for the till and soil/humus data, respectively. The data were then combined (summed) into one anomaly (evidence) map for each surficial medium (till, soil, humus) similar to the summing process for the lithogeochemical data (Fig. 8.4). Thresholds were then calculated using WofE (C values) to produce binary anomaly (evidence) maps which were then input to the modelling procedure.

In contrast, the interpolated (kriged) element maps were not corrected for scavenging effects (Fig. 8.5b) so that differences in the resulting prospectivity maps due to corrected and non-corrected data could be assessed. Thresholds were determined from probability plots (as opposed to using WofE) and were used to create binary anomaly (evidence) maps that were individually input to the index overlay modelling process.

Lake sediment geochemical data: The lake sediment geochemical data were processed somewhat differently than the Quaternary geochemical and lithogeochemical data. Figure 8.6 summarizes the processing methodology, which was applied to the lake sediment geochemical data for both data- and knowledge-driven modelling purposes. A lake sediment sample is representative of a large area defined by a drainage basin, unlike a lithogeochemical sample which is representative of the area immediately around the sample (e.g., has a much smaller zone of influence than a lake sediment sample). Therefore, a map of drainage basins was constructed from a digital elevation model (DEM) using GIS software. Each lake sediment geochemical sample point was then intersected with the map of drainage basins using a “point-in-polygon” GIS operation. If two or more sample points fell within one basin then the average concentration was calculated for that basin. Basins with an anomalous concentration of a given trace element (Au, Ag, Sb) were identified using breakpoints on normal probability plots and WofE for the knowledge and data-driven modelling procedures, respectively. The basins with anomalous concentrations of trace elements were then screened for Fe, Mn and organic scavenging using methods presented by Harris et al., (1999b, 2001). Thus, basins that had anomalous concentrations of a given trace element as well as Fe, Mn and LOI were eliminated from further analysis since these anomalies may reflect scavenging effects rather than mineralization. The basins, screened for scavenging effects, were used in the data-driven modelling process whereas the un-screened basins were used in the knowledge-driven modelling process, again to assess differences due to processing method.

Alteration identified in the field: Heather and Shore (1999) produced a large database of field (point) measurements which included information on alteration type, style, minerals and intensity. Field locations were selected from the database on the basis of style (carbonatization, Fe-carbonatization, chloritization, sericitization and silicification) and intensity. Only samples displaying a moderate to strong degree of alteration were considered. These sample locations were buffered to a distance of 1 km and then combined into a field alteration evidence map for input to the data-driven modelling

process (see Fig. 8.7). This information was not interpolated as the sample density was not sufficient.

Geologic structure: Vector data, such as faults (mapped and interpreted) and mapped lithological contacts, were transformed to continuous surface maps by dilating (buffering) around each line in successive zones from 0 to 2000 meters (e.g., 0 - 50m, 50-100m, 100-150m etc.). In this way the spatial association between gold prospects and selected structural features can be evaluated using WofE to determine whether gold prospects are preferentially located closer to geologic structures (e.g faults, lithologic contacts) than would be expected by chance.

Structural data used in knowledge-driven modelling analysis included : (1) deformation zones (corridors) interpreted from field observations (Fig. 8.1), airborne magnetic and LANDSAT data, (2) E-W trending fault zones (mapped in the field and interpreted from magnetic and LANDSAT data) (3) fault zones (mapped in the field and interpreted from magnetic and LANDSAT data) that intersect the major deformation zones at a low angle ($< 30^\circ$), and (4) faults / conductors interpreted from electromagnetic data. The deformation corridors were of variable width while the width for the fault zones was set at 250 m.

Structural data used in the data-driven modelling process included : (1) mapped deformation zones (Fig. 8.1), (2) deformation zones interpreted from magnetic and LANDSAT data, (3) faults interpreted from magnetic and remotely sensed data as well as mapped faults and, (4) lineaments interpreted from LANDSAT data. One hundred meter buffers were calculated around each structure, out to a maximum of 5 km, to assess the possible spatial association between known gold prospects using WofE. Results from WofE indicated that only the deformation zones interpreted from the magnetic data, mapped faults and the lineaments interpreted from the LANDSAT data showed a significant spatial association with known gold prospects. A distance threshold (based on peaks in the contrast (C) value), of 250 m was used for both the deformation zones and lineaments whereas a 100m buffer was used for mapped faults (Table 8.5).

Lithological contacts, extracted from the regional geological map of the study area (unpublished, OGS) were used in the knowledge-driven modelling. These were selected

based on regional exploration knowledge by Noranda and included mafic-ultramafic, mafic-sediment, mafic-quartz-feldspar porphyry (QFP) contacts. Each contact was buffered to 250 m, a distance thought to be the maximum dispersion of the gold bearing fluids along contacts (zones of weakness).

Contact information was not used in the data-driven modelling, however, distance to a quartz-feldspar-porphyry (QFP) or feldspar porphyry (FP) was used as these small intrusions may have functioned as heat engines responsible for remobilizing gold (Hodgson, 1993). These small intrusive bodies were selected from detailed geological maps of the study area (Heather and Shore, 1999) and 100m buffers were constructed around each to a distance of 5 km. WofE analysis indicated that known gold prospects appeared to be spatially associated with QFP's and FP's to a distance of 1600 m. Thus a binary map of zones less than 1600 m from these intrusive bodies was constructed and used as an evidence map in the data-driven modelling process.

Lithology: Each lithologic unit present on geological map (Fig. 8.1) of the southern SGB were evaluated with respect to the known population of gold prospects using WofE. Units that showed a positive association with known gold prospects were used in the data-driven modelling procedure. Lithologies, thought to be prospective for gold, based on exploration knowledge (Noranda, pers. commun.), were used in the knowledge-driven modelling.

Geophysical data: Anomalies were extracted from airborne magnetic data, supplied by the Geological Survey of Canada (Dods et al., 1985) and the Ontario Geological Survey (OGS, 1997) and from electromagnetic data (OGS, 1997) of the study area. This involved inspection of cumulative probability plots of the geophysical data for upper breakpoints and thresholding the data above this limit, resulting in a map of linear magnetic anomalies. Both the linear zones based on the magnetic data and EM data were used in the data-driven modelling as WofE analysis indicated a positive spatial association between these zones and known gold prospects. Only the EM linear anomalies were used in the knowledge based modelling.

8.4.5 *Summary of different data processing and different weighting methods*

Table 8.5 summarizes the data used for the data-driven (WofE and logistic regression) and knowledge-driven (boolean and index overlay) modelling methods. Note the differences in data used for each modelling method with respect to structure, lithology, geophysics and lithological contacts. This was done purposely to evaluate the spatial differences due to data type and processing method on the resulting prospectivity maps. Table 8.6 summarizes the geochemical thresholds used for producing binary anomaly (evidence) maps used in the data-driven modelling whereas Table 8.7 shows the anomalous geochemical thresholds for selected trace elements (all media), major oxides and alteration indices selected from probability plots for the knowledge-driven modelling. Note that the thresholds determined from the probability plots were, for the most part, similar to the thresholds calculated using the WofE Contrast (C) value (compare Table 8.6 and 8.7).

The weights for the data-driven methods are derived from the spatial association between the known gold prospects and evidence maps, as previously discussed. The knowledge-driven boolean method uses evidence maps that are not weighted. However, the index overlay weighting system requires some elaboration. Thus with reference to Table 8.7, the structural theme was assigned the most importance (weight of 5) while the oxide lithogeochemical theme was assigned the lowest weight (2). In addition each binary evidence map within a theme was assigned an internal weight reflecting its importance within the particular theme. For example, within the structural theme (overall weight of 5), being within a deformation zone was considered more important than being close to an oblique fault mapped from magnetic data (weights of 5 and 1 respectively). The evidence maps were then simply summed using the following equation:

$$\text{Au Prospectivity Map} = (\text{Ev Map1} * W) + (\text{Ev Map2} * W) \dots + (\text{Ev Map2} * w) \quad (1)$$

Where Ev Map = weighted evidence map

W = internal weight

The exploration criteria, weights and the general weighting scheme were established through discussions with Noranda Ltd. based on their experience in regional gold exploration within Canadian greenstone belts.

Table 8.8 summarizes the differences in processing methods for the different geochemical datasets. Different data and processing methods were utilized to, (1) evaluate which processing method (e.g., interpolation vs. points, normalization vs. raw data, screened vs. non-screened data) is best with respect to prediction of known gold prospects, (2) to present a variety of different processing options when preparing geochemical data for input to mineral prospectivity modelling and, (3) to evaluate the spatial differences due to these differences on the resulting gold prospectivity maps.

8.5 Results

Figure 8.8 show the data-driven (WofE and logistic regression) gold prospectivity maps derived from all the data but divided separately into maps produced using the interpolated geochemical data and geochemical data processed as discrete points. Figure 8.9 shows the same except that the maps were produced using the knowledge-driven (index overlay, boolean) techniques. The letters shown on these figures refer to specific locations that will be discussed below with respect to their relevance to regional gold exploration. One consideration with the WofE approach, as previously mentioned, is the issue of conditional independence between the evidence maps. Violation of conditional independence will in the worst case scenario result in an over- or under-estimation of the weights (W^+ and W^-). A Chi-Squared (χ^2) analysis (see Bonham-Carter, 1994) revealed that the lake sediment data were not conditionally independent. Thus these evidence maps (Au, Ag, As, Cu, Zn) were combined into one evidence map using a boolean “OR” operation. Similarly, the individual geological units that showed a positive spatial association with known gold were also found to be conditionally dependent, thus all units were combined into one binary map, again using a boolean “OR” operator. Furthermore, deformation zones interpreted from magnetic and remotely sensed data were conditionally dependent with anomalous concentrations of gold, arsenic and zinc in lake

sediments. A noticeable zone of spatial overlap between the two evidence maps occurs in the southeastern portion of the SGB. Thus, these two evidence maps were also combined using a boolean “OR” operation. The WofE maps shown on Figures 8a and 8b have been corrected for violations of conditional independence. Logistic regression, on the other hand, makes no assumptions about conditional dependencies between evidence maps.

8.5.1 Evaluation of best gold predictors

The best gold predictors (Table 8.9 – see rank by C column) are mapped lithological units (Rideout felsic porphyries, October Lake mafic package, iron formations and felsic volcanics comprising the Marion Formation mapped by Heather and Shore, 1999). The evidence map based on lithogeochemical trace element anomalies (see Fig. 8.3), alteration map based on field mapping proximity to a QFP, alteration indices calculated from the lithogeochemical major oxides and lastly linear magnetic anomalies are also moderately strong predictors of known gold prospects. All these evidence maps have contrast (C) values greater than 1 with the exception of felsic volcanics of the Marion Formation. The geological and geochemical evidence maps are generally the best predictors of known gold prospects.

Table 8.10 shows the WofE results for the individual evidence maps. Geochemical anomalies in humus (Cu, Zn) are the most predictive of all the Quaternary media sampled, followed by anomalies (As, Au) in soil. Geochemical anomalies in lake sediments (Au, Ag, Zn) and in till (Cu, Zn) were mildly predictive. The trace elements sampled from rocks are moderately strong predictors whereas the major oxides are only mildly predictive. Fe_2O_3 (iron oxidization), SiO_2 (silicification) and K_2O (potassic alteration) are the strongest oxide predictors. The alteration indices calculated from the major oxides are also mild to moderately strong predictors, with the Hashimoto and chlorite index the strongest predictors, suggesting that sericitization and chloritization may be important indicators of Au mineralization. Alteration mapped in the field (Heather and Shore, 1999), specifically carbonate alteration, is a moderately strong predictor.

The only evidence maps that were found to be good statistical predictors and also ranked highly using regional exploration knowledge were distance to a QFP, mafic volcanic lithologies (October Lake Formation) and trace element geochemical anomalies (gold in particular). From a statistical viewpoint, the strong spatial association between known gold prospects and the Rideout feldspar porphyry (heat engine?), geochemical oxide anomalies, alteration mapped in field and magnetic anomalies may warrant further attention in a regional exploration program within this greenstone belt. Geochemical anomalies in surficial sediments are only mildly predictive except for gold anomalies in humus.

It is interesting to note that geologic structures, especially E-W trending high strain zones and oblique splays associated with these zones, although known to be targets based on regional exploration knowledge (and thus highly ranked in the knowledge-based modelling), show, at best, only a mild spatial association with known Au prospects as determined using WofE. The deformation zones mapped in the field (Heather and Shore, 1999) (Fig. 8.1) are not good predictors of the known gold prospects whereas the high strain zones interpreted from the magnetic data are only mildly predictive of gold prospects (see Table 8.9). These deformation zones delineate broad areas of major high strain and may form too wide an area to be highly predictive of gold given that many of the gold prospects in Archean greenstone belts tend to occur on smaller splay faults to these major deformation zones (breaks) (Hodgson, 1983). Surprisingly, the best structural predictors were mapped faults and lineaments interpreted from LANDSAT TM data. These lineaments and mapped faults, the majority which strike NW, crosscutting regional lithology including QFP's, represent late brittle faults that are thought to post-date gold deposition. This apparent spatial association may be fortuitous or may suggest a later period of gold remobilization

8.5.2 *Comparison between gold prospectivity maps*

Results from each of the four modelling methods can be compared using Spearman rank correlation coefficients. Table 8.11 shows the Spearman correlation coefficients between

the gold prospectivity maps in which the geochemical data were treated as discrete (buffered) points. Table 8.12 shows the same as Table 8.11 except interpolated geochemical data were used. Table 8.13 shows the correlation coefficients between prospectivity maps produced using the same modelling methods but using interpolated versus point geochemical data.

Gold prospectivity maps produced using geochemical data processed as discrete points are more highly correlated, regardless of modelling method (> 0.56 - Table 8.11) than maps produced using the interpolated geochemical data (Table 8.12). This is primarily due to the effects of interpolation. However the difference is also due to different data used in the modelling process (see Table 8.5). As mentioned previously, the alteration data collected in the field were not interpolated (insufficient sampling density) and therefore were only used in the maps produced using the point geochemical data. This is especially noticeable in area A on Figure 8.8 over the Old Women Iron Formation where intense alteration was observed in the field. Considering the maps produced using the point geochemical data, there is an overall similarity between modelling methods in which the correlation between the same modelling method (eg., data- and knowledge-driven) is slightly higher than the correlations between opposing methods (see Table 8.11). The same is true for the maps produced using the interpolated geochemical data except the correlations are lower. Table 13 indicates that processing method can make a substantial difference in the final prospectivity maps as the correlations range from 0.77 (fairly strong for the boolean method) to 0.25 and 0.28 for the index overlay and WofE method, respectively.

The highest correlation between modelling methods, regardless of processing method, is between the WofE and logistic data-driven methods (> 0.8) (Tables 8.11 and 8.12) indicating that these modelling methods produce prospectivity maps that are similar. The index and boolean methods show a lower correlation (0.77 for maps produced using point geochemical data and 0.25 for maps using interpolated geochemical data). The lowest correlations are between the maps produced using WofE and the knowledge-

driven methods (both index and boolean overlay), reflecting primarily the differences between modelling methods and the different datasets used for modelling.

The analyses discussed above compare the overall similarity between maps regardless of gold potential ranking. However, more important are the similarities and differences for the highest potential areas. Figure 8.10a and 8.10b show difference maps produced by performing a GIS crosstabulation operation on the highest potential areas (top 5% by area) shown on Figures 8.8 and 8.9. The differences shown on Figure 8.10a are based on modelling method irrespective of geochemical processing method whereas the differences shown on Figure 8.10b are based on geochemical processing technique (e.g., point vs. interpolation) irrespective of modelling method.

Table 8.14 shows the results of applying WofE analysis to the highest potential areas (top 5% by area) for each prospectivity map produced. The maps produced by logistic regression and WofE (both data-driven methods) are better predictors of the known gold prospects by virtue of their higher contrast (C) values. The maps produced by the data-driven methods are better predictors of the known gold prospects than the maps produced from the knowledge-based methods regardless of geochemical processing method. This is not entirely surprising, as the spatial relationship between the known gold prospects and the evidence maps is instrumental in determining the weights and subsequently driving the data-driven modelling process. The WofE and logistic regression results are very similar. The maps based on the index overlay are better predictors than the maps produced by the boolean method indicating that a geologist's knowledge in subjectively weighting individual evidence maps is important and results in a more predictive prospectivity map. There does not appear to be any real trend when comparing the highest potential areas with respect to processing method (e.g., points versus interpolated geochemical points).

Spatially the biggest differences between the highest potential maps produced using different modelling methods are indicated by letters on Figure 8.10. With respect to Figure 8.10a (map based on differences between modelling methods), the biggest

differences are over the Old Women Iron Formation (A), central Swayze (D), the Hardiman high strain zone (O) and the Kenty gold prospect (C), all of which are shown as much higher potential zones on the data-driven maps. Areas E (western Swayze), G (southeastern Swayze in the vicinity of the past-producing Jerome mine) and L (Brett River synform) are indicated as higher potential areas on the knowledge based maps. With respect to Figure 8.10b (map based on differences between geochemical processing), areas A, H and L are areas of high potential on the maps produced using point processing of the geochemical data, whereas areas E and G are high potential areas on the maps produced using interpolated geochemical data. Most of these differences can be attributed to processing methods.

8.5.3 Effects of different datasets and data processing techniques used in prospectivity modelling

With respect to Figures 8.8 and 8.9, the biggest difference seen as a result of using different datasets for each modelling method, occurs over the Old Women Iron Formation (A). This area is classified as high potential on the maps produced using data-driven methods largely due to the influence of alteration observations made in the field (compare Fig. 8.8a,c with Fig. 8.8b,d and Fig. 8.8a,c with Fig. 8.9). These data were not used in the knowledge-driven methods. The differences due to slightly different structural information used and the different weight given to the structural data can be seen when comparing the data-driven (Fig. 8.8) and knowledge-driven (Fig. 8.9) gold prospectivity maps. The linear high strain zones are more evident on the knowledge-driven maps (Fig. 8.8) as they were weighted much higher in the knowledge-driven process than in the data-driven process. In the data-driven model, structural data generally received lower weights based on the spatial association between the known gold prospects and high strain zones.

The main difference with respect to processing the lithogeochemical and surficial geochemical data as points or interpolated surfaces lies in the spatial extent of anomalous areas defined by geochemical anomalies (e.g., compare Fig. 8.8a,c and Fig. 8.8b,d; Fig

8.9a,c and Fig. 8.9b,d). The maps, in which point-processed geochemical data were used, are generally characterized by smaller, “bulls-eye” type anomalies, as might be expected. Interpolation of geochemical data often results in maps in which spatial trends are easier to identify; however, anomalous areas are more spatially extensive due to the effects of spatial interpolation (Harris et al., 2001). The trace element and major oxide lithogeochemical anomalies based on buffered points and interpolations (using an inverse distance - IDW algorithm) were evaluated with respect to the known gold prospects using WofE. The results (not shown) indicated that the spatial extent of anomalies and the resulting element concentration were different as a result of the interpolation process. Furthermore, the anomalies based on the buffered points were stronger predictors, based on WofE, W^+ and C values, than the geochemical anomalies derived from the interpolated geochemical maps.

With respect to normalization of lithogeochemical data to lithology, Harris et al., (2000) presented results for this study area that indicated that, generally, lithogeochemical data corrected to take account of lithological variations resulted in geochemical maps that were better predictors of known gold prospects (using WofE). Bonham-Carter et al., (1987) found similar results when applying a regression method to correct lake sediment geochemical data for background lithological variations.

Screening the geochemical data for metal scavenging by Fe and Mn oxides and organic matter will result in a smaller number of geochemical anomalies (and thus smaller areas) which will obviously affect the spatial extent of anomalous zones on the final prospectivity maps. In this study, screening for anomalies did not always produce anomalous zones that were stronger predictors of the known gold prospects.

8.5.4 Geological evaluation of high potential gold zones

The most prominent high potential gold zones present on the data-driven maps (Fig. 8.8) (point processing) are along the Old Women Iron Formation (A) and the footwall felsic volcanics (Marion Formation), an area of predominately mafic rocks (B), a number of

scattered zones in the central portion of the SGB (D and C), and in the vicinity of the Shunsby base metal prospect (J) and in the southern SGB in the vicinity of the past-producing Jerome mine (G1). The major high potential zones on the knowledge-driven map (Fig. 8.9) (both point processing and interpolated geochemical data) are in the southern SGB in the vicinity of the past-producing Jerome mine (G1 and G2), an extensive zone in the western SGB along the RDZ and at the intersection of the WKZ and RDZ (E, F) and an area within the Brett River synform (B).

Area A (Figs. 8.8, 8.9), a high potential area on the data-driven map only, represents a well-known mineralized area along the Old Women iron Formation. Drilling by Falconbridge has revealed sub-economic base-metal and gold mineralization. The high potential zone to the south of the Old Women iron Formation (H on Figs. 8.8 and 8.9) occurs within mafic volcanic rocks and appears to be associated with desegregated iron formation broken up in the RDZ. Areas G1 and G2, present on both the data and knowledge-driven maps (Fig. 8.8 and 8.9), is in the vicinity of the past-producing Jerome mine and occurs within the Rideout felsic porphyry which intrudes strained meta-sediments of the Opeepeesway Formation within the RDZ. Northwest and WNW trending brittle-ductile faults also dissect this area. Area B (Fig. 8.8) occurs within mafic volcanics of the October Lake Formation, a unit high in magnetite that results in strong linear magnetic signatures. A cluster of known gold prospects occur within this Formation in this area. Area J, which occurs on both the data and knowledge-driven maps, is close to the Shunsby base metal prospect. Northeast trending iron formations and felsic volcanics intruded by gabbro/dioritic rocks of unknown association typify this area. Area C, also present on both gold potential maps, is centered on thin, EW trending, magnetically high ultramafic units (cumulate flows) within massive and pillowed mafic volcanic rocks (Newton Formation). A number of known gold prospects occur in this vicinity. Area D, more strongly evident on the data-driven map (Fig. 8.8) occurs along EW trending thin felsic units of the Brett River Formation surrounded by massive to pillowed Mg and Fe-tholeiitic basalt of the Newton Formation. Structurally the area falls on the southern flank of the Brett River synform within an area of highly strained rocks (Brett River high strain zone – see Fig 1). Areas E and F, present on both the

prospectivity maps, occur in the western SGB within highly strained rocks of the RDZ and WKZ. The area is typified by thin, WNW striking intermediate, felsic and ultramafic lithologies within mafic volcanic rocks intruded by several gabbro/dioritic bodies of unknown association. Much of this area is poorly known due to extensive sand cover. Area L, occurs in the core of the Brett River synform in mafic volcanic rocks and is a zone of high potential on both the knowledge- and data-driven maps. Areas O and Q (data-driven only – Figs. 8.8a and 8.8b) are oriented along a northeast trending shear zones (Hardiman Bay high strain zone). Areas M and I are within the RDZ in mafic rocks.

Many of the high potential zones shown in Figure 8.8 and 8.9 are associated with known gold prospects; however, more importantly for exploration are zones that are not associated with known gold prospects (areas I, H present on both the knowledge and data-driven maps and N present on only the data-driven maps).

