GEOCHEMICAL DATA ANALYSIS TECHNIQUES

FOR GOLD EXPLORATION IN

SUMBAWA, INDONESIA

by

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A thesis submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Master of Science (Geochemistry).

Golden, Colorado

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ABSTRACT

Two drainage surveys conducted in southwestern Sumbawa, Indonesia, are used to compare four different multivariate data analysis techniques. The first drainage survey is an orientation survey conducted by Moedjiarto (1994) in 1993. The second drainage survey is a reconnaissance survey conducted by P.T. Newmont Nusa Tenggara in 1987. Both surveys contain geochemical, lithological, stream order, and drainage area data. Both survey areas also contain documented known mineral occurrences.

Factor analysis, discriminant analysis, cluster analysis, and neural networks techniques are all examined, compared and evaluated. R-mode factor analysis provides information on the element associations, or the associations of any variables. These associations can then be examined and mapped spatially to determine which associations represent mineralization and where to follow up.

Discriminant analysis creates a function that can be used to classify unknown samples. The only disadvantages to discriminant analysis are that the method needs enough training data to create the function and that the training data must meet three assumptions. If the data fail to the meet the assumptions, the method can still work; however, it may not be as reliable.

Cluster analysis, originally presented by Sjoekri (1997), was also useful in selecting drainages for future study. Sjoekri (1997) created exploration target classes from the results of the final orientation survey and applied them to the results from the reconnaissance survey. As a result, several drainages were selected for potential follow-up.

Neural networks work much the same way as discriminant analysis, by classifying objects (samples); however, neural networks do not require that the same three

assumptions be met for the data as discriminant analysis. However, the quantity of training patterns provided to the network can significantly influence the results.

Comparisons of the methods were made based upon three factors. The first is reliability, such that a method is deemed reliable if it correctly identifies nearly all of the drainages with known mineral occurrences. The second is ease-of-use, which considers the time and experience required to prepare for and run each technique. The third is cost-effectiveness, which incorporates both reliability and ease-of-use, and also examines the cost of running each technique, in both time and money.

Overall, for the two data sets used, factor analysis was the most reliable and cost-effective and took the least amount of time. Cluster analysis was the second most reliable and is estimated to be the third most cost-effective, based upon the description of all of the steps taken to complete the analysis. Discriminant analysis was the third most reliable, for these two data sets, as two out of the three assumptions were violated. Neural networks analysis was the least reliable of the four methods as there were not enough training patterns available.

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ACKNOWLEDGMENTS

I express my sincerest thanks to Dr. L. Graham Closs for his continuous support and guidance through this, sometimes enduring, processes. I also want to thank the members of my thesis committee, Dr. Geoffrey D. Thyne, Dr. A. Keith Turner, and Dr. Samuel B. Romberger for their helpful insight and encouragement to see this project finished.

I want to thank Adi Sjoekri for his help and insight into the data and for answering my questions. I want to also thank Dr. Oden Christensen of Newmont Industries for giving me permission to use the two data sets for this study. I want to thank Dr. K. K. J. Voorhees of the Chemistry and Geochemistry Department, Colorado School of Mines, for allowing me to use their NeuroShell 2 software.

I also want to thank my husband, Bruce, and the many other members of my family for their support and encouragement. Without them I would not have been able to finish this thesis. Thank you.

CHAPTER 1

INTRODUCTION

1.1 Purpose and Objectives

Mineral exploration is an interdisciplinary process aimed at locating economically viable mineral deposits. It is in this interdisciplinary nature that geological, geophysical, geochemical, and sometimes biogeochemical characteristics of a study area's environment are collected. Rocks, stream sediment, soil, water, and sometimes plant matter are all media that can be sampled during a mineral exploration program. For the geochemist, one principal phase of an exploration project is the interpretation of the data collected during the various stages of the program, e.g. orientation and reconnaissance surveys, to establish the presence or absence of mineralization. The resulting large volume of data that can be produced, along with economic criteria imparted by the investor, makes timely, reliable, and accurate interpretation of the data critical for success of an exploration program.

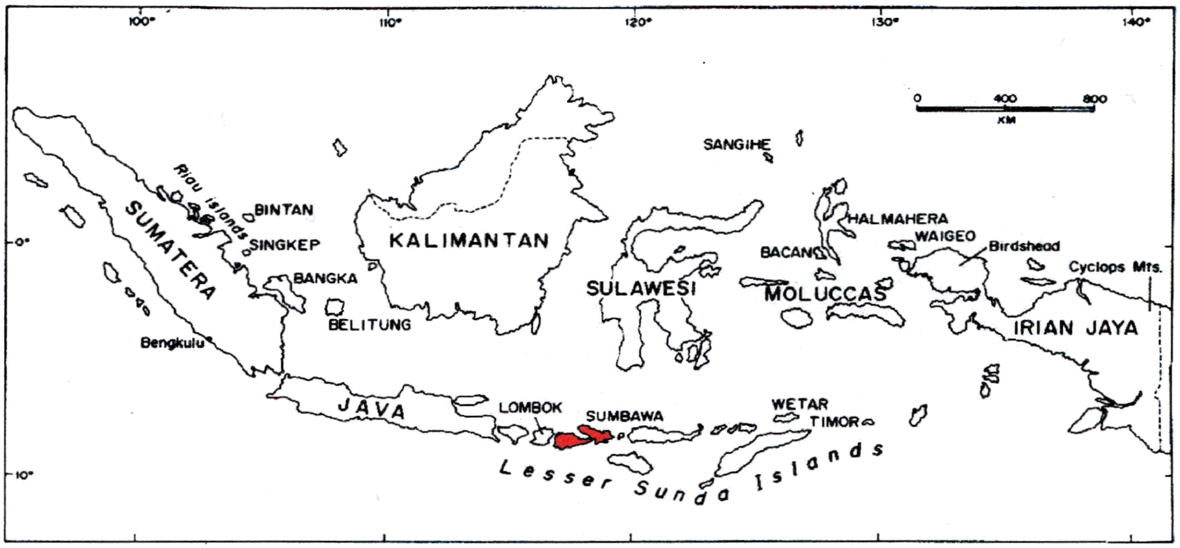
In mineral exploration, multivariate data analysis techniques enable the geochemist to evaluate each sample site for the presence or absence of mineralization by allowing the investigator to examine the relationships between variables, groups of variables, or samples, which often reveal significant information about geological and geochemical processes at work in the environment (Rose et al., 1979). Multivariate statistical techniques such as principal component and factor analysis, discriminant analysis, cluster analysis, and linear regression have been widely used in the past to interpret large volumes of exploration data. Neural network analysis, a data mining technique, has recently received attention in the mining and mineral exploration fields as an interpretive tool for exploration data.

The identification of potentially mineralized areas relies on the relative accuracy of locating anomalous sample sites as well as the presence of diagnostic geochemical associations of elements; for example, Ag, As, Au, Cu, Mo, Pb, and Zn in porphyry copper deposits (Rose et al., 1979). To locate anomalous samples (e.g. typically samples with unusually high concentrations of elements), it is important to establish, or at least estimate, the relative background concentrations of elements for each sample site. Estimation of background concentrations of elements in many types of geological and environmental studies is a controversial issue. A first approximation can be made by selecting threshold values from histograms. The method proposed in Carranza and Hale (1997) is utilized to provide another approach. Their procedure takes into consideration the drainage area and the lithology, both of which significantly affect background geochemistry.

In this study, drainage geochemistry data from an orientation survey and a reconnaissance survey conducted in southwest Sumbawa, Indonesia, are examined and evaluated using four interpretive techniques: factor analysis, discriminant analysis, cluster analysis, and neural networks techniques. Each technique will first be assessed independently. The results from each of these techniques are then compared on the basis of their reliability, ease of use, and cost-effectiveness. For this study a technique is deemed reliable if it correctly identifies at least 80 to 90% of the drainages with known mineral occurrences. Ease of use criteria includes the time and experience required to prepare for and run each technique and interpret the results. Techniques are cost-effective if the overall time to run and interpret each technique is matched by reliable output and a low overhead cost, such as purchase of software or purchase of experience. The goal is to provide recommendations as to which technique or techniques are most effective as aids for mineral exploration projects in environmental settings similar to southwestern Sumbawa, Indonesia.

1.2. Location of Study Area

The island of Sumbawa is one of the two major islands in the Province of West Nusa Tenggara in the Lesser Sunda Islands (Figure 1.1a), which comprise the south-central to southeastern segment of Indonesia (van Leeuwen, 1994; Electronic Information Management Unit (PPED), 1998). Both the orientation and reconnaissance surveys were conducted within the study area denoted on Figure 1.1b.



a)

b)

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1.3 Previous Work

The original data sets consist of an orientation survey conducted by Moedjiarto in 1993 and a reconnaissance survey conducted by P.T. Newmont Nusa Tenggara (NNT) in 1987 (Sjoekri, 1997). Both surveys contain stream sediment drainage geochemical data. Initial data organization, presentation, and cluster analysis was presented by Sjoekri (1997). These data sets were chosen because they contain well-documented areas of known mineralization, including the Batu Hijau porphyry copper-gold deposit.

Multivariate data analysis is often used to aid data interpretation. The four methods that are addressed in this study, factor analysis, discriminant analysis, cluster analysis, and neural networks techniques, all have been used in the past for interpreting geochemical exploration data. Each method has something different to offer the exploration geochemist.

1.3.1 Factor Analysis

Factor analysis is a derivative of principal components analysis (PCA). Both methods are forms of multivariate techniques that reveal underlying patterns or processes in data by examining the interrelationships of the variables (Davis, 1986; Swan and Sandilands, 1995). Principal components analysis retains all of the variability of the variables (Davis, 1986). Factor analysis, in contrast, is based on the assumption that the majority of the variability within a data set can be represented by a smaller number of uncorrelated underlying factors (Davis, 1986). Furthermore, it is anticipated that these factors or element associations can be interpreted as geological or geochemical features present in the survey area, including bedrock geology, surficial processes, and mineralization. It is this feature that is most useful in establishing the underlying processes in an area and thereby assessing if the area has potential for mineral exploration.

Both principal components and factor analysis have been used extensively in the past for mineral and petroleum exploration (Howarth and Sinding-Larsen, 1983). Closs and Nichol (1975) examined the application of R-mode factor analysis in determining the principal metal associations related to both bedrock and surficial processes at work in the Notre Dame Bay district of Newfoundland. The principal assumption was that different lithologies and mineral occurrences are characterized by different element associations. Closs and Nichol (1975) proposed that factor analysis can aid in recognizing these element associations that can sometimes be hidden within the structure of the data. Therefore, various lithological signatures, potential mineral occurrences, and surficial processes can be identified more reliably using factor analysis than when examining single-element data.

Halfpenny and Mazzucchilli (1999) provide a recent example of the use of factor analysis in evaluation of stream sediment drainage survey data in the Himalayan mountains of northern Pakistan. The authors found that the dispersion patterns of a number of elements closely reflected the regional geology; however, five of the 10 factors were believed to represent mineralization in the region. Additional factors contained associations of elements that share weathering characteristics, suggesting that some factors reflect the geochemical weathering environment as well.

Regment and Joreskog (1993) have noted the use of factor analysis in petrology, mineralogy, geochemistry of magmas, and distribution of heavy minerals. They also noted that factor analysis used to study the distribution of heavy minerals from the Gulf of California and the Orinoco-Guyana shelf provided results that were significantly different and more meaningful than those obtained from simple inspection of the raw data.

1.3.2 Discriminant Analysis

Discriminant analysis is a form of classification that requires *a priori* knowledge of the problem to create a function by which unknown samples can be classified (Davis, 1986). In this method multivariate data are combined in such a way to create a linear relationship which optimizes the separation of two or more populations (Rose et al., 1979). This method has been used extensively in mineral exploration because it allows for the discrimination between mineralized and nonmineralized areas. It is also used rather frequently to establish background geochemistry within a study area (Carranza and Hale, 1997). One principal benefit is that this method is statistical and, as such, the alternative solutions can be tested for their statistical significance in addition to evaluating the percentage of correctly classified objects.

Conradsen et al. (1991) utilized discriminant analysis on a data set consisting of Landsat, radiometric, geophysical, and geochemical data to investigate possible uranium mineralization in southern Greenland. While the study was not specifically drainage geochemistry, a parallel is drawn between the pixel size and the drainage basin as they were evaluating the pixels based upon their associated stream geochemistry. Conradsen et al. (1991) were successful in locating potential uranium mineralization using the discriminant analysis method on the combined data set.

Fedikow et al. (1991) used a step-wise discriminant analysis method which only retained those variables that were most valuable to the discrimination between mineralized and nonmineralized areas. They tested the discriminant function by classifying their original training data set to determine the percentage of misclassified samples. Their study led to the location of five potentially mineralized areas, only two of which showed elevated gold values in the single element data analysis.

Clark et al. (1989) used discriminant analysis on tourmaline compositions as a tool for mineral exploration because of the extensive solid solution within the tourmaline structure and tourmaline's relation with hydrothermal deposits. While the authors' findings depended upon the origin of the deposit from which the tourmaline was sampled, they were successful in correctly classifying greater than 72% of the samples as being from a non-granite mineralized, granite-related mineralized, and granite-related barren deposits, depending on the variables that they used to define the discriminant function.

1.3.3 Cluster Analysis

Cluster analysis is a classification scheme that, ideally, forms separate relatively homogeneous groups from an originally heterogeneous data set (Davis, 1986). The principle behind cluster analysis is that the similarities or dissimilarities between samples, as evident from their characteristics (i.e. measured variables, such as geochemistry, lithology, or geophysics data), can be used to group together samples that are the most similar thereby forming clusters. The characteristics of the samples within each cluster can then be examined for potential indications of the target mineralization.

Several studies in the mineral exploration field have utilized cluster analysis, for example, Hesp and Rigby (1973), Obial and James (1973), Rose et al. (1979), and Sjoekri (1997). Rose et al. (1979) noted that for mineral exploration the "goal of cluster analysis might be recognition of separate ore and background clusters" (page 533). Sjoekri (1997) used the technique to produce a classification scheme for mineral exploration in Sumbawa, Indonesia (discussed further in Chapter 7).

Hesp and Rigby (1973) examined the application of cluster analysis to major and trace element concentrations of rock samples from the New England igneous complex in New South Wales, Australia. The authors found that cluster analysis improves the mapping resolution and geochemical characterization of rocks that had been previously mapped. Furthermore, the clusters may reveal information related to processes of ore formation and exploration.

Obial and James (1973) used cluster analysis on stream sediments in Derbyshire, England, to classify catchments into groups based upon their geochemical signatures. Three clusters were produced, the first two included sediments from limestone and shale drainages, respectively. The third group showed indications of Pb-Zn mineralization.

1.3.4 Neural Networks

Neural networks consist of a category of computer applications that use pattern recognition to classify objects. Neural networks, modeled after the human brain, were first developed in the biological and psychological sciences as experiments to better understand observations in behavior and brain construction (Eberhart and Dobbins, 1990). Over the past forty years of development, several variations of neural network applications have been utilized in many different fields including financial, psychological, biological, and more recently geological and petroleum exploration projects for classification, pattern recognition, and predictions (Brown et al., 2000).

Neural networks, like discriminant analysis techniques, require *a priori* knowledge of the problem so that adequate training data can be selected, although there are versions which do not require *a priori* knowledge. The ultimate goal of neural networks applications in mineral exploration is to classify unknown objects as either relating to mineralized or barren areas. Neural networks techniques, unlike discriminant analysis, do not require a normalized data set as the techniques are designed to look for patterns rather than perform regression.

Neural networks techniques are, once trained, supposed to save time and produce more precise results (Wong et al., 1995; Singer and Kouda, 1997; Brown et al., 2000). Both of these aspects are critical to mineral exploration, where inaccurate prospecting can be extremely costly and time consuming. In this respect, a neural network application will be compared with previously mentioned techniques to see if the technique is as useful as it appears to be.

Wu and Zhou (1993) evaluated the application of neural network techniques for ore grade estimation. The authors found that the neural network solution was more reliable and universally applicable to any spatial grade distribution than conventional techniques because the network "learns" the pattern of the ore grade variation. Wu and Zhou (1993) further noted that neural networks work very well with highly variable data. The authors also caution that neural networks should be used in conjunction with traditional methods as the neural networks can produce excellent pattern recognition and the traditional methods can be used for more precise calculations.

Clare and Cohen (2001) evaluated the use of unsupervised neural networks to organize multivariate stream sediment data into classes without *a priori* knowledge. The principal benefit of using the modified form of the unsupervised Kohonen self-organizing map is that it works well with nonlinear, nonparametric data. The authors found that the unsupervised techniques provide a viable alternative to other multivariate statistical methods as it was able to identify both outlier anomalies, those with higher values for some elements, and nonoutlier anomalies, those within the common spread of values for each element.

1.3.5 Previous Comparative Studies

Comparative studies between multivariate statistical techniques abound, however, relatively few are specifically related to mineral exploration. Several authors have compared various multivariate statistical techniques for interpreting geochemical data. Chatterjee and Strong (1984) compared discriminant analysis and factor analysis methods for identifying characteristic element associations related to uranium mineralization. Brown et al. (2000) compared neural networks and principal component analysis to produce gold prospectivity maps. Wong et al. (1995) compared neural networks and discriminant analysis to predict lithofacies properties for genetic reservoir characterization.

1.3.5.1 Chatterjee and Strong (1984)

Chatterjee and Strong (1984) compared discriminant analysis and factor analysis as tools for recognizing and identifying associations of elements indicative of mineralization. The authors examined the Millet Brook uranium prospect in Nova Scotia, using a data set of approximately 128 samples from diamond drill cores through unaltered, altered and mineralized granodiorite.

Discriminant analysis was used to develop a function that could distinguish between altered and unaltered granodiorite, as the altered granodiorites were associated with mineralization within the prospect. Chatterjee and Strong (1984) describe one basic criterion for the evaluation of a discriminant function, which states that the difference between the value of the discriminant scores for each group must be greater than the variation within each group. Their discriminant function failed this criterion, even though the two groups showed a distinct separation, because the altered group, showing four separate subgroups contained a much larger within-group variance compared with the unaltered group. Chatterjee and Strong (1984) examined the samples within the subgroups and noted that they corresponded to different alteration assemblages, e.g. silicification versus potassic, and then created discriminant functions which would differentiate between the unaltered and each type of alteration assemblage separately, for example, unaltered versus silicified granodiorites. When the discriminant score from the first function was plotted against the score for the second function, the different groups – unaltered, silicified, etc – were in clearly separate groupings.

The discriminant analysis needed *a priori* information, i.e. the authors initially grouped the samples as either altered or unaltered granodiorites based upon petrographic descriptions of the samples. For comparison, factor analysis was used to examine if the same grouping of the samples could occur without *a priori* knowledge. The authors used an R-mode factor analysis technique that began with principal components analysis followed by varimax rotation. Different factors were interpreted to represent separate geological and geochemical processes. The authors concluded that the factors "reveal a range of important element associates and patterns which can be associated with the different alteration and mineralization effects, and which may prove to have broader metallogenic and exploration significance" (p. 304). Chatterjee and Strong (1984) stated the difference between discriminant analysis and factor analysis is evident in the need for *a priori* knowledge, which factor analysis did not need. Both multivariate statistical techniques provided the authors with essentially the same information, although in different interpretive ways.

1.3.5.2 Wong et al. (1995)

Wong et al. (1995) compared the application of discriminant analysis with neural network techniques for predicting lithofacies, porosity and permeability for genetic reservoir characterization. Wong et al. (1995) used two well logs, one as a training data set and the other as a validation or testing data set. The authors described discriminant analysis as a "powerful and robust classification technique" (p. 192), which requires normal or multinormal data distribution for each class to be established. In contrast, Wong et al. (1995) described neural networks techniques as a computer model designed to learn from examples, much like the human brain, which does not require normally distributed data.

Wong et al. (1995) stated that while discriminant analysis is an established reliable method for estimating lithofacies, porosity, and permeability, back-propagating neural networks performed as well if not better. They suggested that, while the training time for neural networks can be more intensive than with discriminant analysis, that once the training patterns are in place, the analysis time is substantially reduced. In addition, neural networks techniques work better with nonnormally distributed or extremely complex data. The authors noted that both methods performed equally well in lithofacies classification, but neural networks techniques provided better estimates of porosity and permeability.

1.3.5.3 Brown et al. (2000)

Brown et al. (2000) compared neural networks to various data analysis techniques, including weights of evidence and principal components analysis, for the purpose of producing prospectivity maps for gold exploration in the Timbarra – Poverty Point goldfield in New South Wales, Australia. The authors stated that neural network applications allow data sets to be combined without the "loss of information" that can occur as a result of combining information and converting it into statistically uncorrelated components as in principal component or factor analysis. In contrast, it is not the "loss of information" that could occur during factor analysis, but rather the loss of nonessential variance. The premise of factor analysis is that the loss of variance, not necessarily information, may bring out the underlying patterns or associations within the data that could be representative of significant geological or geochemical processes.

Brown et al. (2000) suggest a key benefit of neural network applications being that the networks can respond in a nonlinear way when assigning high favorability to an output. In mineral exploration, high favorability might correspond to a "most likely" mineralized rating, e.g. an area that should be further investigated for mineralization. For example, if three parameters are required for the prediction of gold favorability, one of which is essential, the neural network will only assign the highest favorability if the essential one is present, thus assigning a lower favorability if only the other two required parameters are present. This contrasts with other interpretive methods that work on more of an additive model, so that even if the one essential parameter is missing, the locality would still receive a high favorability because two of the three parameters are present.

Brown et al. (2000) cite several advantages to neural networks techniques, compared with standard multivariate statistical methods: (1) they can function without pre-existing knowledge; (2) they can extract patterns which are not visible by single element or many of the standard statistical techniques; (3) they can have acceptable accuracy even if data are noisy or contains outliers; and (4) they can perform well when input parameters are interdependent and exhibit significant nonlinearity (p. 758). Thus Brown et al. (2000) confirmed that the properties of neural networks can adequately recognize underlying patterns and classify geochemical data. The authors noted, however, that setting up a neural network is an iterative process. In many, but not all neural networks, the network is trained by adjusting the weights of the connections between nodes to reduce the error between the given output and the desired output, iteratively until the error between the two outputs reaches an acceptable level. In this process the network learns to recognize underlying patterns in the data set that correspond with the characteristics of known mineral occurrences for correct classification. This can increase the initial set up time for the network; however, processing data through the network will be much more efficient than for more conventional multivariate statistical techniques. In conclusion, Brown et al. (2000) noted that through "statistical measures used to compare map quality indicate[d] that the neural network method performs as well as or better than existing methods" (p. 766).

1.4. Outline of Thesis

The geology of southwest Sumbawa and the characteristics of the known mineral occurrences in the survey areas are discussed in Chapter 2. The characteristics of each drainage survey, along with a general synopsis of drainage surveys and how they are useful in mineral exploration are presented in Chapter 3. In Chapter 4, the initial univariate data analysis is presented to aid the interpretation and discussion of the results of the multivariate data analysis techniques that are used in this study.

Chapters 5 through 8 contain more detailed descriptions of each multivariate method, along with the methodology used and results for each survey. A discussion of the individual results for each method is provided at the end of its respective chapter. Chapter 5 addresses factor analysis. Chapter 6 addresses discriminant analysis. Chapter 7 describes the methodology and results from Sjoekri (1997) cluster analysis. Chapter 8 addresses neural networks techniques. Chapter 9 contains the discussion and comparison for the different multivariate techniques examined in this study, along with recommendations for future study.

CHAPTER 2

GEOLOGY OF SOUTHWEST SUBAWA

2.1 Geography

The study area is located in rural southwestern Sumbawa, Indonesia. Sumbawa is generally sparsely populated, with the largest city at Raba in the eastern portion of the island (Figure 1.1b). The island is accessible by boat or local aircraft from neighboring islands.

Sumbawa has a tropical climate with high humidity, averaging 82%, and high temperatures, ranging from 68° to 86° F (20° to 30° C) (Sjoekri, 1997; Electronic Information Management Unit (PPED), 1998). Southwest Sumbawa experiences high rainfall averaging 39 to 51 inches (100 to 130 cm) per year, while localized rainfall at Batu Hijau has been approximated at 86.6 inches (220 cm) per year (DeJong-Boers, 2001; DeMull et al., 2001). A narrow coastal plain along the south and western coasts is cut by river valleys, rising steeply to mountainous terrain (DeMull et al., 2001). The topographic relief of southwestern Sumbawa is dominantly hilly to mountainous with a well-developed drainage system. Plate I is a topographic map of southwest Sumbawa, Indonesia. Southwest Sumbawa contains dense vegetation, ranging from grasses and low scrub brush at lower elevations through deciduous forest into evergreen rain forests in high mountainous terrain (DeJong-Boers, 2001).

2.2 Regional and Local Geology

Sumbawa Island is located within the Sunda – Banda arc system, on the eastern edge of Sunda Shelf (Sillitoe, 1994; Sjoekri, 1997). The Sunda – Banda arc system extends from northern Sumatra to north of the Banda sea, some 3,726 miles (6,000 km) in length (Figure 2.1). The arc system forms the south and southeastern border of Indonesia marking a zone of convergence of three major tectonic plates: the Indian-Australian, the Eurasian and the Pacific plates (Foden and Varne, 1980). While the Sunda – Banda arc system is typically referred to as one system, it is actually comprised of multiple arc systems. The islands in the province of Nusa Tenggara, including Sumbawa, are located at the transition zone between the Sunda arc to the west and the Banda arc to the east (Sjoekri, 1997). At Sumbawa, the northward-moving Indian-Australian plate is being orthogonally subducted beneath the south-facing Banda arc (Cardwell and Isacks, 1981). To the immediate east of this region the Banda arc makes a bend back to the west due to intersection with the westward moving Pacific plate (Barber et al., 1981).