8.6 Discussion and Summary

Each modelling method offers advantages and disadvantages and as there is no right or wrong way of producing a gold prospectivity map per se, this paper has simply endeavoured to illustrate possible methodologies for producing a mineral prospectivity map using a GIS. Even though WofE or logistic regression requires a set of mineral occurrences with which to drive the modelling process, the geologist still has the option of applying the results from one area to an area with an insufficient number of mineral prospects provided that the area is characterized by a similar geologic environment and mineralization style. Estimating the various weights (W^+ etc.) based on expert knowledge thus using WofE in a knowledge-driven sense or employing a more common knowledge-based method such as the index overlay technique presented in this paper, are other options

The data-driven approach using the weights of evidence (WofE) or logistic regression techniques is objective as the weights for each evidence map are derived statistically, although Singer and Kouda (1999) show that WofE may produce biased estimates in some situations. The weights reflect whether more gold prospects fall on a given map pattern (e.g., geochemical anomaly, specific lithology, close to a fault etc.) than would be expected by chance. However, if there appears to be a spatial association between the known gold prospects and a specific map pattern, as reflected by higher weights (W^+ and C for WofE and higher coefficients for logistic regression), the geologist still must ascertain whether this apparent association makes geologic sense. In some cases a spatial association revealed by the WofE or logistic regression approach may result in a causal association that the geologist may have overlooked or had not considered in the exploration process. The knowledge-driven approach, although more subjective, offers more direct control over the modelling process. The index overlay method resulted in a prospectivity map that was more predictive than the boolean method (equally weighted evidence maps) indicating that expert knowledge provided by the geologist is an important part of the knowledge-driven modelling process. In this study the data-driven prospectivity maps were better predictors of the known gold prospects which is not surprising given that the location of known prospects with respect to geochemical, geophysical and geologic anomalies comprising evidence maps drives data-driven modelling techniques. However, more work is required to verify the above results.

The resultant gold prospectivity maps produced in this paper are somewhat different as each used a slightly different dataset, and the data comprising the evidence maps were purposely processed differently. Others researchers (Harris et al., 1995 and Wright and Bonham-Carter, 1996 and) have found that if the same exploration model is used (e.g. mesothermal gold, VMS etc.) and the same evidence maps, processed in the same way, data-driven and knowledge-driven techniques produce comparable results (e.g. mineral prospectivity maps are similar). Some of the data processing factors that may have caused differences in the prospectivity maps produced in this paper are first and foremost, (1) data that were used in one modelling method and not in the other, (2) differences with respect to the spatial extent of geochemical anomalies between interpolated geochemical

data and geochemical data processed as discrete points, (3) processing methods (correction for scavenging applied only to the geochemical data processed as discrete points, (4) normalization of lithogeochemical and lake sediment geochemical to lithology) and finally, (5) slightly different thresholds applied to the geochemical data (using WofE versus probability plots) to define anomalous populations.

With respect to the processing of geochemical data one has to be particularly cognizant of the behaviour of the data with respect to the sampling media. An obvious choice as a zone of influence around a lake sediment sample would be the drainage basin from which it derives an integrated geochemical signal. Quaternary geochemical data may be amenable to interpolation depending on the density of sample points as well as the media sampled. Intuitively, one would expect that geochemical samples taken from humus and soil would be more site specific, reflecting a relatively small zone of influence around each sample point. A sample taken from till, on the other hand, may represent an integrated signature from a much broader area depending on whether the till is residual or transported (e.g., moved by ice). Data sampled from rock would tend to have a small zone of influence depending on the rock type and degree of alteration. Geostatistical methods such as variograms should be employed to determine the spatial behaviour of the geochemical data under question before interpolation is attempted (see Harris et al., 2001). Poorly structured variograms, in which little apparent spatial association between data points is apparent, indicate that interpolating the data may not be warranted. In these cases treating geochemical data as discrete (buffered) points may be more desirable. The results from this paper indicate that geochemical anomalies derived from buffered geochemical points were better predictors of the known gold prospects than were anomalies based on interpolated data; however, more work needs to be undertaken to determine whether this will always be the case.

Correcting surficial geochemical data (soil, humus and lake sediments especially) for scavenging effects is more accurate when implemented on coincident sample points where more than one sample media is sampled, as was done for the surficial media (till, soil, humus) sampled for this study. The correction can still be made on interpolated data

(also done in this study); however, the effects of interpolation may affect the correction process. The results of normalizing lithogeochemical data to lithology will depend on the scale and accuracy of the geological map being used. In the absence of a reliable geological map a geochemical classification (e.g., Jensen, 1976) could be undertaken and normalization performed on the basis of the geochemical classification. Both correction for scavenging effects and normalization have generally resulted in more predictive geochemical anomalies with respect to known gold prospects (also see results by Harris et al., 2000).

The best predictors for gold in this study include specific geologic units (mafic volcanics, quartz-feldspar porphyries, iron formations), trace element anomalies in rock, alteration indices calculated from major oxide data, alteration mapped in the field, anomalies in major oxide elements (reflecting alteration) and linear magnetic anomalies (reflecting iron formations and magnetite-bearing mafic and ultramafic lithologies). The most predictive surficial geochemical anomalies were sampled from humus. This indicates that humus may be a good medium to sample for gold exploration perhaps because of its scavenging ability as well as its apparent broad geochemical signature (footprint) representative of vegetation, surficial media and rock.

Several areas of high gold potential, many of which are coincident with known gold prospects, are evident on the gold prospectivity maps produced using both modelling methods. The majority of these occur in mafic rocks within high strain zones, which is typical of many Archean greenstone belts. Some of these areas have been visited by the authors (e.g., the Wakami high strain zone (E, F on Figs. 8.8 and 8.9), the Old Women Iron Formation (A) and along the Rideout high strain zone (G). In most cases, the rocks in these areas are highly deformed and altered (carbonatized) and are similar to many of the gold producing environments found in more productive belts such as the Abitibi.

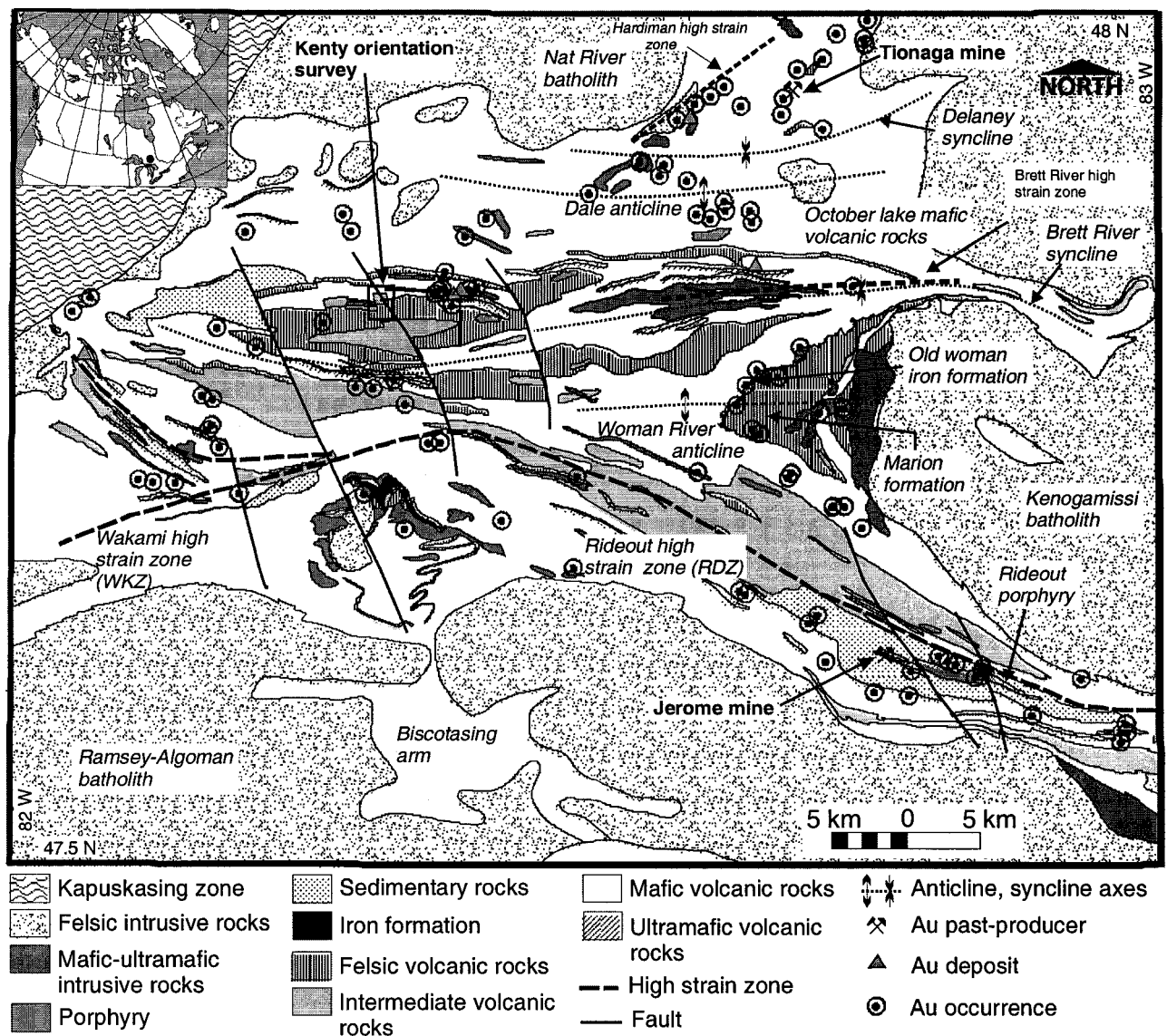


Figure 8.1 Study area – Swayze greenstone belt, Ontario

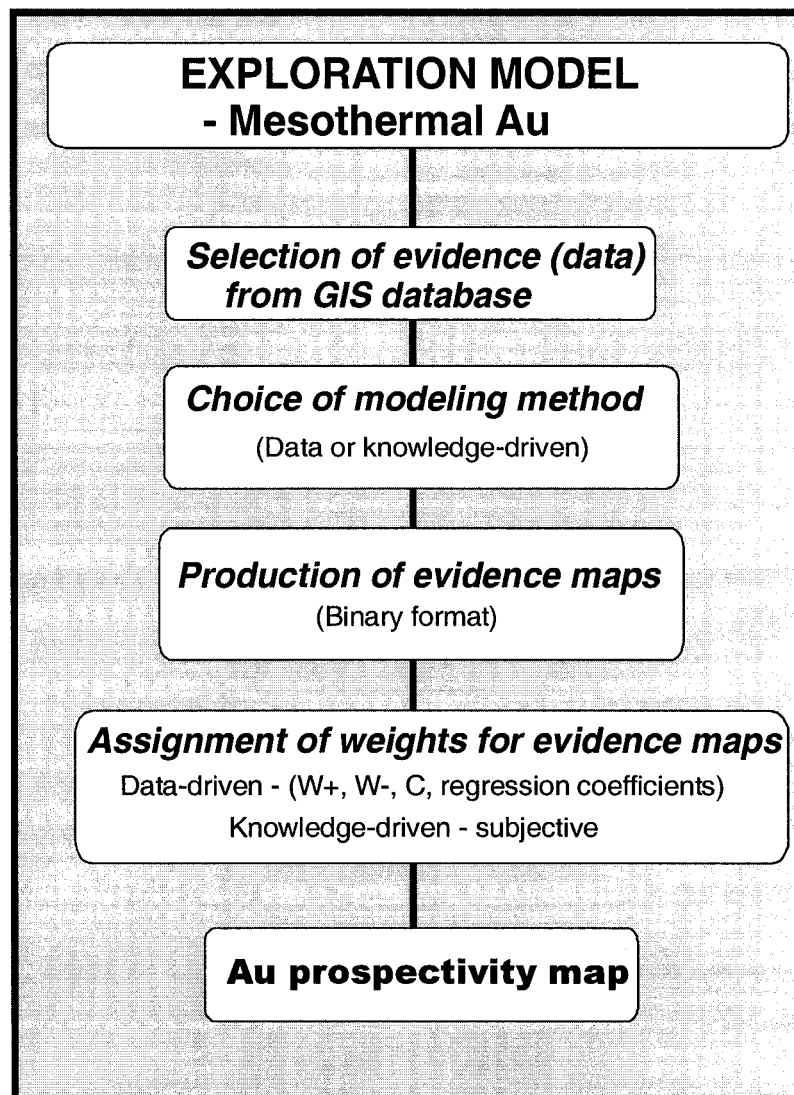


Figure 8.2 GIS modelling methodology

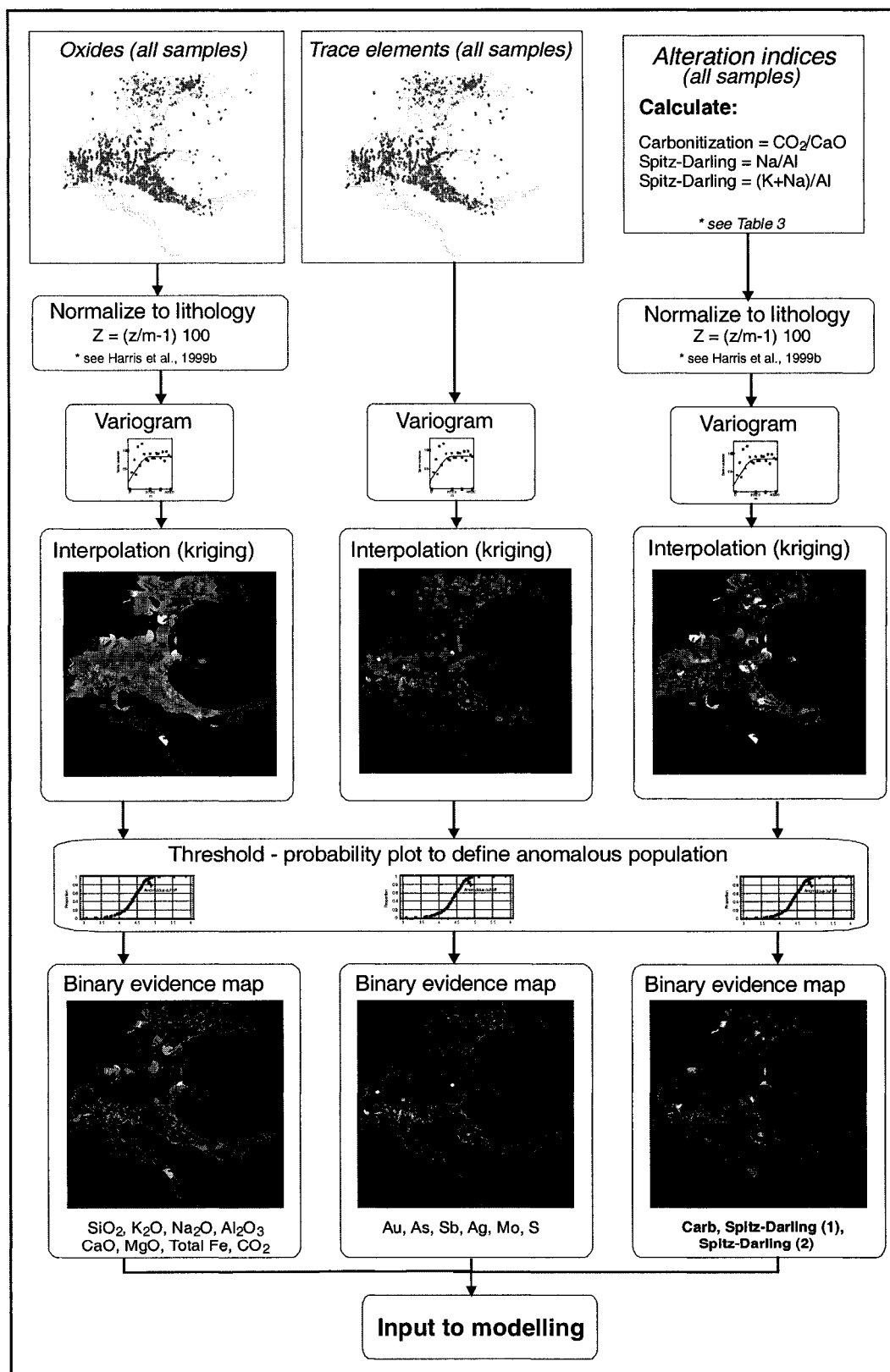


Figure 8.3 Processing method for interpolated lithogeochemical data

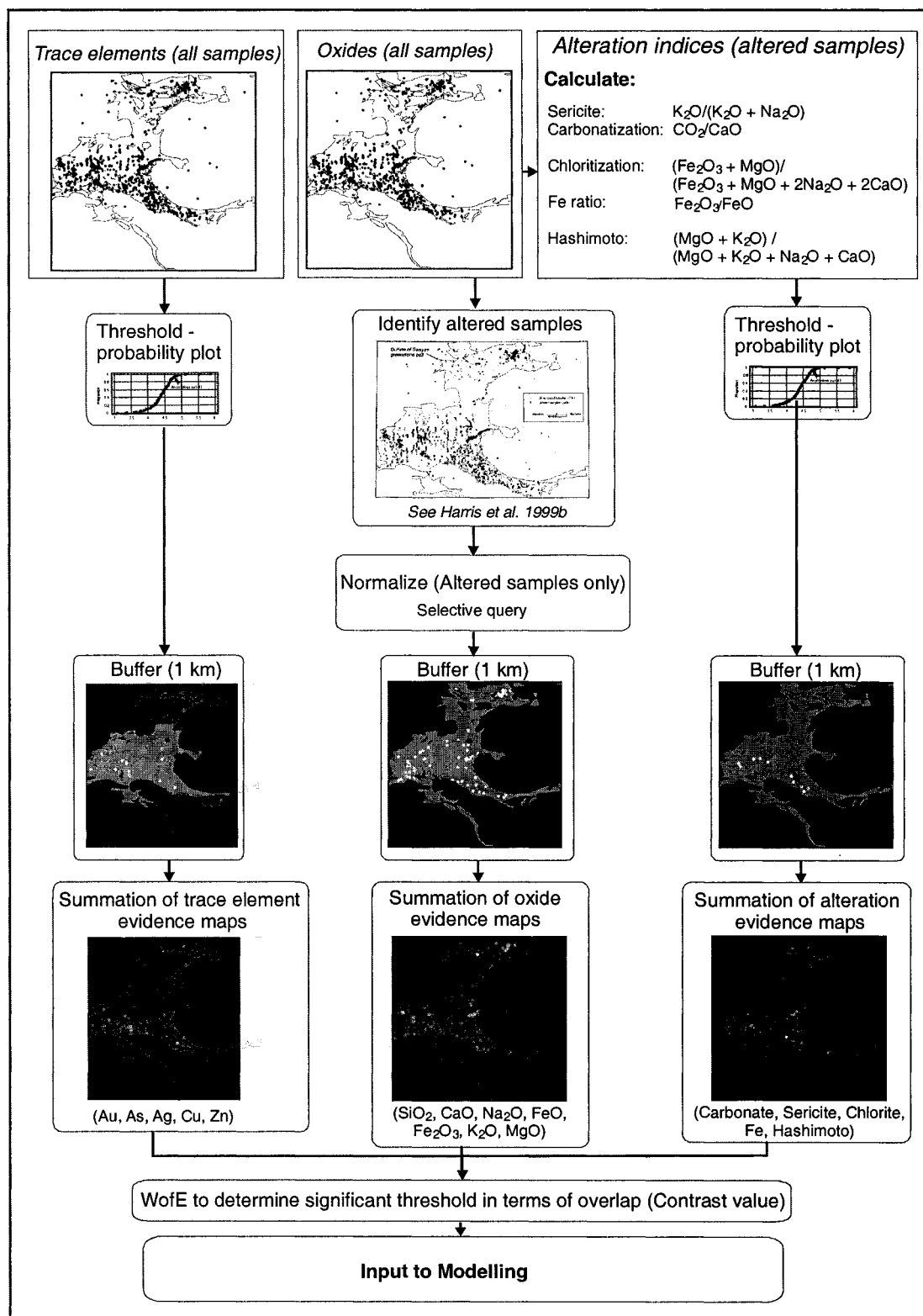


Figure 8.4 Processing method for lithogeochemical data processed as discrete (buffered) points

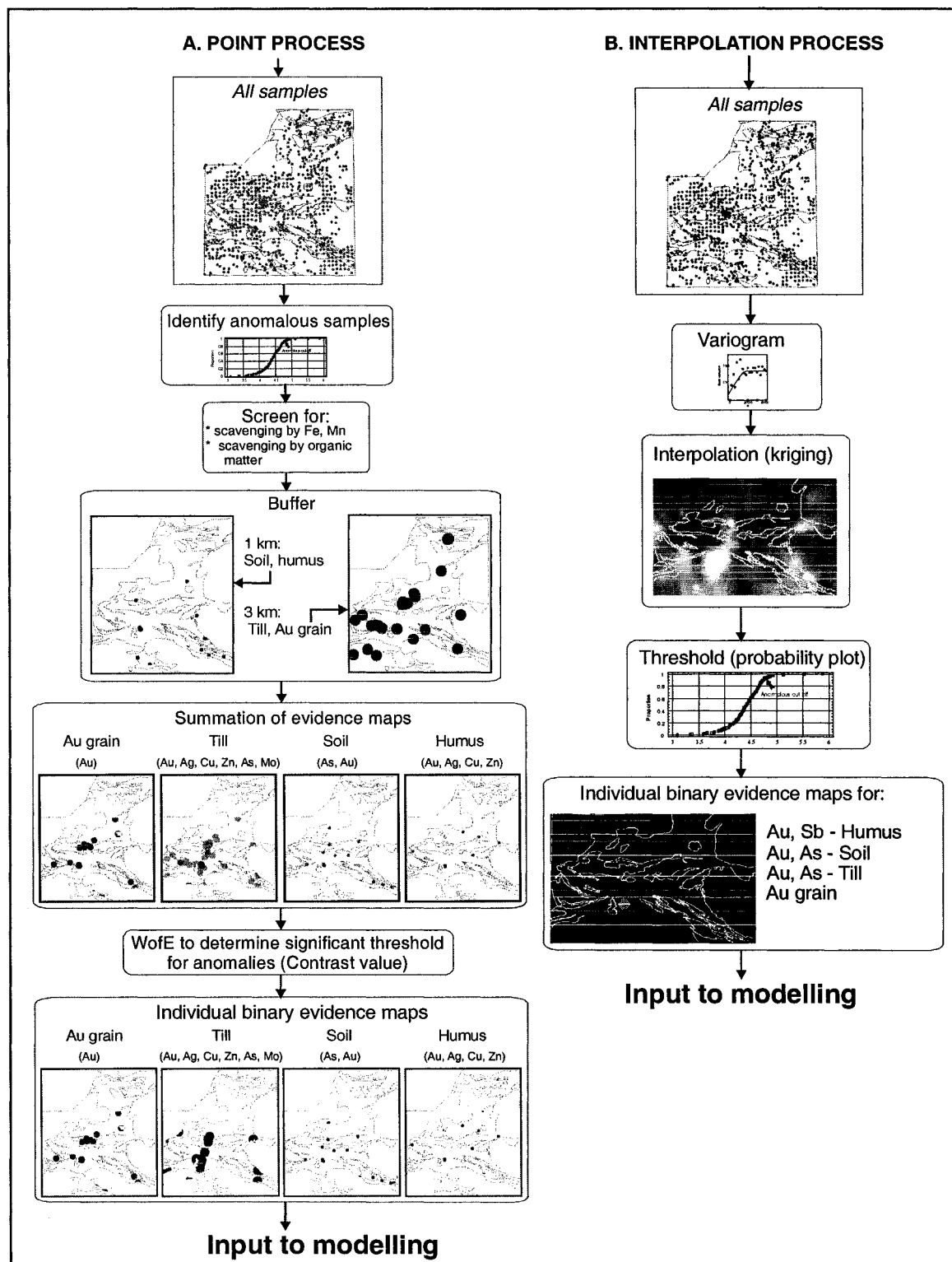


Figure 8.5 Processing method for surficial geochemical data

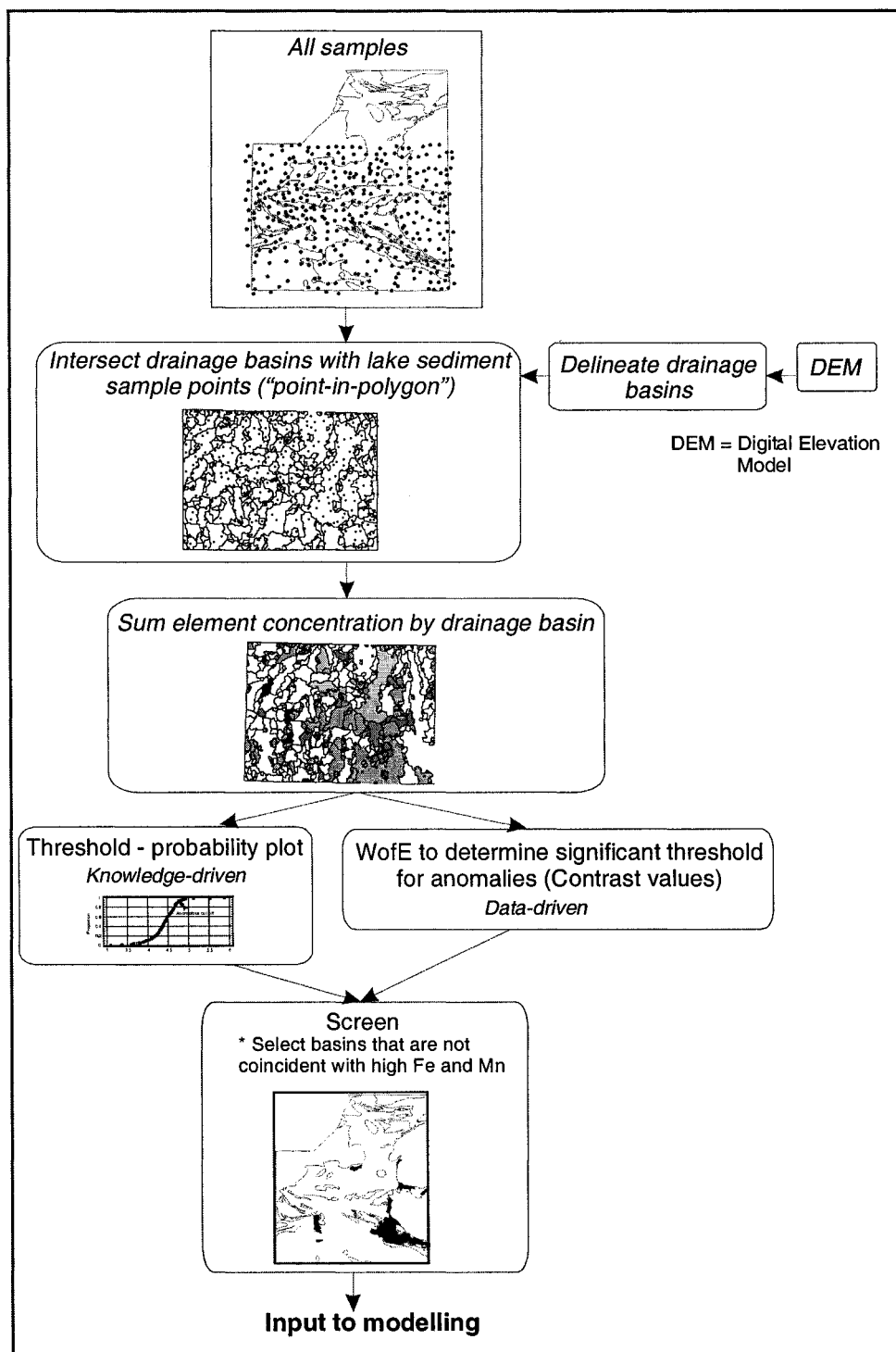


Figure 8.6 Processing method for lake sediment geochemical data

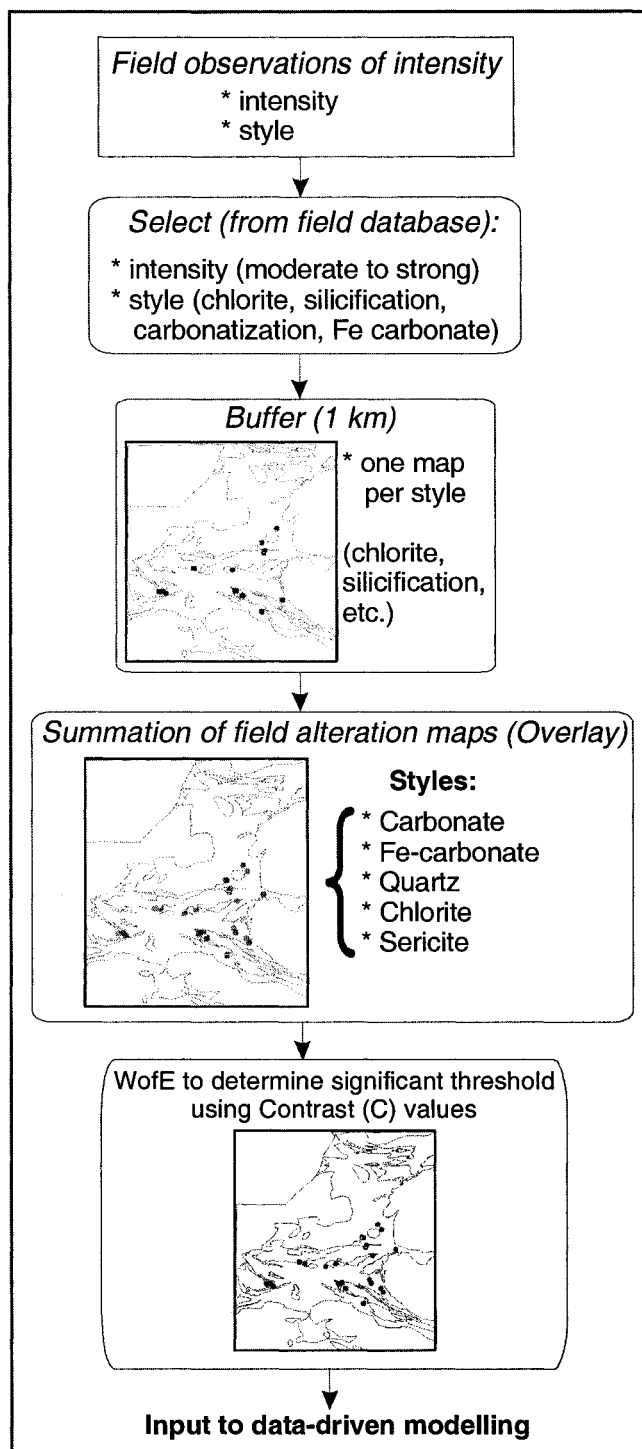


Figure 8.7 Processing methods for alteration data collected in the field

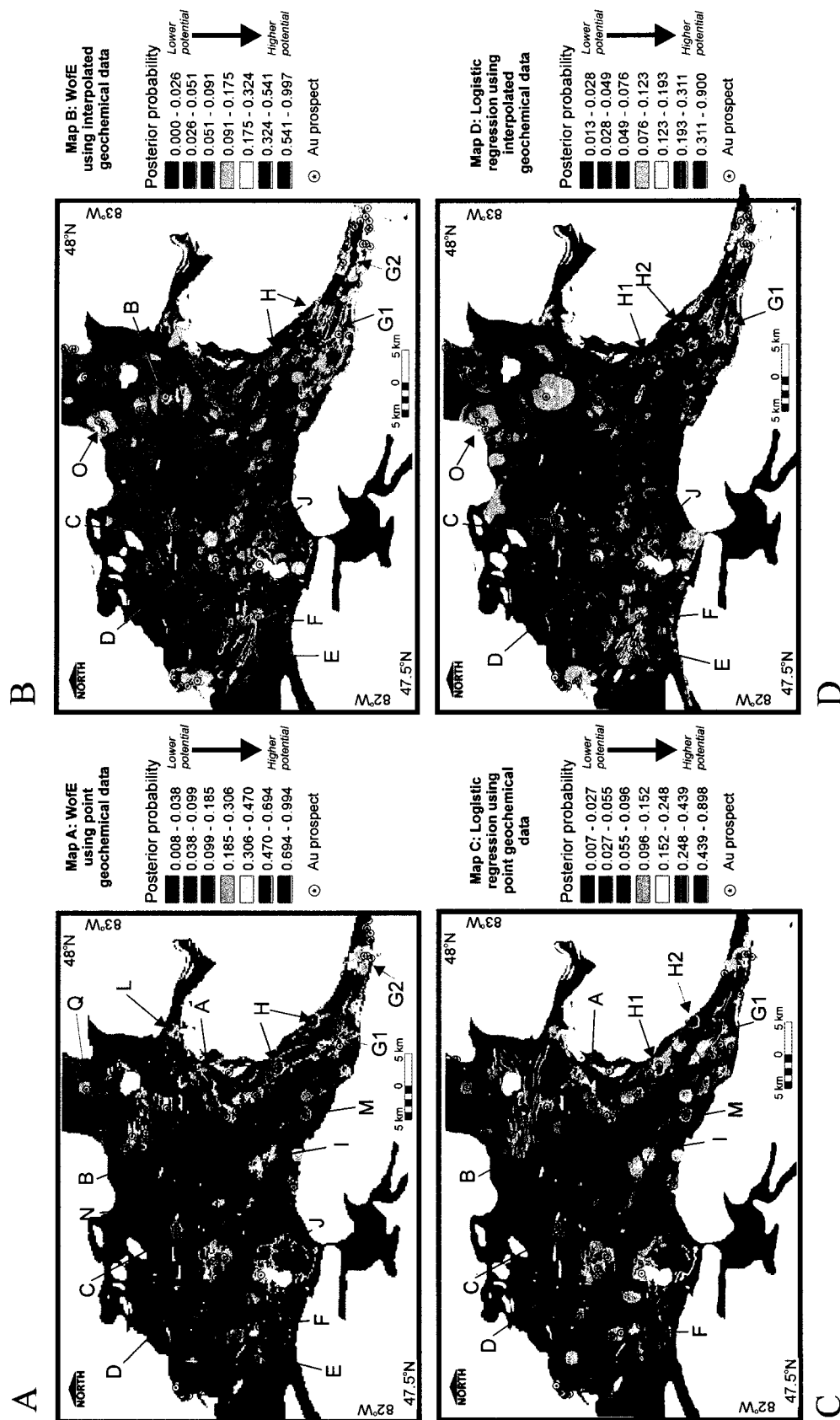


Figure 8.8 Data-driven gold prospectivity maps, (a) WofE using all data including point geochemical data, (b) WofE using all data including interpolated geochemical data, (c) logistic regression using all data including point geochemical data, (d) logistic regression using all data including interpolated geochemical data

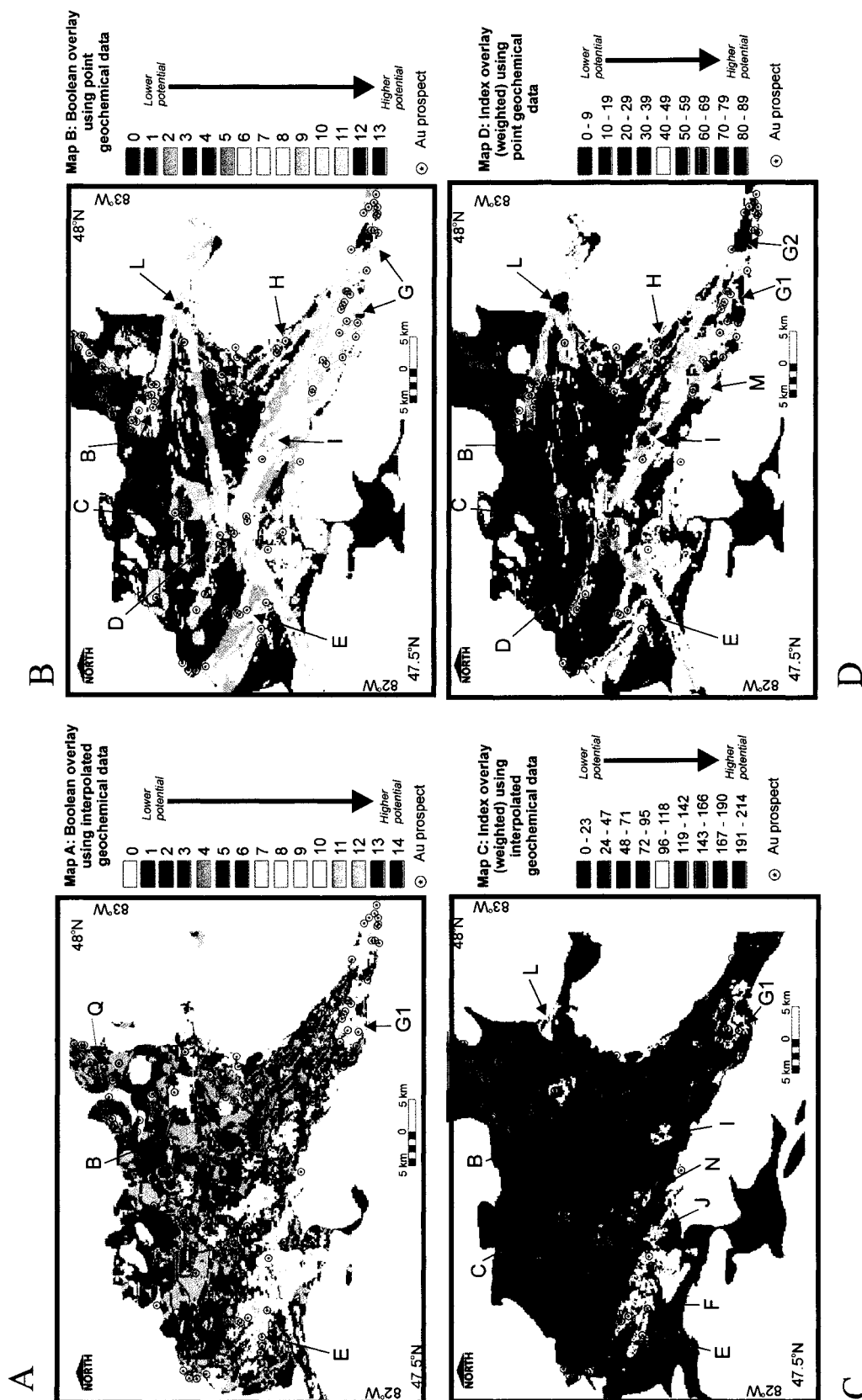


Figure 8.9 Knowledge-driven gold prospectivity maps, (a) Boolean overlay using all data including interpolated geochemical data, (b) Boolean overlay using all data including point geochemical data, (c) Index overlay using all data including interpolated geochemical data, (d) Index overlay using all data including point geochemical data

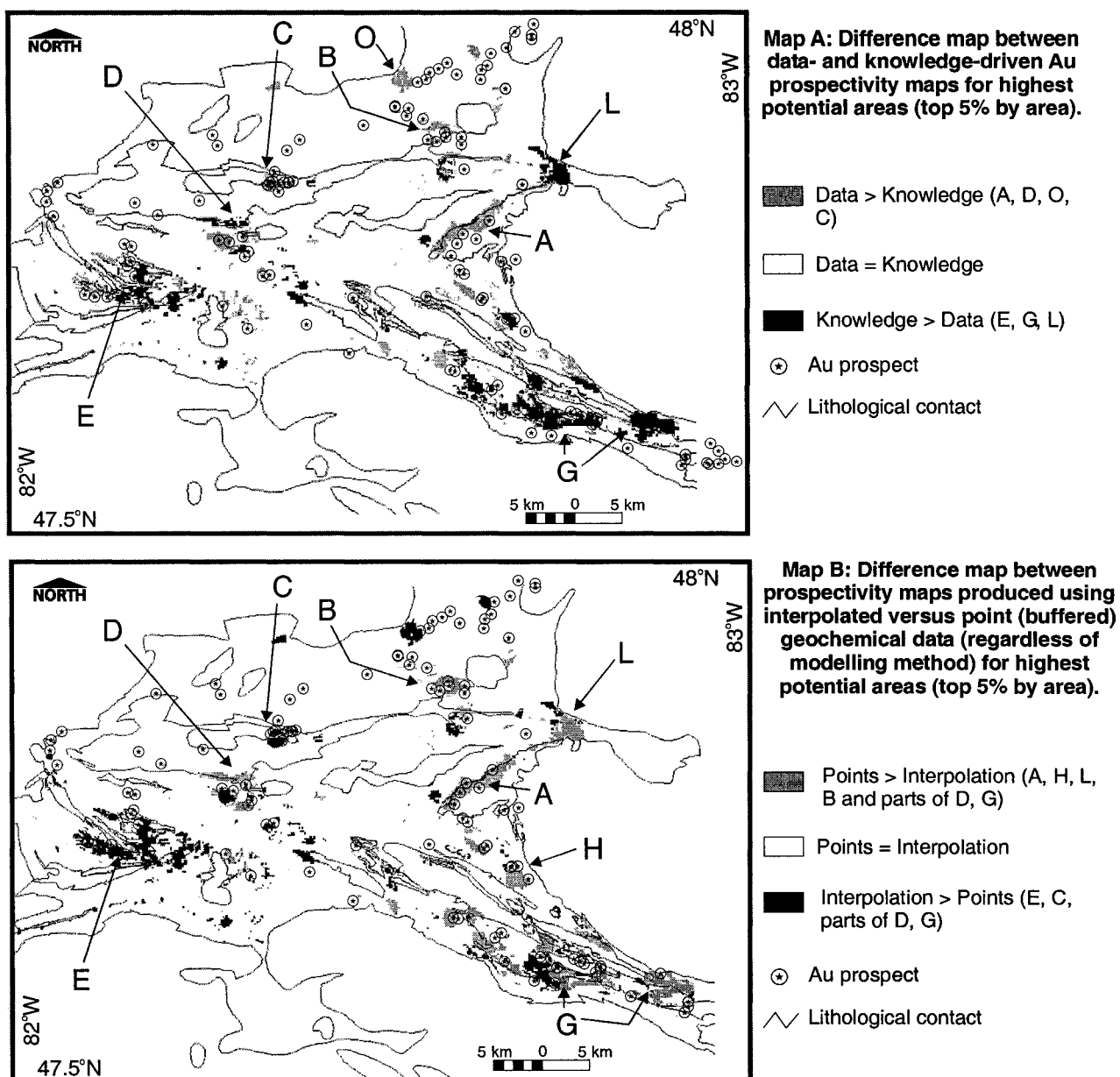


Figure 8.10 Difference maps - based on crosstabulation between prospectivity maps showing the highest potential areas, (a) difference map between data- and knowledge-driven maps (top 5% by area), (b) difference map between prospectivity maps (top 5% by area) produced using point geochemical data (regardless of method) and interpolated geochemical data

Method	Model parameters	Criteria for combining input data
<i>Data-driven methods</i>		
Weights of Evidence (WofE) (Bonham-Carter et al., 1988; Wright and Bonham-Carter, 1996; Agterberg, 1992; Wilkinson et al. 1999a)	Training area (knowledge of existing mineral deposits)	Establish spatial relationship between known occurrences and input data (use of Bayesian probabilities)
Logistic regression (Chung and Agterberg, 1980; Reddy and Bonham-Carter, 1991)	Training area (knowledge of existing mineral deposits)	Use of training areas around each deposit to gather statistics from each of the input layers - used to predict the presence or absence of a mineral deposit
Neural networks (Harris and Pan, 1999, Singer and Kouda, 1999, Singer and Kouda, 1996, Brown et al., 2000)	Training area (knowledge of existing mineral deposits)	Use of training areas around each deposit to gather statistics from each of the input layers - used to predict the presence or absence of a mineral deposit
<i>Knowledge-driven methods</i>		
Boolean operations (Harris, 1989)	Estimated by geologist	Summing of binary maps
Index overlay (Rencz et al., 1994)	Estimated by geologist	Summing of weighted binary maps
Inference networks and decision trees in an expert system (Duda et al., 1978; An et al., 1992; Reddy and Bonham- Carter, 1991)	Estimated by geologist	
Demster-Shafer belief theory (Moon, 1990)	Estimated by geologist	
Fuzzy logic (An et al., 1991; Chung and Moon, 1990)	Estimated by geologist	Each input predictor map assigned a fuzzy weight ranging from 0 to 1 - all predictor maps then combined using fuzzy operator (and, or, gamma)
Analytical hierarchy process (AHP) (Harris et al., 1995)	Estimated by geologist	Summing of weighted favourability (continuous maps)

Table 8.1 Review of methods for producing a mineral prospectivity map

Lithology	Comments
<i>Lithology</i>	
Variable	Ultramafic, mafic and felsic volcanic and sedimentary rocks (See Table 5)
Felsic intrusions (QFP- Quartz feldspar porphyry))	Apparent association with late tectonic, felsic, especially quartz-bearing intrusions Source of Au-bearing hydrothermal fluids, sink for Au, or heat engine mobilizing Au-bearing fluids
<i>Structure</i>	
High strain (deformation zones)	Generally EW-trending (major "breaks"), 100's km in length and several km's in width Late tectonic event, transecting all lithologies Mostly simple shear - oblique transcurrent movement although late vertical movement also known Conduits for Au-bearing fluids
Smaller-scale splay faults	Generally oblique (low angle) to major deformation zones Dilational zones of enhanced permeability Occur within and outside major deformation zones
Lithological contacts	Conduits for Au-bearing fluids
<i>Alteration</i>	
Carbonatization	Dominant alteration style and widespread Replacement of magnesite, ankerite, dolomite, calcite Distinct from lower grade seafloor diagenesis where calcite, epidote, actinolite and zeolites are the major alteration minerals
Silicification	Quartz flooding (quartz veining - variable orientations)
Potassic alteration	Potassium metasomatism (Sericite and biotite growth)
Albitization	Metasomatism (Alkali feldspar growth)
Chloritization	Metasomatism (Chlorite growth)
Iron sulphides	Pyrite, pyrrhotite, arsenopyrite
<i>Geochemistry</i>	
Oxides and volatiles	Enrichment of CO ₂ , K ₂ O, S, H ₂ O, and Al ₂ O ₃
Trace elements	Enrichment of Au, As, Sb, W, Mo, Ag, Cu, Zn, Pb

Table 8.2 Summary of mesothermal gold exploration criteria (compiled from Colvine, 1983; Colvine and others, 1988; Robert, 1990; Hodgson, 1993)

Data type	Format	Source
Airborne magnetics	Raster	OGS, 1997; Dods et al., 1985
Airborne electromagnetics (EM)	Raster	OGS, 1997, Dods et al., 1985
Lithogeochemistry	Points	Wilkinson et al., 1999b
Quaternary geochemistry (till, soil, humus, Au grain counts)	Points	Bernier, 1995; Bernier and Kaszycki, 1995
Lake sediment geochemistry	Points	GSC 1988, 1987
Geology (lithology and structure)	Polygons and vectors	Ayer, 1995; Heather and Shore (1999)
Geology (lithology)	Polygons	OGS, unpublished (available on CD-ROM Harris et al., 1999a)
Geology (field measurements)	Points	Ayer, 1995; Heather and Shore (1999)
Remotely-sensed data (Landsat)	Raster	Radarsat International Inc.
Mineral prospects	Points	Fumerton et al., 1993; Fumerton and Houle, 1993

Table 8.3 Summary of data used in the GIS modeling

Alteration index	Alteration process	Reference
Chlorite $(\text{Fe}_2\text{O}_3 + \text{MgO}) / (\text{Fe}_2\text{O}_3 + \text{MgO} + 2\text{Na}_2\text{O} + 2\text{CaO})$	Addition of Fe and Mg as chlorite	Saeki and Date, 1980
Hashimoto $(\text{MgO} + \text{K}_2\text{O}) / (\text{MgO} + \text{K}_2\text{O} + \text{Na}_2\text{O} + \text{CaO})$	Addition of Mg and K as chlorite and sericite. Loss of Ca and Na by destruction of feldspar.	Ishikawa et al., 1975
Sericite $\text{K}_2\text{O} / (\text{K}_2\text{O} + \text{Na}_2\text{O})$	Alteration of feldspar to sericite	Saeki and Date, 1980
Fe ratio $(\text{Fe}_2\text{O}_3 / \text{FeO})$	Iron oxidation	
Carbonatization $(\text{CO}_2 / \text{CaO})$	Carbonate species (calcite to dolomite to ankerite)	Whithead et al., 1981
Spitz Darling $\text{Na}_2\text{O} / \text{Al}_2\text{O}_3$	Sodium depletion	Spitz and Darling, 1978
$(\text{K}_2\text{O} + \text{Na}_2\text{O}) / \text{Al}_2\text{O}_3$	Alkali depletion or enrichment	