The regional geology of Sumbawa consists of Tertiary and Quaternary volcanic and sedimentary rocks and Tertiary intrusive rocks. Northern parts of Sumbawa are covered by Quaternary andesitic volcanic rocks, erupted from Tambora, an active volcano on the northern portion of Sumbawa (Meldrum et al., 1994). Tambora's most recent eruption was in 1985 and covered Sumbawa with ash up to 24 inches (60 cm) thick. Cardwell

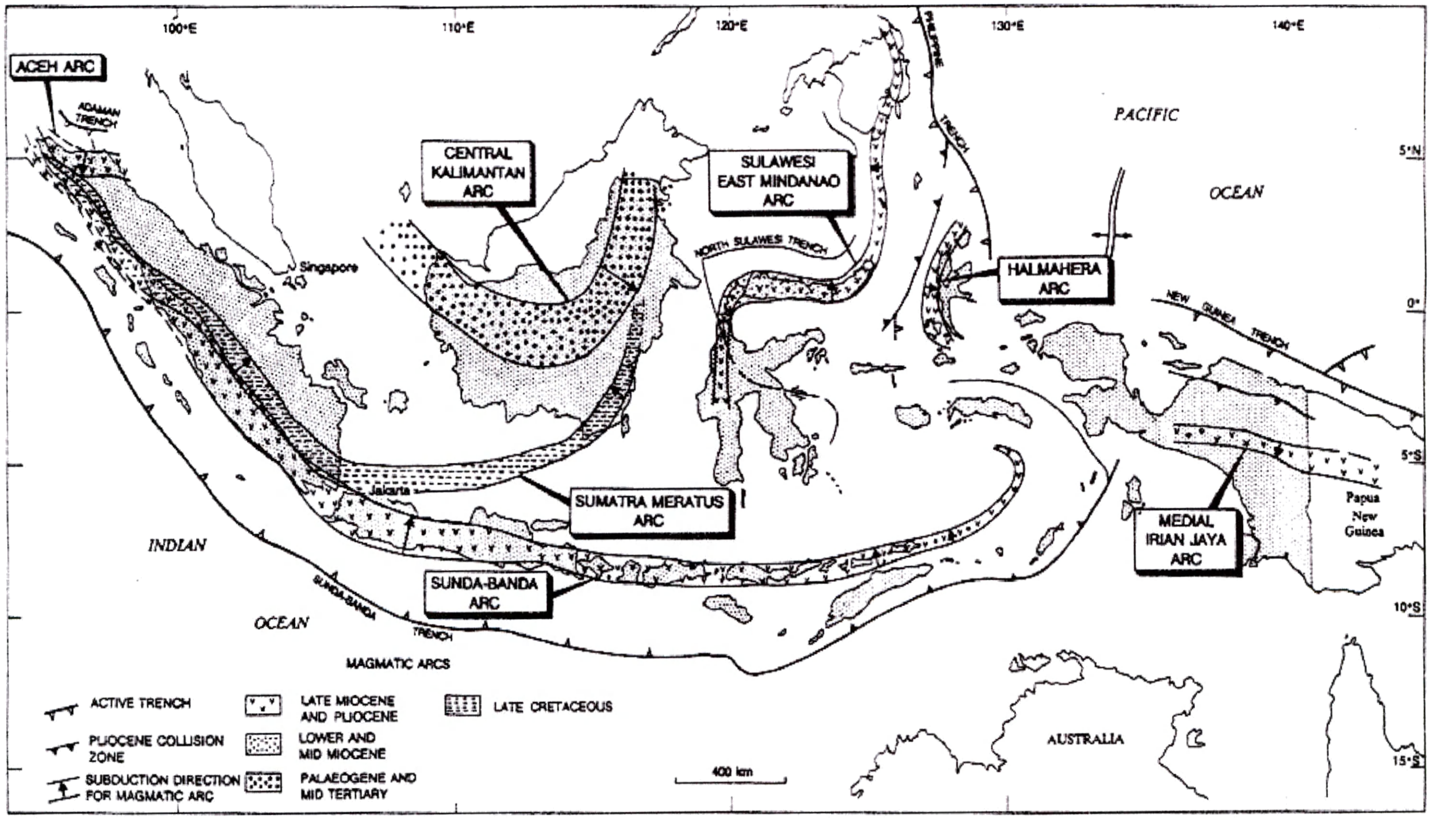

Figure 2.1. Tectonic framework of Late Cretaceous to Pliocene magmatic arcs in Indonesia. Arrows indicate dip direction of subducting crust. (Carlile and Mitchell, 1994)

and Isacks (1981) described the regional characteristics of the calc-alkaline basaltic to andesitic rocks as generally glassy, containing strongly zoned plagioclase (An_{80} to An_{50}), augite, hypersthene and accessory ilmenite and magnetite. Nishimura et al. (1981) provided a range of 23.7 to 5.3 Ma for tuff samples in the central portion of western Sumbawa, just northeast of the study area.

The oldest exposed rocks in southwestern Sumbawa are Tertiary andesitic pyroclastic flows and intermediate intrusion with minor shallow marine sedimentary rocks (Meldrum et al, 1994; Sjoekri, 1997). Intrusive rocks are distributed along an east-west trend (Figure 2.2 and Plate II). Older diorite and microdiorite intrusions occur as dikes and stocks within the volcanic and sedimentary rocks. Younger intrusive rocks consist of quartz diorites and tonalites, which host the Batu Hijau porphyry copper-gold deposit (Sjoekri, 1997).

2.3 Mineralization

Several mineral deposit types have been identified throughout Indonesia, including: (1) porphyry copper-gold; (2) porphyry molybdenum; (3) skarn copper-gold; (4) low-sulfidation epithermal gold; (5) high-sulfidation epithermal gold-copper; and (6) volcanogenic massive sulfide gold (Sillitoe, 1994). Porphyry copper-gold and low-sulfidation epithermal gold deposits are known in southwestern Sumbawa (Figure 2.3) (Sjoekri, 1997). The most famous of the porphyry copper-gold deposits in this region is the Batu Hijau deposit.

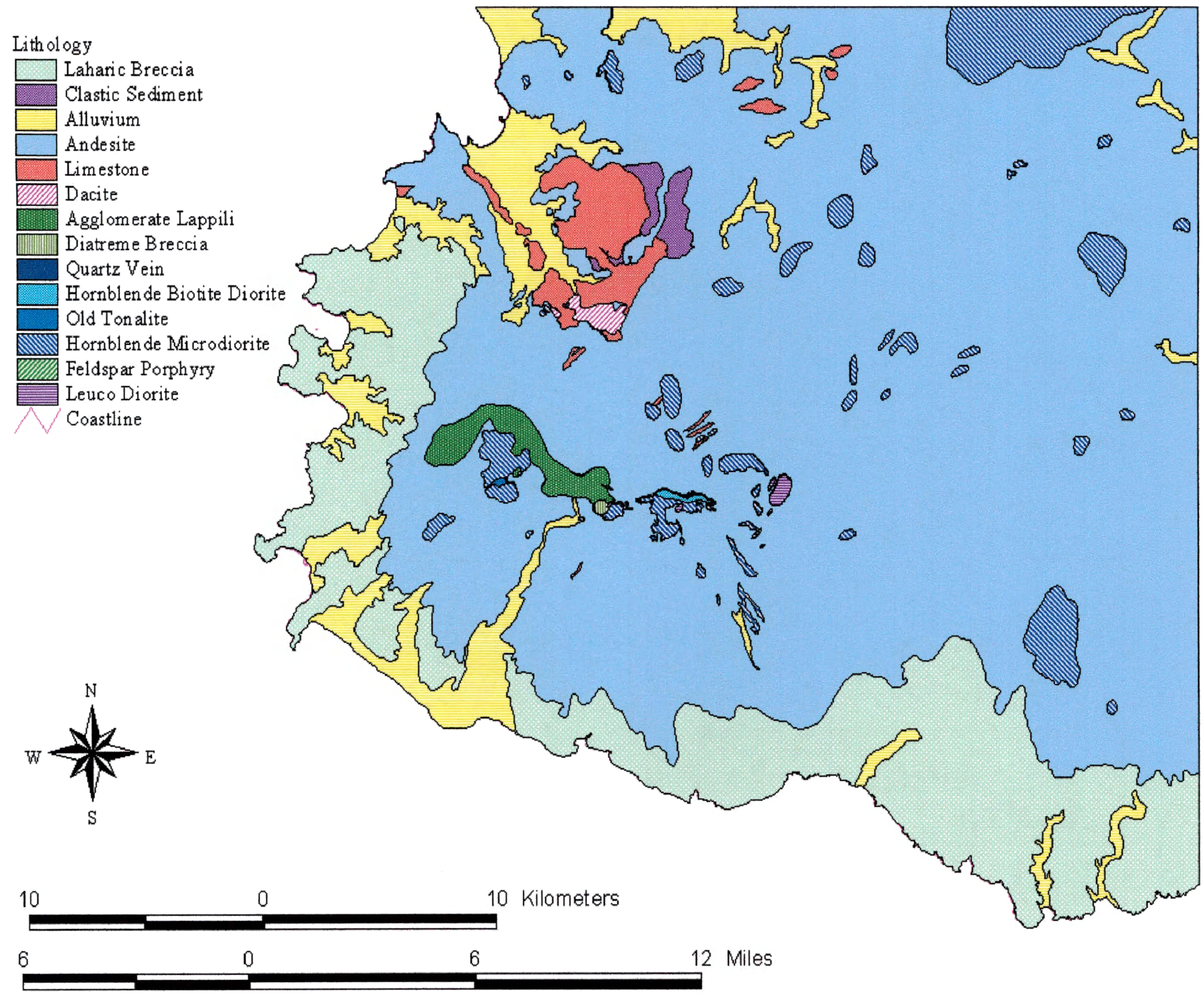

Figure 2.2. Geology of southwest Sumbawa, Indonesia. (pers. comm. Sjoekri, 2000)

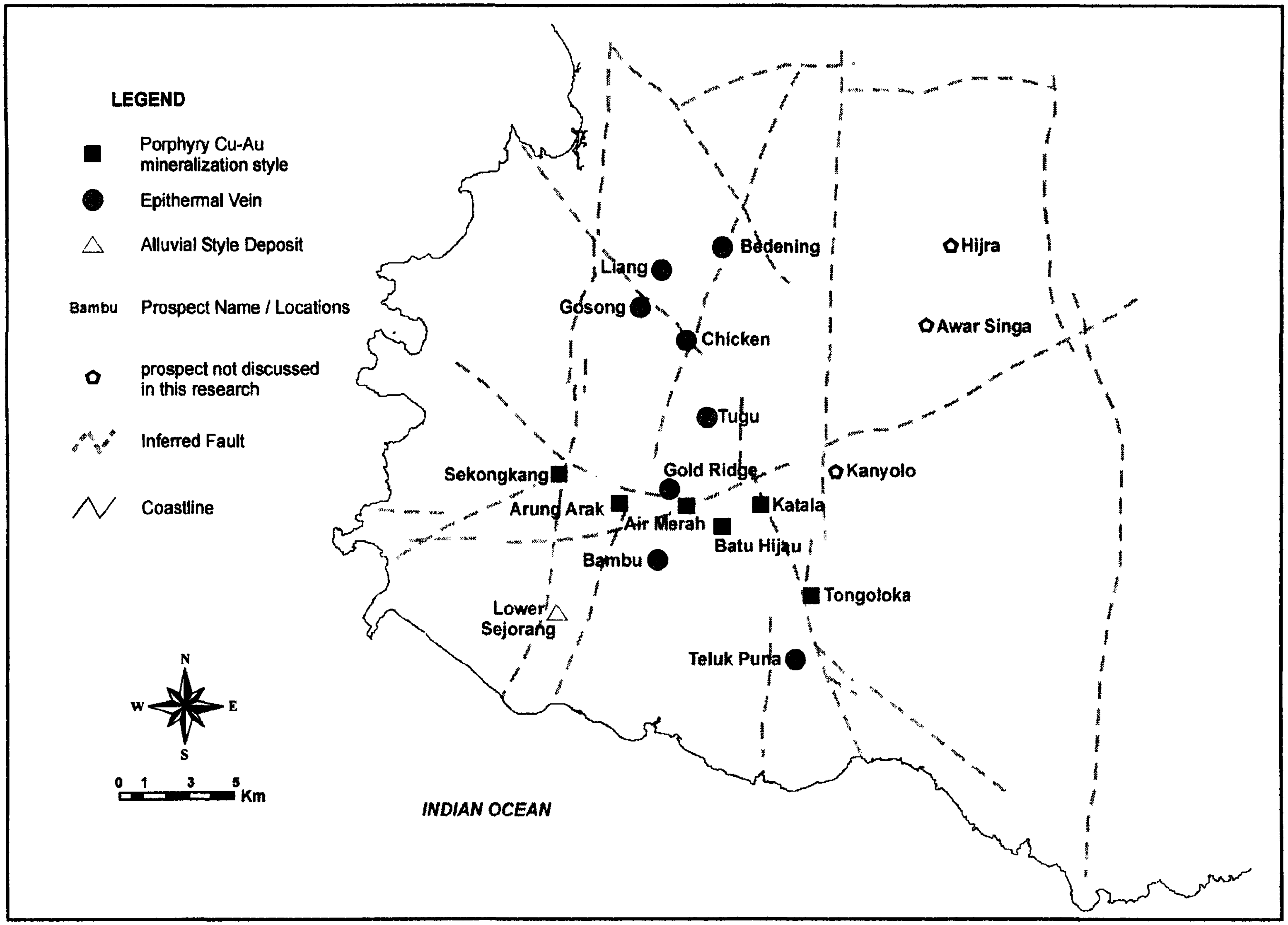

Figure 2.3. Location of known mineral occurrences in southwest Sumbawa, Indonesia. (Sjoekri, 1997)

2.3.1 Porphyry Copper-Gold Deposits

Porphyry copper-gold deposits are frequently found along the circum-Pacific ring in island-arc volcanic settings (Cox and Singer, 1992) with ages ranging between Cretaceous and Quaternary, the most common being Tertiary (Edwards and Atkinson, 1986; Cox, 1992). Porphyry copper-gold deposits are high tonnage, low-grade ore deposits (Edwards and Atkinson, 1986) related to igneous activity along subduction zones. Porphyry copper-gold deposits are typically found in felsic plutonic host rocks, such as tonalite, monzogranite, and various other felsic rocks (Cox, 1992; Sjoekri, 1997). Mineralization typically consists of disseminated ore bodies, controlled on the local scale by structures such as fractures (Sutulov, 1975; Edwards and Atkinson, 1986; Cox, 1992; Corbett and Leach, 1998).

Extensive hydrothermal alteration of the host intrusion and surrounding country rocks accompanies formation of these deposits (Cox and Singer, 1992; Sjoekri, 1997). Alteration zones, therefore, are important characteristics of porphyry copper-gold deposits. Sutulov (1975), Edwards and Atkinson (1986), Guilbert and Park (1986) and Cox (1992) describe four general alteration zones common to most porphyry copper-gold deposits:

1) Potassic – this zone is typically central to the ore and consists of primarily biotite, orthoclase and quartz. Additionally, accessory albite, sericite, anhydrite, apatite,

magnetite, chalcopyrite, bornite and pyrite may also be present.

2) Phyllic – this zone is generally gradational outward from and commonly overprints the potassic zone and consists primarily of quartz, sericite and pyrite, and possibly chlorite if Mg is present.

3) Argillic – this zone is also gradational outward from phyllic and/or potassic alteration zones; however, overprinting of original alteration zones such as potassic or propylitic is common. This zone consists primarily of quartz, pyrite, and clays. Intermediate argillic alteration is characterized by montmorillonite, illite, chlorite, and possibly kaolinite. Advanced argillic alteration is characterized by kaolinite, quartz or amorphous silica, and possibly corundum.

4) Propylitic – this zone typically forms the outer halo of alteration and can be quite extensive. It is characterized by chlorite, epidote and calcite. Additional accessory minerals may include sericite, apatite, hematite, anhydrite and ankerite, pyrite and chalcopyrite.

These alteration zones can be, collectively, quite large and extend more than 2,500 feet (762 m) beyond the main ore body (Sutulov, 1975). Propylitic alteration, while one of the general types of alteration characteristic of porphyry copper-gold deposits, is not always related to mineralization, as the mineral assemblage is commonly found in nonmineralized metamorphic terranes.

Porphyry copper-gold deposits located in southwestern Sumbawa include the Batu Hijau and Dodo-Elang deposits. Both deposits are located in andesitic volcanic terranes which are intruded by igneous complexes. The intrusive igneous complexes may contain shallow granodiorites, diorites, feldspar porphyries and tonalites (van Leeuwen, 1994). Both the Batu Hijau and Dodo-Elang deposits were discovered during regional exploration for gold mineralization (van Leeuwen, 1994). The Dodo-Elang deposit is located east of the study area and is not discussed further in this study.

2.3.1.1 Batu Hijau Deposit

The Batu Hijau deposit is a porphyry copper-gold deposit that is currently in production under PT. Newmont Nusa Tenggara (NNT) (Figure 2.3). It is located approximately 6.2 miles (10 km) from the southern coast in the southwest corner of Sumbawa at the headwaters of the Sejorang and Tongoloka drainages (Meldrum et al, 1994; Sjoekri, 1997). The top of the deposit is at 1640 ft (500 m) above sea level in mountainous terrain having well-developed drainage (Sjoekri, 1997; Rendu, 1998; De Mull et al., 2001).

The Batu Hijau deposit is Late Tertiary in age, estimated to be between 4.9 to 5.1 Ma (Sillitoe, 2000). Most of the mineralization is located within an intrusive complex within andesitic metavolcanic terrane (Meldrum et al., 1994; Sjoekri, 1997; DeMull et al, 2001). The intrusive complex consists of an early intrusion of hornblende microdiorite, followed by two subsequent intrusions of tonalite. The first tonalite intrusion, here called "old tonalite," is light gray and porphyritic, containing quartz, plagioclase, hornblende and primary biotite within a matrix of the same mineralogy and hosts the main portion of the mineralization (Meldrum et al., 1994; DeMull et al., 2001). The second intrusion of tonalite, here called "young tonalite," has similar mineralogy; however, it is more quartz rich with fewer mafic minerals. Figure 2.4 is a geological cross section through the Batu Hijau deposit looking northeast, which displays the cross-cutting relationships of the multiple intrusions as well as their relationship to ore mineralization.

Figure 2.5 is a map of the alteration zones at Batu Hijau, which are similar to the general descriptions given in section 2.3.1; however, the spatial relationships are somewhat different. The potassic zone, which is located central to the ore body and hosts the majority of the copper-gold mineralization (van Leeuwen, 1994), consists of quartz, magnetite, and biotite. Epidote has been found below 2,133 feet (650 m) (Meldrum et al, 1994). Propylitic alteration is peripheral to the potassic alteration zone, consisting of chlorite, epidote, magnetite, calcite, and pyrite (Meldrum et al, 1994). Intermediate argillic alteration, characterized by sericite, chlorite, specular hematite and, in places, pyrite overprints the potassic and propylitic alteration zones. The overprinting is controlled by fractures and veins (Meldrum et al, 1994). Advanced argillic alteration zone, characterized by kaolinite, quartz, alunite, pyrophyllite, and tourmaline, is located within the main argillic alteration zone (Meldrum et al, 1994). The main argillic alteration, including sericite, kaolinite, and pyrite borders the potassic alteration zone on both the east and west sides. Phyllic alteration is nearly absent at the surface of Batu

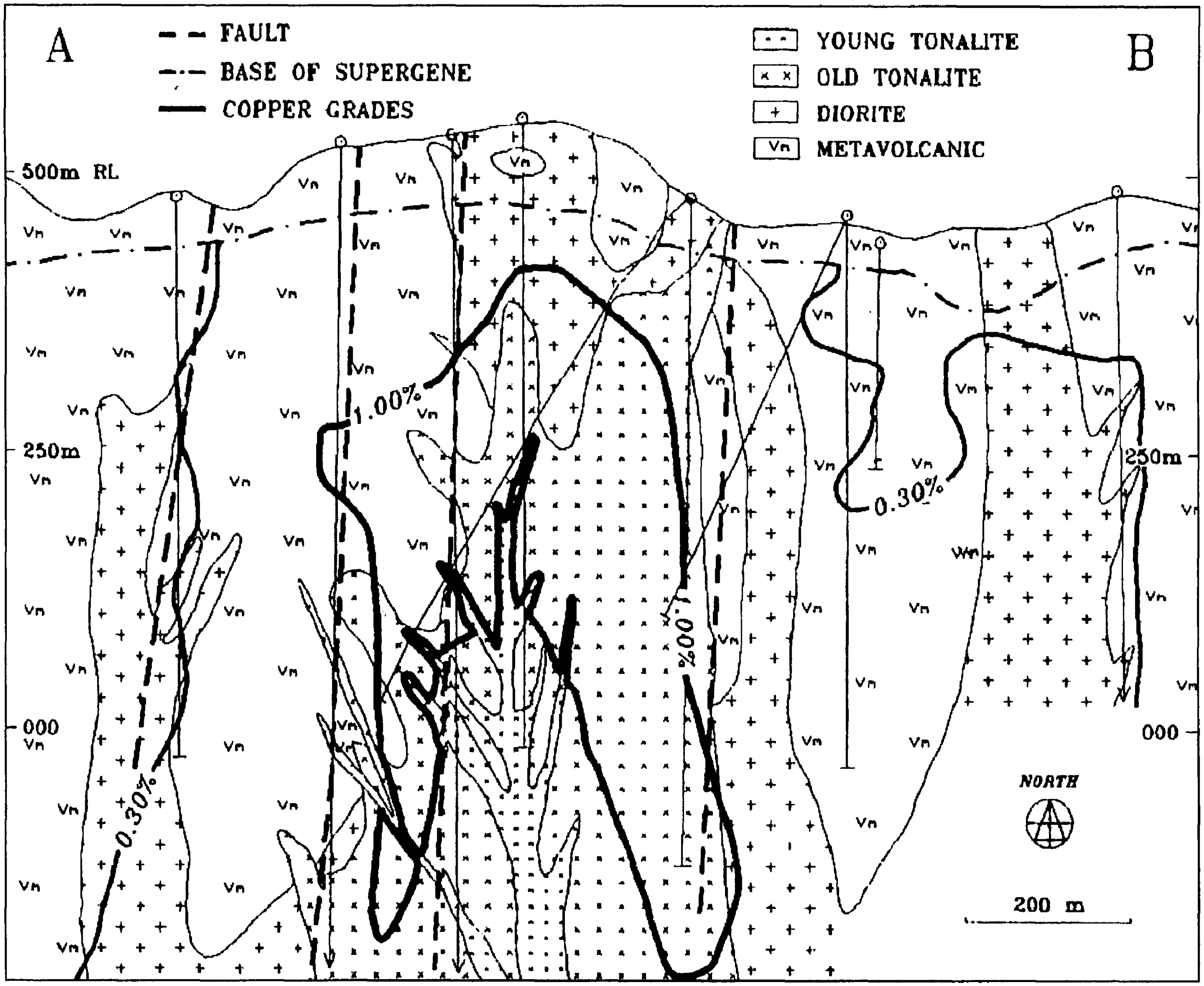

Figure 2.4. Geological cross section looking northeast through Batu Hijau deposit. (Meldrum et al., 1994)

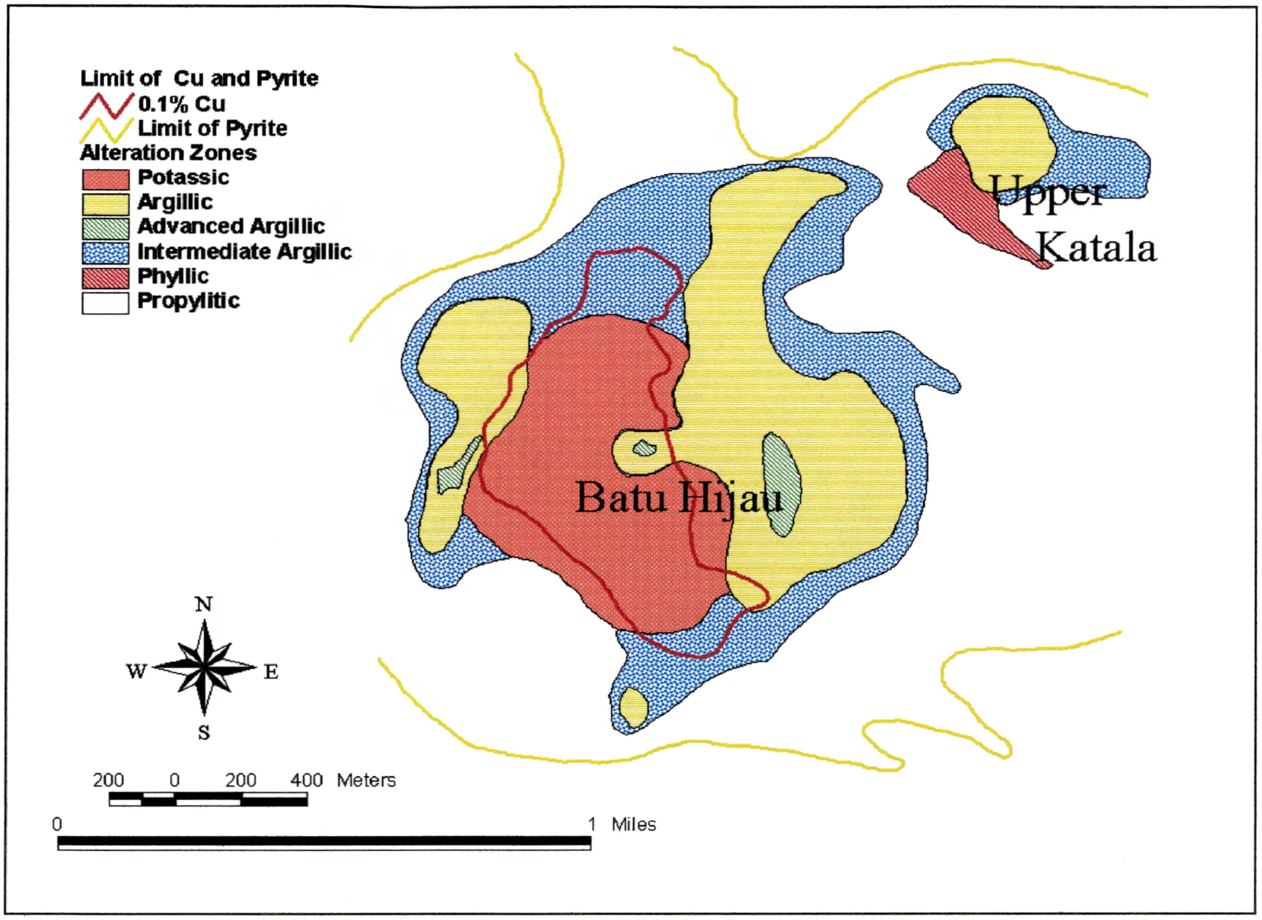

Figure 2.5. Alteration zones about Batu Hijau. Intermediate argillic alteration overprints propylitic alteration. All of the potassic alteration is also overprinted by intermediate argillic alteration (redrawn from Meldrum et al., 1994)

Hijau deposit, but is present at depth. It is best developed in the young tonalite where it overprints the central portion of the potassic alteration (Meldrum et al., 1994).

2.3.1.2 Other Porphyry Copper-Gold Occurrences

Several other porphyry copper-gold occurrences are located in southwestern Sumbawa, along a west-northwest to east-southeast trend (Figure 2.3). The Air Merah and Katala prospects are the two most closely resembling Batu Hijau. Located 0.6 miles (1 km) northwest and 1.2 miles (2 km) northeast of Batu Hijau, respectively, the two occur in hornblende microdiorite, hornblende biotite diorite, and feldspar hornblende quartz porphyry intruded into propylitically altered andesitic volcanic rocks (Sjoekri, 1997). Pyrite is the predominant mineral phase at Air Merah. Both prospects contain "weaker" geochemical signatures compared with that at Batu Hijau. Sjoekri (1997) notes that mineralization at Katala is subeconomic.

The Arung Arak prospect, located 2.2 miles (3.5 km) west of Batu Hijau, occurs in hornblende biotite diorite and feldspar porphyry intruding propylitically altered andesitic porphyry (Sjoekri, 1997). Potassic alteration occurs within the hornblende biotite diorite intrusion, which also hosts the bulk of the mineralization (Sjoekri, 1997).

The Tongoloka and Sekongkang prospects are located 3.1 miles (5 km) southeast and 4.3 miles (7 km) northwest from Batu Hijau, respectively. The Tongoloka prospect occurs in consists of a diorite intrusion with intermittent quartz veins within andesitic volcanic rocks (Sjoekri, 1997). Potassic alteration zones are present within the

Tongoloka prospect; however, the distribution is associated with a narrow quartz diorite dike (Sjoekri, 1997). The Sekongkang prospect occurs in quartz diorite and andesite porphyry which intrudes multiple altered quartz porphyry stocks within andesitic metavolcanic country rock (Sjoekri, 1997). Sjoekri (1997) also noted a significant molybdenum content at the Sekongkang prospect, with molybdenum values greater than 10 ppm in soils. Both prospects exhibit weak copper mineralization.

2.3.2 Low-Sulfidation Epithermal Gold Deposits

Low-sulfidation epithermal gold occurrences are common within southwest Sumbawa, with vein systems described as the crystalline-quartz-illite type (Sjoekri, 1997). Vein breccias are found within the study area (Sillitoe, 1994). Figure 2.6 depicts the spatial and potentially genetic relationship between low-sulfidation epithermal gold deposits and porphyry copper-gold deposits. Not all of the deposits shown in Figure 2.3 are discussed in the text as information was unobtainable.

2.3.2.1 Gold Ridge Prospect

The Gold Ridge prospect is an example of a low-sulfidation epithermal gold mineralization within the study area. Located approximately 1.9 miles (3 km) west-northwest from the Batu Hijau deposit, it occurs within metavolcanic rocks intruded by diorite and feldspar porphyry dikes (Sjoekri, 1997). Mineralization is structurally

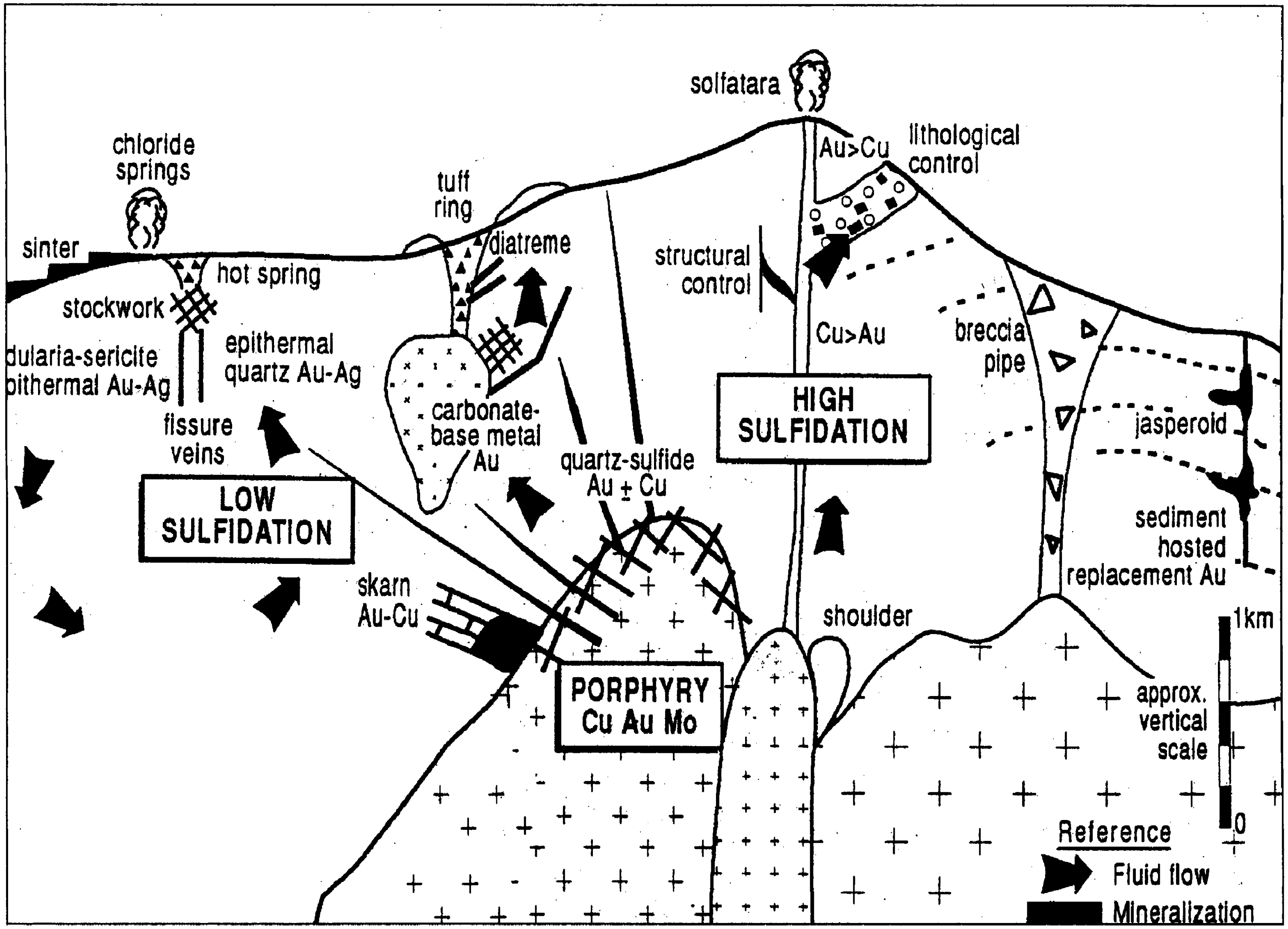

Figure 2.6. Spatial and genetic relationship between porphyry copper-gold and low-sulfidation epithermal gold deposits. (Corbett and Leach, 1998)

controlled, mainly by fractures trending northeast. The northeast-trending structures, mostly faults, are argillized with pyrite and minor silica (Sjoekri, 1997). A diatreme breccia has been mapped in this area by NNT geologists.

2.3.2.2 Jereweh Prospect

The Jereweh prospect, located approximately 6.2 miles (10 km) northwest of Batu Hijau, is comprised of four mineralized areas: The Chicken vein, the Liang anomaly, the Gosong vein, and Bedening silicified zone (Sjoekri, 1997). The prospect occurs in andesites with minor diorite intrusions that occur in a north-south trend (Sjoekri, 1997). Limestone and clastic sediment overlay the andesites and are unconformably overlain by laharic sediment.

The Chicken vein is oriented northeast-southwest and is highly silicified and brecciated. The Liang anomaly, consisting of argillized andesitic tuffs, is centered about an area where a major east-west-trending structure is cut by a north-south trending structure (Sjoekri, 1997, page 32). The Gosong vein contains clasts of silicified limestone within a gossan at the contact of dacite lavas and overlying limestone (Sjoekri, 1997). The Bedening zone comprises a silicified zone along contacts between carbonate sedimentary rocks and volcanic units.

2.3.2.3 Other Low-Sulfidation Epithermal Gold Occurrences

Located 3.1 miles (5 km) southwest of Batu Hijau, the Bambu prospect, contains mineralization within a multiple vein system hosted by andesitic lava with bedded limestone, calcareous siltstone and shale (Sjoekri, 1997). Propylitic and weak argillic alteration are present within the prospect. Veins measured roughly 7 to 16 feet (2 to 5 meters) wide with some colloform banding and 3% to 10 % sulfide content.

The Teluk Puna prospect, located 3.1 miles (5 km) southeast of Batu Hijau, contains several strong north-northeast and north-northwest structures. Quartz veining is podiform and discontinuous (Sjoekri, 1997).

2.3.3 Alluvial Style Gold Occurrence

Elevated gold concentrations have been documented in the tributaries entering the Lower Sejorang prospect; however, follow-up studies to date have not discovered the source of the anomalies (Sjoekri, 1997). This occurrence could simply be the accumulation of gold within the Sejorang River basin due to weathering of the numerous deposits upstream.

CHAPTER 3

DRAINAGE SURVEYS

3.1 Drainage Surveys

Drainage surveys are commonly used in mineral exploration programs as a means of collecting composite samples representative of their respective drainage areas. Data collected during drainage surveys can contain the elemental concentrations of stream sediment and water. One sample, or a small number of samples, can be used to evaluate large areas for possible mineralization. It is for this reason that many reconnaissance programs start with or include stream sediment geochemistry (Rose et al., 1979).

Two main types of drainage surveys are commonly used in mineral exploration: orientation surveys and reconnaissance surveys. Orientation surveys are detailed surveys of areas with known mineralization. They provide technical specifications to guide the design of routine reconnaissance surveys used to locate similar mineralization within a search area of interest (Rose et al., 1979). Reconnaissance surveys typically have a sample density of one sample per 1 to 100 km^2, covering thousands of square kilometers (Rose et al., 1979), with the purpose of identifying potentially mineralized areas for more specific follow-up surveys.

Stream sediment sampling is the most common sampling method used in drainage surveys for three reasons. First, the collection and analysis of stream sediment is easier than for water samples because it doesn't involve special containers that won't react with the water or the debate about acidification of samples. Second, at least initially, stream sediment was preferable to water samples because detection limits for elements in water were very high. Even as the detection limits for elements in solution have become lower via improvements in instrumental analysis, stream sediment is still preferred simply because it is easier to sample and can be done by people with minimal training. Third, stream sediment can provide useful results in most climatic regions and terrains provided the area is covered by well-developed drainage systems (Rose et al., 1979; Plant and Hale, 1994). Stream sediment data allow the exploration geochemist to evaluate extensive areas for possible mineral occurrences because of the way in which weathering products are transported in the surficial environment (Rose et al., 1979). For example, samples of stream sediment are representative of all lithologies upstream, with the assumption that they represent the same proportion as the lithologies in the corresponding drainage area. This assumption is true for drainages that contain lithologies with similar weathering rates, however, it is not true for drainages containing lithologies with significantly different weathering rates (Stallard and Edmond, 1987). For this study, it is assumed that the majority of drainages contain lithologies with approximately the same weathering rate.

Another important characteristic of stream sediment data is the incorporation of effects from processes present between the aqueous environment in contact with the stream sediment. For example, a drainage contains 85% andesitic volcanic rocks and

15% hornblende microdiorite, in an ideal world or a situation of purely mechanical weathering, the sample representing that drainage would have sediment representing the same ratio of andesitic volcanics to hornblende microdiorite. This is, however, far from reality, as many different processes in the aqueous environment can cause the ratio to change. For example, highly acidic, oxidizing conditions commonly cause many elements to go into solution, and once in solution different ions behave differently thus changing the ratio of the parent rock types, especially in the fine-gained portion of stream sediment.

The general behavior of chemical components within the environment, and specifically with relation to stream sediment, is an important part of interpreting the results of the multivariate statistical techniques that are compared in this study. Macro-environmental factors such as topology, climate (which includes temperature and rainfall), vegetation, and anthropogenic processes must be kept in mind when interpreting results as these factors affect the degree and predominant type of weathering. Intermediate environmental factors affecting an element's geoavailability in the stream environment include the physical and chemical weathering characteristics of the source material and how that material moves downstream (Smith and Huyck, 1999). At the micro-environmental level, the interactions between water and stream sediments are dominated by changes in pH and Eh of the water and the overall sediment content of clays, Fe- and Mn-oxides, and organic matter. Geochemical barriers represent significant changes in the micro-environment over short distances and can be used to better understand where an element might be placed within the system (Perel'man, 1986). Appendix A contains a more thorough discussion of drainage geochemistry and Table A.1 which outlines the characteristics of the more common geochemical barriers. Appendix B contains selected geochemical characteristics of the elements used in this study.

3.1.1 Orientation Survey

Sjoekri (1997) used data collected in 1993 from an orientation survey conducted within the Sejorang and Tongoloka drainages by Moedjiarto. The orientation survey was designed to examine the dispersion characteristics of metals weathered from the Batu Hijau deposit (Sjoekri, 1997). Figure 3.1 is the outline of sampled drainages in the two main drainages for the Batu Hijau deposit, Sejorang and Tongoloka. Plate III is a map of the drainages and corresponding sample locations along with a table with the data set.

Traditionally, orientation surveys are conducted prior to reconnaissance surveys; however, the Batu Hijau deposit was not discovered until after the reconnaissance survey in 1987. The discovery of Batu Hijau led to the need for more information on dispersion of weathered material from the Batu Hijau deposit (Sjoekri, 1997). This information could then be used to search for other porphyry copper-gold deposits on Sumbawa or it's neighboring islands.

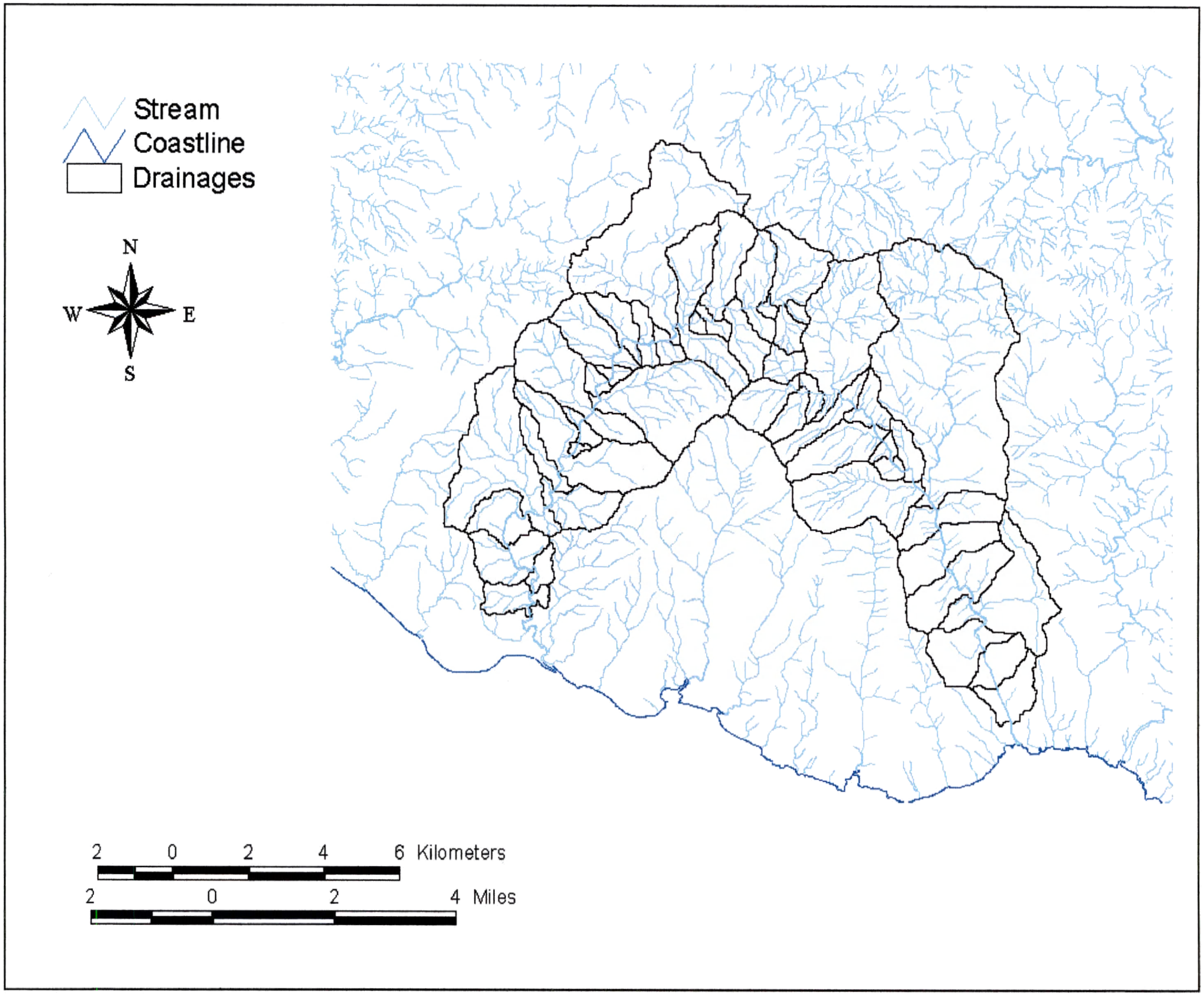

Figure 3.1 Outline of sampled drainages for the orientation survey.

Forty-nine stream sediment samples were collected. Near the Batu Hijau deposit, samples were collected at 1640 ft (500 m) intervals. The last seven samples in the Sejorang drainage and last eight in the Tongoloka drainage were collected in the lower reaches at 3,281 ft (1,000 m) intervals. The orientation survey includes analytical data for –30 mesh (#) + 40#, -40# + 80#, -80# + 140#, -140# + 200#, and -200# grain size fractions of stream sediment for the elements Au, Cu, Pb, Zn, As, Sb, and Mo. Moedjiarto (1994) used dry sieving techniques to isolate the -30# + 40#, -40# + 80#, and -80# + 140# fractions and wet sieving for separation of the –140# + 200# and –200# fractions. Figure 3.2 is a flow chart for the sample collection methods used in the orientation survey. Gold was determined by AAS after a portion of each sample was subjected to fire assay, followed by aqua regia digestion (Sjoekri, 1997). The Cu, Pb, and Zn were obtained by AAS after acid digestion. Concentrations for As, Sb, and Mo were obtained via pressed pellet XRF techniques. Drainage area outlines were automatically generated using the ARC/INFO hydrologic function on digital DEM data obtained from aerial photography (Sjoekri, 1997). The automatically generated drainage boundaries closely matched those obtained manually employing traditional air photographic interpretive procedures, especially in high relief areas (Sjoekri, 1997).

3.1.2 Reconnaissance Survey

In 1987 P.T. Newmont Nusa Tenggara (NNT) carried out the reconnaissance survey. The principal target was gold mineralization since previous studies suggested

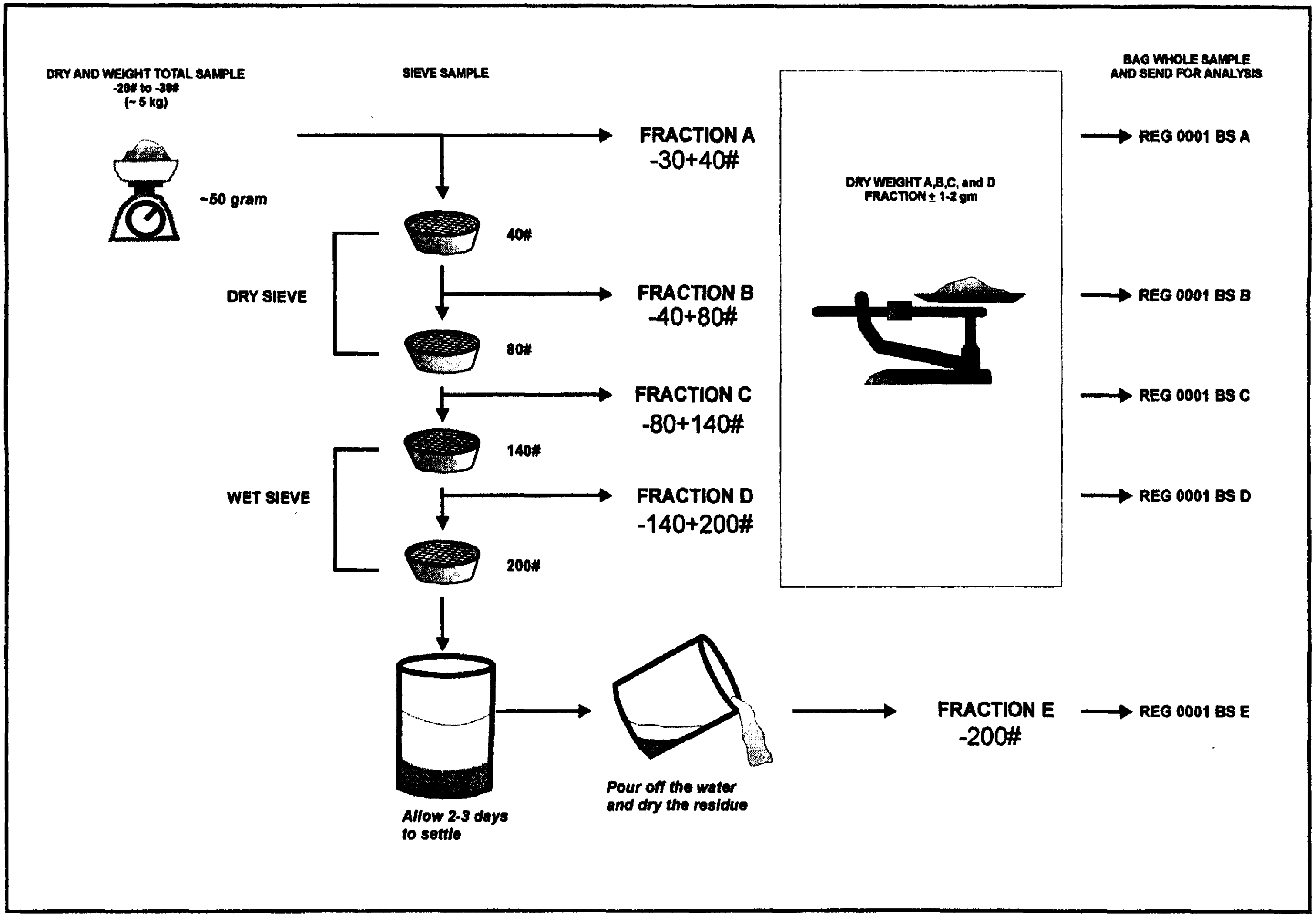

Figure 3.2 Stream sediment sample collection for orientation survey (Sjoekri, 1997).

that the regional geology was favorable for epithermal precious metal deposits (Sjoekri, 1997, page 65). The survey was also designed to detect copper and other base-metal mineral occurrences (Meldrum et al., 1994; Sjoekri, 1997). The reconnaissance survey was conducted in the southwest region of Sumbawa after Newmont staff found disseminated copper sulfides in float samples of altered diorite at the coastal areas of the Sejorang drainage basin (Meldrum et al., 1994). The reconnaissance stream sediment survey revealed anomalous Au and Cu concentrations within the Sejorang and Tongolka drainages, which lead to the discovery of the Batu Hijau deposit. In addition to the stream sediment geochemical data, information on drainage basin characteristics such as drainage area and lithologic composition, were also collected.

Sample sites were selected to reflect a 3.9 mi^2 (10 km^2) maximum drainage area. The average area sampled was 2.3 mi^2 (6 km^2). Figure 3.3 provides an outline of the drainage areas in the reconnaissance survey. Plate IV contains the labeled sample drainages for the reconnaissance survey. As with the reconnaissance survey, Sjoekri (1997) used automated methods to produce the drainage basin outlines for the orientation survey. The lithology information collected during the reconnaissance survey was used in connection with the drainage outlines to determine the lithologic composition for each drainage.

Lithologic information was collected in stages (Sjoekri, 1997). The first stage involved photo geological interpretation at 1:60,000 scale plotted on a 1:50,000 scale

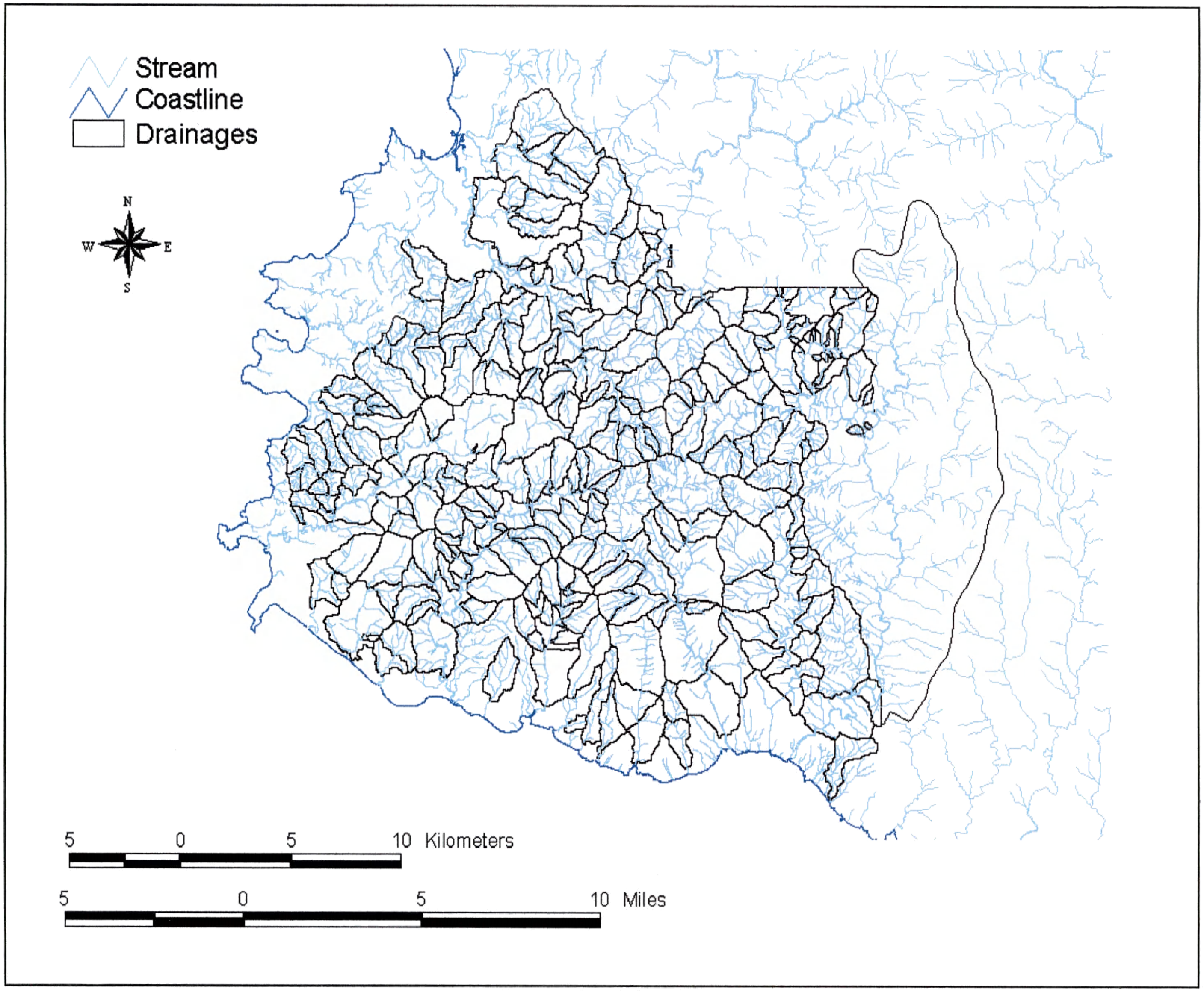

Figure 3.3 Outline of sampled drainages for the reconnaissance survey.

base map. Through field work and ridge and spur mapping, information was added to update the base map. This increased the scale of survey coverage between 1:10,000 and 1:5,000 within the regions around Batu Hijau (Sjoekri, 1997). During the establishment of Batu Hijau as a prospect, geological map compilation improved again to 1:1,000 scale (Sjoekri, 1997, page 67). The geologic composition of each drainage was determined by overlaying the drainage outlines onto the geologic map and calculating the area of each lithologic unit in each drainage.