Table 8.4 Alteration Indices (modified form Table 1 in Franklin, 1997)

Evidence theme - Data-driven modeling		Evidence theme - Knowledge-driven modeling	
Structural data			
Deformation zones	Mapped (Heather and Shore, 1999a-i)	Deformation zones	Mapped (Heather and Shore, 1999) and interpreted from magnetic and remotely-sensed data
Deformation zones	Interpreted from magnetic and remotely-sensed data		
Faults < 100m	Mapped (Heather and Shore, 1999a-i)	E-W trending faults	Interpreted from magnetics data
Faults < 250m	Interpreted from Landsat TM data	Oblique faults	Interpreted from magnetics data (< 30° orientation from major E-W trending faults)
Geophysical data			
Magnetic anomalies	Interpreted from interpolated EM data. Most anomalies are linear and reflect sulphide conductors and iron formation	Faults/conductors	Interpreted from EM and magnetics data
EM anomalies	Threshold from upper breakpoint on normal probability plot. Most anomalies are linear zones reflecting oxide iron formation or mafic to ultramafic lithologies		
Lithology data			
Felsic porphyry	Rideout series	Ultramafic volcanic rocks	Au falling within mapped unit
Mafic volcanic rocks	October Lake formation	Mafic volcanic rocks	Au falling within mapped unit
Iron formation	Various (e.g., Old Woman iron formation)	Sedimentary rocks	Au falling within mapped unit
Felsic volcanic rocks	Marion formation - Rideout series	Felsic intrusions (Quartz-feldspar and feldspar porphyries)	Au falling within 250m of a porphyry (e.g., representing a zone of influence - maximum spread of Au-bearing fluids)
Sedimentary rocks			
Quartz-feldspar porphyry	Any		
Lithological Contact data			
Quartz-feldspar porphyry	Within 1600m of a quartz-feldspar porphyry (distance threshold determined from Contrast (C) using WofE)	Mafic volcanic/ sedimentary rocks	Au falling within 250m from a contact
		Mafic volcanic/ultramafic volcanic rocks	Au falling within 250m from a contact
		Felsic intrusion/mafic volcanic rocks	Au falling within 250m from a contact
		All other contacts	Au falling within 250m from a contact
Geochemistry data			
Alteration	Mapped in field (Heather and Shore, 1999a-i). Sum map of alteration styles (chlorite,sericite, potassic, silicification)		
Alteration indices	Sum map of alteration indices calculated from major oxide data	Carbonatization Spitz and Darling (Na ₂ O / Al ₂ O ₃)	Spitz and Darling (K ₂ O + Na ₂ O / Al ₂ O ₃)
Major oxides	Sum map (Mg, Al, Ca, Si, K, Na, Fe)	Individual maps (Mg, Al, Ca, Si, K, Na, Fe, CO ₂)	
Trace elements	Sum map (Au, As, Ag, Cu, Sb, W, Zn)	Individual maps (Au, AS, Sb, Ag, S, Mo)	
Humus	Sum map (Au, Ag, Cu, Zn)	Individual maps (Au, Sb)	
Soil	Sum map (Au, As)	Individual maps (Au, As)	
Till	Sum map (Cu, Zn)	Individual maps (Au, As, Au grain counts)	
Lake sediments	Sum map (Au, Ag, Sb)	Individual maps (Au, As, Sb)	

Table 8.5 Summary of evidence maps used in GIS modeling

Evidence theme	Threshold ¹
<i>Alteration (Mapped in the field)</i>	
Quartz	Moderate to strong - selected from GIS database of field measurements
Chlorite	Moderate to strong - selected from GIS database of field measurements
Carbonate	Moderate to strong - selected from GIS database of field measurements
Fe-Carbonate	Moderate to strong - selected from GIS database of field measurements
<i>Alteration indices - not normalized (see Table 4)</i>	
Chlorite	> 95th percentile value
Hashimoto	> 95th percentile value
Sericite	> 95th percentile value
Fe oxidation	> 95th percentile value
Carbonatization	> 95th percentile value
<i>Major oxides (using altered samples only)</i>	
MgO	> 23% (95th percentile)
CaO	> 11.0% (90th percentile)
Fe ₂ O ₃	> 13.7% (96th percentile)
K ₂ O	> 3.4% (95th percentile)
Na ₂ O	> 4.3% (80th percentile)
SiO ₂	> 74% (96th percentile)
<i>Trace elements (not normalized)</i>	
As	> 30 ppm (95th percentile)
Ag	> 80 ppm (97th percentile)
Au	> 100 ppb (98th percentile)
Cu	> 500 ppm (97th percentile)
Sb	> 5 ppm (97th percentile)
W	> 60 ppm (98th percentile)
Zn	> 400 ppm (99th percentile)
<i>Quaternary geochemistry (screened)</i>	
Humus (Cu, Zn)	(Cu > 42 ppm OR Zn > 400 ppm) AND (Fe <= 1.4 ppm OR Mn <= 550 ppm)
Humus (Au, Ag)	(Au > 16 ppb OR Ag > 1.2 ppm) AND (Fe <= 1.4 ppm OR Mn <= 550 ppm)
Soil (Au)	(Au > 20 ppb) AND Fe <= 4.5 OR Mn <= 325 ppm)
Soil (As)	(As > 7.1) AND (Fe <= 4.5 OR Mn <= 325 ppm)
Till (Cu, Zn)	(Cu > 250 ppm OR Zn > 80 ppm) AND (Fe <= 7 ppm OR Mn <= 900 ppm)
Till (Au, Ag)	(Au > 35 ppb OR Ag > 1 ppm) AND (Fe <= 7 ppm OR Mn <= 900 ppm)
<i>Lake sediment geochemistry (screened)</i>	
Cu	(Cu > 62 ppm) AND (Fe < 2 ppm OR Mn <= 600 ppm OR LOI <= 76 ppm)
Au	(Au > 4 ppb) AND (Fe < 2 ppm OR Mn <= 600 ppm OR LOI <= 76 ppm)
Sb	(Sb > 0.6 ppm) AND (Fe < 2 ppm OR Mn <= 600 ppm OR LOI <= 76 ppm)
Zn	(Zn > 150 ppm) AND (Fe < 2 ppm OR Mn <= 600 ppm OR LOI <= 76 ppm)
As	(As > 9 ppm) AND (Fe < 2 ppm OR Mn <= 600 ppm OR LOI <= 76 ppm)
Mo	(Mo > 10 ppm) AND (Fe < 2 ppm OR Mn <= 600 ppm OR LOI <= 76 ppm)

¹ Thresholds based on breakpoints on probability plots

Table 8.6 Summary of geochemical thresholds used to produce binary evidence maps for data-driven (WofE and logistic regression) modeling

Evidence theme	Description	Sub-theme weight	Total score	Maximum total
Structure (Theme rank = 5)				
Deformation zones	Mapped (Heather and Shore, 1999a-i) and interpreted from magnetic and remotely-sensed data	5	25	
E-W trending faults	Interpreted from magnetics data	3	15	45 ^a
Oblique faults	Interpreted from magnetics data (< 30° orientation from major E-W trending faults)	1	5	
Faults/conductors	Interpreted from EM data	1	5	
Lithology (Theme rank = 4)(Lithological units from unpublished OGS compilation)				
Ultramafic volcanic rocks	Au falling within mapped unit	4	16	
Mafic volcanic rocks	Au falling within mapped unit	5	20	
Sedimentary rocks	Au falling within mapped unit	2	8	40 ^a
Felsic intrusions (Quartz-feldspar and feldspar porphyries)	Au falling within 250m of a porphyry (e.g., Representing a zone of influence - maximum spread of Au-bearing fluids)	5	20	
Contacts (Theme rank = 3)				
Mafic volcanic/sedimentary rocks	Au falling within 250m from a contact	3	9	
Mafic volcanic/ultramafic volcanic rocks	Au falling within 250m from a contact	5	15	15 ^b
Felsic intrusion/mafic volcanic rocks	Au falling within 250m from a contact	5	15	
All other contacts	Au falling within 250m from a contact	1	3	
Till - Au grain counts (Theme rank = 4)				
> 98th percentile	Anomalous threshold determined from upper breakpoint in normal probability plot of Au grain counts	5	20	
95th to 98th percentile	As above	4	16	20 ^b
Quaternary geochemistry (Theme rank = 4)(Un-screened data)				
Au in till > 35 ppb	> 96th percentile in normal probability plot	5	20	
Au in humus > 16 ppb	> 95th percentile in normal probability plot	5	20	60 ^a
Au in soil > 20 ppb	> 95th percentile in normal probability plot	5	20	
Quaternary geochemistry (Theme rank = 3)(Un-screened data)				
As in till > 40 ppm	> 97th percentile in normal probability plot	5	15	
Sb in humus	> 95th percentile in normal probability plot	5	15	45 ^a
As in soil > 7.1 ppm	> 96th percentile in normal probability plot	5	15	
Trace element lithogeochemistry (Theme rank = 4) (Not normalized to lithology)				
Au > 100 ppb	> 95th percentile in normal probability plot	5	20	20
Pathfinder trace element lithogeochemistry (Theme rank = 3) (Not normalized to lithology)				
As > 30 ppm	> 95th percentile in normal probability plot	5	15	
Sb > 5 ppm	> 97th percentile in normal probability plot	5	15	65 ^b
Ag question 80 ppm	> 97th percentile in normal probability plot	5	15	
S > 150 ppm	> 95th percentile in normal probability plot	2	10	
Mo > 30 ppm	> 95th percentile in normal probability plot	2	10	
Alteration indices (Theme rank = 4) (Calculated from major oxide data)				
Carbonitization	> 95th percentile in normal probability plot	5	15	
Spitz and Darling (Na ₂ O / Al ₂ O ₃)	> 95th percentile in normal probability plot	2	15	60 ^b
Spitz and Darling (K ₂ O + Na ₂ O / Al ₂ O ₃)	> 95th percentile in normal probability plot	3	15	
Lake sediment geochemistry (Theme rank = 4)				
Au > 4 ppb	> 90th percentile in normal probability plot	5	20	20
Pathfinder lake sediment geochemistry (Theme rank = 3)				
As > 9 ppm	> 95th percentile in normal probability plot	5	15	30 ^b
Sb > 0.6 ppm	> 95th percentile in normal probability plot	5	15	
Major oxide lithogeochemistry (Theme rank = 2) (Normalized to lithology)				
SiO ₂ - Silicification	> 95th percentile in normal probability plot	5	10	
MgO - Chloritization/Serpentinization	> 95th percentile in normal probability plot	2	4	
Fe (total) - Oxidation	> 95th percentile in normal probability plot	3	6	
K ₂ O - Potassic alteration	> 95th percentile in normal probability plot	4	8	60 ^b
Na ₂ O - Albitization	> 95th percentile in normal probability plot	2	8	
Al ₂ O ₃	> 95th percentile in normal probability plot	2	8	
CaO - Carbonatization	> 95th percentile in normal probability plot	5	10	
CO ₂ - Carbonatization	> 95th percentile in normal probability plot	3	6	

^a Maximum total represents non-mutually exclusive themes. For example, Au in mafic volcanics and Au within 250 m of a quartz feldspar porphyry would have a maximum total of 40 (20 + 20 = 40).

^b Maximum total represents mutually exclusive themes. For example, areas of Au grain counts above the 98th percentile cannot overlap areas of Au grain counts in the 95-98th percentile range. Here the maximum total represents simply the highest total score for the related themes.

Table 8.7 Summary of data and weighting scheme used in knowledge-based modeling (Index overlay only)

Normalization to lithology – applied to lithogeochemical data only		
	<i>Data-driven modeling</i>	<i>Knowledge-driven modeling</i>
<i>Major oxides</i>	Yes (used only altered samples – selective query method)	Yes (used all samples – altered and un-altered - equation method)
<i>Alteration Indices</i>	No (because used only altered samples)	Yes (used all samples – equation method)
<i>Trace elements</i>	No (high concentrations assumed to be more reflective of alteration / mineralization)	No (high concentrations assumed to be more reflective of alteration / mineralization)
Screening for Scavenging (e.g., true vs. false anomalies) – applied to surficial and lake sediment geochemical data		
<i>Surficial</i>	applied to data processed as points only - using selective query	applied to data processed as points only - using selective query
<i>Lake sediments</i>	Yes	No

Table 8.8 Summary of different processing techniques applied to geochemical data

<i>Map Class</i>	<i>Area (km²)</i>	<i>No. of Au prospects</i>	<i>W+</i>	<i>W-</i>	<i>C</i>	<i>Stud. C^a</i>	<i>Used in model?</i>	<i>Rank by C value</i>
Structure								
Mapped deformation zones	545.0	29	0.04	-0.01	0.06	0.29	N	
Interpreted deformation zones	424.0	34	0.46	-0.16	0.62	2.98	Y	
Mapped faults < 100m	122.0	14	0.87	-0.08	0.96	3.10	Y	
Interpreted faults < 250m	348.0	35	0.69	-0.22	0.91	4.39	Y	
Geophysics								
Magnetic anomalies	58.0	10	1.20	-0.07	1.33	3.95	Y	9
EM anomalies	312.0	19	0.18	-0.03	0.21	0.86	Y	
Geology								
Rideout series felsic porphyry	4.9	4	2.90	-0.03	2.99	5.38	Y	1
Mafic volcanic rocks	21.7	6	1.70	-0.05	1.80	4.21	Y	2
Iron formation	19.3	4	1.40	-0.03	1.49	2.87	Y	5
Marion formation felsic volcanic	40.1	5	0.94	-0.03	0.97	2.09	Y	11
Sedimentary rocks	58.6	6	0.74	-0.03	0.77	1.81	Y	
Quartz-feldspar porphyry	11.6	1	0.56	0.00	0.56	0.56	Y	
Contacts								
Quartz-feldspar porphyry	109.0	27	1.20	-0.22	1.40	5.10	Y	6
Geochemistry								
Alteration mapped in field	67.8	14	1.40	-0.11	1.55	5.30	Y	4
Alteration indices	113.0	18	1.20	-0.16	1.39	5.20	Y	7
Major oxides	49.4	9	1.30	-0.07	1.36	3.80	Y	8
Trace elements	110.0	25	1.50	-0.21	1.74	7.40	Y	3
Humus	23.1	4	1.20	-0.02	1.27	2.40	Y	10
Soil	41.4	5	0.88	-0.02	0.91	1.90	Y	
Till	237.0	16	0.28	-0.04	0.32	1.20	Y	
Lake sediments	266.3	23	0.57	-0.11	0.68	2.70	Y	

^a Stud. C is studentized Contrast value (Contrast / Standard deviation of the Contrast)

Table 8.9 Results of weights of evidence (WofE) statistics for the summed evidence maps (see Table 8.5)

<i>Map Class</i>	<i>Area (km²)</i>	<i>No. of Au prospects</i>	<i>W+</i>	<i>W-</i>	<i>C</i>	<i>Stud. C^a</i>	<i>Rank^b</i>
<i>Alteration - Mapped in the field</i>							
Quartz	16.4	4	1.60	-0.03	1.64	3.14	2
Chlorite	42.9	8	1.32	-0.05	1.38	3.70	4
Carbonate	9.4	4	2.19	-0.03	2.23	4.19	1
Fe-Carbonate	40.2	8	1.39	-0.06	1.45	3.80	3
<i>Alteration indices</i>							
Chlorite	34.0	8	1.56	-0.06	1.63	4.30	2
Hashimoto	45.8	12	1.67	-0.10	1.78	5.60	1
Sericite	39.5	4	0.69	-0.02	0.71	1.38	5
Fe oxidation	31.8	5	1.20	-0.03	1.24	2.66	3
Carbonatization	31.2	5	1.16	-0.03	1.20	2.57	4
<i>Major oxides</i>							
MgO	43.2	4	0.60	-0.01	0.62	1.21	5
CaO	175.0	15	0.53	-0.06	0.59	2.10	6
Fe ₂ O ₃	54.4	10	1.31	-0.07	1.38	4.10	1
K ₂ O	85.1	11	0.95	-0.06	1.01	3.16	3
Na ₂ O	130.6	16	0.89	-0.10	0.99	3.63	4
SiO ₂	160.2	23	1.05	-0.16	1.22	5.10	2
<i>Trace elements</i>							
As	24.1	4	1.20	-0.02	1.23	2.38	6
Ag	17.1	4	1.56	-0.03	1.59	3.05	4
Au	43.0	11	1.65	-0.09	1.74	5.30	3
Cu	44.2	9	1.42	-0.06	1.48	4.19	5
Sb	3.2	1	1.85	0.00	1.85	1.80	2
W	7.6	3	2.10	-0.02	2.13	2.13	1
Zn	37.8	4	0.74	-0.02	0.76	1.48	7
<i>Quaternary geochemistry (screened)</i>							
Humus - Cu and Zn	13.5	3	1.50	-0.02	1.53	2.56	1
Humus - Au and Ag	13.7	1	0.36	0.00	0.36	0.36	(4)
Soil - Au	15.8	9	1.34	-0.02	1.36	2.29	2
Soil - As	28.8	3	0.72	-0.01	0.74	1.25	(3)
Till - Cu and Zn	237.0	16	0.28	-0.04	0.32	1.20	(5)
Till - Au and Ag	319.0	17	0.04	0.00	0.04	0.21	(6)
<i>Lake sediments (screened)</i>							
Cu	377.0	17	-0.12	0.02	-0.14	-0.54	(6)
Au	228.0	22	0.65	-0.11	0.77	3.10	2
Sb	10.2	1	0.66	0.00	0.66	0.66	(3)
Zn	353.0	24	0.29	-0.07	0.36	1.50	4
As	63.7	9	1.04	-0.05	1.10	3.10	1
Mo	215.0	14	0.25	-0.03	0.28	0.98	(5)

^a Stud. C is studentized Contrast value (Contrast / Standard deviation of the Contrast)

^b Rank is based on C (Contrast) values. Ranks in brackets indicate poor confidence in the significance of the Contrast value due to studentized Contrast values of less than 1.5.

Table 8.10 Results of weights of evidence (WofE) statistics for the individual binary evidence maps (see Table 8.6)

	Index overlay	Boolean	Logistic regression	WofE
Index overlay		0.77	0.80	0.56
Boolean			0.72	0.60
Logistic regression				0.80
WofE				

Table 8.11 Spearman correlation coefficients between gold prospectivity maps produced using geochemical data processed as discrete (buffered) points (significant above the 95th percentile confidence limit) – highest correlations shown in bold $\geq .8$

	Index overlay	Boolean	Logistic regression	WofE
Index overlay		0.25	0.30	0.25
Boolean			0.25	0.25
Logistic regression				0.89
WofE				

Table 8.12 Spearman correlation coefficients between gold prospectivity maps produced using interpolated geochemical data (significant above the 95th percentile confidence limit) – highest correlations shown in bold $\geq .8$

		<i>Point geochemical data</i>			
		Index overlay	Boolean	Logistic regression	WofE
<i>Interpolated geochemical data</i>	Index overlay	0.25			
	Boolean		0.77		
	Logistic regression			0.53	
	WofE				0.28

Table 8.13 Spearman correlation coefficients between gold prospectivity maps, comparison by modeling methods (data- vs. knowledge-driven) and geochemical processing method (point vs. interpolation) (significant above the 95th percentile confidence limit) – highest correlations shown in bold $\geq .5$

Method	Contrast (C)
Logistic regression (points)	3.19
Logistic regression (interpolation)	2.57
WofE (points)	2.21
WofE (interpolation)	2.13
Index overlay (points)	1.56
Index overlay (interpolation)	1.10
Boolean overlay (interpolation)	0.94
Boolean overlay (points)	0.82

Table 8.14 Contrast value (determined from WofE analysis) for the highest potential areas (top 5% by area) for each gold prospectivity map (by modeling method and geochemical processing method) (all C values are significant as the studentized values C/SD – see Bonham-Carter (1994) are all greater than 1.5)

CHAPTER IX

SUMMARY and CONCLUSIONS

9.1 Geochemical data processing

9.1.1 Statistical comparison of geochemical data

Geochemical data should be analysed by specific groups based on geologic rationale. The GIS can be effectively employed to partition geochemical populations into geologically meaningful groups such as lithologic or surficial units, drainage basins, till sheets, altered vs. un-altered samples or by geochemical classification for further statistical characterization. Box and whisker plots are a particularly useful for assessing the differences between geochemical populations. It is often advantageous to log-transform geochemical data (especially trace elements) thus allowing for statistical procedures which assume a normal distribution (e.g. principal component analysis), to be applied and for geostatistical analysis and interpolation purposes. Much more spatially coherent variograms result from log-transformed geochemical data.

9.1.2 Identification of geochemical anomalies

A number of univariate and multivariate techniques useful for separating geochemical data into anomalous and background populations have been presented. However more geologically meaningful results can be achieved if:

- the populations are partitioned into geologically meaningful groups using the GIS (as discussed above)
- lithogeochemical data, and to lesser extent surficial geochemical data are corrected for background lithological variations using normalization techniques (equation, selective query methods)
- surficial geochemical data are corrected for surficial effects (i.e., scavenging) using the techniques presented in this thesis

- dispersions effects in till data are taken into account using techniques presented in this thesis (i.e., *DTIA*)
-

Normal probability plots of geochemical data offer a simple method for identifying thresholds which may reflect mineralization and /or lithologic processes and are recommended over the use of thresholds based on standard deviations or percentile values.

Multivariate techniques such as principal component analysis, and N-dimensional clustering are useful for establishing statistical relationships between more then three oxide elements and are useful for identifying anomalous populations. The components generated from principal component analysis often reflect a specific geologic process; in this thesis (Chapter 4) the first and second components generated from a principal component transform of the log-ratioed altered samples reflect a felsic and mafic alteration style, respectively. A log-ratio transform of the oxide data, as suggested by Aitchison (1986), is recommended when applying multivariate statistical techniques to alleviate the negative effects of closure.

Techniques that allow for variable thresholds, based on lithologic and chemical variations (selective querying and normalization), are arguably the best for characterizing alteration patterns in a lithogeochemical dataset.

Analysis of scatterplots, although useful for detecting unusual groups of samples, should be treated with caution for identifying alteration. Harris et al. (1999) show that groups of outliers visually identified on scatterplots can sometimes represent geochemically unusual rocks such as komatiites as opposed to alteration trends.

9.1.3 *Separating true from false anomalies*

Altered vs. unaltered lithogeochemical samples: A large lithogeochemical dataset has been compiled over the SGB from a diverse source of both proprietary and non-proprietary geochemical datasets. The data have been screened (Wilkinson et al., 1999), and divided into two populations, one containing altered samples, identified using a number of different methods, and the other containing un-altered samples. Methods for detecting altered samples involving normative minerals, and the index of typicality are more appropriate for felsic to intermediate volcanic samples, while methods based on excessive LOI, volatile and the Hashimoto and ACNK indices are best for mafic to ultramafic samples which generally contain more hydrous minerals. Alteration trends are easily identified on 2D and 3D scatterplots, and the identified samples may then be plotted spatially using the GIS to assess relationships with lithology and structure.

Atypical normative minerals and LOI methods identified the largest number of altered samples, and result in the highest correlation with altered samples identified by other criteria. Altered samples are characterized by higher SiO_2 , K_2O and MnO concentrations, and lower MgO and TiO_2 concentrations. Ultramafic rocks are characterized by the highest proportion of altered samples, identified best by the LOI, scatterplot and alteration index methods. The atypical normative mineral method is more sensitive to felsic rocks (felsic volcanic rocks, granitoids), whereas the volatile method is more sensitive to mafic volcanic rocks, granitoids and sedimentary rocks.