Samples were collected from active stream sediment and were wet sieved through 40# and 80# sieves (Sjoekri, 1997). Figure 3.4 is a depiction of the sampling procedure used during the reconnaissance survey. The –40# samples were analyzed using bulk leached extractable gold (BLEG) techniques followed by determination of Au, Ag, and Cu by atomic absorption spectroscopy (AAS). The –80# silt samples were split: one portion was used to determine Au content by aqua regia digestion and carbon rod techniques (Sjoekri, 1997); the second portion was used to determine Ag, Cu, Pb, and Zn data by acid digestion and AAS procedures; and the third portion was used to determine As, Sb, and Mo concentrations using pressed pellet X-ray fluorescence (XRF) methods. Silver data for the –80# samples were not included in the data sets accompanying Sjoekri (1997), thus could not be used for this study.

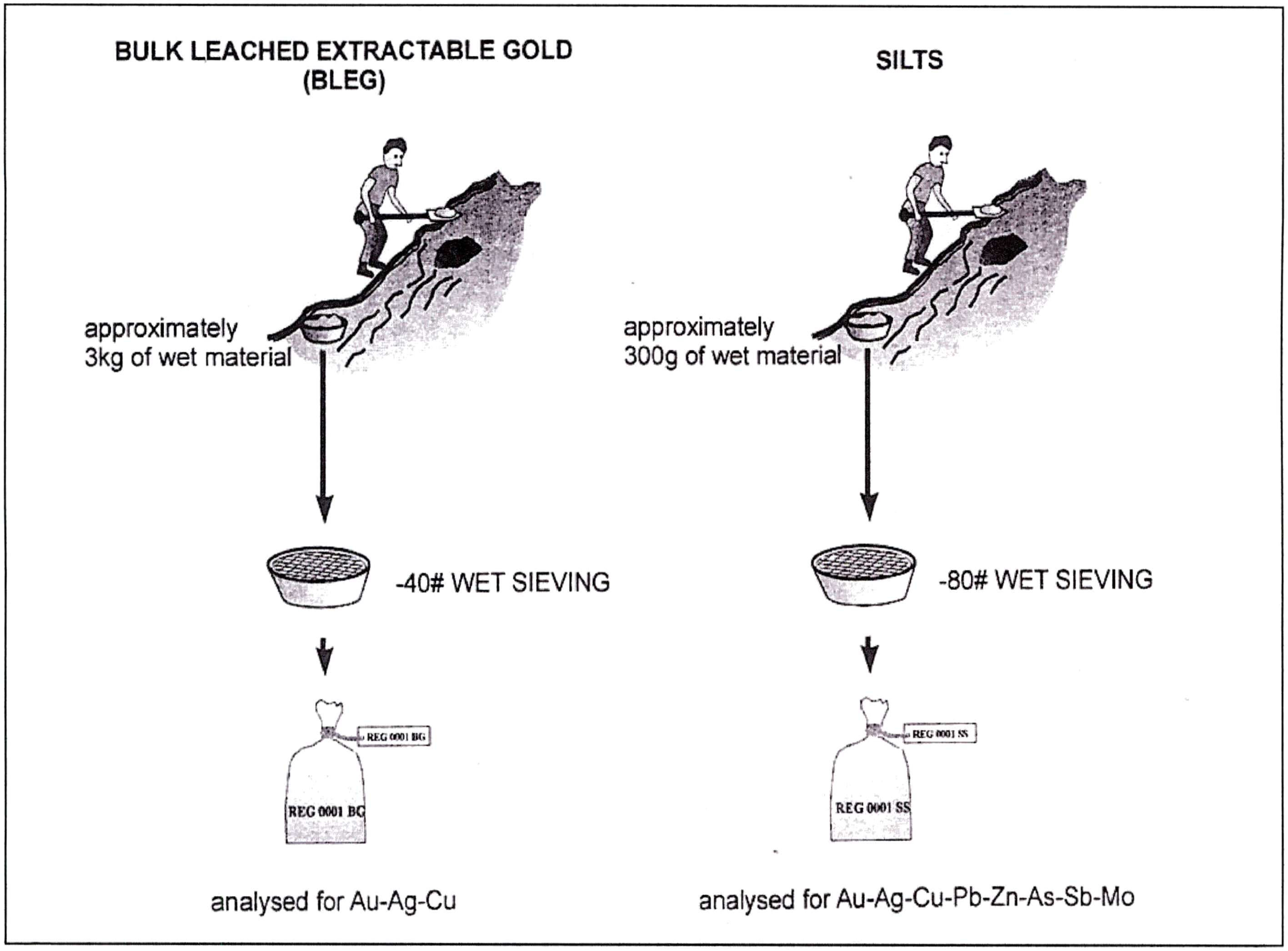

Figure 3.4 Stream sediment sample collection for reconnaissance survey (Sjoekri, 1997).

3.1.3 Stream Ordering, Lithology and Drainage Area Treatment

Strahler (1981) defines a drainage basin as an organized stream network that is bounded by a drainage divide and has only one exit point. The smallest unit within a drainage basin is a first order basin, which is the aerial extent of the land that is drained by a first order stream, and is also known as a catchment (University of Delaware Water Resources Agency, 2001). The term drainage area is used to denote the area upstream from a sample site which can consist of a set of catchments or drainages. It is important to note that a drainage may in fact only be comprised of one sampled catchment.

Stream orders were established using the Strahler stream ordering method as presented by Sjoekri (1997). Figure 3.5 is an example of a hypothetical stream network with each stream's corresponding stream order. The Strahler (1981) method denotes a stream without tributaries as a first order stream and involves the addition of like numbered streams in order to increase a stream's order. For example, two first order streams combine to form a second order stream, and two second order streams combine to form a third order stream; however, a first order stream combined with a second order stream will not increase to a third order stream, instead it remains at the highest level of the join, a second order stream.

Areas were calculated for individual drainages in each data set using the automated method described in section 3.1.1. Those drainages that are comprised of more than one catchment or drainage resulted in the addition of all catchment and drainage areas upstream from the sample point (Figure 3.6). For this, drainage divides were outlined

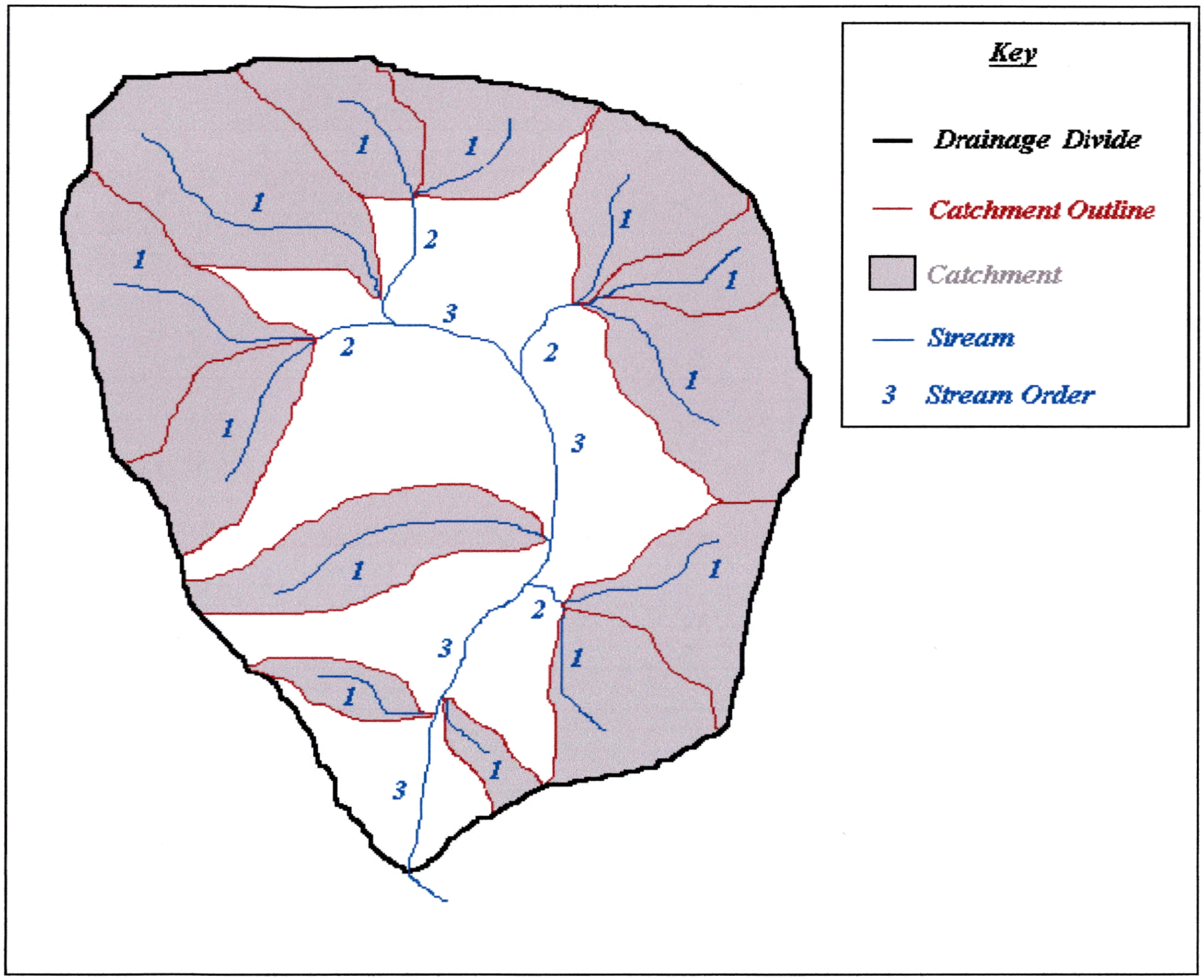

Figure 3.5 Schematic depiction of Strahler's stream ordering method and drainage basin nomenclature. (Based upon Strahler, 1981).

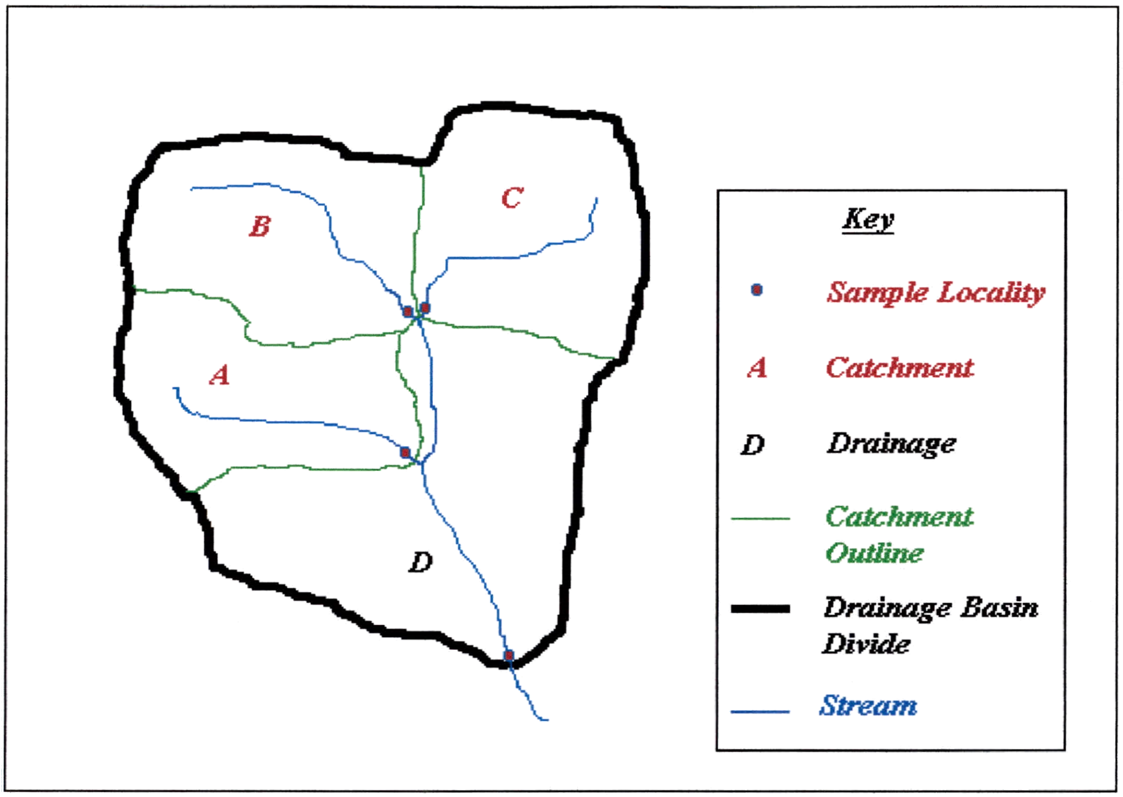

Figure 3.6. Schematic drawing of a drainage basin with more than one catchment. The area and lithology corresponding to the sample taken in drainage D will include the area and lithology of D in addition to the areas and lithologies of catchments A, B, and C.

and the sequence of catchments and drainages from the border of the divide to the main mouth of the drainage basin were recorded. Then the individual areas were recalculated to represent the total area drained at each sample point.

The geologic composition of each catchment and drainage were determined as described in section 3.1.2. The drainage basins that were comprised of more than one catchment or drainage resulted in the recalculation of the total upstream lithologic composition at each sample site. For example, the lithologies from catchments A, B, and C on Figure 3.6 were added to the lithologic composition of drainage D in order to adequately represent the geology in the entire area upstream from sample site D. This was done by taking the individual catchment (A, B, and C) and drainage (D) areas within the overall drainage basin and multiplying by the percent lithologic unit. The resulting number represents the area of each lithology in each individual catchment (A, B, and C) or drainage (D). The sums of the total area of each lithologic unit were calculated and divided by the sum of the entire area drained at sample site D to create the correct percent of each lithology present.

3.2 Data Quality

Information on quality control measures, such as duplicate sample analyses, precision of the analytical instruments used, and evaluation of the sampling and analytical variability during data collection, for both surveys is unavailable. Initially it was proposed that estimates of the sample variance might be feasible by comparing the results for the –80# fraction samples for drainages that overlap between the two surveys. These early attempts to estimate the sampling variability were abandoned for the several reasons. First, the subset of the reconnaissance survey which overlapped the orientation survey does not fully represent the reconnaissance data set as a whole due to the difference in the number of "barren" drainage basins found in the overall data set as compared with the subset. Second, the methods of selecting the sample sites were different for the two surveys. In many cases reconnaissance survey samples were collected from tributaries and main streams, rather than only along main streams as in the orientation survey. Thus, the catchment outlines for sampling in the two surveys do not always correspond. Third, the samples were collected at different time periods by different people and thus the sampling variability, which evaluates the variability at a given sample site either in the geological material or due to human error at the sample site, cannot be calculated. Sjoekri (1997) reassured that:

> The data represent current accepted practice during mineral exploration programs… Geochemical surveys were conducted using accepted field practices to determine appropriate sample locations. Analytical processes in geochemical laboratories were undertaken so that appropriate standards of accuracy and precision were assured. Different geochemical elements had different standards of accuracy and precision depending on the method of analysis used. (p. 84)

It is assumed that the overall proportion of total data variability related to regional variation, as opposed to that related to sampling or analytical variation, is greater than 50% for each survey. Therefore, the patterns generated from the survey data would represent the regional variation of the elements rather than site specific (sampling) variance or possible human-induced (analytical) error.

3.3 Summary of Data for This Study

Plant and Hale (1994) state that the -80# fraction of stream sediments is well suited for exploration in areas of predominantly chemical weathering, which typifies the main form of weathering in southwestern Sumbawa. Grain size fractions between 80 and 200# show the maximum contrast between background and anomalous values (Rose et al., 1979). Thus, for the purpose of this study, only the –80# fraction in the reconnaissance survey and the –80# + 140# fraction in the orientation survey are used.

It is important to note that the overall size range for the sediment fractions at the –80# level are slightly different between the two surveys. For the reconnaissance survey, the –80# fraction includes all grains less than 177 μm. In comparison, the –80# + 140# fraction of sediment in the orientation survey contains grains from 177 to 107 μm (Boggs, 1995). Lithology, drainage area and stream order data will also be used since these parameters influence stream sediment geochemistry and are valuable for interpretation of the results from the multivariate statistical techniques.

CHAPTER 4

INITIAL GEOCHEMICAL DATA ANALYSIS

4.1 Objectives

It is important to understand the univariate characteristics of the data sets used in this study to better interpret the results from the multivariate data analysis techniques that are described in subsequent chapters (Swan and Sandilands, 1995). Univariate elementary statistics provide measurements of central tendency (mean, median, mode) and distribution (variance, standard deviation, skewness) and contribute to the initial data interpretation. To further understand the distribution of the data within the drainage survey, subgroups based upon stream order, drainage area, and lithologic composition are also evaluated for possible trends, such as decreased overall composition within increased drainage area possibly suggesting downstream dilution. The estimation of thresholds, the upper limit of background, and thus the background levels, assists the interpreter when examining the data for true anomalies, i.e. samples with abnormal concentrations of one or more elements related to mineralization (Rose et al., 1979).

The first objective of examining the univariate characteristics is to become better oriented with respect to the range of possible values and the possible correlations between different variables. The second objective of examining the univariate characteristics is to gain insight into the geochemical environment by comparing data between two groups. For example, if the average concentration of Zn and Cu in stream sediment suddenly increased from third order streams to fourth order streams, it might be due to adsorption onto clay minerals or other factors that bring the elements out of solution or the presence of mineralization (Rose et al., 1979; Perel'man, 1986; Horowitz, 1991). The third objective is to aid in the selection of the multivariate statistical approach which might work best, considering the properties of a given data set.

4.2 Methodology

For the initial data analysis the structure of each data set is examined to determine if any pretreatment might be warranted. Subgroups of each data set are made based upon stream order, drainage area, and lithologic composition. Univariate statistics are computed for each survey as a whole and for the subgroups. The *t*-test is used to compare the two surveys overall and the subgroups within each survey. Finally, thresholds and background concentrations are estimated for each element for each survey.

4.2.1 Data Pretreatment

The data for the orientation survey contains 49 sample points arranged in progression down the Sejorang and Tongoloka drainages. The orientation survey contains element concentrations for As, Au, Cu, Mo, Pb, Sb, and Zn on the –80# + 140# (177 to 107 μm) size fraction along with stream order, drainage area, and lithologic composition. All elements were analyzed for each sample site. The orientation survey did not require any data pretreatment prior to the univariate, *t*-test, and background calculations. Plate III contains a table of the data set for the orientation survey.

The reconnaissance survey contains data for 261 catchments. Of the 261 catchments, 258 contain values for Au, 255 contain values for As, Cu, Pb, Sb, and Zn, and 79 contain values for Mo for the –80# (less than 177 μm) size fraction. Unlike the orientation survey, several sample sites contained Au, As, Mo, Pb, and Sb concentrations that were below the detection limit; denoted by –33333 values in the original file that accompanied Sjoekri (1997). For Mo and Sb, 60% and 62% respectively, of the data were below detection limit, while 65% of the Au values were below detection limit. Copper and Zn values were all above detection limits. To avoid the problem of "censored data," as described by Gilbert (1987), one half of the detection limit was used in place of the –33333 value noted above. "Censored data" refers to data sets that contain large numbers of sample points with values below detection limits, thus the information for very low concentrations (below detection limit) is missing (Miesch, 1976; Gilbert, 1987). Plate V contains a table of the data set for the reconnaissance survey.

As information on the actual detection limits for the instruments used during the collection of the geochemical data was not available, published values from Varma (1984) and Haswell (1991) for AAS and Van Grieken and Markowicz (1993) for XRF are used to provide an estimate of the detection limits for each element. Then one half of the published detection limits were substituted into the data set for the –33333 values to maintain a value greater than zero, but less than the estimated detection limit. This is important because if a value is below detection it can be suggested that, in most cases, it is not anomalous. Table 4.1 contains the published values for detection limits for each element, along with the values used in this study.

Table 4.1 Published detection limits for elements used in this study based upon the analytical instrument used to collect the data, along with the corresponding value used in this study to represent concentrations below the detection limit. (Compiled from Varma, 1984; Haswell, 1991; and Van Grieken and Markowicz, 1993).

Method/Element	**Published Detection Limit**	**Corresponding Value Used**
AAS/		
Au (ppb)	5.0	2.5
Pb (ppm)	0.03	0.015
XRF/		
As (ppm)	0.04	0.02
Mo (ppm)	0.05	0.025
Sb (ppm)	0.08	0.04

4.2.2 Subgroups of Survey Data

Each survey was subdivided into groups according to stream order, drainage area, and lithologic composition. The average element concentrations by stream order are examined for trends which might indicate changes in geochemical environment with changing stream order. Such trends, like dilution, can also be loosely correlated to drainage area. The average element concentrations by drainage basins with respect to changes in lithologic composition, such as 70% andesite volcanic rocks versus 85%

andesite volcanic rocks, are examined for correlation between overall changes in concentration with changing predominant lithology.

4.2.3 Univariate Statistics

Univariate elementary statistics, such as mean, median, range, standard deviation, variance, and skewness were calculated for elements for each survey as a whole and for each survey subgroup. Histograms and cumulative frequency plots for each element in each survey were used to assess the possibility of multiple populations, data distribution (skewed versus normal), and to estimate threshold values (Appendix C). Multiple populations are suggested by more than one peak or an elongated tail on a histogram and by inflection points on cumulative frequency plots. Histograms exhibiting elongated tails towards high (potentially anomalous) values indicate positively skewed data. Skewed data distributions indicate nonnormally distributed data (Swan and Sandilands, 1995).

Threshold values represent the upper limit of background and signify the break between background and anomalous concentrations (Rose et al., 1979). Thresholds were estimated by evaluating histograms for natural breaks between the mean and upper limit of the range, the upper quartile, the value corresponding to the highest value representing the lower 80% of data, and the published average concentrations of mafic and granitic rocks for each element. While the prominent lithologies in the southwestern Sumbawa region are intermediate, rather than mafic or granitic, these values provide a possible range.

4.2.4 *t*-tests

The *t*-test is used to test the equivalence of means between two groups (Davis, 1986). The standard *t*-test assumes equivalence of variance between two groups. This assumption is tested using the F-test. If the variances are not equal, a modified *t*-test is used (Davis, 1986). Data from the orientation survey is compared with data from the reconnaissance survey, along with several subgroups within each survey, were tested using the *t*-test to determine if the groups represent statistically similar samples, i.e. they represent the same population (Davis, 1986).

The *t*-tests were used to evaluate the effect of different stream orders upon element concentrations. The tests were used to determine if comparisons of drainages with different stream orders within each survey are statistically similar, thus representing similar populations. For example, the environmental geochemistry within a first stream order (no tributaries) and a fourth order stream, are probably significantly different and thus would not be statistically similar.

The *t*-tests were also used to evaluate the effect of differences in drainage area to determine if drainages with different areas might not be statistically similar, possibly indicating diluted geochemical signatures. For example, the effect of dilution might be more prevalent in drainages with large areas as opposed to drainages with significantly smaller areas, which might be reflected in the two groups being statistically dissimilar.

The *t*-tests were also used to compare drainages of different lithologic compositions to evaluate if drainages with different dominant lithologies produced statistically similar (or dissimilar) element concentrations, i.e. are the dominant lithologies different enough, geochemically, to produce a statistically significant difference in element signatures.

4.2.5 Estimating Background

Background is a controversial issue and its value and calculation is highly dependent upon its intended use (Runnells, 1998). To establish the "barren" or non-mineralized class, i.e. background class, for the discriminant analysis and neural networks techniques, it is important to understand what average values indicate drainages with potentially background signatures. It is noted, however, that a drainage can be "barren" even if it has elevated concentrations (values above background) for one or more elements. Several methods of determining background levels have been suggested and debated (Hawkes, 1976; Runnells et al., 1992; Carranza and Hale, 1997; Runnells, 1998; Runnells et al., 1999; Kesar and Asti, 1999; Matschullat et al., 2000).

The estimated thresholds established during the univariate analysis and a method for estimating background concentrations which takes into account changes in lithology and drainage area presented by Carranza and Hale (1997) were used to estimate the average background concentrations for this region. The Carranza and Hale (1997) method is outlined in Appendix D.

4.3 Initial Data Analysis Results

The results of the initial data analysis for the orientation survey are presented first, followed by the results of the reconnaissance survey, and then the *t*-test results for the comparison between the orientation survey and the reconnaissance survey as a whole are presented. Appendix E contains plots of each element's distribution by drainage for each survey. Within each survey, the univariate statistics as a whole are presented followed by the breakdown for each subgroup. Then *t*-test results for the subgroups are presented. Thresholds, although established during the univariate analysis, are presented with the background calculations from the Carranza and Hale (1997) method for comparison.

4.3.1 Orientation Survey

The orientation survey was subdivided into four stream order groups: a) second and third order streams (which only contains three data points); b) fourth order streams; c) fifth order streams; and d) sixth order streams. Subdivision into six drainage area groups was based upon 10 km^2 intervals from 0 to 60 km^2.

The first breakdown by lithology is according to the two most predominant lithologies, andesitic volcanic rocks and hornblende microdiorite. The data range for andesite volcanic rocks is predominantly between 75 to 95% of the drainage area, with two sample sites having values of 7 and 54%. The next most abundant lithology in the study area was hornblende microdiorite, which hosts the old tonalite intrusion containing the Batu Hijau deposit. This lithology was also subdivided into three groups so that number of samples would be at least 1/3 of the data to maintain some of the original structure of the data. It is important to note that 13 of the 16 samples in the greater or equal to 85% andesitic volcanic rocks also contained between 6 and 10% hornblende microdiorite. The second breakdown by lithology, involves the occurrence of greater than 1% diatreme breccia, and the presence of quartz veins, which might be related to low-sulfidation epithermal gold deposits in the area. Also, the presence of greater than 0.25% old tonalite was examined, as old tonalite hosts the Batu Hijau deposit.

4.3.1.1 Orientation Survey: Univariate Statistics

Table 4.2 is a summary of the elementary statistics for the orientation data set. The histograms showed positively skewed data (Appendix C), thus the data were transformed to log normal distribution using the natural logarithm (ln) to reduce the skewness. The skewness of distributions for Pb and Zn actually increased slightly with transformation. Both elements had near normal distributions in the nontransformed data (zero skewness being normal).

Cumulative frequency plots for As, Au, Cu, and Mo contain multiple inflection points, suggesting several possible populations (Appendix C). The cumulative frequency plot for Pb has two inflection points, suggesting three possible populations, while Zn does not have any inflection points, indicating one population. Approximately 90% of the data for Sb are at the 4 ppm concentration. The cumulative frequency plot for Sb has one inflection point at 5 ppm, which represents the break in the data from 4 ppm.

Table 4.2 Summary of the univariate statistics for the orientation survey.

	Orientation Survey Results						
Parameter	Au (ppb)	Cu (ppm)	Pb (ppm)	Zn (ppm)	As (ppm)	Sb (ppm)	Mo (ppm)
n	49	49	49	49	49	49	49
Mean	0.27	457.22	27.31	153.10	25.88	4.16	4.90
Median	0.06	161.00	27.00	157.00	25.00	4.00	4.00
Mode(s)	0.01, 0.03	77.00, 99.00, 135.00	25.00	138.00, 157.11, 164.00, 182.00, 189.00	25.00	4.00	2.00
Min - Max	0.01-2.79	68.00-2740.00	11.00-43.00	102.00-211.00	10.00-49.00	4.00-7.00	2.00-22.00
Variance	0.27	488844.26	38.47	768.22	79.53	0.31	15.59
Std. Dev.	0.52	699.17	6.20	27.72	8.92	0.55	3.95
Skewness	3.39	2.35	-0.14	-0.03	0.54	3.92	2.61
Skewness after ln-transformation	0.45	1.21	-1.12	-0.34	-0.44	3.60	0.82

Arsenic, Au, Pb, and Zn concentrations all increase with increasing stream order and drainage area, while average concentrations for Cu and Mo decrease with increasing stream order. The breakdown by stream order and area contained nearly identical trends. Figure 4.1 shows the average drainage area with respect to corresponding stream order. Table 4.3 contains the average concentrations for elements by stream order and drainage area.

Average element concentrations for subgroups based on lithology are provided in Table 4.4. Overall, the average concentration for the greater than 80% andesite volcanic rocks are greater for As, Au, Pb and Zn, while the greater than 11% hornblende microdiorite group contains greater average concentrations for Cu and Mo. This may be due to the association of porphyry copper-gold with the intrusive felsic rocks (Cox, 1992). The greatest average concentration of Cu and Mo is in the greater than 0.25% old tonalite, which corresponds to the Batu Hijau porphyry copper-gold deposit. The greatest average concentrations of As, Pb, Sb and Zn for the groups examined are in the greater than 1% diatreme breccia group, which may be related to low-sulfidation epithermal gold deposits, such as at Gold Hill. Arsenic, Au, Pb and Zn have greater average concentrations for the drainages with quartz veins present and for drainages with greater than 1% diatreme breccia, but are lower for drainages with less than 0.25% old tonalite.

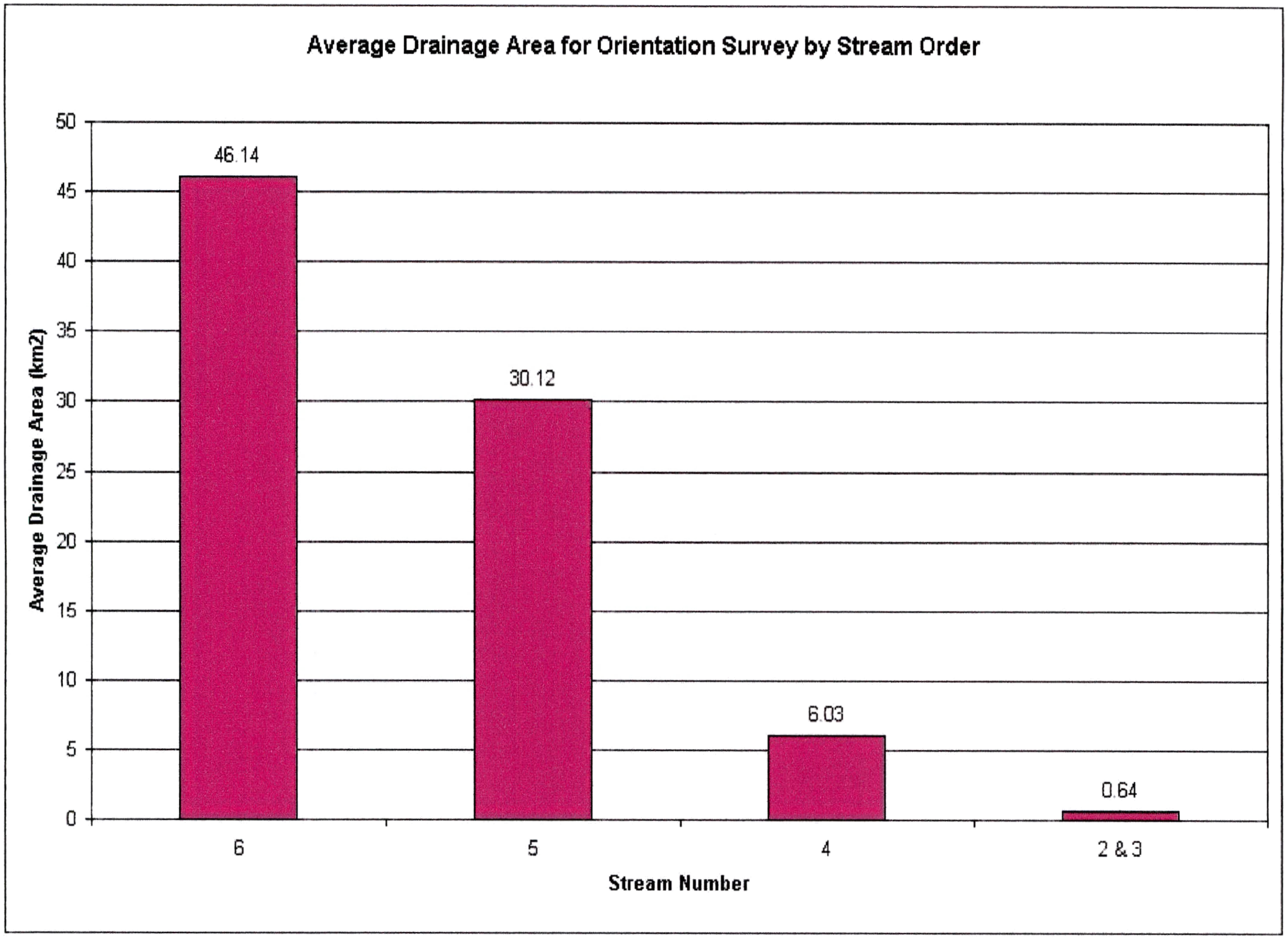

Figure 4.1 hart showing drainage area (km^2) and corresponding stream order for the orientation survey. The second and third stream order group only contains three samples.

Table 4.3 Average concentration for elements grouped by stream order and drainage area for the orientation survey. Groups with less than ten data points have been denoted with alpha superscripts.

Grouping	Element						
	As (ppm)	Au (ppb)	Cu (ppm)	Mo (ppm)	Pb (ppm)	Sb (ppm)	Zn (ppm)
Stream No.	Average Concentration						
2&3[a]	12	0.04	1,183	16	24	4	107
4	24	0.19	793	8	25	4	160
5	29	0.37	324	3	28	4	157
6[b]	24	0.37	173	2	28	4	147
Area (km^2)							
< 10	20	0.16	1,013	9	23	4	144
11 – 20[b]	24	0.08	600	4	27	4	137
21 – 30[c]	31	0.53	131	4	33	5	169
31 – 40[d]	26	0.25	171	3	27	4	152
41 – 50[d]	29	0.47	110	3	30	4	163
51 – 60[d]	31	0.25	28	3	28	4	165

a. Only contains three data points.
b. Only contains eight data points.
c. Only contains seven data points.
d. Only contains six data points.

Table 4.4 Average concentration for elements grouped by lithology for the orientation survey.

Grouping	Element						
	As (ppm)	Au (ppb)	Cu (ppm)	Mo (ppm)	Pb (ppm)	Sb (ppm)	Zn (ppm)
Andesite Volcanic Rocks	Average Concentration						
> 85%	21	0.13	723	4	27	4	135
80 – 85%	29	0.38	453	5	25	4	165
< 80%	28	0.29	179	7	30	4	159
Hornblende Microdiorite							
≤ 5%	29	0.44	418	4	30	4	161
6 – 10%	24	0.11	317	3	27	4	146
≥ 11%	23	0.15	705	9	23	4	148
Quartz Veins							
Present	32	0.41	120	4	30	4	173
Absent	21	0.14	756	6	25	4	135
Old Tonalite							
> 0.25%	19	0.11	1,471	6	24	4	122
< 0.25%	28	0.31	164	5	28	4	162
Diatreme Breccia							
> 1%	33	0.40	146	4	31	5	177
< 1%	24	0.24	537	5	26	4	147

4.3.1.2 Orientation Survey: *t*-tests

Table 4.5 contains the results of the *t*-tests for the stream order and drainage area subgroups within the orientation survey. For subgroups based upon stream order, Mo is the only element which is consistently different between the groups, while Au, Pb, and Sb are consistently similar. Copper is statistically similar between groups with only one order change, e.g. fifth versus fourth order streams. For subgroups based upon drainage area, Au and Sb were consistently similar. All elements for comparisons between drainage areas greater than 31 km^2 were statistically similar. The greatest variation in behavior is seen in the comparison between the smaller drainages, those less than 20 km^2.

Table 4.6 contains the results of the *t*-tests for the lithology subgroups within the orientation survey. Gold, Pb, and Sb are all statistically similar despite the change in percent andesite volcanic rocks, while only Au and Sb are statistically similar throughout the change in percent hornblende microdiorite. Arsenic, Cu, Pb, and Zn are all statistically different between the drainage with greater than 0.25% old tonalite, greater than 1% diatreme breccia, and the presence of quartz veins than those without those properties.

4.3.1.3 Orientation Survey: Background

Table 4.7 contains the published values for average concentrations of elements in mafic and granitic rocks, the estimated thresholds from examination of histograms and

Table 4.5 Results of *t*-tests for stream order and drainage area subgroups within the orientation survey. S indicates statistically similar, D indicates statistically different.

	Element						
Comparison	As	Au	Cu	Mo	Pb	Sb	Zn
Stream Orders							
6 vs. 2/3	**D**	S	S	**D**	S	S	**D**
6 vs. 4	S	S	**D**	**D**	S	S	S
6 vs. 5	S	S	S	**D**	S	S	S
5 vs. 2/3	**D**	S	**D**	**D**	S	S	**D**
5 vs. 4	S	S	S	**D**	S	S	S
4 vs. 2/3	S	S	S	**D**	S	S	**D**
Drainage Area (km^2)							
< 10 vs. 11-20	S	S	S	**D**	S	S	S
< 10 vs. 21-30	**D**	S	**D**	**D**	**D**	S	**D**
< 10 vs. 31-40	S	S	**D**	**D**	S	S	S
< 10 vs. 41-50	**D**	S	**D**	**D**	**D**	S	S
< 10 vs. 51-60	**D**	S	**D**	**D**	**D**	S	S
11-20 vs. 21-30	**D**	S	**D**	S	**D**	S	**D**
11-20 vs. 31-40	S	S	**D**	S	S	S	S
11-20 vs. 41-50	S	S	**D**	S	S	S	**D**
11-20 vs. 51-60	S	S	**D**	S	S	S	**D**
21-30 vs. 31-40	S	S	S	S	**D**	S	**D**
21-30 vs. 41-50	S	S	S	S	S	S	S
21-30 vs. 51-60	S	S	S	S	**D**	S	S
31-40 vs. 41-50	S	S	S	S	S	S	S
31-40 vs. 51-60	S	S	S	S	S	S	S
41-50 vs. 51-60	S	S	S	S	S	S	S

Table 4.6 Results of t-tests for lithology subgroups within the orientation survey. S indicates statistically similar, D indicates statistically different.

	Element						
Comparison	As	Au	Cu	Mo	Pb	Sb	Zn
Andesite Volcanic Rocks							
< 80% vs. 80-85%	S	S	S	S	S	S	S
< 80% vs. > 85%	S	S	**D**	**D**	S	S	**D**
80-85% vs. > 85%	**D**	S	S	S	S	S	**D**
Hornblende Microdiorite							
≤ 5% vs. 6-10%	S	S	S	**D**	S	S	S
≤ 5% vs. ≥ 11%	**D**	S	**D**	**D**	**D**	S	S
6-10% vs. ≥ 11%	S	S	S	**D**	S	S	S
Quartz Veins							
Present vs. Absent	**D**	S	**D**	S	**D**	S	**D**
Old Tonalite							
> 0.25% vs. < 0.25%	**D**	S	**D**	S	**D**	S	**D**
Diatreme Breccia							
> 1% vs. < 1%	**D**	S	**D**	S	**D**	S	**D**

Table 4.7 Published average concentrations, estimated thresholds based upon examination of histograms, and average estimated contribution of lithology to background using the Carranza and Hale (1997) method for the orientation survey.

Element	Average Concentration*		Estimated Thresholds	Estimated Contribution due to Lithology via Carranza and Hale (1997) method	
	Mafic	Granitic		Avg.	R^2
As (ppm)	1.0-1.5	2.1-3.0	29	26	0.99
Au (ppb)	2.0-3.2	2.0-2.3	0.4	0.1	0.75
Cu (ppm)	72-80	12	480	451	0.98
Mo (ppm)	1.2-1.5	1.3-1.5	6	4	0.90
Pb (ppm)	4	18-20	32	27	0.98
Sb (ppm)	0.1-0.2	0.2-0.3	4	4	0.98
Zn (ppm)	94-120	51-200	180	166	0.99

* from Rose et al. (1979) and Reimann and de Caritat (1998)

the calculated average background using the Carranza and Hale (1997) method. Table 4.7 also contains the R^2 value, as it relates to the goodness of fit of the multiple linear regression that was used in the Carranza and Hale (1997) method. All estimated threshold values are similar but slightly above the value computed using the Carranza and Hale (1997) method. Furthermore, all R^2 values are above 0.9 except for Au. Thus the regression used in the Carranza and Hale (1997) method fits 90% of the data except for Au, which only fits 75% of the data.

4.3.2. Reconnaissance Survey

The reconnaissance survey was subdivided into six stream order groups according to the occurrence of first, second, third, fourth, fifth, and sixth order streams. The sixth order stream group only contains two samples. Subdivision by drainage area was a bit more complicated. The average drainage area is 6 km^2, however, it ranges from less than 1 km^2 to 185 km^2, with only five of the drainages having areas greater than 50 km^2. The groups were selected to reflect intervals which might represent different geochemical properties, such as increased downstream dilution for drainages above 15 km^2.

The first breakdown for lithologic subgroups is based upon the dominant overall geology, such as percentage of andesite volcanic rocks and hornblende microdiorite, and the presence of limestone, which can create at geochemical barrier (see discussion on geochemical barriers in section A.4). The second breakdown for lithologic subgroups is based on the presence versus absence of old tonalite, quartz veins, and diatreme breccia, which have all been documented to occur with either porphyry copper-gold or low-sulfidation epithermal deposits.

4.3.2.1 Reconnaissance Survey: Univariate Statistics

Table 4.8 is a summary of the univariate statistics for the reconnaissance survey as a whole. The histograms for each element were positively skewed (Appendix C), as evident by the positive skewness values for all elements in Table 4.8. The data were transformed using the natural logarithm (ln) to provide a more normal distribution since discriminant analysis methods require normally distributed data due to the regression procedures. Sjoekri (1997) also noted a positive skewness in the data and thus log-transformed the data prior to manipulation by cluster analysis.

Cumulative frequency plots for Cu and Zn contained only one inflection point, suggesting two populations, while plots for As, Au, Mo, Pb, and Sb contained multiple inflection points (Appendix C). The histogram for Zn also contained a second peak on the right-side of the bell curve suggesting a second population overlapping the first. The second peak could be representative of an anomalous population overlapping the background population.

Table 4.9 contains the average element concentrations for groups based upon stream order and drainage area. Figure 4.2 shows the correlation of increasing drainage area with increasing stream order. Gold, Sb and Mo increase, overall, with increasing stream

Table 4.8 Summary of the univariate statistics for the reconnaissance survey.

	Reconnaissance Survey Results						
Parameter	Au (ppb)	Cu (ppm)	Pb (ppm)	Zn (ppm)	As (ppm)	Sb (ppm)	Mo (ppm)
n	258	255	255	255	255	255	79
Mean	16.50	54.57	18.24	140.71	15.32	2.85	2.03
Median	2.50	42.00	12.00	118.00	12.00	0.04	0.03
Mode	2.50	44.00	10.00	105.00	8.00, 16.00	0.04	0.03
Min - Max	0.13-800.00	8.00-1400.00	0.02-1140.00	5.00-670.00	0.02-440.00	0.04-74.00	0.03-38.00
Variance	4365.22	9085.57	5076.69	6204.99	827.92	34.44	30.00
Std. Dev.	66.07	95.32	71.25	78.77	28.77	5.87	5.48
Skewness	9.48	11.89	15.49	1.88	12.85	7.40	5.47
Skewness after ln-transformation	1.62	1.45	-3.69	-0.61	-2.59	0.55	0.51

Table 4.9 Average concentrations for elements grouped by stream order and drainage area for the reconnaissance survey. Groups with less than ten data points have been denoted with alpha superscripts.

Grouping	Element						
	As (ppm)	Au (ppb)	Cu (ppm)	Mo (ppm)	Pb (ppm)	Sb (ppm)	Zn (ppm)
Stream No.	Mean						
1	21	7	46	2	12	1	96
2	14	23	48	1	18	2	158
3	12	11	66	2	25	3	138
4	21	11	51	4	13	3	148
5	14	13	42	---	10	4	143
6[a]	11	401	33	---	9	6	95
Area (km^2)							
< 1	16	18	68	2	16	2	135
1 – 2.9	12	11	49	2	26	3	140
3 – 4.9	11	6	43	1	11	3	154
5 – 14.9	30	13	48	8[b]	11	5	138
15 – 185[c]	15	60	40	---	9	6	155

--- Not represented in group

a. Only contains two data points.

b. Only contains four data points.

c. Only five of the 18 data points have areas greater than 50 km^2.

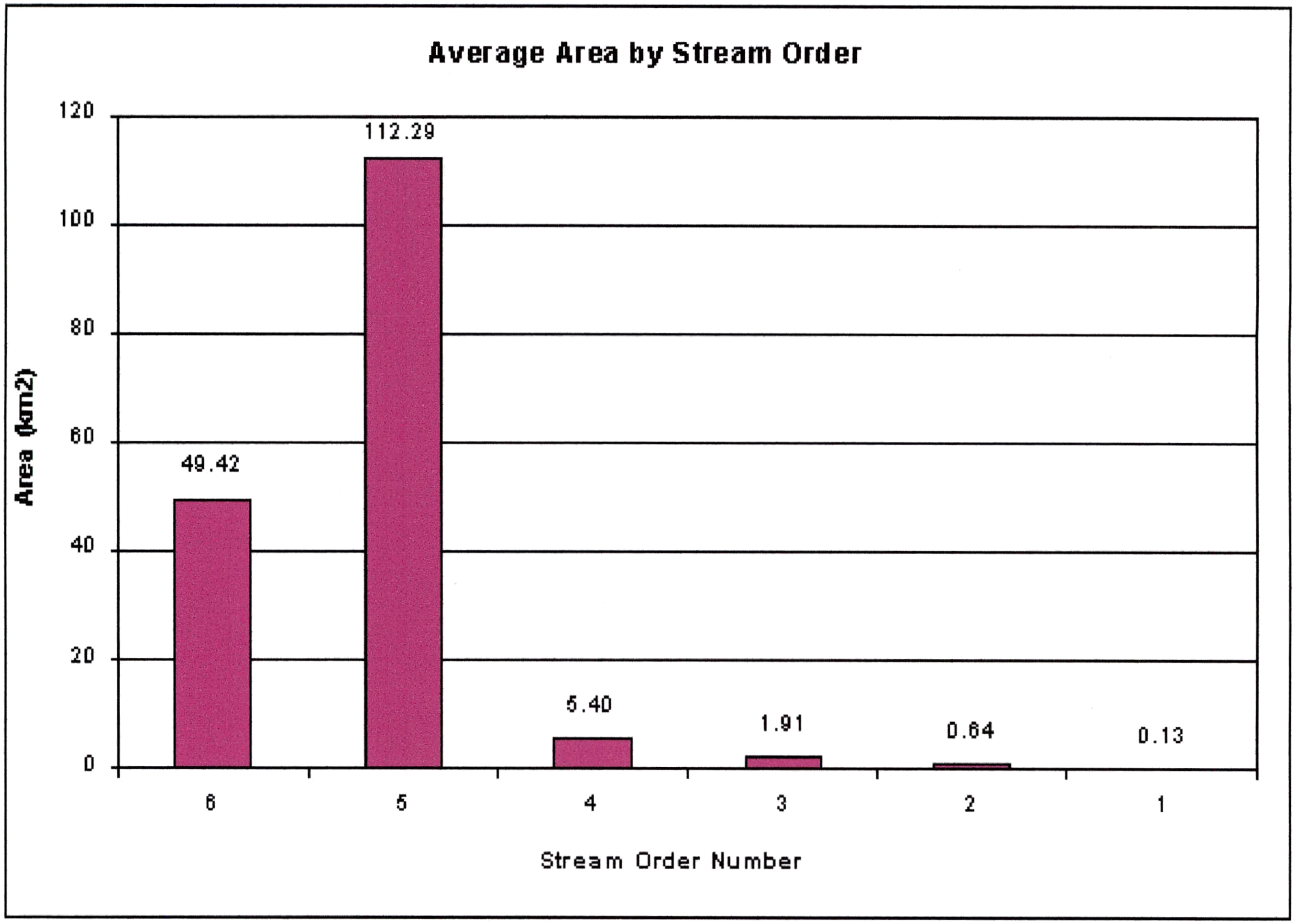

Figure 4.2 Chart showing drainage area (km^2) and stream order for the reconnaissance survey. The sixth stream order group only contains two data points.

order and drainage area. Copper and Pb both increase overall with decreasing stream order and drainage area, reaching a peak in third order streams and in groups with less than 2.9 km^2. Zinc and As do not show a specific pattern, although Zn is greatest in second and fourth order streams, while As is greatest in first and fourth order streams.

Table 4.10 contains the average composition of samples grouped by lithology. The greatest average concentrations for Au and Cu are found in the group with old tonalite present. The group where diatreme breccia is present contains the greatest average concentration for As and second highest concentration of Au, probably due to its association with the Gold Hill low-sulfidation epithermal gold deposit. Drainages with greater than 0.01% limestone contain the greatest concentration of Mo, Pb, and Zn. In general, average concentrations for the 100% andesite volcanic rocks group contained lower average concentrations than the 50 to 100% hornblende microdiorite group, except for Zn which has an average concentration nearly twice that of the hornblende microdiorite group.

4.3.2.2 Reconnaissance Survey: *t*-tests

Table 4.11 contains the results of the *t*-tests for the stream order and drainage area subgroups within the reconnaissance survey. In general, Cu and Au are statistically similar throughout the stream orders. Also, changes in one magnitude of stream order, e.g. from fifth to fourth, were statistically similar, with the exception for the first, second

Table 4.10 Average concentrations for elements grouped by lithology for the reconnaissance survey. Groups with less than ten data points have been denoted with alpha superscripts.

Grouping	Element						
	As (ppm)	Au (ppb)	Cu (ppm)	Mo (ppm)	Pb (ppm)	Sb (ppm)	Zn (ppm)
Andesite Volcanic Rocks	Average Concentration						
100%	13	13	44	1	14	2	134
85 – 99%	21	29	45	1	15	3	156
70 – 84%	16	11	113	2[a]	55	3	149
55 – 69%	12	7	42	1[b]	10	10	120
25 – 54%	17	9	78	2[a]	15	2	140
0 – 24%	12	16	50	5	12	2	133
Hornblende Microdiorite							
50 – 100%[c]	20	86	116	---	21	5	62
20 – 49%	17	12	109	2[d]	11	11	91
10 – 19%	18	15	175	2[d]	13	2	110
1 – 9%	15	37	50	1[c]	14	4	124
0 – 0.9%	15	13	44	2	20	2	150
Limestone							
5 – 94%[e]	19	9	28	7[d]	14	3	183
0.01 – 4.9%	18	19	41	2[b]	86	3	189
0%	15	18	58	2	13	3	134
Quartz Veins							
Present[f]	23	38	72	---	22	5	181
Absent	15	16	54	2	18	3	139
Old Tonalite							
Present[f]	12	115	227	---	14	5	82
Absent	15	13	48	2	18	3	143
Diatreme Breccia							
Present[a]	26	47	88	---	26	5	154
Absent	15	16	54	2	18	3	140

--- Not represented in group
a. Only contains six data points.
b. Only contains three data points.
c. Only contains four data points.
d. Only contains two data points.
e. Only four of the 18 data points are above 30% limestone.
f. Only contains nine data points.