Maps showing the presence or absence of alteration have been constructed using several methods. There is a high degree of coincidence between these maps as would be expected, since they were derived from the same group of altered samples. Generally the methods based on excessive volatiles and LOI concentrations and high alteration index values are best for identifying altered samples from ultramafic and mafic rocks, whereas the method based on atypical normative minerals is best for felsic rocks. The alteration map based on excessive total volatile concentrations was the best predictor of known gold prospects. This is not unexpected as mafic volcanic rocks were typified by the

highest percentage of altered samples identified using excessive volatile concentrations and also the highest percentage of gold prospects. In general, with the exception of the altered samples identified from scatterplots, all methods for identifying altered samples resulted in maps that were mildly to moderately predictive of known gold prospects. This indicates that the presence of alteration, regardless of type and intensity, is an important indicator of gold mineralization within the SGB.

Normalization: Normalization of lithogeochemical data to account for background lithologic variations, either by using the approach based on statistical equations, or by selectively querying of the point data by lithologic and geochemical classification, is recommended. This aids in highlighting geochemical anomalies that may have originated by hydrothermal activity as opposed to being caused by gross lithologic variations. The selective query process can identify anomalous elemental concentrations by lithology. The success of the normalization process in identifying anomalies depends on the element, and in this thesis, because Zn concentration is both reflective of lithologic variations as well as mineralization, selective querying by rock unit may be too liberal in that anomalies due to lithologic variations are also being identified. The majority of Cu anomalies reflect mineralization. Generally, the geochemical anomaly maps produced from the normalization methods were better predictors of known gold prospects than other geochemical maps.

Scavenging effects in surficial and lake sediment geochemical data: Correcting (screening) geochemical data (soil, humus, lake sediments) for extraneous effects such as scavenging is important to help identify anomalies more likely due to mineralization. Providing the geochemical data pertain to the same geographic location, the selective query method presented in this paper is the simplest and most straightforward method for screening scavenging effects. The correction can still be made on interpolated data (also done in this study) however, the effects of interpolation may affect the correction process. Correction for scavenging effects has generally resulted in more predictive geochemical anomalies with respect to known gold prospects.

Bedrock / surficial signatures in surficial geochemical data: Copper and to a lesser extent Zn, show larger variations in concentration between media for each lithologic unit than within each medium over the various lithologies. Copper concentration is generally more variable between lithologic units than is Zn. Distinctive Zn and Cu signatures are evident in surficial media, but are suppressed with respect to the signatures in rock due to the homogenizing effect of weathering and erosion processes. The similarity in Zn and Cu concentrations in rock and lake sediments indicates that geochemical signatures in lake sediments (at least for Zn and Cu) reflect local bedrock concentrations. Till, soil and humus, with the exception of Zn concentrations in humus, do not reflect bedrock signatures as closely.

9.1.4 Interpolation

Continuous surface (interpolated) geochemical maps can only be generated if certain criteria, discussed in this thesis, are met (e.g. sufficient sample density, well-behaved variograms). Otherwise, the data should be visualized and analyzed as discrete points or with a natural zone of influence (e.g. drainage basin for lake sediment data) or using small zones of influence (e.g. buffers). Variogram analysis in conjunction with kriging is the most powerful method of interpolating geochemical data. Variograms provide critical information on spatial associations between points, directional biases and spatial structure. The degree of smoothing desired in the interpolation process obviously depends on what the data will be used for. If the goal is to preserve all high frequency variability, which may be important for regional mineral exploration, then less smoothing, as obtained from the IDW interpolations, is desirable. However, if the goal is to produce a geochemical map useful for characterizing surficial or lithologic patterns then a certain degree of smoothing is warranted.

9.1.5 Down-ice dispersal in till data

DTIA can be useful for automatically identifying potential dispersal trains in regional till data. It has been shown that the algorithm works satisfactorily on simulated data, and on data from an area in Cape Breton with known geochemical dispersal trains. When it was applied to data from the Swayze greenstone belt, with no previously identified dispersal trains, *DTIA* recognized a number of candidate trains whose directions agree with directions determined from glacial striations. The user has control of a number of algorithm parameters that can be used to model dispersal train patterns, such as wedge length and angle. The user also has the option of searching in any given direction to look for patterns in the data that may be related to glacial dispersion.

The experiments using simulated data show that the search algorithm is quite robust as it can identify dispersal trains even in moderate to high levels of background noise. Ribbon trains are easier to identify than fan-shaped trains due to their more compact and continuous pattern. Fan-shaped trains are difficult to identify in situations with relatively high background levels.

DTIA is, however, not a *black box* that can be applied without careful selection of various thresholds for parameters, and the results treated with caution and evaluated against geological knowledge of an area and its glacial history. The geologist must carefully screen each candidate point found by *DTIA* using the following criteria:

- *pmed* and *diff* must be high, demonstrating that the average value of points occurring inside the candidate wedge are generally high, and anomalous with respect to local background
- The value of *ts*, a statistic to test that the slope of the line fitted to points within the wedge is significant, should be greater than about -2.0
- Search wedges that are significant in other ways must be checked to see whether the sampling point closest to the apex (at distance *rmin*) is no further than some

threshold--in most instances less than 1 km. Otherwise the fit may be good, but the wedge apex may be an inappropriate candidate as the head of a dispersal train.

- Visual analysis of the values of sample points inside the wedge versus distance from the apex to evaluate the character of the dispersal pattern, and how well the fitted exponential model (and 95% confidence limit) accounts for the data points.

9.2 Multi-media comparison

Copper and to a lesser extent Zn, show larger variations in concentration between media for each lithologic unit than within each medium over the various lithologies. Copper concentration is generally more variable between lithologic units than is Zn. Distinctive Zn and Cu signatures are evident in surficial media, but are suppressed with respect to the signatures in rock due to the homogenizing effect of weathering and erosion processes. The similarity in Zn and Cu concentrations in rock and lake sediments indicates that geochemical signatures in lake sediments (at least for Zn and Cu) reflect local bedrock concentrations. Till, soil and humus, with the exception of Zn concentrations in humus, do not reflect bedrock signatures as closely.

9.3 Visualization

GIS can be used effectively to visualize geochemical data in a variety of ways ranging from traditional proportional symbol maps to interpolated maps and to combinations of the data in RGB ternary plots. Ternary maps are particularly useful as they not only show the presence or absence of alteration (or areas where no samples are present), but also give an indication of alteration intensity and the spatial association between different methods used to identify alteration. Furthermore, the ternary concept can be extended to include RGB images which show the spatial associations in terms of pattern and concentration, between major oxides or trace elements (Harris and Wilkinson, 1999).

9.4 Data integration

Each modelling method offers advantages and disadvantages and as there is no right or wrong way of producing a gold prospectivity map per se, this paper has simply endeavoured to illustrate possible methodologies for producing a mineral prospectivity map using a GIS. Even though WofE or logistic regression requires a set of mineral occurrences with which to drive the modeling process, the geologist still has the option of applying the results from one area to an area with an insufficient number of mineral prospects provided that the area is characterized by a similar geologic environment and mineralization style. Estimating the various weights (W^+ etc.) based on expert knowledge thus using WofE in a knowledge-driven sense or by employing a more common knowledge-based method such as the index overlay technique presented in this paper, are other options

The data-driven approach using the weights of evidence (WofE) or logistic regression techniques is objective as the weights for each evidence map are derived statistically although Singer and Kouda (1999) show that WofE may produce biased estimates in some situations. The weights reflect whether more gold prospects fall on a given map pattern (e.g., geochemical anomaly, specific lithology, close to a fault etc.) than would be expected by chance. However, if there appears to be a spatial association between the known gold prospects and a specific map pattern, as reflected by higher weights (W^+ and C for WofE and higher coefficients for logistic regression), the geologist still must ascertain whether this apparent association makes geologic sense. In some cases a spatial association revealed by the WofE or logistic regression approach may result in a causal association that the geologist may have overlooked or had not considered in the exploration process. The knowledge-driven approach, although more subjective, offers more direct control over the modeling process. The index overlay method resulted in a prospectivity map that was more predictive than the boolean method (equally weighted evidence maps) indicating that expert knowledge provided by the geologist is an important part of the knowledge-driven modeling process. In this study the data-driven prospectivity maps were better predictors of the known gold prospects which is not

surprising given that the location of known prospects with respect to geochemical, geophysical and geologic anomalies comprising evidence maps drives data-driven modeling techniques. It is recommended that if a sufficient number of prospects are available (≥ 30) then a data-driven technique should be the first priority in any study as data-driven methods better predict known prospects and may reveal spatial associations that the geologist may have not originally considered.

The resultant gold prospectivity maps produced in this paper are somewhat different as each used a slightly different dataset, and the data comprising the evidence maps were purposely processed differently. Others researches (Harris et al., 1995 and Wright and Bonham-Carter, 1996 and) have found that if the same exploration model is used (e.g. mesothermal gold, VMS etc.) and the same evidence maps, processed in the same way, data-driven and knowledge-driven techniques produce comparable results (e.g. mineral prospectivity maps are similar). Some of the data processing factors that have caused differences in the prospectivity maps produced in this paper are first and foremost, (1) data that were used in one modeling method and not in the other, (2) differences with respect to the spatial extent of geochemical anomalies between interpolated geochemical data and geochemical data processed as discrete points, (3) processing methods (correction for scavenging applied only to the geochemical data processed as discrete points, (4) normalization of lithogeochemical and lake sediment geochemical to lithology) and finally, (5) slightly different thresholds applied to the geochemical data (using WofE versus probability plots) to define anomalous populations.

9.5 Future research

DTIA could be optimized so that at each search point a full search involving an entire suite of directions, wedge angles and lengths could be undertaken to determine the best dispersal train parameters on a local basis. The algorithm should be tested on other datasets including kimberlite indicator minerals. *DTIA* should be converted from

FORTRAN to Visual Basic within the Arc/Info environment so that other geologists can easily access and make use of this technique.

With respect to processing geochemical data, other algorithms for normalization of lithogeochemical data, such as the use of standard scores converted to natural logarithms, to suppress the effects of outliers, should be investigated. The effects of closure should be further studied with an aim to interpreting the results in a geological perspective. The author has found that statistical results based on log ratio transforms are often more difficult to interpret geologically than results based on raw oxide data.

Modelling of geoscience data is left to the preference of the individual geologist although data-driven techniques are more objective and often lead to better predictions of the known mineral prospects. Furthermore data-driven methods such as WofE often lead to spatial associations between known mineral prospects and evidence maps that the geologist previously had not considered. More research is required on a comparison of data- and knowledge-driven techniques.

9.6 Conclusion

In summary, the GIS offers geologists a powerful tool with which to manage, evaluate, analyze and visualize geochemical data sampled from a variety of media. GIS, in concert with statistical analysis and geostatistical analysis packages, can be used to fully assess the statistical and spatial characteristics of geochemical data using techniques ranging from simple SQL queries to more complex multivariate methods. Furthermore, analysis

of geochemical data using a GIS can be conducted in a timely fashion which is an important factor when working under exploration deadlines. The GIS, in conjunction with other software tools, assists the geologist in extracting the most information from their data. More time can be spent on the analysis and visualization of the data rather than the laborious task of overlaying maps manually. Analysis of geochemical data using a GIS, in addition to providing information on geochemical anomalies, can often reveal subtle associations between different geochemical elements and/or different media through the integration and overlay of multiple layers of geochemical data. Lastly, but not of insignificance, the GIS provides an organized and geo-referenced archive for large volumes of geochemical data that can be accessed and updated quickly and efficiently.

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APPENDIX A-1

The data contained on this CD forms a large part of the geoscience database compiled under a Northern Ontario Development Agreement (NODA) project between the Ontario Geological Survey and the Geological Survey of Canada involving the compilation and analysis of geoscience data over the Swayze Greenstone Belt in Ontario (see Fig. 1 for location). Data has been provided by industry partners (Falconbridge Ltd., Noranda Inc.), government agencies (Ontario Geological Survey, Geological Survey of Canada), purchased, or digitized from maps. In all cases, as much of the raw data attributes have been retained as possible. As part of the compilation process, however, some changes have been made to standardize formats, projection, and legend information to facilitate multiple uses of the data.

For novice GIS users, data is provided in ARC/INFO format along with ARCVIEW II (a GIS viewer that operates under Windows and has been locked for use with this dataset only!) for displaying and querying the data. For more advanced GIS users, ARCVIEW III in conjunction with Spatial Analyst and the Weights of Evidence mineral potential modeling package (WofE) may be used. In addition the data is supplied in a number of common formats; .BIL for raster, .DXF for point, line and polygons, MapInfo and Arc shape files for input to other GIS or image analysis systems, etc.

Instructions for Installing the CD Program

- insert CD-ROM into CD drive.
- in Windows 95 click on "Start", then "Run", then "Browse".
- navigate to your CD drive, then double-click "Setup.exe".
- click on "OK" to start installation.
- (during installation, click on "Continue" to proceed).
- at "Please choose component(s) you would like to install", choose "NODA" (required).
Only choose "DATA" as well if you want to store and access the data from your hard drive (Caution: contains nearly 600MB of data!). Do this for copying or using data (which have been supplied in a variety of formats) in other GIS's.
- at "Path", enter a path where NODA Swayze GIS Viewer will be installed, or leave the default path as is.
- a DOS window will open to copy files to your PC. When the "File(s) copied" message appears, terminate the DOS window by clicking on the upper right hand "X" button.
- wait while a Program Window appears and icons for the Viewer are copied. Wait until the message window appears, then click on "Continue".
- You can copy the NODA Swayze GIS Viewer shortcut icon to your desktop and use it to start the program, or you can select the program from "Start", "Programs", "NODA" in Windows 95.

APPENDIX A-2

SQL statements for normalizing lithogeochemical data (reference to Chapter 4)

DATA	QUERY	ALTERATION STYLE
OXIDES		
K	[K > 3.4%] AND [CR,TR,CA,TA] AND [IF]	K metasomatism
	[K > 3.4%] AND [CR,TR,CA,TA] AND [QFP]	K metasomatism
	[K > 1.3%] AND [HMT,HFT,CB] AND [MAFIC VOLC]	<i>sericitization</i>
	[K > 0.5%] AND [PK,BK] AND [ULTRAMAF VOLC]	<i>sericitization</i>
Ca	[Ca > 9.5%] AND [CR,TR,CA,TA] AND [IF, FELSIC VOLC]	carbonatization (mod – strong)
	[Ca > 6%] AND [HMT,HFT,CB] AND [MAFIC/INT VOLCS]	carbonatization (weak-mod)
Si	[Si > 49%] AND [HMT,HFT,CB] AND [MAFIC VOLCS]	silicification/Qtz veining
	[Si > 76.5%] AND [CR,TR,CA,TA] AND [IF]	Si metasomatism
	[Si > 76.5%] AND [CR,TR,CA,TA] AND [QFP]	silicification
	[Si > 76.5%] AND [CR,TR,CA,TA] AND [FELSIC VOLC]	silicification/Qtz veining
Fe (ferrous)	[Fe > 12.5%] AND [HMT,HFT,CB] AND [MAFIC VOLCS]	Oxidation (gossans) and possible ankerite alt
	[Fe > 9.8%] AND [CR,TR,CA,TA] AND [IF]	
	[Fe > 9.8%] AND [CR,TR,CA,TA] AND [QFP]	
	[Fe > 9.8%] AND [CR,TR,CA,TA] AND [FELSIC VOLC]	
Na	[Na > 6.6%] AND [CR,TR,CA,TA] AND [IF]	Na metasomatism
	[Na > 6.6%] AND [CR,TR,CA,TA] AND [QFP]	
	[Na > 6.6%] AND [CR,TR,CA,TA] AND [FELSIC VOLC]	albitization
Mg	[Mg > 10%] AND [HMT,HFT,CB] AND [MAFIC VOLC]	chloritization (mod)
	[Mg > 34%] AND [PK,BK] AND [ULTAMAFIC VOLC]	serpentinization
	[Mg > 32%] AND [TA,CA,CD] AND [FELSIC/INT VOLC]	chloritization(mod-strong)

Geochemical classification derived from a Jensen ternary classification for Archean volcanic rocks (Jensen,1976) – see text for details. → BK = basaltic komatiite; PK = picritic komatiite; CA = calc-alkaline andesite; CB = calc-alkaline basalt; CD = calc-alkaline dacite; CR = calc-alkaline rhyolite; HFT = high Fe tholeiite; HMT = high Mg tholeiite; TA = tholeiitic andesite; TD = tholeiitic dacite; TR = tholeiitic rhyolite

APPENDIX A-3

Summary of WofE

This section provides a short introduction to the weights of evidence method. For a more detailed description, see Agterberg et al (1990) or Bonham-Carter (1994, ch.9).

Producing a mineral favourability (potential) map can be accomplished, with a GIS, using two different approaches. The first approach, termed “data-driven” (statistical) involves establishing the spatial association between evidential themes (predictor maps e.g., geochemical anomaly maps), and a known set of training points (e.g., mineral prospects or deposits). The WofE technique falls in this category, as well as methods that use regression analysis and neural networks. “Knowledge-driven” approaches use expert exploration knowledge to generate the weights needed to create a favourability map, as opposed to relying on the spatial association between a set of points and evidential themes to guide the modeling process. Knowledge-driven approaches include index overlay techniques, fuzzy logic and Dempster-Shafer belief theory.

In the WofE approach, applied by Spiegelhalter (1986) for medical diagnosis, and applied to mineral exploration by Bonham-Carter et al. (1988), Harris et al. (1995), Wright et al. (1996) and other geoscientists, the spatial association between an evidential theme and a known set of points is assessed by calculating a set of weights, with one weight for each theme class. In this paper, the set of points is known gold prospects, and the evidential themes are binary geochemical anomaly and alteration maps. For binary evidential

themes, there are two weights per theme and these reflect the degree of spatial association between the evidential theme classes and the points; and in a second step the weights are then applied to build a favourability map, combining two or more themes together.

Fundamental to understanding WofE, is the concept of prior and posterior probabilities.

Prior probability is the expected outcome of an event in the absence of evidence, whereas posterior probability is defined as:

Posterior probability = prior probability * factor for each evidential theme

The loglinear form of this model used in weights of evidence is:

Posterior logit = prior logit + weight for each evidential theme,

where logit is the natural logarithm of odds, and the odds of an event is defined as the ratio of probability of an event divided by 1.0 minus probability of an event.

In WofE, each training point (gold prospect) is assumed to occupy a small area or unit cell allowing the probability of a point location to be defined as the probability per unit area. The choice of a unit cell size affects the prior and posterior probability values but the weights are relatively insensitive to unit cell size, and approach an asymptotic value as the unit cell becomes very small. The prior probability is usually taken as the average density of points per area with the area measured in unit cells:

$N(D) / N(T)$

where,

$N(D)$ = count of unit cells containing a deposit or mineral prospect

$N(T)$ = count of unit cells in the study area

The weights for each evidential theme are determined by counting the number of points on each theme class, and the area (in unit cells) of each class of the evidential theme.

Figure A-1 summarizes calculation of the weights ($W+$, $W-$) for a binary evidential theme (e.g., geochemical anomaly map in which areas of anomalous concentrations are assigned a value of one and background a value of 0).

An example of the calculation of the weights, using the following parameters, is provided below. The total study area is 10,000 unit cells, the area where the binary theme (e.g. geochemical anomaly) is present (class 1) is 3,600 unit cells (so the other class, class 0 (background), has an area of 10,000 – 3,600 cells) and 180 out of 200 (total mineral prospects) occur on class 1 of the theme.

Then for the values given above:

$$W+ = \ln \frac{(\text{probability that binary class} = 1, \text{ given the presence of a mineral prospect})}{(\text{probability that binary class} = 1, \text{ given the absence of a mineral prospect})}$$

$$W- = \ln \frac{(\text{probability that binary class} = 0, \text{ given the presence of a mineral prospect})}{(\text{probability that binary class} = 0, \text{ given the absence of a mineral prospect})}$$

and:

[1] Probability of binary class = 1, given the presence of a mineral prospect:

$$180 / 200 = 0.9$$

[2] Probability of binary class = 1, given the absence of a mineral prospect):

$$(3600-180) / (10000-200) = 0.3490$$

[3] Probability of binary class = 0, given the presence of a mineral prospect:

$$(200-180) / 200 = 0.1$$

[4] Probability of binary class = 0, given the absence of a mineral prospect:

$$(10000-3600-200+180) / (10000-200) = 0.65$$

$$W+ = \ln([1] / [2])$$

$$(0.9 / 0.3490) = 0.41$$

$$W- = \ln ([3] / [4])$$

$$(0.1 / 0.65) = -0.81$$

The contrast value (C), which for a binary theme is defined as $W+ - W-$, provides an overall measure of association of the evidential theme and points. Thus, for the example above:

$$C = (W+) - (W-)$$

$$0.41 - (-0.81) = 1.22$$

If there is no spatial association between the points and evidential themes, then $W+ = W- = 0$, whereas a positive $W+$ value indicates a stronger association than would be expected due to chance, and a negative $W-$ value indicates that fewer points occur on the pattern than due to chance. A relatively large C value indicates a strong association and suggests that the evidential theme is a good predictor of the known points.

In the example, $W+$ indicates the evidential class = 1 is mildly predictive (.41) whereas $W-$ (-.81) indicates that there is a relatively strong down-weighting if the evidential class = 0. Thus, overall the C value of 1.21, in this case, indicates a moderately strong association between the points (gold prospects) and evidential theme (geochemical anomaly).

To generate a favourability map, the appropriate weights ($W+$ for presence, and $W-$ for absence) for each layer are added to the logarithm of prior odds to find the logarithm of the posterior odds, and then the odds (O) are converted to a probability (P). The relationship between probability and odds is $O=P/(1-P)$. The posterior probability is simply a constant equal to the prior probability if no evidence is known. However, given one or more evidential themes (e.g., geochemical binary anomaly map), the posterior probability can increase or decrease depending on the values of the weights. Missing data is assigned a weight of zero and does not affect the posterior probability.

This method assumes that the evidential themes are conditionally independent with respect to the points (e.g., one evidential theme has no influence on another evidential theme with respect to the locations of known gold prospects- see Bonham-Carter, 1994, Ch. 9). This is often not the case in data used for mineral exploration. Violation of this assumption will result in a mineral favourability map that overestimates the posterior probability values. Thus, maps that severely violate the conditional independence assumption are either disregarded, or sometimes combined into a single map using Boolean operators (e.g., AND, OR) before their use in the WofE modeling procedure.