Table 4.11 Results of *t*-tests for stream order and drainage area subgroups within the reconnaissance survey. S indicates statistically similar, D indicates statistically different, NA indicates that one or both of the groups compared did not contain data for the element.

	Element						
Comparison	As	Au	Cu	Mo	Pb	Sb	Zn
Stream Orders							
6[a] vs. 1	S	S	S	NA	S	**D**	S
6[a] vs. 2	S	S	S	NA	S	**D**	S
6[a] vs. 3	S	S	S	NA	S	S	S
6[a] vs. 4	S	S	S	NA	S	S	S
6[a] vs. 5	S	S	S	NA	S	S	S
5 vs. 1	S	S	S	NA	S	**D**	**D**
5 vs. 2	S	S	S	NA	**D**	**D**	S
5 vs. 3	**D**	S	S	NA	S	S	S
5 vs. 4	S	S	S	NA	S	S	S
4 vs. 1	**D**	S	S	S	S	**D**	**D**
4 vs. 2	S	S	S	S	S	S	S
4 vs. 3	S	S	S	S	S	S	S
3 vs. 1	S	S	S	S	S	S	S
3 vs. 2	**D**	S	S	**D**	S	S	**D**
2 vs. 1	**D**	S	S	**D**	S	S	**D**
Drainage Area (km^2)							
< 1 vs. 1 – 2.9	S	S	S	S	S	S	S
< 1 vs. 3 – 4.9	S	S	S	S	S	S	S
< 1 vs. 5 – 14.9	S	S	S	S	S	**D**	S
< 1 vs. 15 – 185	S	S	**D**	NA	**D**	**D**	**D**
1 – 2.9 vs. 3 – 4.9	S	S	S	S	S	S	S
1 – 2.9 vs. 5 – 14.9	S	S	S	S	S	**D**	S
1 – 2.9 vs. 15 – 185	**D**	S	S	NA	S	**D**	S
3 – 4.9 vs. 5 – 14.9	S	S	S	S	S	**D**	S
3 – 4.9 vs. 15 – 185	S	S	S	NA	S	**D**	S
5 – 14.9 vs. 15 – 185	S	S	S	NA	S	S	S

a) Only contains two data points.

and third stream orders. For subgroups by drainage area, Au was statistically similar throughout. Copper, Pb and Zn were only statistically different for the less than 1 km^2 versus 15 to 185 km^2 groups. Antimony was statistically similar in groups of less than 5 km^2 compared with similar sized groups, but statistically different when compared with groups greater than 5 km^2.

Table 4.12 contains the results of the *t*-tests for lithology subgroups within the reconnaissance survey. For the andesite volcanic rocks groupings, only Au and Pb were statistically different for drainages of 100% andesite volcanic rocks versus less than 100% andesite volcanic rocks. Molybdenum and Pb were statistically similar throughout the hornblende microdiorite groups. Gold, Mo, and Sb were statistically similar throughout the limestone groupings. All elements displayed the same pattern for the presence versus absence of quartz veins and presence versus absence of diatreme breccia, notably that only Sb and Zn were statistically similar. The presence versus absence of old tonalite resulted in statistically different means for Au, Sb, and Zn.

4.3.2.3 Reconnaissance Survey: Background

Table 4.13 contains the published values for average concentrations of elements in mafic and granitic rocks, estimated thresholds, and the calculated average contribution due to lithology, or background, using the Carranza and Hale (1997) method. Table 4.13 also contains the R^2 values from the regression equation for the Carranza and Hale (1997) method. The greatest R^2 value is 0.22, meaning that the equation fits 22% of the data,

Table 4.12 Results of *t*-tests for lithology subgroups within the reconnaissance survey. S indicates statistically similar, D indicates statistically different, NA indicates that one or both of the groups compared did not contain data for the element.

	Element						
Comparison	As	Au	Cu	Mo	Pb	Sb	Zn
Andesite Volcanic Rocks (%)							
100 vs. 0 – 24	S	S	S	S	**D**	S	S
100 vs. 25 – 54	S	S	S	S	S	S	S
100 vs. 55 – 69	S	S	S	S	**D**	S	S
100 vs. 70 – 84	S	**D**	S	S	S	S	S
100 vs. 85 – 99	S	**D**	S	S	S	S	S
85 – 99 vs. 0 – 24	S	S	S	S	S	S	S
85 – 99 vs. 25 – 54	S	S	S	S	S	S	S
85 – 99 vs. 55 – 69	S	S	S	S	S	S	S
85 – 99 vs. 70 – 84	S	S	S	S	S	S	S
70 – 84 vs. 0 – 24	S	S	S	S	S	S	S
70 – 84 vs. 25 – 54	S	S	S	S	S	S	S
70 – 84 vs. 55 – 69	S	S	S	S	S	S	S
55 – 69 vs. 0 – 24	S	S	S	S	S	S	S
55 – 69 vs. 25 – 54	S	S	S	S	S	S	S
25 – 54 vs. 0 – 24	S	S	S	S	S	S	S
Hornblende Microdiorite (%)							
20 – 100[a] vs. 0 – 0.9	**D**	**D**	**D**	S	S	S	**D**
20 – 100[a] vs. 1 – 9	S	S	**D**	S	S	S	**D**
20 – 100[a] vs. 10 – 19	S	S	S	S	S	S	S
10 – 19 vs. 0 – 0.9	**D**	**D**	S	S	S	S	S
10 – 19 vs. 1 – 9	S	S	S	S	S	S	S
1 – 9 vs. 0 – 0.9	S	**D**	S	S	S	**D**	S

Table 4.12 (continued)

	Element						
Comparison	As	Au	Cu	Mo	Pb	Sb	Zn
Limestone (%)							
5 – 94 vs. 0.01 – 4.9	S	S	**D**	S	S	S	S
5 – 94 vs. 0	S	S	**D**	S	S	S	**D**
0.01 – 4.9 vs. 0	**D**	S	S	S	**D**	S	**D**
Quartz Veins							
Present vs. Absent	**D**	**D**	**D**	NA	**D**	S	S
Old Tonalite							
Present vs. Absent	S	**D**	S	NA	S	**D**	**D**
Diatreme Breccia							
Present vs. Absent	**D**	**D**	**D**	NA	**D**	S	S

a) Only six of the data points are above 50% hornblende microdiorite and so the 20 – 40% and 50 – 100% were combined for the *t*-tests.

Table 4.13. Published average concentrations, estimated thresholds based upon examination of histograms, and average estimated contribution of lithology to background using the Carranza and Hale (1997) method for reconnaissance survey.

Element	Average Concentration*		Estimated Threshold	Estimated Contribution due to Lithology via Carranza and Hale (1997) method	
	Mafic	Granitic		Avg.	R^2
As (ppm)	1.0-1.5	2.1-3.0	19	5	0.16
Au (ppb)	2.0-3.2	2.0-2.3	12	4	0.22
Cu (ppm)	72-80	12	90	38	0.17
Mo (ppm)	1.2-1.5	1.3-1.5	3	1	0.25
Pb (ppm)	4	18-20	22	3	0.15
Sb (ppm)	0.1-0.2	0.2-0.3	5	1	0.06
Zn (ppm)	94-120	51-200	200	454	0.18

* from Rose et al. (1979) and Reimann and de Caritat (1998)

which implies a poor fit to the data and probably less reliable results from the Carranza and Hale (1997) method. The estimated threshold values are also well above the values computed using the Carranza and Hale (1997) method, with the exception of Zn.

4.3.3 Orientation Survey versus Reconnaissance Survey: *t*-tests

All of the elements were not statistically similar between the orientation and reconnaissance survey as a whole. The *t*-test revealed that while the difference between some of the means and variances are not substantial (Tables 4.2 and 4.8), the two surveys do not represent the same population.

4.4 Discussion of Results

The results presented in the previous sections lead to interesting insight into the structure and behavior of each data set and the geochemical environment in place during the data collection. Furthermore, the interpretation of the multivariate statistical techniques discussed in subsequent chapters is improved by understanding some of the factors, other than mineralization, that may affect the data.

4.4.1 Orientation Survey

The results of the univariate statistics from subgroups within the orientation survey suggest that the greatest concentration of Zn, contained in fourth order streams, could be due to zinc's initial mobility in highly acidic conditions such as would be expected about

Batu Hijau and then subsequent precipitation and possibly sorption once the pH increased (Rose et al., 1979; Perel'man, 1986; Smith and Huyck, 1999). Arsenic, Au, and Pb are greatest in the fifth order streams, also probably due to changes in the geochemical environment that cause these to either precipitate or otherwise be removed from the suspended load. The second and third order stream group contained the highest value for Cu and Mo because the three data points are in the immediate vicinity of the Batu Hijau deposit.

The results from the univariate statistics for the lithology subgroups suggest that, at least for the orientation survey, elevated Cu and Mo might be better pathfinders of porphyry copper-gold mineralization, as they occur in samples with greater than 0.25% old tonalite, less than 1% diatreme breccia, and the absence of quartz veins. In contrast, elevated As, Au, Pb and Zn might be better pathfinders, at least for the orientation survey, for low-sulfidation epithermal gold mineralization since these elements are enriched in drainages with greater than 1% diatreme breccia and the presence of quartz veins, and are depleted in drainages with greater than 0.25% old tonalite. This contrasts with Rose et al. (1979), who listed Cu as an indicator and Mo, Au, As, Pb and Zn as pathfinders for porphyry copper deposits, and Au as an indicator and Sb and As (of the elements used in this study) as pathfinders for epithermal precious metal mineralization.

The results of the *t*-tests for different stream order subgroups revealed that Mo was statistically different for all combinations possibly reflecting molybdenum's highly variable behavior in the geochemical environment. With the exception of Mo, changes in one level of stream order, e.g. fourth to fifth, were statistically similar, while changes in two or more levels of stream order had statistically different characteristics. This may reflect the different geochemical environments associated with increases in stream orders. Copper is enriched in lower stream orders, which is probably due to proximity of Batu Hijau which occurs within or near all of these drainages. Zinc and As, however, are depleted in the second and third order streams and enriched in fifth order streams, suggesting that the two elements are taken into solution better in the low stream order group and cross a geochemical barrier, thus coming out of solution by the fifth order streams.

The results of the *t*-tests for different drainage areas suggest that Cu and Mo are both enriched in small drainages, less than 20 km^2 and 10 km^2, respectively. This characteristic can probably be best attributed to downstream dilution. Arsenic and Pb show similar patterns to Cu and Mo. Overall, the chemistry for drainage above 31 km^2 compared with drainage above 41 km^2 all have statistically similar means. Thus the effect of downstream dilution, either by increased water flow or increased "background" lithologic material, is most variable in drainages of less than 31 km^2.

The results of the *t*-tests for changes in lithology reveal that Au and Sb are statistically similar throughout all groups, probably related to their low overall variance for the survey as a whole. Arsenic and Pb have statistically lower concentrations in the greater than 11% hornblende microdiorite. Compared to the less than 5% hornblende microdiorite. In contrast, Cu and Mo are statistically greater in the greater than 11%

versus less than 5% hornblende microdiorite, probably related to the old tonalite intrusion within the hornblende microdiorite unit which hosts the Batu Hijau deposit.

4.4.2 Reconnaissance Survey

The overall univariate trends for stream order and drainage area subgroups in the reconnaissance survey appear to generally follow the mobility characteristics of each element in the environment. Appendix B contains a summary of the mobility characteristics for each element used in this survey. For example, Sb which travels most readily in solution under normal conditions (Horowitz, 1991), increases with increasing stream order, along with Mo, which is also mobile in neutral to alkaline conditions (Smith and Huyck, 1999). The increased mobility for Sb and Mo result in potential anomalies being dispersed further downstream, which correspond with increasing stream order. The peak values in third order streams for Cu and Pb could be due to changes in pH and stream chemistry between second and third order streams that cause Cu to come out of solution, such as a complex alkaline-adhesion geochemical barriers (Perel'man, 1986; Smith and Huyck, 1999). Zinc is a fairly immobile element and will only go into solutions under oxidizing, strongly acidic conditions (Smith and Huyck, 1999), which can occur at sulfide-rich ore deposits (Perel'man, 1986). As such, it is not surprising to see an increase in average composition from first order streams to second order streams, which might indicate a change in aqueous environment such as an alkaline barrier (Perel'man, 1986; Smith and Huyck, 1999).

Drainages with 100% andesite volcanic rocks contain relatively low concentrations of all elements compared with the other andesite volcanic rocks subgroups. This suggests that other lithologic units exert a greater degree of variability on element concentration than the percent andesite volcanic rocks. Drainages with greater than 0.01% limestone contain the greatest concentration of Mo, Pb, and Zn. This may be due to the development of alkaline geochemical barriers that cause Pb and Zn to precipitate as carbonates or adsorb onto hydrous Fe- and Mn-oxides (Perel'man, 1986; Plumlee and Nash, 1995; Smith and Huyck, 1999). The presence of quartz veins and diatreme breccia corresponds to increased concentrations of As, Au, Cu, Pb, Sb, and Zn. The presence of old tonalite results in substantial increases in Au and Cu, which is probably due to the Batu Hijau deposit.

Comparisons of the stream order subgroups by *t*-tests reveal that, as with the orientation survey, one level change in streams does not create statistically different data. The only exceptions are from first to second and second to third order streams. This reflects the geochemical environment, such that low order streams can have different geochemical properties compared with higher order streams. In contrast, streams of third order or greater reflect more gradual changes in geochemical environment possibly due to downstream dilution effects.

Comparisons of the drainage area subgroups by *t*-tests reveal a significant difference between conditions in the 15 to 185 km^2 group versus the groups with less than 5 km^2. The greatest concentrations of Cu and Pb appear upstream, in the smaller drainages, and become statistically smaller as the drainage area increases, suggesting downstream dilution. Samples from the larger (greater than 15 km^2) drainages are associated with reduced variability in Zn and As, and increased Au and Pb variability. This could be due to more neutral to alkaline conditions that favor immobility for Zn and As. Local occurrences of mineralization within the larger groups might cause fluctuations in Au and Pb concentrations, thus increasing variability.

Statistical comparisons for subgroups broken down by lithology indicate that the average concentrations for elements based upon their percent andesite volcanic rocks generally have statistically similar means. The exceptions are that of Au and Pb (Table 4.12), which probably correspond to the presence of other lithologic units. The subgroups in percent hornblende microdiorite reveal that Mo and Pb are statistically similar throughout, while Au has statistically smaller average concentrations for drainages in the 0 to 0.9% than for those in the greater than 1% group. Copper is statistically greater in the greater than 20% group versus the less than 9% hornblende microdiorite group. Zinc is inversely related to Cu. The inverse relationship between Cu and Zn and the statistically greater concentration of Au in drainages with greater than 1% hornblende microdiorite suggest that the presence of hornblende microdiorite might be related to porphyry copper-gold mineralization.

The presence of limestone in a drainage can buffer acidic conditions and result in an alkaline geochemical barrier. The average composition of Cu is statistically greater in drainages with less then 5% limestone, relative to drainages with greater than 5%

limestone. Average concentrations of Zn, however, are statistically greater for drainages with greater than 0.1% limestone. This is probably due to the presence of an alkaline geochemical barrier, which Zn is more sensitive to than Cu. Gold, Mo, and Sb are statistically unaffected by the presence of limestone for this data. Molybdenum tends to be affected by limestone, however, only two to three data points were available that contain Mo data for each limestone group.

In drainages where quartz veins that might be host or related to low-sulfidation epithermal gold deposits are present, mean concentrations for Zn and Sb are statistically similar to drainages without quartz veins. Average concentrations for As, Au, Cu, and Pb are all statistically greater for those drainages with quartz veins as opposed to those without. Therefore, associations which might represent epithermal gold mineralization include As, Au, Cu, and Pb.

Drainages containing old tonalite have average concentrations of As, Cu, and Pb that are statistically similar to drainages without old tonalite. Gold and Sb concentration are statistically higher, and Zn concentrations statistically lower than drainages without old tonalite. The Batu Hijau deposit is hosted in old tonalite.

Drainages containing diatreme breccia, which has been documented at the low-sulfidation epithermal gold deposit at Gold Ridge, have average concentrations for Zn and Sb that are statistically similar to drainages without diatreme breccia. Average concentrations for As, Au, Cu, and Pb are all statistically greater for drainages with diatreme breccia present than for drainages without diatreme breccia.

4.4.3 Orientation Survey versus Reconnaissance Survey

The results of the *t*-test comparison between the two surveys revealed that they do not represent the same population. This is consistent with the observation that the reconnaissance survey contains a larger proportion of background, or "barren," catchments in comparison to the orientation survey. For example, the orientation survey contains nine known mineral occurrences in a total of two drainages covering 42 mi^2 (109 km^2). In comparison, the reconnaissance survey contains 17 known mineral occurrences in a total of 19 complex drainages, covering 211 mi^2 (548 km^2).

It is expected that average background concentrations will be elevated in this region due to the high number of mineral occurrences in the area (Runnells et al., 1992). This is evident in the substantial differences in estimated thresholds between the two surveys (Tables 4.7 and 4.13). The thresholds for As, Cu, Mo, and Pb are all greater for the orientation survey relative to the reconnaissance survey, which is probably related to the substantial presence of known porphyry copper-gold occurrences per area in the orientation survey. The threshold for Au is substantially lower for the orientation compared to the reconnaissance survey, which may be due to the different ways in which the samples were collected and processed or the different size fractions collected.

As a result, the orientation data set is not used as the training data set for the discriminant analysis and neural network techniques. Instead a subset of the drainages for each survey was selected for training sets and the two surveys were treated separately. The drainages selected for the training sets consist of drainages with known mineral occurrences and “barren” drainages. “Barren” drainages were selected by looking for drainages that were more than four drainages removed from those with known mineral occurrences or contained element concentrations similar to the estimated threshold values discussed in section 4.3.1.3 and 4.3.2.3.

CHAPTER 5

FACTOR ANALYSIS

5.1 Introduction

Factor analysis, as described in section 1.3.1, is a derivative of principal components analysis. The R-mode factor analysis allows the investigator to examine the relationships between variables, such as element concentrations. The relationships between variables might reflect certain geological or geochemical aspects of the environment, such as bedrock geology, surficial processes and mineralization. The goal for geochemical exploration is to identify and map factors that reflect mineralization.

5.2 Methodology

Factor analysis can be done utilizing either Q-mode or R-mode techniques. Q-mode techniques focus on the similarities between individuals or sample sites, whereas R-mode techniques focus on the similarities or correlations among the variables, e.g. elements (Jackson, 1983; Davis, 1986). The R-mode techniques are used in this study to evaluate the relationships among the geochemical variables in hopes of recognizing associations that assist in identifying geologically significant features.

It is assumed in using factor analysis that the underlying patterns or processes in the data can be represented in fewer factors than the number of variables measured, i.e. $p <$

m, where p is the number of factor models, and m is the number of variables (Davis, 1986). The southwestern portion of Sumbawa, Indonesia, is presently known to have three types of mineralizations, e.g. porphyry copper-gold, low-sulfidation epithermal gold, and alluvial style gold (Sjoekri, 1997). In addition, fluctuations in stream chemistry within tropical, humid climates probably result in some complexing and sorption between heavy metals in suspension and in sediment. The best indicator elements for these processes are Mn and Fe but they, unfortunately, were not determined in the initial sample analysis. Sudden depletions in Zn, Cu, and Pb could, however, be indicative of sorption processes (Rose et al., 1979). Finally, changes in the lithologies drained could potentially result in another factor, especially for basins with a predominant lithology. Based upon these probable factors, it is estimated that out of the seven elements, four or five geologically relevant factors may be found.

Another assumption is that the variances observed within the data are the result of correlations between variables and underlying factors (Davis, 1986). This assumption is critical, in that if it is correct, the analysis will result in a few factors which explain the majority of the variance. If this assumption is incorrect, the communalities will be low and the number of factors needed to explain the majority of variation will increase substantially. The later case indicates that factor analysis will probably prove inconclusive.

Key components of factor analysis include eigenvalues, eigenvectors, factor loadings, factor scores and communalities. Eigenvalues are the numerical equivalent of the amount of total variability accounted for in a given factor model (Davis, 1986). Eigenvectors represent the orientation in *n*-dimensional space of the orthogonal factors to one another. Eigenvectors also reflect the percentage of variation represented by individual factors in their respective factor models. Eigenvalues and eigenvectors are calculated by obtaining the determinant of the matrix, finding *n* roots of the matrix's characteristic polynomial, and then solving *n* sets of *n* simultaneous equations (Davis, 1986). For example, a 2 x 2 matrix would have 2 eigenvalues. The eigenvalues would represent the long and short axes of the ellipse that encloses the data. The eigenvectors in this case would represent the orientation of the long and short axes of the ellipse relative to the factor axes.

Factor loadings represent the individual weights that are assigned to each variable in order to project the objects onto the factor axes as scores (Davis, 1986). The loadings for each factor are obtained by multiplying an eigenvector by its corresponding eigenvalue. The loadings also represent the correlations of the individual variables with the factors (Davis, 1986). The factor scores are calculated by multiplying the original data matrix by the factor loadings. The factor scores can be graphically displayed and examined. Finally the communalities are calculated by squaring each factor entry and adding them together for each respective variable. The communalities represent the percent of variance of a variable explained by a given factor model(Davis, 1986).

The factor analysis module of the Statistica software package is used for the calculations. Only the geochemical data are used for the analysis, and Mo data are not included from the reconnaissance survey as it would have reduced the total drainages interpreted to 79. The ln-transformed data is used for both surveys for comparative reasons, even though normally distributed data are not required by this method. Once all of the calculations have been made, a table of the factor models, corresponding eigenvalues, communalities and factor loadings is produced to examine the element associations that have been revealed. The factor scores for associations that could indicate mineralization are plotted geographically to identify the drainage basins that contain potential mineral occurrences.

Selection of the appropriate factor model will be made according to the following criteria: (1) are any of the elemental associations within a factor model representative of geological, geochemical, or exploration processes; (2) are the spatial relationships between a factor model and known mineral occurrences consistent; and (3) does the factor model explain a significant amount of the total data variance. Scree plots, plots of eigenvalue versus factor model, can also be helpful for selecting factor models. StatSoft (1995) suggests that the factor models prior to the point on the plot where eigenvalues appear to drop off to the right are most valuable.

5.3 Orientation Survey Results

Table 5.1 contains the correlations for elements within the orientation survey. Nine statistically significant correlations are indicated in bold. Table 5.2 contains the communalities for each element for each factor model. The four factor model explains 85% of the overall variance and a minimum of 85% of the variance for each element,

Table 5.1 Correlation matrix for geochemical data from the orientation survey. Correlations with values greater than 0.29 for n=49 are statistically significant at the 95% confidence level. Statistically significant correlations are in bold.

Element	Au	Cu	Pb	Zn	As	Sb	Mo
Au	1						
Cu	-0.06	1					
Pb	0.18	**-0.37**	1				
Zn	**0.32**	**-0.76**	0.26	1			
As	0.27	**-0.72**	**0.50**	**0.76**	1		
Sb	0.13	-0.03	0.14	0.01	-0.03	1	
Mo	0.02	**0.41**	-0.21	-0.24	**-0.48**	0.04	1

Table 5.2 Communalities table for geochemical data from the orientation survey.

	Factor Model						
Element	1	2	3	4	5	6	7
Au	0.11	0.56	0.81	0.86	0.98	1.00	1.00
Cu	0.74	0.77	0.77	0.85	0.88	0.98	1.00
Pb	0.33	0.39	0.51	0.85	0.99	0.99	1.00
Zn	0.72	0.73	0.81	0.92	0.93	0.94	1.00
As	0.86	0.86	0.86	0.87	0.87	0.96	1.00
Sb	0.00	0.49	0.85	0.98	1.00	1.00	1.00
Mo	0.29	0.47	0.59	0.62	0.99	0.99	1.00
Eigenvalues (in %)	43.6%	60.7%	74.2%	85.0%	94.9%	98.1%	100.0%

except Mo (62%) which is best explained by the fifth factor. Figure 5.1 contains the scree plot for the orientation survey data. Based upon the scree plot, factor models 2, 3, 4, or 5 might significantly contribute to the interpretation of the data. The most significant changes in communalities are between second and third, third and fourth, and fourth and fifth (for Mo only).

Figure 5.2 is a plot of the factor loadings. Factor loadings can be both positive and negative, as represented by the "+" and "-" on the bottom row of figure 5.2. Thus elements, within the same factor, with opposite signs are inversely associated. The four factor model is probably the best model since the first factor is probably indicative of mineralization, containing high values of Zn and As, inversely related to high values of Cu and Mo. This was also suggested by the univariate and *t*-test results presented in section 4.4.1, which suggests that Cu and Mo might be better pathfinders for porphyry copper-gold, while As, Au, Pb, and Zn might be better pathfinders for low-sulfidation epithermal gold mineralization.

Figure 5.3 is a plot of the factor scores for factor one of the four factor model. Factor one of the four factor model [As, Zn, -Cu, -Mo], where high positive scores represent high As and Zn values [As, Zn] and large negative factor scores represent high Cu and Mo values [-Cu, -Mo], is weakly related to mineralization. Many of the drainages that contain porphyry copper-gold have low factor scores. Drainages with low-sulfidation epithermal gold and alluvial style mineralization have high factor scores. Figure 5.4 is a

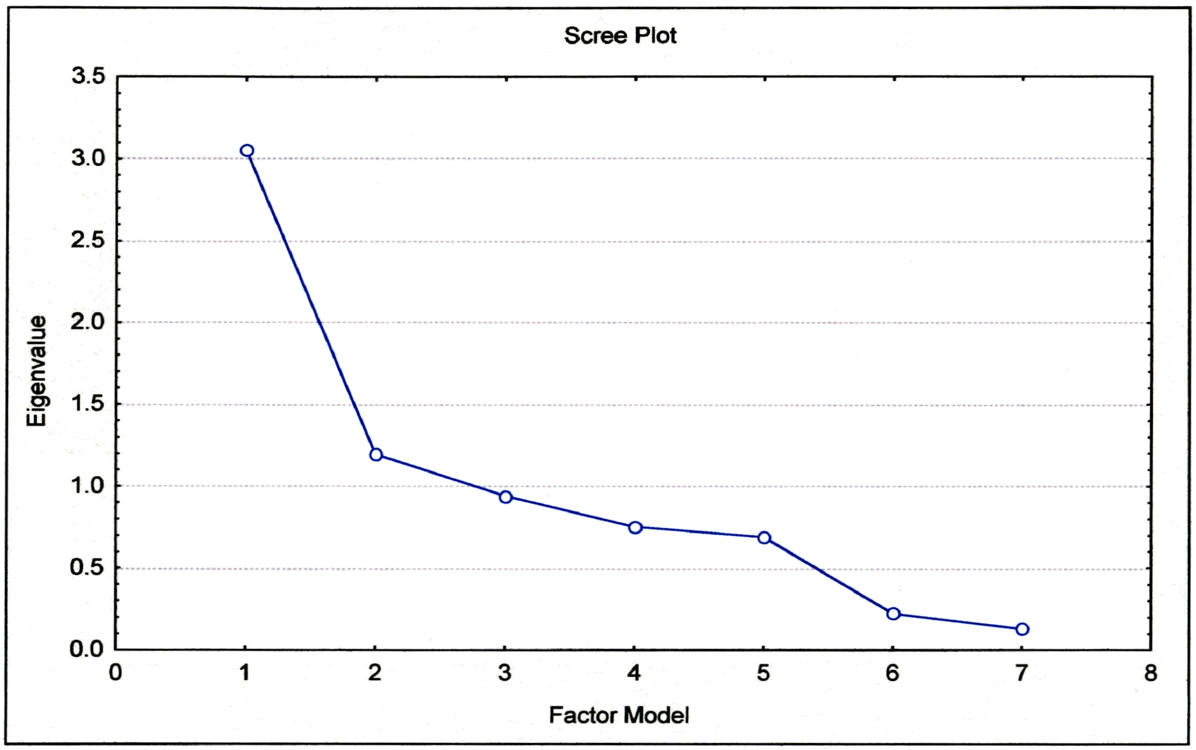

Figure 5.1 Scree plot for the orientation survey showing eigenvalue versus corresponding factor model.

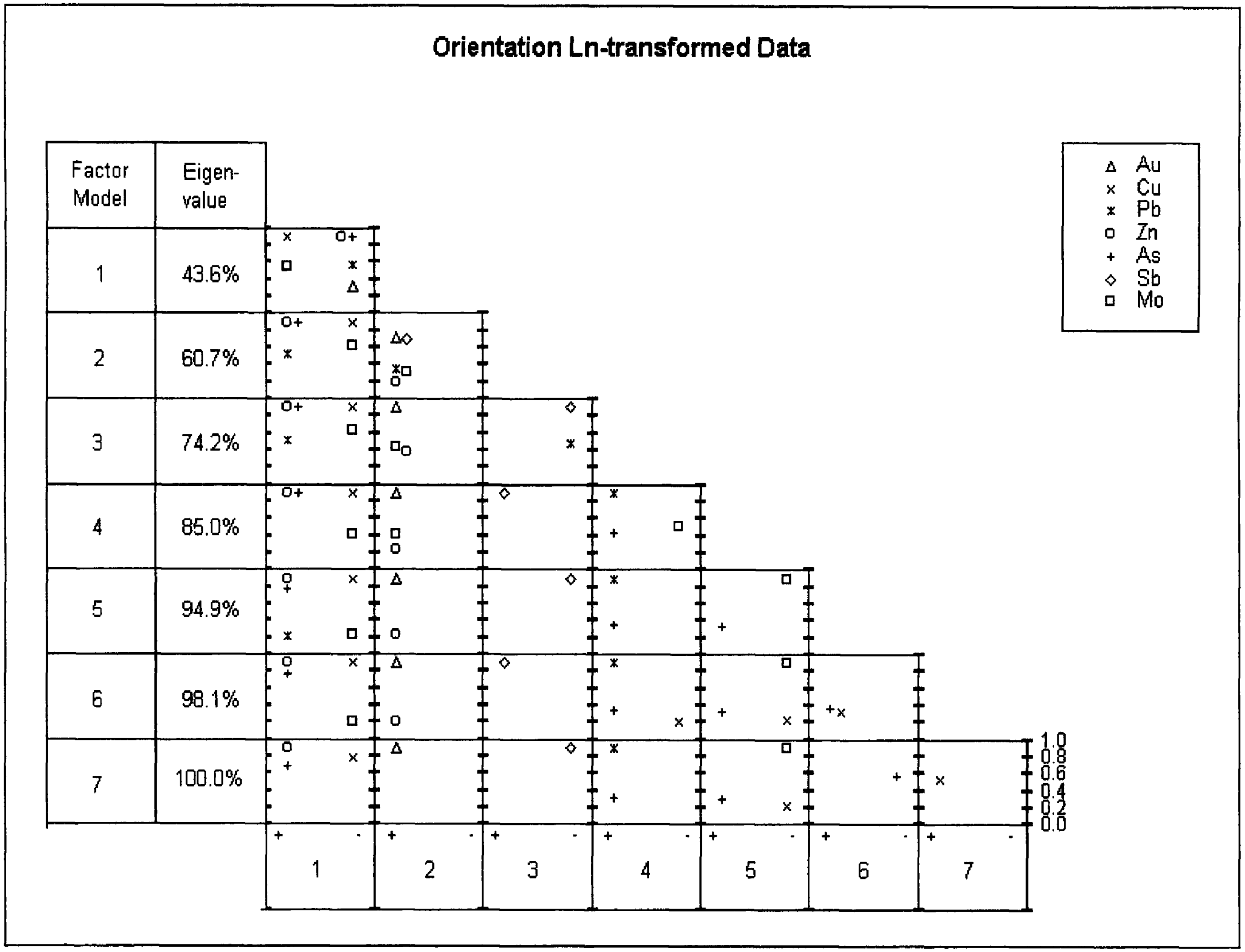

Figure 5.2 Plot of factor loadings for factor models for the orientation survey. Only factor loadings greater than 0.20 are plotted to keep the plot easy to read. The "+" and "-" symbols along the in the boxes in the bottom row indicate positive and negative factor loadings, respectively.

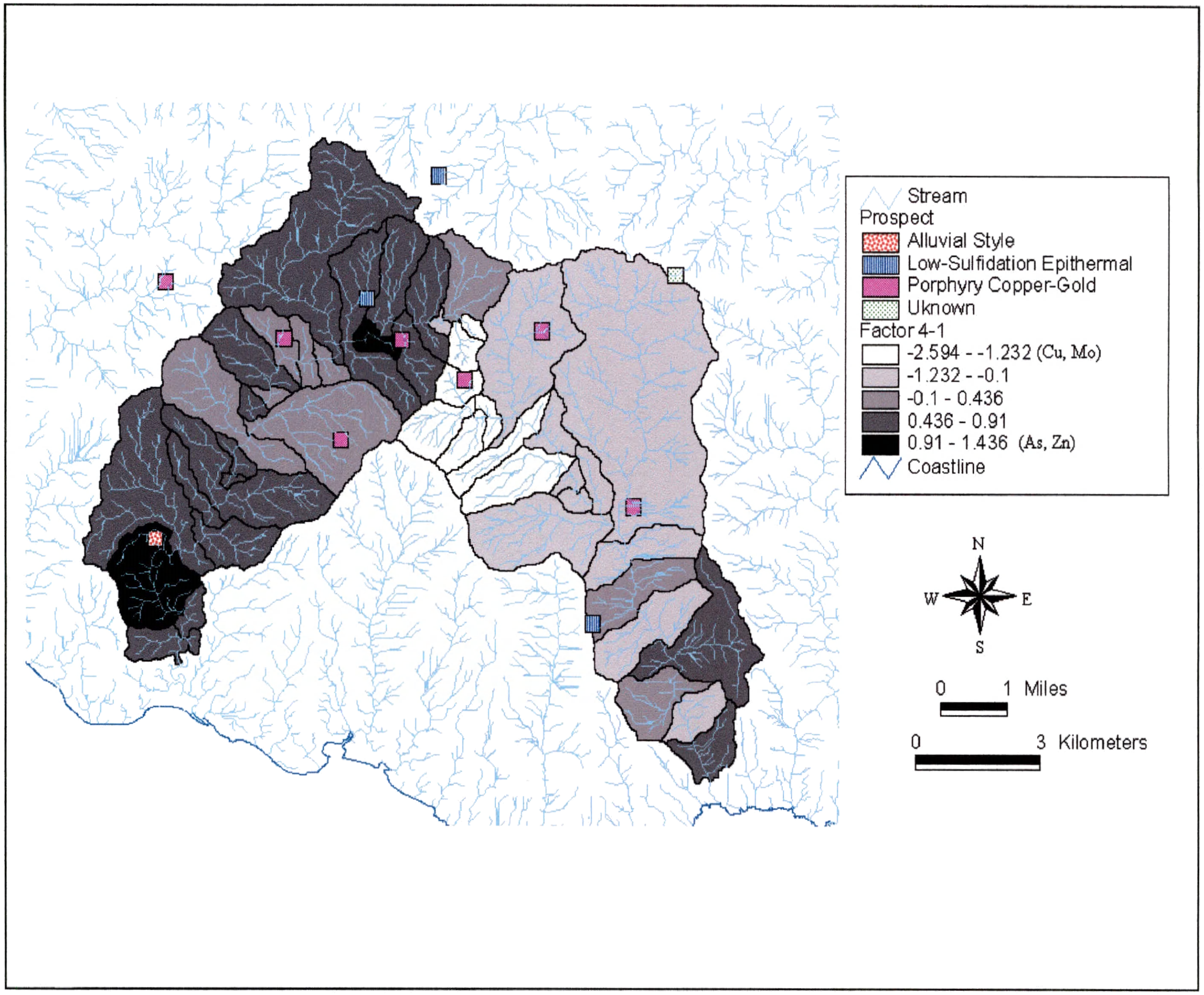

Figure 5.3 Factor one of the four factor model [As, Zn, -Cu, -Mo] by drainage for the orientation survey.

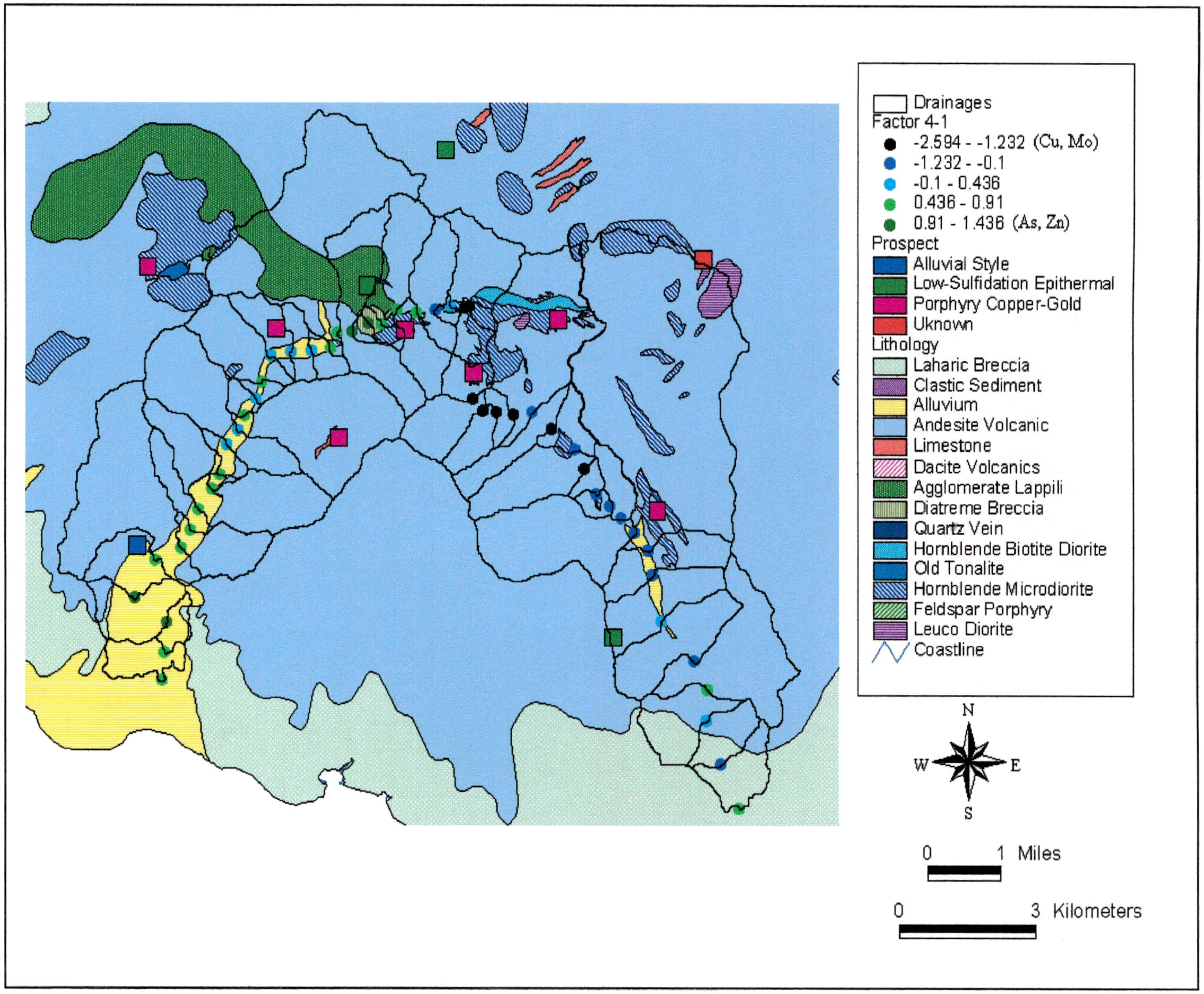

Figure 5.4 Factor one of the four factor model [As, Zn, -Cu, -Mo] versus lithology for the orientation survey.

plot of factor one scores versus lithology. Factor one doesn't appear to be related to lithology; however, the higher values are typically found near the bottom of the drainages especially with relation to the distribution of alluvium.

Figure 5.5 is a plot of the factor scores for factor two of the four factor model by drainage. Factor two [Au, Mo, Zn] appears to also be related to porphyry copper-gold mineralization. The smaller the drainage area with a porphyry copper-gold deposit the greater the factor score, which might also indicate diluted signatures with increased size. Moderate values are seen for drainages with low-sulfidation epithermal gold and alluvial style mineralization. Figure 5.6 is a plot of the factor scores for factor two versus lithology. Factor two does not appear to be clearly related to any lithologic unit as high and low values occur in sequential drainages with no apparent change in lithology.

Figure 5.7 is a plot of the factor scores of factor three of the four factor model by drainage. Factor three [Sb] does not appear to be correlated with any of the known mineral occurrences. Figure 5.8 is a plot of the factor scores for factor three of the four factor model versus lithology. Factor three is possibly related to hornblende microdiorite occurrence, as drainages that contain hornblende microdiorite upstream tend to have high scores, although there are a couple of exceptions. The exceptions might be related to close proximity to porphyry copper-gold occurrences which can cause the stream to become more acidic.

Figure 5.9 is a plot of the factor scores for factor four of the four factor model by drainage. Factor four [As, Pb, -Mo] may also represent mineral occurrences, although, a

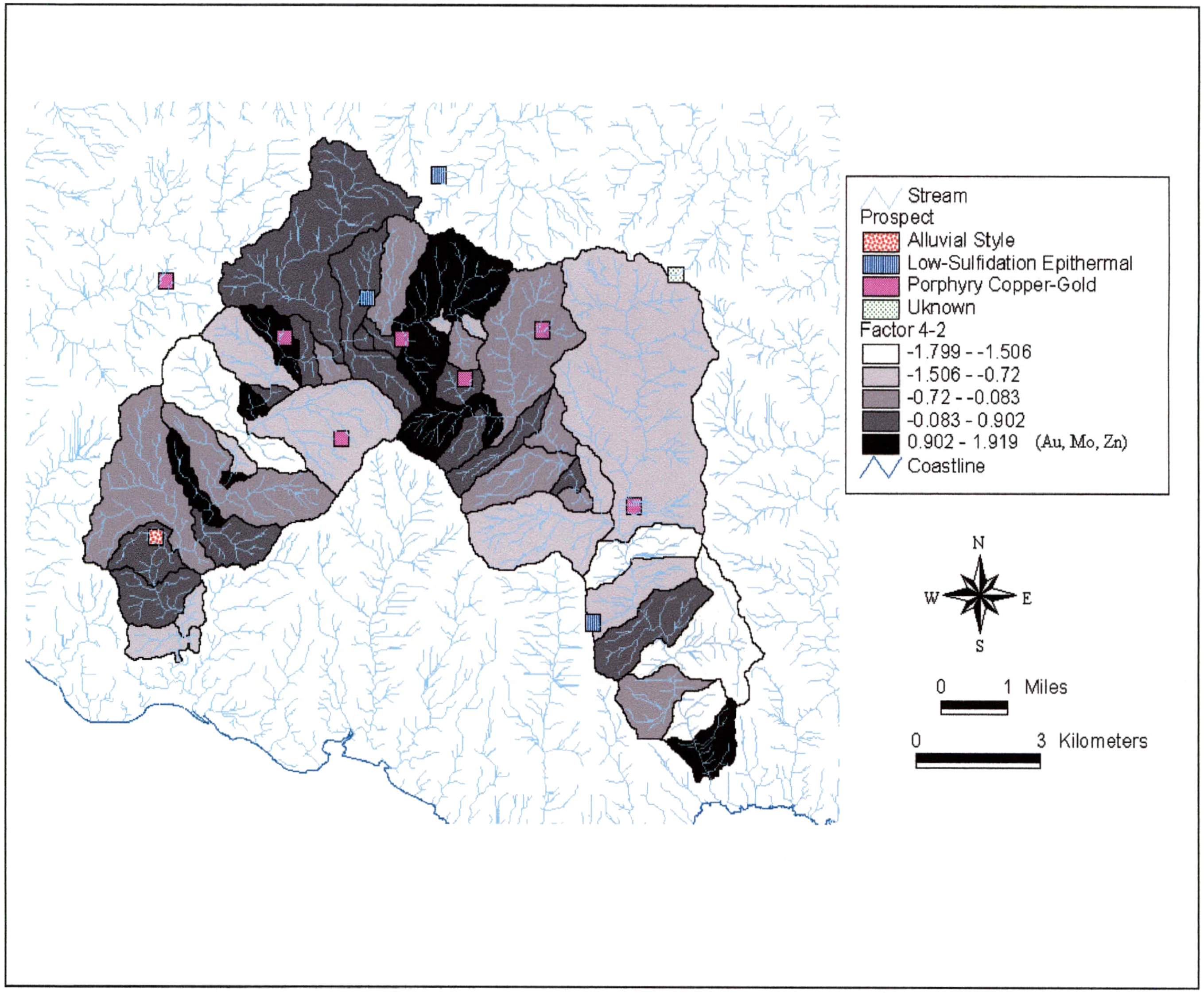

Figure 5.5 Factor two of the four factor model [Au, Mo, Zn] by drainage for the orientation survey.

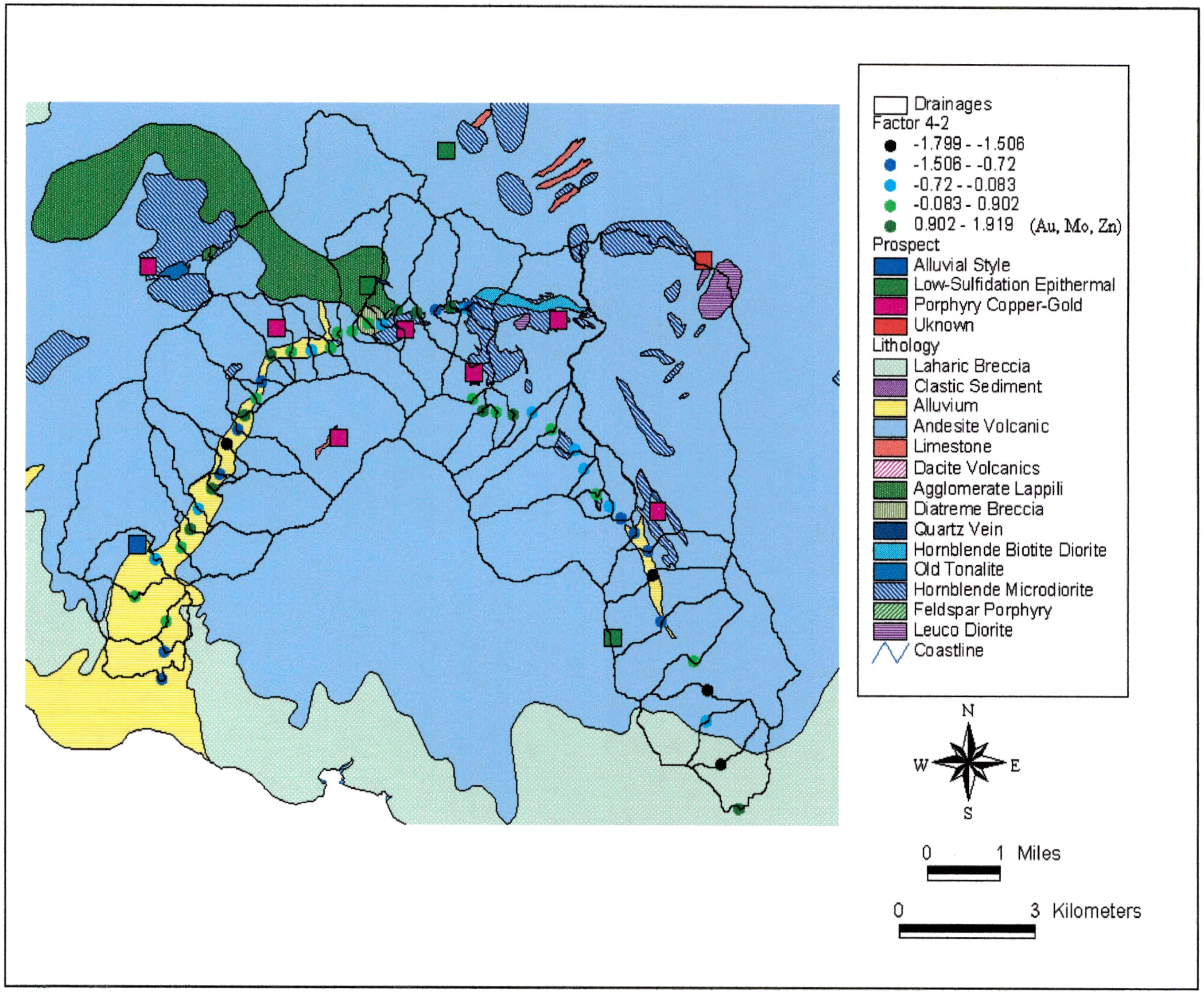

Figure 5.6 Factor two of the four factor model [As, Mo, Zn] versus lithology for the orientation survey.

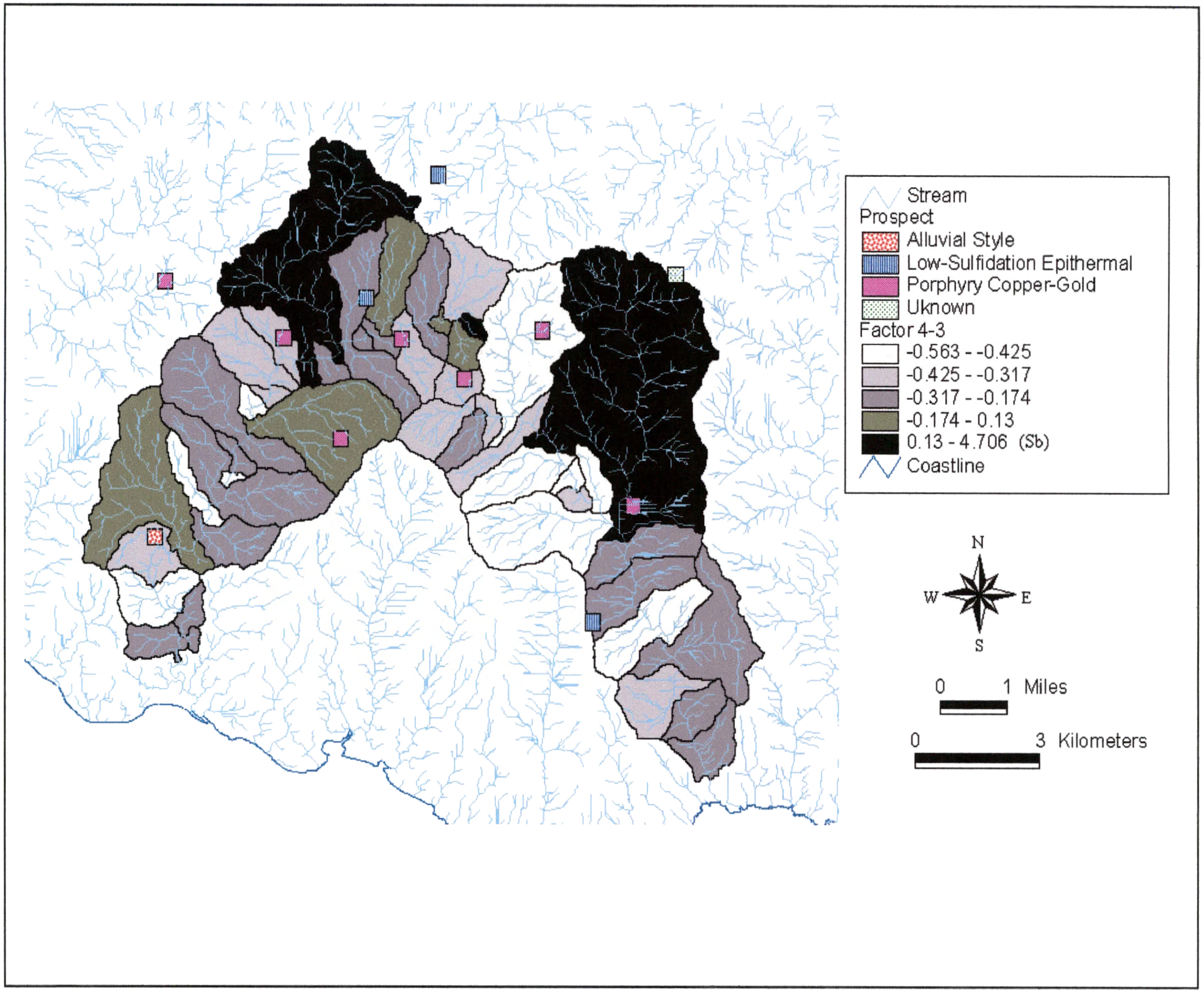

Figure 5.7 Factor three of the four factor model [Sb] by drainage for the orientation survey.