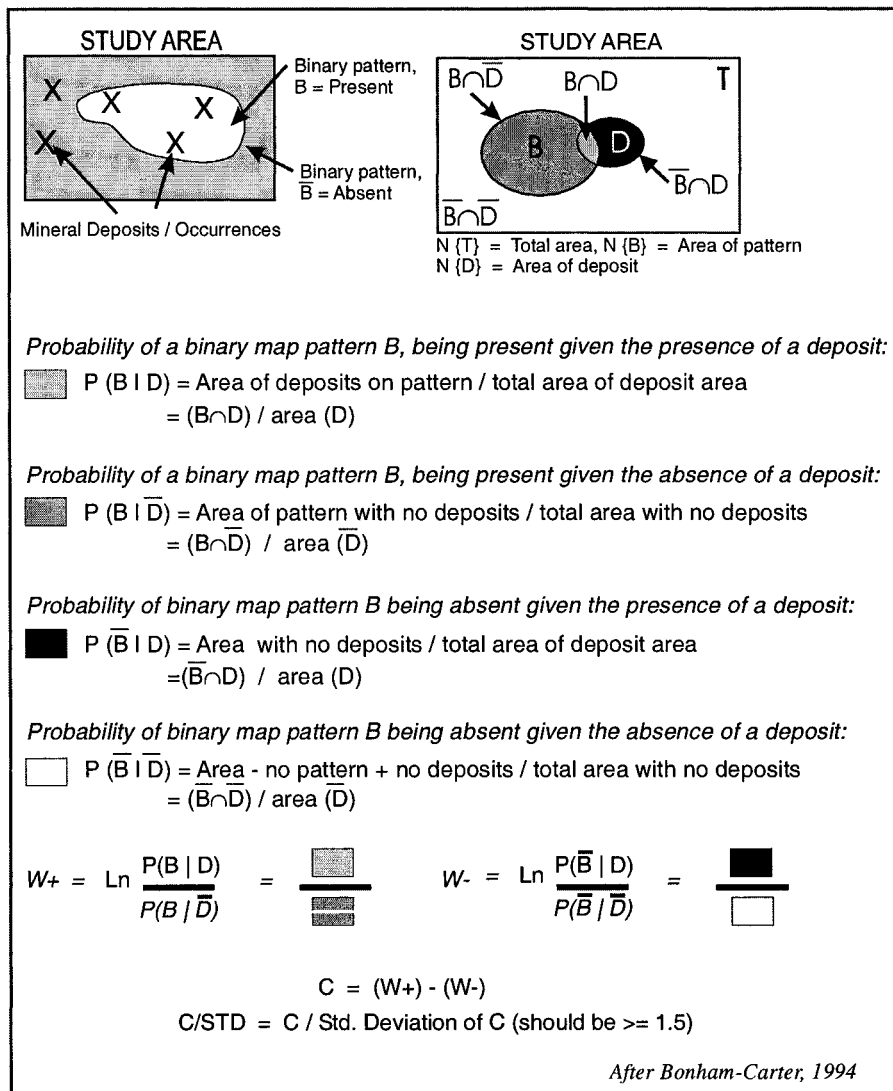


Fig. A-3.1 Summary of WofE methods

APPENDIX A-4

Summary of Simulations (reference to Chapter 7)

A ribbon train (Fig.A-4.1a) comprised seven data points along a N-S line, ranging in values from 100 in the north to 3 ppm in the south, with a mean value of 39 ppm. A fan-shaped dispersal train (Fig. A-4.1b) comprised 22 points, again running N-S and ranging in value from 100 in the north to 5 ppm in the south with a mean of 35 ppm. Both the fan- and ribbon-shaped dispersal trains were embedded in various levels of background isotropic noise, generated with a random number generator. These values were drawn from a uniform distribution with various selected ranges. The locations of background points for the ribbon train were defined by 400 points on a grid, within which the train points were embedded. For the fan-shaped train, the locations of background points were generated with a random number generator.

The search points for the ribbon simulations were the same points as the original sample points (Fig A-4.2a), whereas the fan simulations used two sets of search points; one set of evenly distributed points of low spatial density and the second comprising a much higher density of evenly distributed points (Fig A-4.2b).

Figure A-4.3 shows wireframe perspective maps derived from a N-S search applied to the simulated data comprising the ribbon dispersal train embedded in background noise having a range (0- 5) (Fig A-4.3a) and (0-40) ppm (Fig A-4.3b). A wedge angle of 20° and a length of 60 pixels were used which allowed for complete capture of the dispersal train. Figure A4-3a is a simulation using low background noise (maximum 5 ppm) and shows calculated parameters including wedge mean (*pmed*), slope (*b*), difference between wedge mean and local mean (*diff*), and the studentized test value (*ts*) based on a simple linear regression of data points within the wedge (see Fig. 7.4). Figure A-4.3b shows the same parameters except for a higher background noise level (maximum of 40 ppm which is approximately equal to the mean of the ribbon train). The ribbon dispersal train can be uniquely identified based on large positive values for *pmed*, *diff*, and large negative

values for ts and b . The train can still be identified in the higher noise images (Fig. A-4.3b).

A number of experiments were designed using the simulated data to test the sensitivity of various *DTIA* parameters (wedge length, angle, direction as well as density of search grid) for the identification of potential dispersal trains.

Experiment 1

This experiment involved searching from a single point directly above the ribbon-shaped dispersal train (Fig. A-4.2a) in a N-S (180°) direction (same direction as the dispersal train) using various wedge lengths (10 – 80 pixels) and angles (10° – 60°). The dispersal train was embedded in a maximum background noise level of 5 ppm. Plots of ts and $pmed$ vs. wedge angle and length were constructed (not shown). These plots indicated that the best length and angle for capturing the ribbon-shaped dispersal train (as determined by the highest ts and $pmed$ values) was a wedge length of 60 pixels and an angle of 20° .

Experiment 2

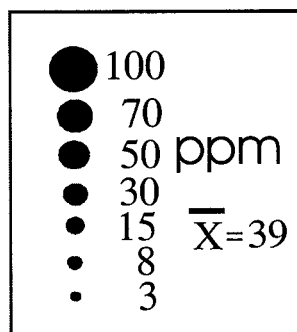
An experiment was designed using a search from a uniform grid of points (Fig. A-4.2a) over the ribbon-shaped fan which was embedded in various levels of background noise ranging from a maximum of 5 ppm to 100 ppm (equal to the maximum value of the dispersal train). The search was conducted in directions from 0° to 360° in 15° increments using a $pmed$ threshold > 40 , $diff > 20$ and $b < 0$. The best wedge parameters, determined from Experiment 1, included a length of 60 (pixels) and a wedge of 20° (as the train is very narrow). Figure A-4.4 shows the results of the best points and fitted models. The best points have directions that trend N-S, in the direction of the ribbon-dispersal train. Point 1, characterized by a high ts value (-27.1) is located just to the north of the train whereas Point 2, with the highest ts value (-33.6), is located directly over the first data

point (100 ppm) comprising the dispersal train. The experiments on the data with higher maximum noise levels indicated that although spurious points were found when noise levels reached 60 and 80 ppm, the correct location for the dispersal train could still be found but only by using the *ts* values. Figure A-4.5 shows the results of *DTIA* applied to the N-S ribbon train embedded in a maximum background level of 80 ppm. Figure A-4.5a shows the best points by direction. Note that only one point correctly identifies the dispersal train and is located just to the north of the train and indicates a best fit in a N-S direction corresponding to the direction of the train. The other spurious points are affected by the high levels of background noise. Figure A-4.5b show the same points as Figure A-4.5a displayed as squares which are proportional to *pmed* values. Note that the correct point does not have the highest *pmed* value. Figure A-4.5c shows the best points as squares proportional to *ts*. Note that the correct point has, by far, the highest *ts* value (-27.1). The other points have *ts* values less than 2.5. This experiment indicates that, (1) *ts* (and a negative slope) are the most diagnostic *DTIA* parameters and, (2) as background noise increases to approximately > than 1 standard deviation from the mean value of the train, spurious points begin to appear. However, the correct point can still be identified using *ts*, in combination with *pmed* and *diff*. Only when the noise (background) level is equal to the maximum value of the train, is the dispersal train impossible to identify using *DTIA*. This situation would not be common in nature.

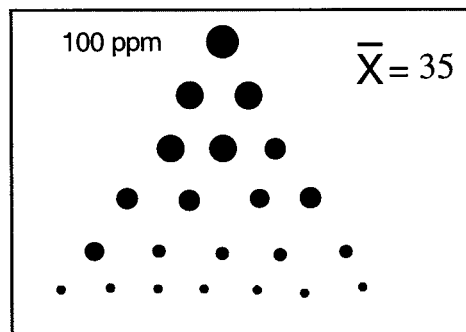
Experiment 3

The same experiments as above were conducted using the fan-shaped dispersal train (Fig. A-4.1b, A-4.2b). The best length and wedge angle for capturing the train were determined to be, 15 pixels and 45°. A wider wedge angle was required to capture the dispersal train in this case as the train is much broader (fan-shaped). Figure A-4.6 shows the best points identified by *DTIA* using a sparse search grid (A-4.6a) and a dense search grid (A-4.6b) applied to the fan-shaped dispersal train embedded in background noise of 5 ppm. Both searches have identified candidate points but only one point has been identified with the true direction (N-S, 180°). This was found using the dense search grid.

Figure A-4.7 shows the best points using a dense search grid with a higher level of background noise (40 ppm). Point 1 was the only point identified by *DTIA* that successfully located the dispersal train. The other three points are spurious. This experiment revealed the following; firstly, fan-shaped (distributed) dispersal trains are more difficult to identify especially in high background noise levels. In this case when the maximum background value (40 ppm) approximated the mean value of the dispersal train (35 ppm), *DTIA* although identifying the true location of the dispersal train, also identified spurious points. Secondly, the denser search grid was best for identifying the true location of the dispersal train in low to moderate background noise. Thirdly, the *pmed* and *diff* values must be increased when using dense search grids and datasets with high background noise to screen out spurious points.



A-1a Ribbon-shaped dispersal train



A-1b Fan-shaped dispersal train

Figure A-4.1 – (a) Simulated ribbon-shaped dispersal train, (b) simulated fan-shaped dispersal train

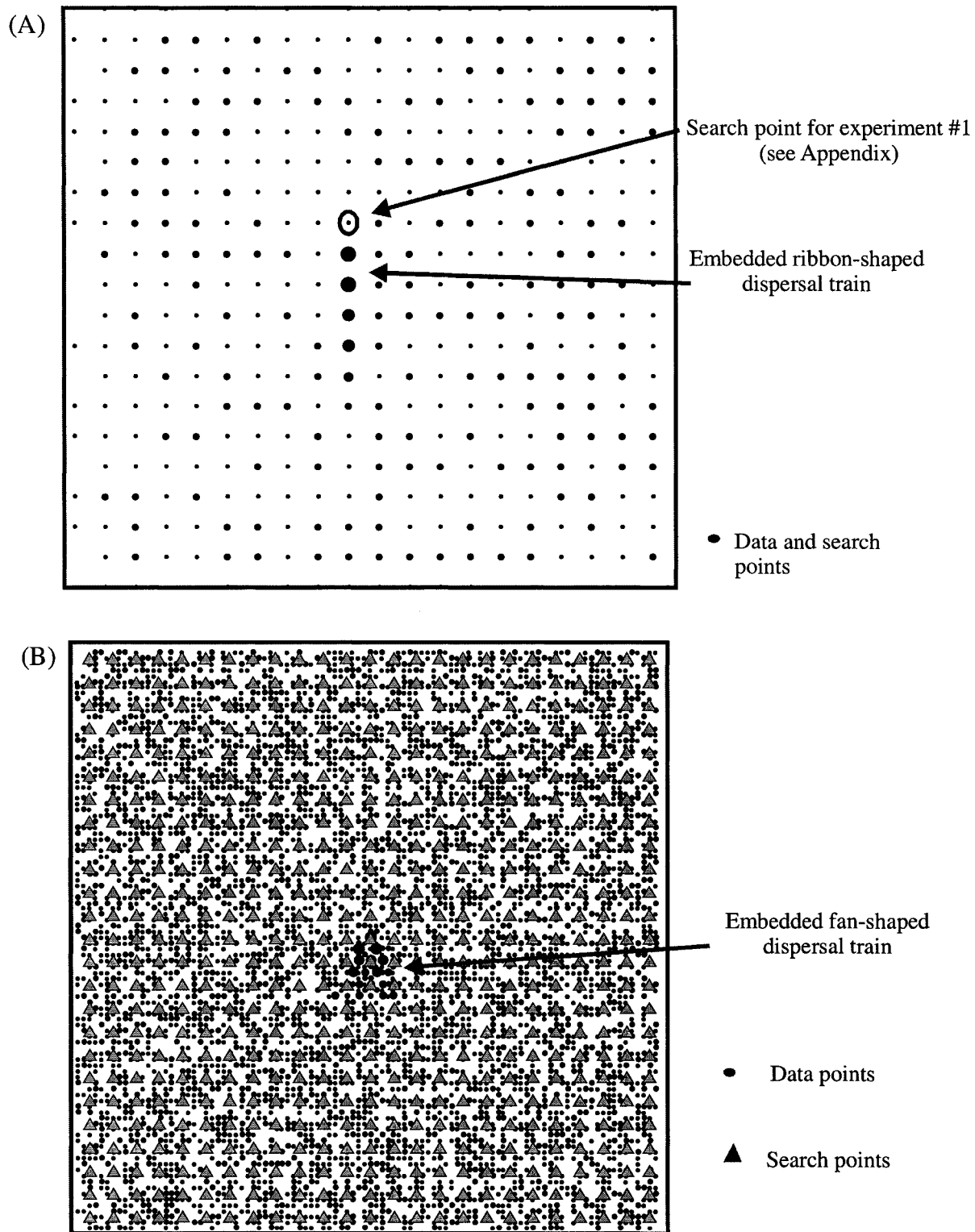
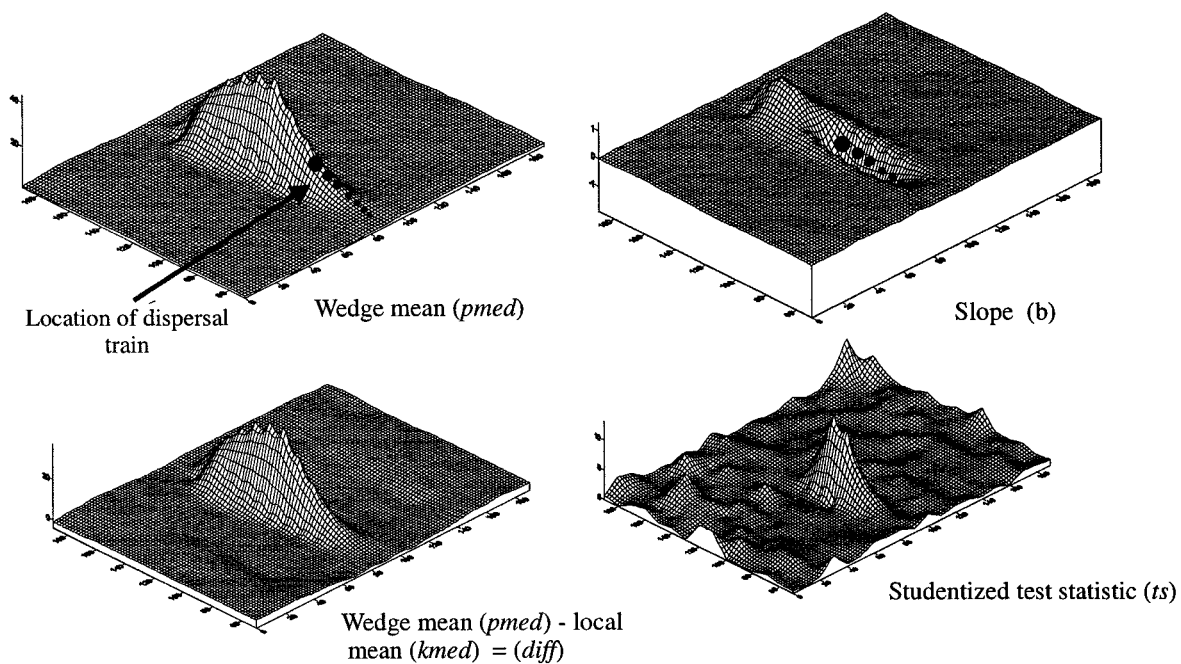
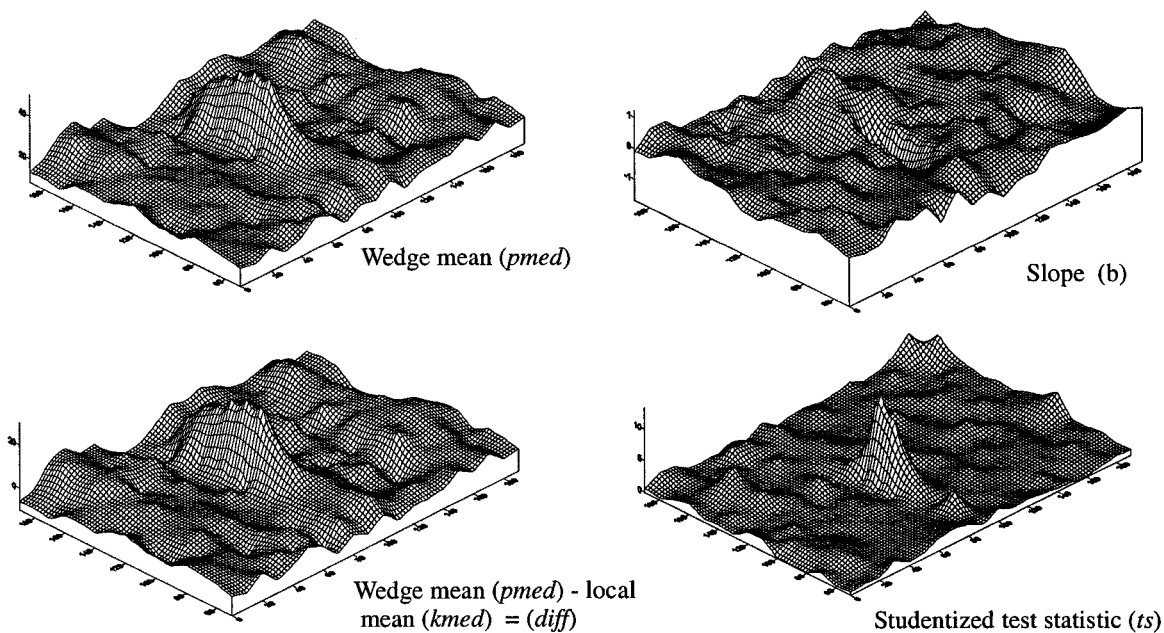


Figure A-4.2 - Search and data points for (a) ribbon train and (b) fan train

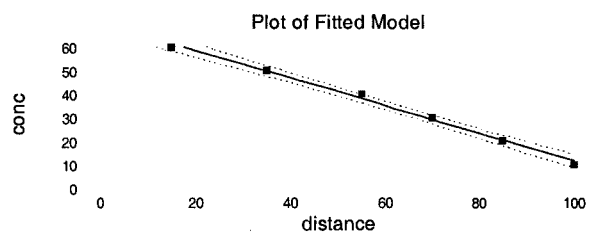
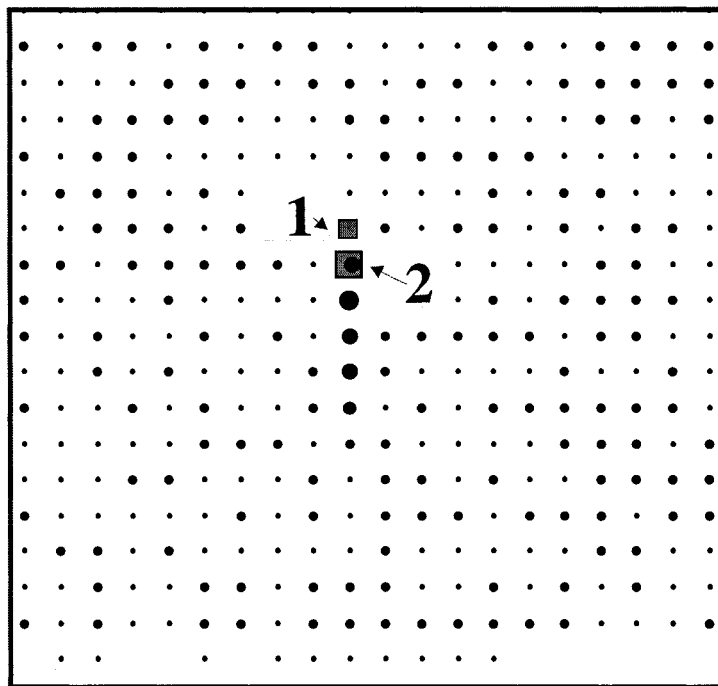


A Plots of *DITA* parameters - derived form a grid search applied to a ribbon-shaped dispersal train embedded in low noise (0 -5 ppm)

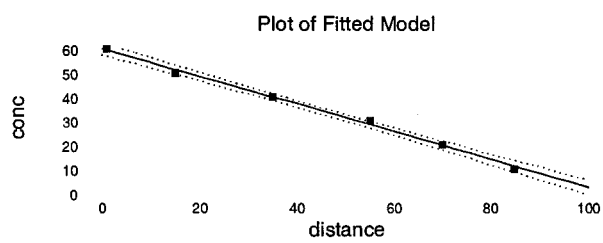


B Plots of *DITA* parameters - derived form a grid search applied to a ribbon-shaped dispersal train embedded in moderate noise (0 - 40 ppm)

Figure A-4.3 - Plots of *DTIA* parameters, (a) ribbon fan, noise (0 –5 ppm), (b) ribbon fan, noise (0 – 40 ppm)



Point 1- $ts = -27.1$



Point 2 - $ts = -33.6$

Figure A-4.4 – *Best points* identified by *DTIA* for ribbon train embedded in low noise (0 – 5 ppm)

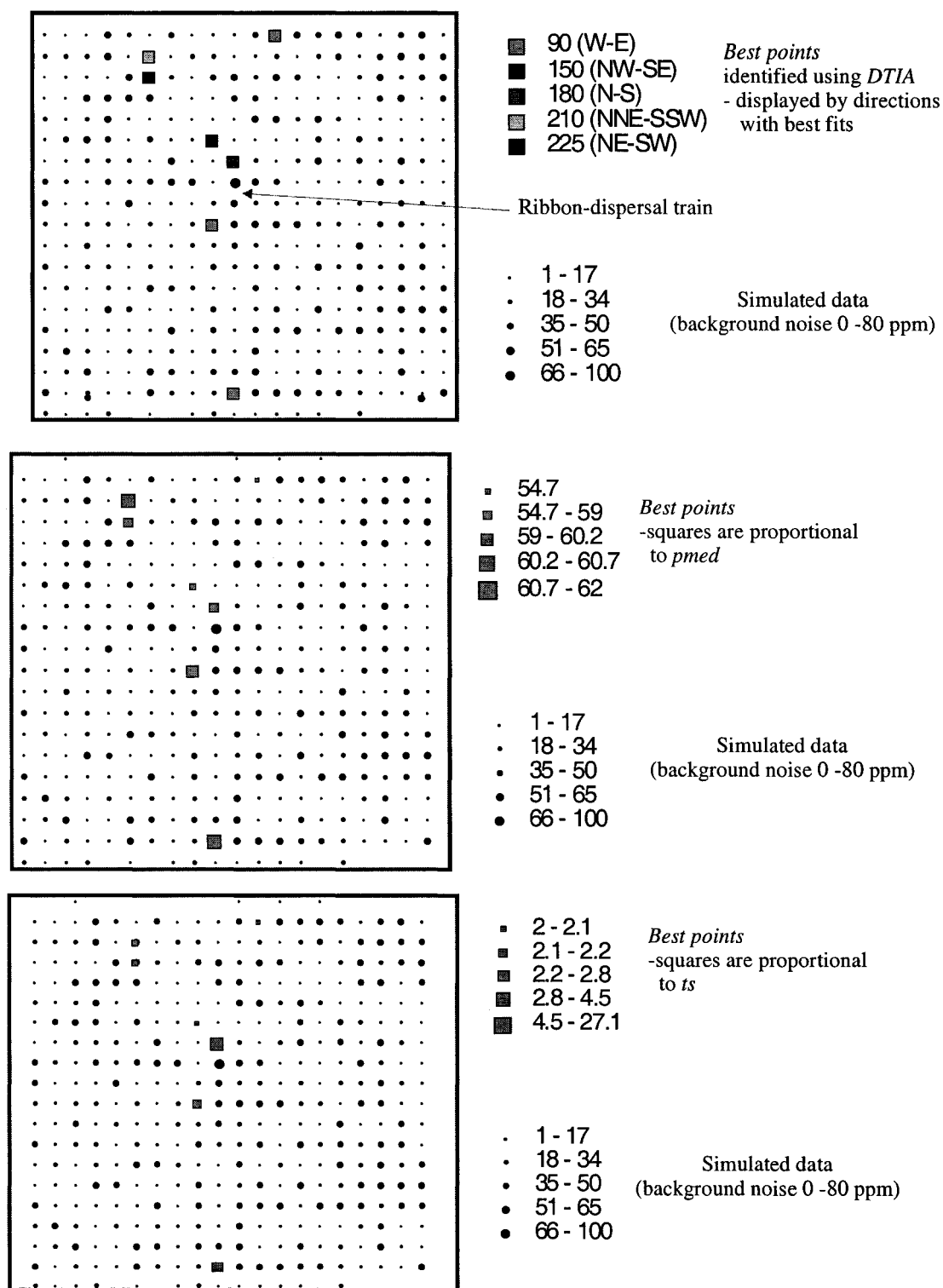
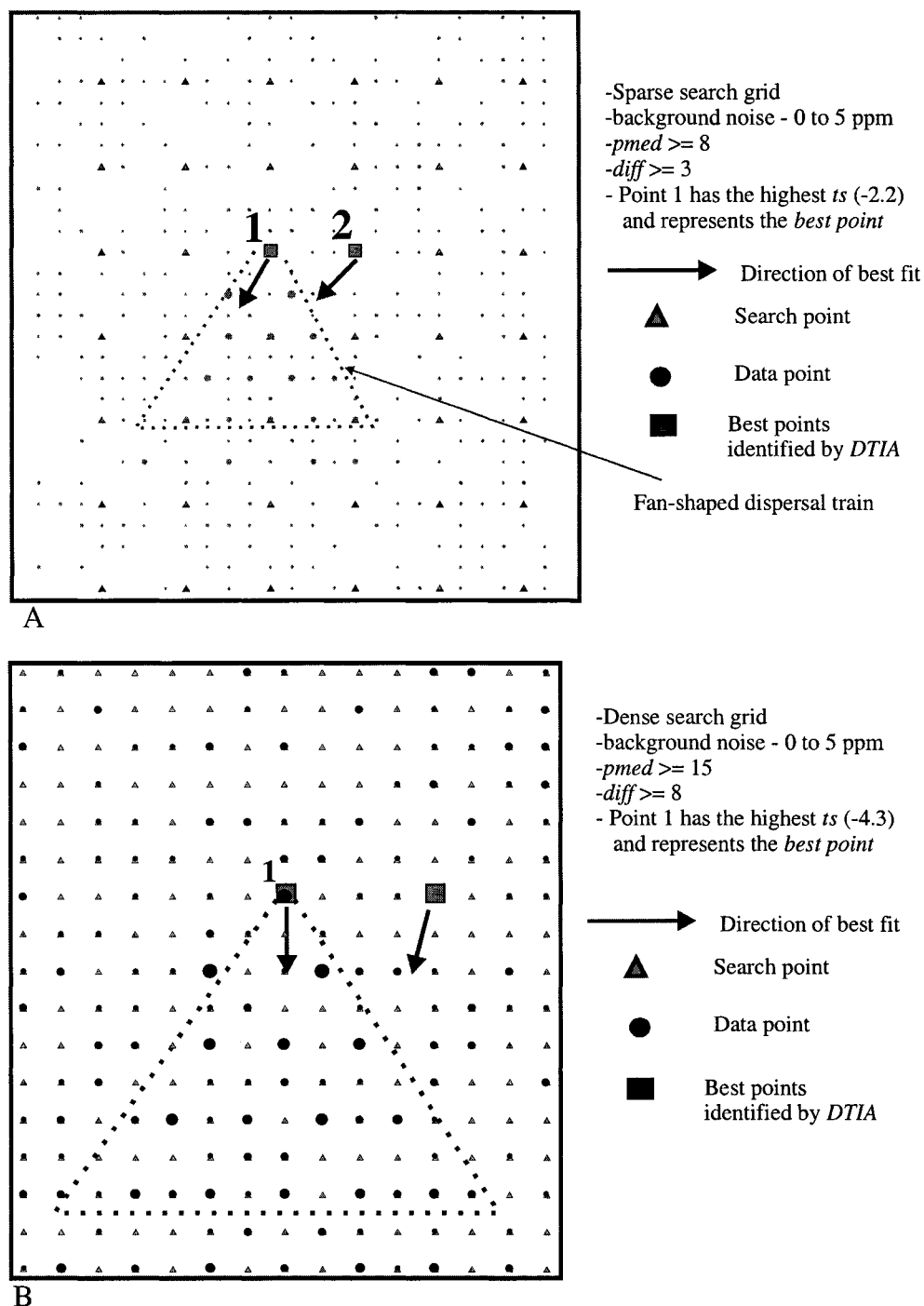
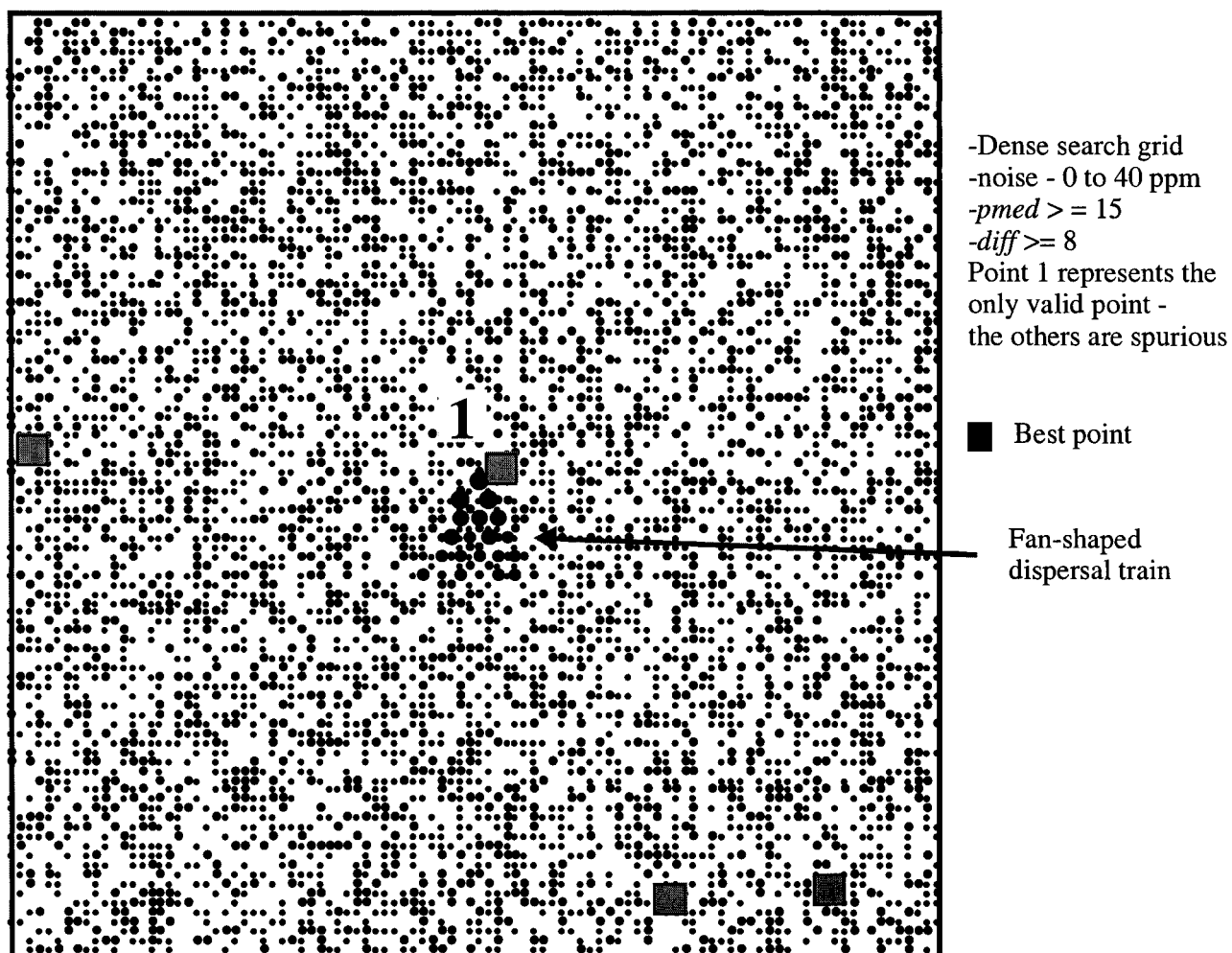


Figure A-4.5 – *Best points* identified by DTIA for ribbon fan embedded in high noise (0 – 80 ppm), (a) *best points* displayed by direction of best fit line, (b) best points displayed by p_{med} values, (c) best points displayed by t_s values



Best points identified by DTIA

Figure A-4.6 – *Best points* identified by DTIA for fan train embedded in low noise (0- 5 ppm), (a) using low density point search grid, (b) using high density point search grid



Best points for fan-shaped dispersal train

Figure A-4.7 – *Best points* identified by DTIA for fan train embedded in moderated background noise (0-40 ppm) and using high density point search grid

The data contained on this CD forms a large part of the geoscience database compiled under a Northern Ontario Development Agreement (NODA) project between the Ontario Geological Survey and the Geological Survey of Canada involving the compilation and analysis of geoscience data over the Swayze Greenstone Belt in Ontario (see Fig. 1 for location). Data has been provided by industry partners (Falconbridge Ltd., Noranda Inc.), government agencies (Ontario Geological Survey, Geological Survey of Canada), purchased, or digitized from maps. In all cases, as much of the raw data attributes have been retained as possible. As part of the compilation process, however, some changes have been made to standardize formats, projection, and legend information to facilitate multiple uses of the data.

For novice GIS users, data is provided in ARC/INFO format along with ARCVIEW II (a GIS viewer that operates under Windows and has been locked for use with this dataset only!) for displaying and querying the data. For more advanced GIS users, ARCVIEW III in conjunction with Spatial Analyst and the Weights of Evidence mineral potential modeling package (WofE) may be used. In addition the data is supplied in a number of common formats; .BIL for raster, .DXF for point, line and polygons, MapInfo and Arc shape files for input to other GIS or image analysis systems, etc.

Instructions for Installing the CD Program

- insert CD-ROM into CD drive.
- in Windows 95 click on "Start", then "Run", then "Browse".
- navigate to your CD drive, then double-click "Setup.exe".
- click on "OK" to start installation.
- (during installation, click on "Continue" to proceed).
- at "Please choose component(s) you would like to install", choose "NODA" (required).
Only choose "DATA" as well if you want to store and access the data from your hard drive (Caution: contains nearly 600MB of data!). Do this for copying or using data (which have been supplied in a variety of formats) in other GIS's.
- at "Path", enter a path where NODA Swayze GIS Viewer will be installed, or leave the default path as is.
- a DOS window will open to copy files to your PC. When the "File(s) copied" message appears, terminate the DOS window by clicking on the upper right hand "X" button.
- wait while a Program Window appears and icons for the Viewer are copied. Wait until the message window appears, then click on "Continue".
- You can copy the NODA Swayze GIS Viewer shortcut icon to your desktop and use it to start the program, or you can select the program from "Start", "Programs", "NODA" in Windows 95.

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Selected geoscience data from the NODA Swayze greenstone belt GIS
Database Project, Superior Province, Ontario

GSC Open File: D3730
OGS Open File: MRD 47

J. Harris, L. Wilkinson, R. Vanderkam

and the Swayze Greenstone Belt Geoscience Team,
K. Heather, M. Bernier, J. Ayer, S. Fumerton, J. Broome

and Falconbridge Ltd., and Noranda Inc.

Les données enregistrées sur ce disque compact forment une grande partie de la base de données géoscientifique compilée dans le cadre de l'Entente de développement du nord de l'Ontario (EDNO), un projet auquel collaborent la Commission géologique de l'Ontario et la Commission géologique du Canada, comprenant la compilation et l'analyse de données géoscientifiques sur la Swayze Greenstone Belt en Ontario (voir la figure 1 pour en connaître l'emplacement). Les données ont été achetées, numérisées à partir de cartes ou fournies par des partenaires de l'industrie (Falconbridge Exploration Co. Ltd., Noranda) et des organismes gouvernementaux (Commission géologique de l'Ontario, Commission géologique du Canada). Dans tous les cas, on a cherché à conserver le maximum d'attributs des données brutes. Cependant, lors de la compilation, certains changements ont été apportés pour normaliser les formats, les projections et les légendes afin de rendre les données plus accessibles à un plus grand nombre d'utilisateurs.

Pour les nouveaux utilisateurs des SIG, les données sont fournies en format ARC/INFO avec ARCVIEW II (qui fonctionne sous Windows) pour l'affichage et la recherche des données. Pour les utilisateurs plus expérimentés des SIG, on recommande ARCVIEW III avec Spatial Analyst et le logiciel de modélisation du potentiel minéral Weights of Evidence (WofE). De plus, les données sont fournies dans plusieurs formats courants : .bil pour les images raster, .dxf pour les points, les lignes et les polygones, ainsi que des fichiers MapInfo et des fichiers de formes Arc pour la saisie dans d'autres SIG ou des systèmes d'analyse d'images.

Instructions pour le chargement du disque compact

- insérez le disque compact dans le lecteur de CD-ROM du PC;
- dans Windows 95_, cliquez sur « Démarrer », puis sur « Exécuter » et, enfin, sur « Parcourir »;
- naviguez jusqu'à votre lecteur de CD-ROM et cliquez deux fois sur « Setup.exe »;
- cliquez sur « OK » pour lancer l'installation;
- (au cours de l'installation, cliquez au besoin sur « Continue » pour poursuivre);
- lorsque le système affiche le message « Please choose component(s) you would like to install », choisissez « NODA » (obligatoire). Sélectionnez « DATA » seulement si vous voulez enregistrer les données sur votre disque dur (600 Mo!) pour y accéder au lieu d'utiliser le disque compact;
- sous « Path », entrez le chemin de l'endroit où vous voulez installer la visionneuse du SIG pour la Swayze Greenstone Belt (EDNO) ou conservez le

chemin par défaut;

- le système ouvre alors une fenêtre DOS pour copier les fichiers dans votre PC.

Lorsque le système affiche le message « File(s) copied », fermez la fenêtre

DOS en cliquant sur le bouton « X » dans le coin supérieur droit de la fenêtre;

- attendez pendant que le système affiche la fenêtre du programme et copie les

icônes de la visionneuse. Ne faites rien jusqu'à ce que le système affiche un

message. Cliquez alors sur le bouton « Continue »;

- Vous pouvez copier l'icône du raccourci de la visionneuse du SIG pour la

Swayze Greenstone Belt (EDNO) de la fenêtre du programme et la coller sur

votre bureau. Pour lancer le programme, vous pouvez utiliser cette icône ou

cliquer sur « Démarrer », « Programmes » et « NODA » dans Windows 95_.

AFFICHES SÉLECTIONNÉES RÉSUMANT LES RÉSULTATS DES RECHERCHES
MENÉES AVEC LE SIG, DANS LE CADRE DU PROJET GÉOSCIENTIFIQUE EDNO
SUR LA SWAYZE GREENSTONE BELT

The data contained on this CD forms a large part of the geoscience database compiled under a Northern Ontario Development Agreement (NODA) project between the Ontario Geological Survey and the Geological Survey of Canada involving the compilation and analysis of geoscience data over the Swayze Greenstone Belt in Ontario (see Fig. 1 for location). Data has been provided by industry partners (Falconbridge Exploration Co. Ltd., Noranda), government agencies (Ontario Geological Survey, Geological Survey of Canada), purchased, or digitized from maps. In all cases, as much of the raw data attributes have been retained as possible. As part of the compilation process, however, some changes have been made to standardize formats, projection, and legend information to facilitate multiple uses of the data.

For novice GIS users, data is provided in ARC/INFO format along with ARCVIEW II (a GIS viewer that operates under Windows and has been locked for use with this dataset only!) for displaying and querying the data. For more advanced GIS users, ARCVIEW III in conjunction with Spatial Analyst and the Weights of Evidence mineral potential modeling package (WofE) may be used. In addition the data is supplied in a number of common formats; .BIL for raster, .DXF for point, line and polygons, MapInfo and Arc shape files for input to other GIS or image analysis systems, etc.

Instructions for Installing the CD Program

insert CD-ROM into CD drive
in Windows 95 click on "Start", then "Run", then "Browse"
navigate to your CD drive, then double-click "Setup.exe"
click on "OK" to start installation
(during installation, click on "Continue" to proceed)
at "Please choose component(s) you would like to install", choose
"NODA" (required).
Only choose "DATA" as well if you want to store and access the data
from your hard drive (Caution: contains nearly 600MB of data!). Do this
for copying or using data (which have been supplied in a variety of
formats) in other GIS's
at "Path", enter a path where NODA Swayze GIS Viewer will be installed,
or leave the default path as is
a DOS window will open to copy files to your PC. When the "File(s)
copied" message appears, terminate the DOS window by clicking on the
upper right hand "X" button
wait while a Program Window appears and icons for the Viewer are
copied. Wait until the message window appears, then click on "Continue"
You can copy the NODA Swayze GIS Viewer shortcut icon to your desktop
and use it to start the program, or you can select the program from
"Start", "Programs", "NODA" in Windows 95.

USER'S GUIDE

*Selected geoscience data from the NODA Swayze greenstone belt GIS database project, Superior Province,
Ontario.*

GSC Open File: D3770
OGS Open File: MRD 47

*J. Harris, and L. Wilkinson, and R. Vanderkam
and the Swayze greenstone belt geoscience team,
K. Heather, M. Bernier, J. Ayer, S. Fumerton, J. Broome
and
Falconbridge Ltd., and Noranda Inc.*

July/99

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1. Introduction

As geologic terrane is explored and re-explored, it has become increasingly important in mineral exploration to develop and acquire large geoscience databases in consistent formats that on-going or future work can incorporate and build upon. Traditionally, these databases have been compiled in analog format, but as more data become available in digital format, digital databases have increased in popularity. Unfortunately, a large amount of older data remain in analog format. Conversion to digital format is often time consuming and expensive. Furthermore, even digital data may require cleaning, processing, georeferencing, or other time consuming procedures to provide data suitable for analysis by Geographic Information Systems (GIS). The advent of affordable GIS technology has greatly facilitated this process, providing a host of new data import tools and more importantly, integrated georeferencing, display, image manipulation and analytical procedures.

In January 1993 the Geological Survey of Canada in conjunction with the Ontario Geological Survey initiated a three year project involving the compilation and analysis of a wide range of digital data over the Swayze greenstone belt (Figure 1) using geographic information system (GIS) technology. The project was funded by the four-year Northern Ontario Development Agreement (NODA), a subsidiary agreement to the Canada-Ontario Economic and Regional Development Agreement (ERDA) initiated by the governments of Canada and Ontario.

The scope of the project involved the compilation and analysis of geoscience data and the production of digital datasets, hardcopy maps and analysis methodologies useful for regional mapping and exploration within Ontario. Data have been provided by industry partners (Falconbridge Ltd., Noranda Inc.) and government agencies (Ontario Geological Survey, Geological Survey of Canada), purchased, or digitized from maps. In all cases, as much of the raw data attributes have been retained as possible. As part of the compilation process, however, some changes have been made to standardize formats, projection, and legend information to allow ease of use on various platforms and GIS software.

Exploration companies, Falconbridge Ltd., and Noranda Inc., contributed proprietary data (both digital and analog) as well as exploration expertise which was essential for a thorough analysis of the data with respect to regional geologic exploration

models. Working directly with exploration companies within the scope of the project was essential as the data and analysis techniques developed were directly utilized by companies working in the study area. Furthermore, the expertise held by exploration companies were directly utilized within a GIS framework, allowing for realistic and useful results to be obtained.

The objective of this CD-ROM release is thus to provide a ready-made, georeferenced, digital database that the novice GIS user can immediately use with the provided viewer, and that more advanced GIS users can import easily into their GIS system directly or by using the provided common interchange formats. **Please note that hydrological, lake-sediment geochemical data and remotely sensed data (listed in Appendix A) have not been included on this issue of the CD as royalty charges for these data would make the cost of this CD prohibitive. However, pertinent ordering information for the 1:50000 scale NTS map sheets that cover the area, available digital lake sediment data, and remotely sensed data has been included for the users convenience in Appendix A.**

Another GSC Open File, (CD-ROM) (D3771), contains many of the various posters prepared by J. Harris, L. Wilkinson, and others dealing with analysis of many of the datasets included in this CD release. These posters which summarize how the data may be visualized, analyzed and integrated into mineral favourability maps are stored in .PDF format for viewing with Adobe Acrobat® .

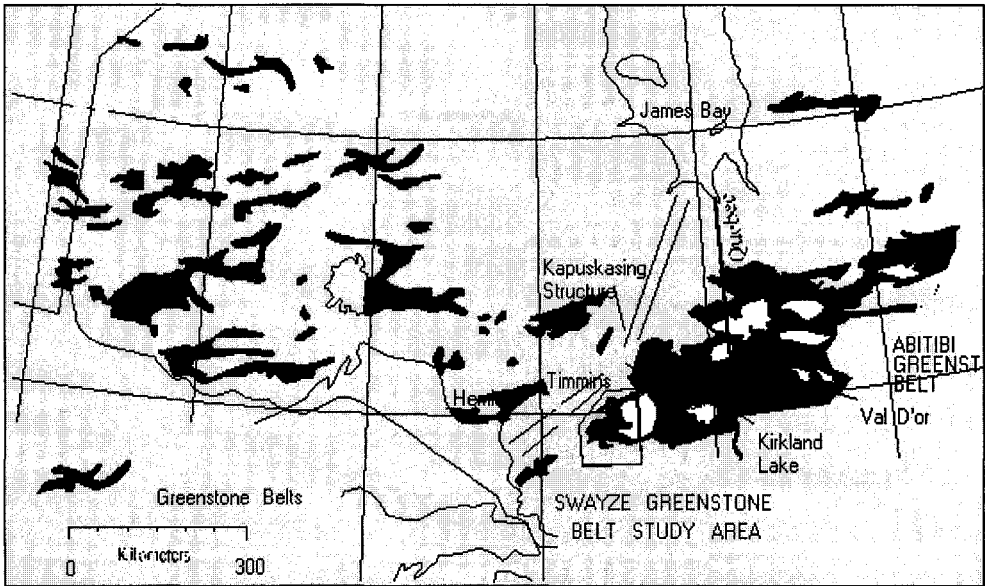


Figure 1 – Location of Swayze

greenstone belt

2. Hardware and Software Requirements

For PC users, a free data viewer, created on the CD with ESRI's Arcview Data Publisher®, is included. The *NODA Swayze GIS viewer*, a clone of ArcviewII that can only be used with this CD, is useful for those with no installed GIS software of their own, or with little experience with GIS software. It comes with a set of pre-made graphical views of the data, and allows users to create their own views, and query and analyze the data sets via these views. To install this program requires a minimum of 7 Megabytes of hard disk space and allows the user to access the over 600 Megabytes of data directly from the CD. No viewing software is provided for Mac or Unix clients on this CD.

Installation of provided viewer

- insert CD-ROM into CD drive of PC.
- on Windows 95 click on "Start", then "Run", then "Browse".
- navigate to your CD drive, then double-click "Setup.exe".
- click on "OK" to start installation .
- (during installation, click on "Continue" to proceed when required).
- at "Please choose component(s) you would like to install", choose "NODA" (required). Only choose "DATA" if you want to store and access the data from your hard drive (600MB!) instead of the CD.
- at "Path", enter a path where NODA Swayze GIS Viewer will be installed, or leave the default path as is.
- a DOS window will open to copy files to your PC. When the "File(s) copied" message appears, terminate the DOS window by clicking on the upper right hand "X" button.
- wait while a Program Window appears and icons for the Viewer are copied. Continue waiting until the message window appears, then click on "Continue".
- you can copy the NODA Swayze GIS Viewer shortcut icon from the Program Window to your desktop and use it to start the program, or you can select the program by clicking on "Start", then "Programs", then "NODA" in Windows 95® .

Alternatively, the data can be copied directly to a users hard drive for use by software of their own choosing. This does not require 600 plus Megabytes of hard disk space since a user will normally only use one or two of the available formats with their GIS system. The individual formats typically take 100 to 150 Megabytes of hard disk space each (see section 4 – Data Formats).

For more advanced GIS users, Arcview III[®] in conjunction with *Spatial Analyst* and the *Weights of Evidence* mineral potential modeling package (*WofE*) can be used to view and analyze the data on this CD-ROM.

Due to space constraints on the CD, two versions of the data set have been compressed. The DXF and MapInfo (MIF) formats (see section 4 – Data Formats) are not needed by the included viewing software and the data in these formats have been compressed with PKZIP software. They can be uncompressed to your harddrive using PKZIP version 2.04g or higher. PKZIP version 2.04g for DOS and PKZIP version 2.5 for Windows (32 bit) are both available on this CD in the \DATA\SOFTWARE\ directory. To install these shareware programs, simply copy them to your hard drive, double –click on the file in Windows Explorer, and follow the directions.

1. CD Information

This CD-ROM conforms to the ISO-9660 system independent standard. An ISO-9660-formatted CD works identically on a PC, Macintosh or Unix workstation. The directory and file structure of the CD can be viewed as if it were a conventional hard disk. Although the file structure is system independent, the user must still deal with differences in the way different operating systems format files, in particular ASCII files. ASCII files are provided in IBM-compatible format. In order to use these files on Unix workstation, they must be converted to Unix ASCII file format using the Unix "dos2unix" command (see your Unix documentation).

Compact disks are a cost effective way of distributing large quantities of data but do have some limitations. Data transfer rates of CD-ROMs are comparable to hard disks but access times are much slower. The slow access time can have negative implications for applications that require concurrent querying of several files. The speed of access to the data can be greatly improved by copying them to the hard disk and reading them from there.

2. Data Formats

1. *Standard Data Formats*

There are sub-directories under the \DATA directory that contain the data in a variety of formats such as Arc/Info coverages, shape files (.shp), MapInfo files (.mif/.mid), ASCII files (.dat/.def), and raster files (.tif, .bil). The \SHP and \MIF sub-directories have been further sub-divided into \POLY, \LINE, \POINT, and \TEXT directories as required for the database structure of these formats (see below).

1. ARC

Stored in the \DATA\ARC sub-directory, Arc/Info format files can be read directly by Arc/Info, ArcExplorer and Arcview on all supported platforms. They include point, vector, and polygon coverages as well as grids. All grids are named with *_g extension.

2. MIF

Stored in the \DATA\MIF sub-directory, MapInfo files include both .mif and .mid files for geometry and attribution. Note that these files are zipped to reduce file size and that point, vector, and polygon files within this format are stored in separate sub-directories within the zip files.

3. SHP

Arc/Info shape files are stored under the \DATA\SHP sub-directory and can be opened directly in Arcview or the included viewer. Note that each data set is separated further by data type (i.e., vector, polygon, point, or text).

4. ASCII

ASCII data files are composed of matching pairs of files with .def and .dat extensions. The .def files provide a listing of the database field definitions (name, length, type, etc.).

The .dat files are comma delimited text files containing complete listings of all the records of all point coverages, including easting and northing information. These files may be imported into spreadsheet or database software packages.

Note that this data can be very useful to CAD users. Since the DXF files (see below) can not contain values for all the attributes of the database records when converting to .dxf format, one of the fields in the database has been provided as a reference, or look-up field. For example, the record number, or an identifier string from the record, is viewable from within AutoCAD. Using this reference, the ASCII .dat file can be used to view the record's

remaining attributes.

5. RASTER

Arcview raster images are provided in .bil (band interleaved by line) and .tif (TIFF) format. BIL and TIF images can be displayed directly in Arcview II or imported to other software packages such as MapInfo. Additional files (.hdr, .stx, .clr for .bil and .tfw for .tif) included on the CD are required for the image to display properly in Arcview. These raster files can also be directly imported into Arc/Info as grids by using the *imagegrid* command with Arc/Info software (not included on this CD).

2. Interchange Formats

Several common interchange file formats are provided on the CD-ROM to ensure maximum compatibility of the data with a wide range of GIS and CAD systems. File formats are identified by their subdirectory name (e.g. E00, DXF) and each format is discussed below.

1. E00

Stored in the \DATA\E00 sub-directory, Arc/Info's ASCII interchange format allows Arc/Info coverages to be read by Arc/Info on all platforms. The format is also supported by many other GIS packages. As with any ASCII files on the CD-ROM, .e00 files must be converted to UNIX ASCII format for use on UNIX workstations.

2. DXF

Stored in the \DATA\DXF sub-directory, ASCII-format .dxf files are widely used by both CAD and GIS software to interchange line and point data. By definition, .dxf files do not support topology for polygon files. However, polygon attribute information can be associated to .dxf files as attributes tagged to text located inside polygons. Note that some maps have no attributes usable as layer names in .dxf format, and, no map has kept the non-dxf attributes during the conversion. However, the non-dxf attributes from point files can be viewed from the associated ASCII-format .dat/.def files mentioned in section 4.1.4 above. For vector (line) files, the type of line (e.g., fault, contact, etc) is often used as the layer name for use by the CAD program, and they can therefore be sorted by layer name to differentiate line types. The .dxf file set has been zipped to reduce file size. Once unzipped, the .dxf files must be converted to UNIX ASCII format for use on UNIX workstations.

3. Support Formats (metadata)

Several files are included on the CD-ROM to support and enhance the digital data information, including marginal notes, data structure and legends. These files are also identified by their extension and are listed below:

1.

APR

In the root directory of the CD-ROM is a file called SWAYZE.APR. This .apr file format is used by Arcview to store a collection of views of the data which are immediately useable in Arcview. See Section 2, Hardware and Software Requirements, for more information.

2. TXT

All data structure files, marginal notes and metadata are provided in DOS compatible ASCII format in files ending with the .txt extension. As with any ASCII files on the CD-ROM, .txt files must be converted to UNIX ASCII format for use on UNIX workstations.

3.

DOC

Marginal notes and other supporting documentation are provided in Microsoft Word for Windows, version 6, as files ending with .doc.

4.

HTM

This user guide is also provided in HTML and can be opened with any Internet browser or any HTML viewer.

5.

KEY

These files duplicate the full polygon legend presented on the hardcopy map in DOS-compatible format. They can be read for better understanding of the map data but are specifically intended for use by Arc/Info users to plot a simple legend for the map. As with any ASCII files on the CD-ROM, .key files must be converted to UNIX ASCII format for use on UNIX workstations.

6. AVL

Also included in the directories for the geology polygon files are .avl files. These can be used to colour each map when in Arcview by double clicking on the geology polygon theme and then loading the .avl file. The geology maps have already been coloured using these .avl files in the geology view from the swayze.apr project file.

3. Projection

All data is provided in UTM Zone 15, NAD83 projection. In the case of point data such as till geochemistry where the original coordinates provided were in a different projection, both the original coordinates and the UTM projection coordinates are provided.

4. Directory Structure

Root directory:

The root directory of the CD-ROM contains various federal government regulatory files:

citation.txt Proper citation for the CD-ROM

license.txt License agreement information

readme.txt Brief overview to get you started using the CD-ROM

lisezmoi.txt Version Francais - commencer a utiliser la disque.

Sub-directories:

DATA Contains all the actual digital data divided first by format (ARC, E00, DXF, MIF, SHP, RASTER, ASCII) and then by data set (e.g. DRILCORE, GEOLOGY, GEOPHYS, QUAT, LITHCHEM, MINERAL, NTS, ROADS, TWP) and lastly by source or type or other characteristic (e.g. GEOLOGY\GOO, GEOLOGY\GSC, GEOPHYS\EM, GEOPHYS\GAMMA). For example, the Arc/Info map TRACE83 would be found in \DATA\ARC\LITHCHEM\TRACE\TRACE83, and the e00 version of the Geology of Ontario map would be found in \DATA\E00\GEOLOGY\GOO\GOOGEOL.E00. All files needed to use the Arc/Info versions of the digital data (e.g. structure of data information, legend information) are also provided in each directory with the data.

DOC Holds the user guide (this document in various formats).

SOFTWARE Contains miscellaneous shareware or freeware useful in dealing with these datasets.

5. Data Sets

The following data sets are provided on this CD-ROM. Data format sub-directories can be substituted for "{FORMAT}" in the path (See Section 4.1, Interchange formats, for descriptions of each format).

1. National Topographic System boundaries (\DATA\{format}\NTS)

Map	Source	Description
nts250	GSC	Boundaries of 1:250,000 NTS map sheets
nts50	GSC	Boundaries of 1:50,000 NTS map sheets

2. Township boundaries (\DATA\{format}\TWP)

<i>Map</i>	<i>Source</i>	<i>Description</i>
swayze	GSC	Boundaries of study area
twp	OGS	Township boundaries

3. **Roads (\DATA\{format}\ROADS)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
kbroads	GSC	Logging roads compiled from airphotos, field work and NTS map sheets
mbroads	OGS	Logging roads compiled from airphotos, field work and NTS map sheets

4. **Drillcore (\DATA\{format}\DRILCORE)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
dc83	OGS	Location of drillholes and associated attributes

5. **Lithogeochemical data (\DATA\{format}\LITHCHEM)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
<i>path \DATA\{format}\LITHCHEMMAJORS</i>		
wra83 / wracl83	OGS, GSC, Falconbridge Ltd.	Lithogeochemical data – raw and cleaned / screened
<i>path \DATA\{format}\LITHCHEMTRACE</i>		
trace83		Includes all oxides (as in wra83) as well as trace elements

6. **Mineral data (\DATA\{format}\MINERAL)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
min83	OGS	Locations as well as basic attributes of mineral deposits and occurrences

7. **Quaternary data (\DATA\{format}\QUAT)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
<i>(path \DATA\format\QUAT\SURFMAPS)</i>		
gooquat	OGS	Surficial polygons (1:1,000,000 scale)
mbqto10	OGS	Surficial polygons for NTS 52o10 (1:50,000)
<i>(path \DATA\format\QUAT\AUGRAIN)</i>		
augr83	OGS	Gold grain counts
<i>(path \DATA\format\QUAT\BSOIL)</i>		
bhor83	OGS	Geochemical analysis of b-horizon soil profile
<i>(path \DATA\format\QUAT\TILL)</i>		
tilicp83 / tilina83	OGS	Geochemical analysis of till (C-horizon) ICP and INAA analyses
<i>(path \DATA\format\QUAT\STRIAE)</i>		
mbstriae	OGS	Glacial striae measurements

8. **Geophysics (\DATA\format)\GEOPHYS)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
<i>(path \DATA\format\GEOPHYS\EM)</i>		
swdc_g /swdcs_g	OGS	Decay constant (raw values and stretched 8 bit values from 0 to 255)
swde_g /swdes_g	OGS	Decay constant (deherringboned)
swres_g /swress_g	OGS	Resistivity (raw values and stretched 8 bit values from 0 to 255)
swrdf_g /swrdfs_g	OGS	Resistivity (raw values and stretched 8 bit values from 0 to 255 – deherringboned and filtered))
<i>(path \DATA\format\GEOPHYS\GAMMA\LOW)</i>		
ura_g83 /urae_g83	GSC	Equivalent uranium (eU) (linear and equalized stretch of raw data – 8 bits from 0 to 255)
thor_g83 /thoe_g83	GSC	Equivalent thorium (eTh)(linear and equalized stretch of raw data – 8 bits from 0 to 255)
pota_g83 /pote_g83	GSC	Percent potassium (%K)(linear and equalized stretch of raw data – 8 bits from 0 – 255)
<i>(path \DATA\format\GEOPHYS\GAMMA\MEDIUM)</i>		

uraw_g /urawe_g	GSC	Equivalent uranium (eU) (linear and equalized stretch of raw data – 8 bits from 0 – 255)
thraw_g /thrawe_g	GSC	Equivalent thorium (eTh)(linear and equalized stretch of raw data – 8 bits from 0 – 255)
kraw_g /krawe_g	GSC	Percent potassium (%K)(linear and equalized stretch of raw data – 8 bits from 0 – 255)
thrk_g /thrk_g	GSC	Thorium/potassium ratio grid (linear and equalized stretch of raw data – 8 bits from 0 – 255)
urk_g /urke_g	GSC	Uranium/potassium ratio grid (linear and equalized stretch of raw data – 8 bits from 0 – 255)
urth_g /urthe_g	GSC	Uranium/thorium ratio grid (linear and equalized stretch of raw data – 8 bits from 0 – 255)

(path \DATA\{format}\GEOPHYS\GRAVITY)

grv_g83	GSC	Raw data (milligals)
grvs_g83	GSC	Raw data stretched to 8 bits from 0 – 255

(path \DATA\{format}\GEOPHYS\MAG\GSC)

mg_g83 /mgse_g83	GSC	Mag from southern Swayze (raw, and stretched, equalized from 0 to 255)
mg0_g83 / mg45_g83	GSC	Shaded relief mag from southern Swayze (raw, 0 degrees (N) and 45 degrees (NE) using 30 degree elevation)
gsm_g83 /gsms_g83	GSC	Low resolution mag (raw, and stretched to 8 bits from 0 – 255)
gm0_g83/gm45_g83	GSC	Shaded relief low res mag (0 degrees (N), and 45 degrees (NE) using 30 degree elevation)

(path \DATA\{format}\GEOPHYS\MAG\NORANDA)

swtf_83g /swtfse_g / swtfsl_g	Noranda Inc.	Mag data (raw, and equalized, and linear stretch from 0 to 255)
swvgs_g /swvgse_g	Noranda Inc.	Vertical gradient (linear stretch, and equalized stretch)
swtf0_g /swtf45_g	Noranda Inc.	Shaded relief (0 degrees (N), and 45 degrees (NE) – 30 degree elevation)

(path \DATA\{format}\GEOPHYS\MAG\OGS)

swmols_g/swmoss_g	OGS	Total field smoothed, and total field smoothed and stretched between 0 and 255)
swvds_g /swvdss_g	OGS	Vertical gradient – smoothed, smoothed and stretched from 0 to 255

9. **Geology data (\DATA\{format}\GEOLOGY)**

<i>Map</i>	<i>Source</i>	<i>Description</i>
<i>(path \DATA\{format}\GEOLOGY\COMPOSIT)</i>		
compgeol	OGS	Geology polygons and arcs (OGS 1:253,000 map series)
compdyke	OGS	Mapped Dykes
compflt	OGS	Mapped faults
compfold	OGS	
<i>(path \DATA\{format}\GEOLOGY\FALCGEOL)</i>		
falgeol	OGS	Compilation of OGS open file maps
falcolay	OGS	Contacts, faults
<i>(path \DATA\{format}\GEOLOGY\GOO)</i>		
googeol	OGS	Geology polygons (1:1,000,000 scale)
goodyke	OGS	Dykes
gooflt	OGS	Faults
<i>(path \DATA\{format}\GEOLOGY\NSWAYZEMAP)</i>		
nswaygeo	OGS	Geology polygons (1:50,000 sclae)
nswaylay	OGS	Contacts, faults, dykes
nswaypts	OGS	Field measurements
nswaymin	OGS	Mineral occurrences
<i>(path \DATA\{format}\GEOLOGY\NSWAYZENFIELD)</i>		
jastruc	OGS	Field measurements
<i>(path \DATA\{format}\GEOLOGY\GSC\FIELD)</i>		
alter83	GSC	Alteration mapped in the field
fold83	GSC	Fold type mapped in the field
foli83	GSC	Foliation measurements
fract83	GSC	Fracture measurements
geochn83	GSC	Locations and descriptions of geochron samples
outcr83	GSC	Locations and descriptions of outcrops
photo83	GSC	Locations of photos taken in field
sample83	GSC	Locations of rock samples taken in field
shearz83	GSC	Locations and descriptions of shear zones mapped in the field
struct83	GSC	Structural measurements

(path \DATA\format\GEOLOGY\GSC\MAPS*)

* - this section duplicated for sub-directories \NTS41o8, \NTS41o10, \NTS41o15, \NTS41o16, \NTS41p5, \NTS41p12, \NTS41p13 and \GENERAL

geopoly	GSC	Lithological polygons
hst83	GSC	High strain zones mapped in the field
geolline	GSC	Faults, fold axes, contacts
geoltext	GSC	Annotations for labelling (text)
geochron	GSC	Geochronology sample locations
outcrops	GSC	Outcrop locations
structur	GSC	Locations of structural measurements (for map display only – see \gsc\field\foli83, shearz83, fold83, and fract83 (above) for full data on structural observations)
general	GSC	Generalized geology map of study area

6. Disclaimer and Copyright

Although every attempt has been made to ensure that the contents of this CD-ROM are as accurate as possible, the data on this CD-ROM is provided on an "as-is" basis.

The data on this CD-ROM, including this user’s guide, are protected by Crown copyright. The receiving institution, or person, shall not sell, distribute, rent, sub-license or lease the CD-ROM or its contents or any part of the contents.

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- *Geological Survey of Canada*
– J. Broome, K. Heather, G. Shore, S. Colvine, J. King, S. Lucas

- 1.
- 2.

APPENDIX A - Data sources and ordering information

GEOCHEMISTRY

Till / Soil / Humus -

Bernier, M.A. and Kaszyki, C.A., 1995. Till, humus and B-horizon soil geochemical database, Surficial Sediment Sampling Program, Swayze greenstone belt, Northern Ontario, 1992-94; Ontario Geological Survey, miscellaneous Release - Data 15

Gold Grain Counts

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Lithogeochemistry

Haus, M. and Pauk, T. 1993. PETROCH lithoeochemical data; Ontario Geological Survey, Open File Report 5855, 18p

Ayer, J. 1997. Precambrian geology of the northern Swayze greenstone belt, OGS Report 297

Heather, K- GSC- (unpublished)

Texas Gulf Survey – supplied by Falconbridge Ltd. (unpublished)

Falconbridge Survey – supplied by Falconbridge Ltd. (unpublished)

Fumerton, S. (OGS) – compilation of assessment files

GEOPHYSICS

Magnetics

GSC – 800 m grid regional data – Geophysical Data Centre (contact : Joan Todd, W. Miles – 615 Booth Street – 613-992-6438)

OGS - high resolution data – ERLIS dataset CD 1015 – Swayze greenstone belt

EM

OGS - high resolution data – ERLIS dataset CD 1015 – Swayze greenstone belt

DRILLHOLE

Ontario GEOservices Centre 1995. The Ontario Drill Hole Database (ODHDB), Ontario Geological Survey, 28 Mbytes – Data Set 13

MINERAL PROSPECTS

Fumerton, S.L., Houle, K.A. and Archibald, G. 1995. Digital data on mineral prospects in the Swayze greenstone belt. Plus a computer application to update and edit data using FoxPro: Ontario Geological Survey, Open File Report 5911,120p.

GEOLOGY

Northern Swayze

Ayer, J., and G. T. Shore, 1995. Precambrian Geology, Northern Swayze greenstone belt, Ontario Geological Survey, 2000 Map Series, M2549

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Heather, K.B.1999: Legend and notes for Open Files 3384b-3384i (NTS 41P/05, 08, 09, 10, 12, 13, 15, 16), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384a.

1999: Geology, Rollo Lake sheet (41P/15), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384b, 1:50 000 scale.

1999: Geology, Rush Lake sheet (41P/16), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384c, 1:50 000 scale.

1999: Geology, Mattagami Lake sheet (41P/13), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384d, 1:50 000 scale

1999: Geology, Sultan sheet (41P/10), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384e, 1:50 000 scale.

1999: Geology, Opeepeesway Lake sheet (41P/09), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384f, 1:50 000 scale.

1999: Geology, Gogama sheet (41P/12), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384g, 1:50 000 scale.

1999: Geology, Biscotasing sheet (41P/08), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384h, 1:50 000 scale.

1999: Geology, Westree sheet (41P/05), Swayze greenstone belt, Ontario, Geological Survey of Canada, Open File 3384i,

1:50,000 scale.

NTS – BASE DATA (drainage, topography)

This data has not been included on this CD due to royalty issues as previously mentioned. However the following 1:50,000 maps sheets cover the study area and are available in digital format: 41O/15, 41O/16, 41P/13, 41O/10, 41O/9, 41P/12, 41O/8, 41P/5. These are available for purchase from:

Geomatics Canada

NTDB Customer Support Group

Centre for Topographic Information

2144 King St. West, suite 010

Sherbrooke, Quebec

J1J 2E8

tel: 1-800-661-2638

fax: 819-564-5698

Internet: <http://www.ccg.rncan.gc.ca>

LAKE SEDIMENT DATA

This data is also not included on the CD but the area is covered by National Geochemical Reconnaissance (NGR) lake sediment surveys available as GSC Open File Reports # 1357 and # 1657. This data can be purchased from the Geological Survey of Canada (P. Friske).

REMOTELY SENSED DATA

Remotely sensed data for the study area can be ordered directly from Radarsat International:

RADARSAT International Headquarters

13800 Commerce Parkway

MacDonald Dettwiler Building

Richmond, British Columbia

V6V 2J3

CANADA

Tel: (604) 231-5000

Fax: (604) 231-4900

3. Appendix B – Reports and papers dealing with compilation and analysis of the data on this CD-ROM

Ayer, J., 1995. Precambrian geology, northern Swayze greenstone belt, District of Sudbury; Report 297, Ontario Geological Survey, 57 pp.

Bernier, M.A., C.A. Kaszycki, I. Wilkinson and J.R. Harris 1995. Proportionally Sized Circle Plot of Particulate Gold Abundance in Surficial Sediments (-10 Mesh Size Fraction), Swayze greenstone belt, Superior Province, Ontario, GSC Openfile Map 3130, OGS Preliminary Map P. 3326.

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Fumerton, S. and Houle, K., 1993. Mineral showings, occurrences, deposits and mines of the Swayze greenstone belt, interim report. Volumes 1 and 2; Ontario Geological Survey, Open File Report 5871, 763 pp.

Fumerton, S., Houle, K. and Archibald, G., 1993. Digital data on the mineral showings, occurrences, deposits and mines of the Swayze greenstone belt, plus a computer application to update and edit the data using Foxpro_, interim report; Ontario Geological Survey, Open File Report 5872, 112 pp.

Harris J.R., L. Wilkinson, E. Grunsky, K. Heather, and J. Ayer 1999. Techniques for Analysis and Visualization of Lithogeochemical Data with Applications to the Swayze greenstone belt, Ontario, (submitted to Journal of Geochemical Exploration – in press).

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Harris J.R., Wilkinson L. and J. Broome 1995. The GIS/Database project: Progress in the Swayze greenstone belt, NODA Summary Report, edited by L. Owsiacki, M. Walters, H. Brown , R. Shannon, pp. 110-116.

Harris, J. and Wilkinson, L. 1999. Swayze Greenstone Geoscience Dataset : Results form data analysis using GIS technology, GSC Open File CD – D3731.

Harris, J. R., Broome, J. and Heather, K.B. 1993. Swayze greenstone belt GIS Project. NODA Summary Report 1993-1994 pp. 115-121.

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Harris, J.R. and Wilkinson L. 1999. Drift Exploration in Glaciated Terrain, Short Course Notes presented during the 19th International geochemical Exploration Symposium, Vancouver, British Columbia, sponsored by the Association of Exploration Geochemists, Chapter 6, pp. 182-210.

Harris, J.R., Grunsky, E.C. and Wilkinson, L. 1997. Developments in the effective use and interpretation of lithogeochemistry in regional exploration programs: application of GIS technology. Proceedings of Exploration 97: Fourth Decennial International Conference on Mineral Exploration, edited by A.G. Gubins, pp. 285 – 292.

Harris, J.R., Grunsky, E.C. and Wilkinson, L. 1999. Effective use and interpretation of lithogeochemical data in regional exploration programs, (submitted to *Ore Geology Reviews* – in press).

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rocks in the vicinity of the Swayze greenstone belt, southern Superior Province, Ontario; *in* Current Research 1994-C; Geological Survey of Canada, p. 259-268.

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