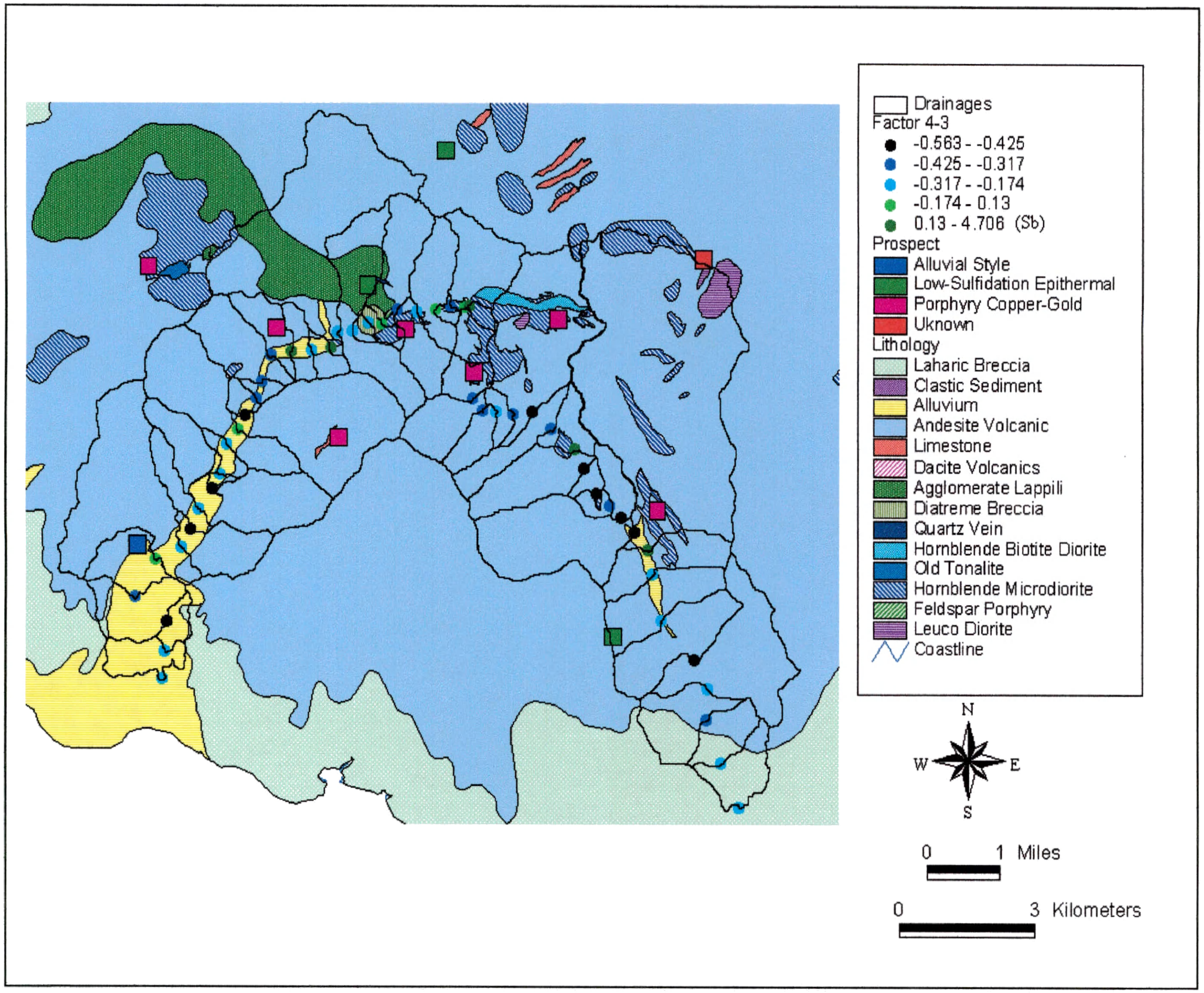

Figure 5.8 Factor three of the four factor model [Sb] versus lithology for the orientation survey.

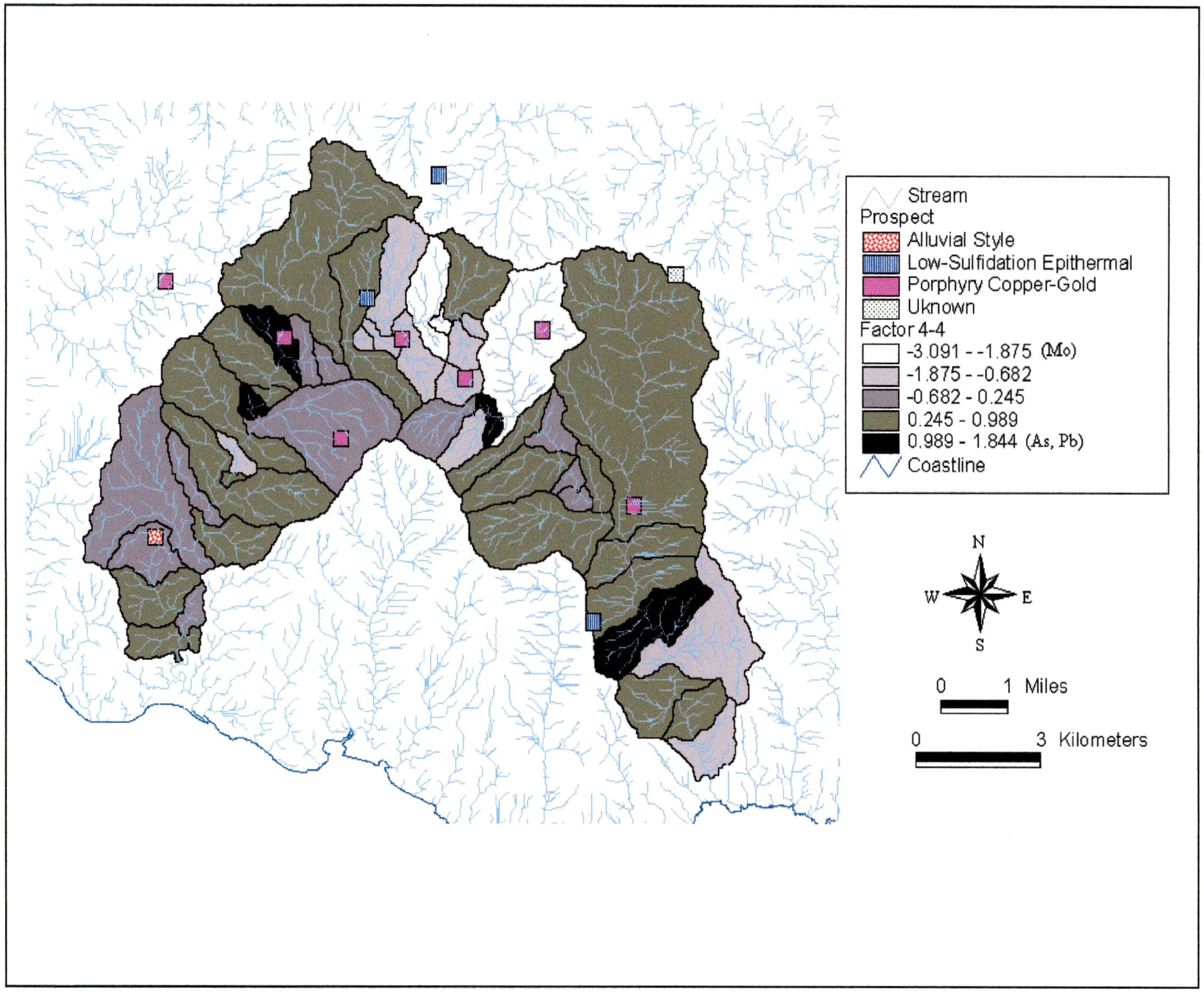

Figure 5.9 Factor four of the four factor model [As, Pb, -Mo] by drainage for the orientation survey.

consistent relationship is not identifiable. Figure 5.10 is a plot of the factor scores for the factor four of the four factor model versus lithology. Factor four does not have a consistent relationship with lithology; however, moderate to elevated values (high Pb and As) typically occur downstream, while low values (elevated Mo) typically occurs upstream near the concentration of porphyry copper-gold deposits and hornblende microdiorite. This may be more reflective of the surficial geochemical environment and mobility rather than mineralization and lithology.

5.4 Reconnaissance Survey Results

Table 5.3 is the correlation matrix for the reconnaissance survey. Five statistically significant correlations are indicated in bold. Table 5.4 contains the communalities for the different factor models from the reconnaissance survey. The greatest significant increase of percentage variance represented in a model is from the third to the fourth factor models. A second increase is from fourth to fifth factor model. Figure 5.11 is the scree plot for the factor models. While there is no clear break point in the scree plot, it is expected that the third to fifth factor models are probably the most useful because the slope change is a bit more pronounced after the fifth factor model. The scree plot and the increase in communalities and percent variance of data accounted for suggest that the fourth or fifth factor model might be the best options to investigate further.

Figure 5.12 is a plot of the factor loadings by factor model. Factor loadings can be both positive and negative, as represented by the "+" and "-" on the bottom row of figure

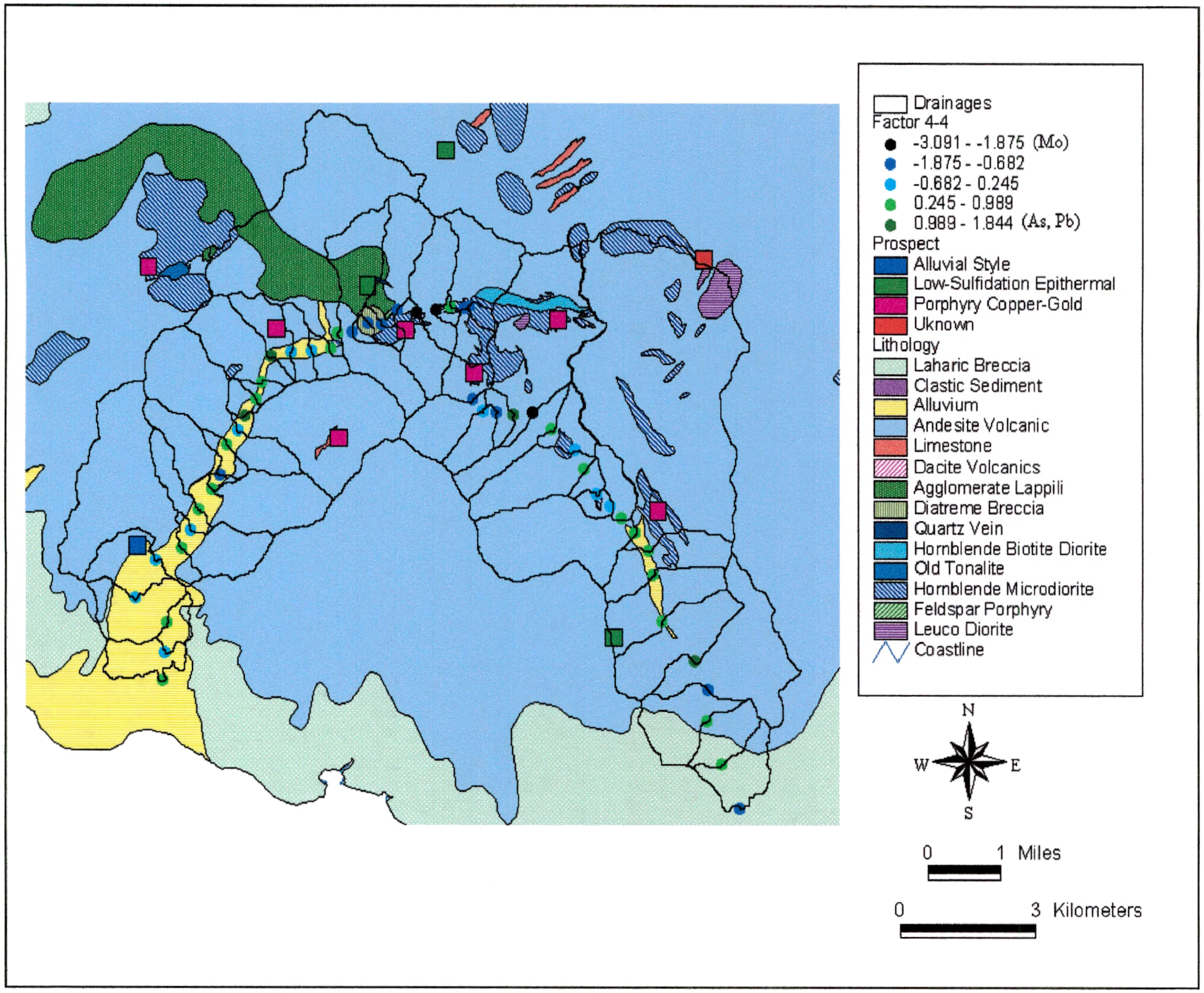

Figure 5.10 Factor four of the four factor model [As, Pb, -Mo] versus lithology for the orientation survey.

Table 5.3 Correlation matrix for geochemical data, not including Mo data, for the reconnaissance survey. Correlations with values greater than 0.20 for n=255 are statistically significant at the 95% confidence level. Statistically significant correlations are in bold.

Element	Au	Cu	Pb	Zn	As	Sb
Au	1					
Cu	**0.32**	1				
Pb	0.07	**0.24**	1			
Zn	-0.03	-0.04	0.19	1		
As	0.17	0.14	**0.29**	**0.21**	1	
Sb	-0.01	-0.14	-0.09	-0.13	-0.15	1

Table 5.4 Communalities table for geochemical data from the reconnaissance survey.

	Factor Model					
Element	1	2	3	4	5	6
Au	0.21	0.59	0.60	0.87	0.88	1.00
Cu	0.35	0.63	0.65	0.72	0.80	1.00
Pb	0.42	0.45	0.55	0.86	0.86	1.00
Zn	0.14	0.58	0.61	0.71	0.99	1.00
As	0.45	0.49	0.53	0.58	0.94	1.00
Sb	0.16	0.22	0.96	0.96	0.97	1.00
Eigenvalues (in %)	29.0%	49.0%	65.0%	78.6%	90.6%	100.0%

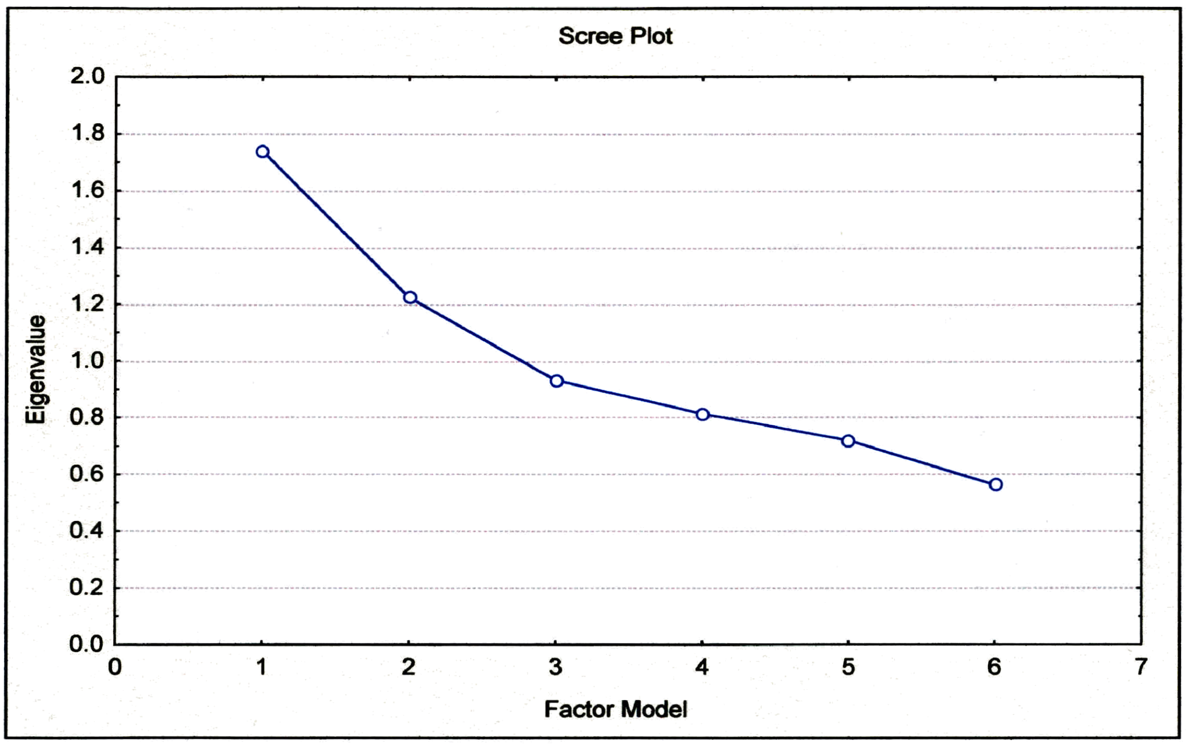

Figure 5.11 Scree plot for the reconnaissance survey data showing eigenvalue versus corresponding factor model.

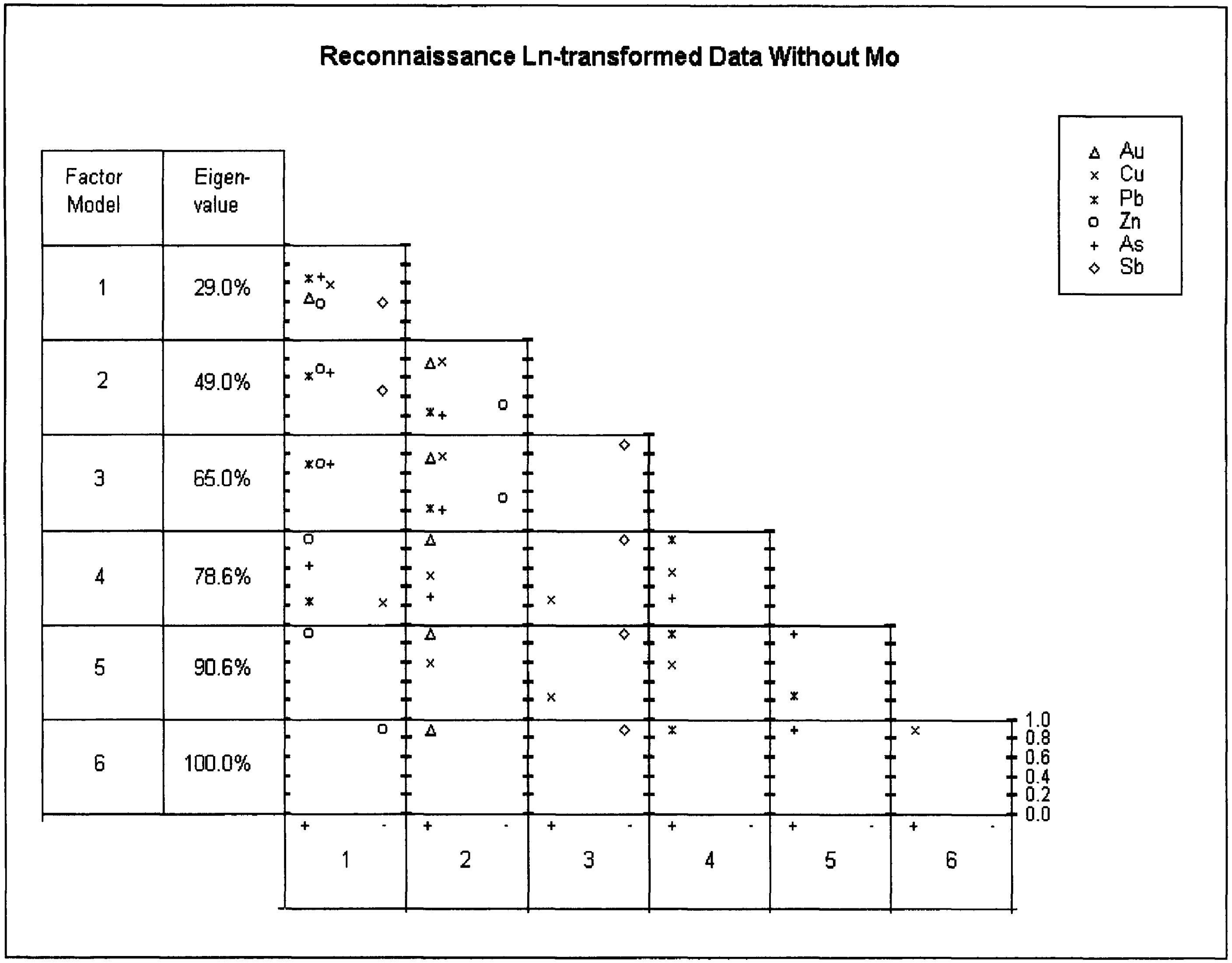

Figure 5.12 Plot of factor loadings for factor models for the reconnaissance survey. Only factor loadings greater than 0.20 are plotted to make the plot easier to read. . The "+" and "-" symbols along the in the boxes in the bottom row indicate positive and negative factor loadings, respectively.

5.12. Thus elements, within the same factor, with opposite signs are inversely associated. From Figure 5.12 the fourth factor model is selected, as opposed to the fifth, because it has more potentially useful element associations. The fifth factor model starts to break down into single and double element factors, which may be related to mineralization; however, the third or fourth element in an association can provide, in many cases, just a little more information. Element associations for the fourth factor model are: factor one, Pb, Zn and As with inverse relationship with Cu; factor two, Au, Cu and As; factor three, Cu and inverse Sb; and factor four, Pb, Cu, As for the four factors in the four factor model. The Au, Cu, As is most probably related to mineralization as these elements are indicator and pathfinder elements (Rose et al., 1979) for porphyry copper-gold and low-sulfidation epithermal gold mineralization. Zinc, As, Pb, and Cu could be related to mineralization; however, this association might also be related to the predominance of andesite volcanic rocks within drainages. Antimony and Cu are probably related to the mobility of Pb, Cu, and As. Appendix A contains a discussion of mobility and environmental geochemistry that effects the placement of elements in the surficial geochemical environment.

Figure 5.13 is a plot of the factor scores for factor one of the four factor model. Factor one has large positive values for elevated As, Pb, and Zn and large negative values representing elevated Cu [As, Pb, Zn, -Cu]. Factor one does not appear to be significantly related to mineralization. Figure 5.14 is a plot of the factor scores for factor one of the four factor model versus lithology. Factor one does not appear to be

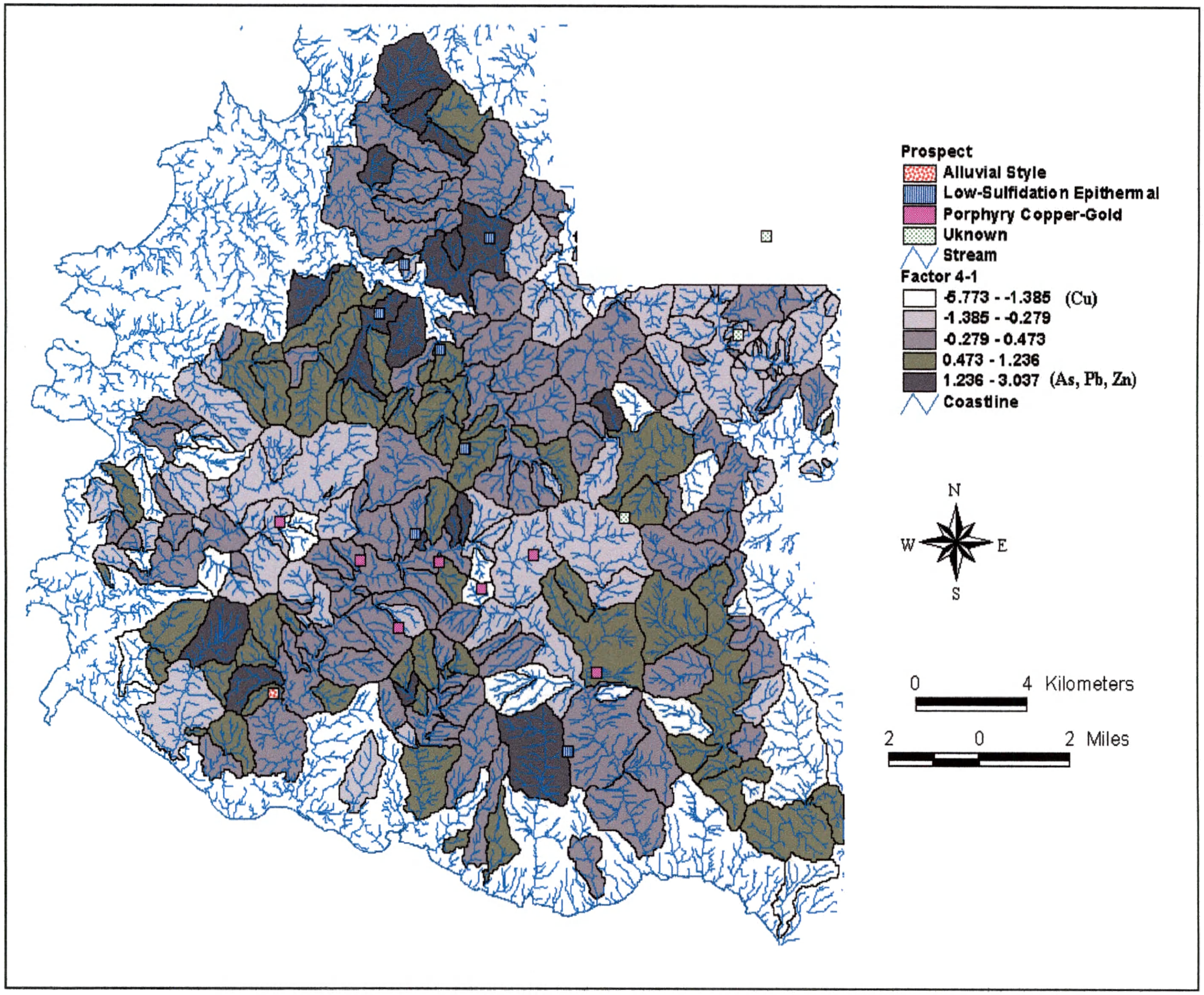

Figure 5.13 Factor one of the four factor model [As, Pb, Zn, -Cu] by drainage for the reconnaissance survey.

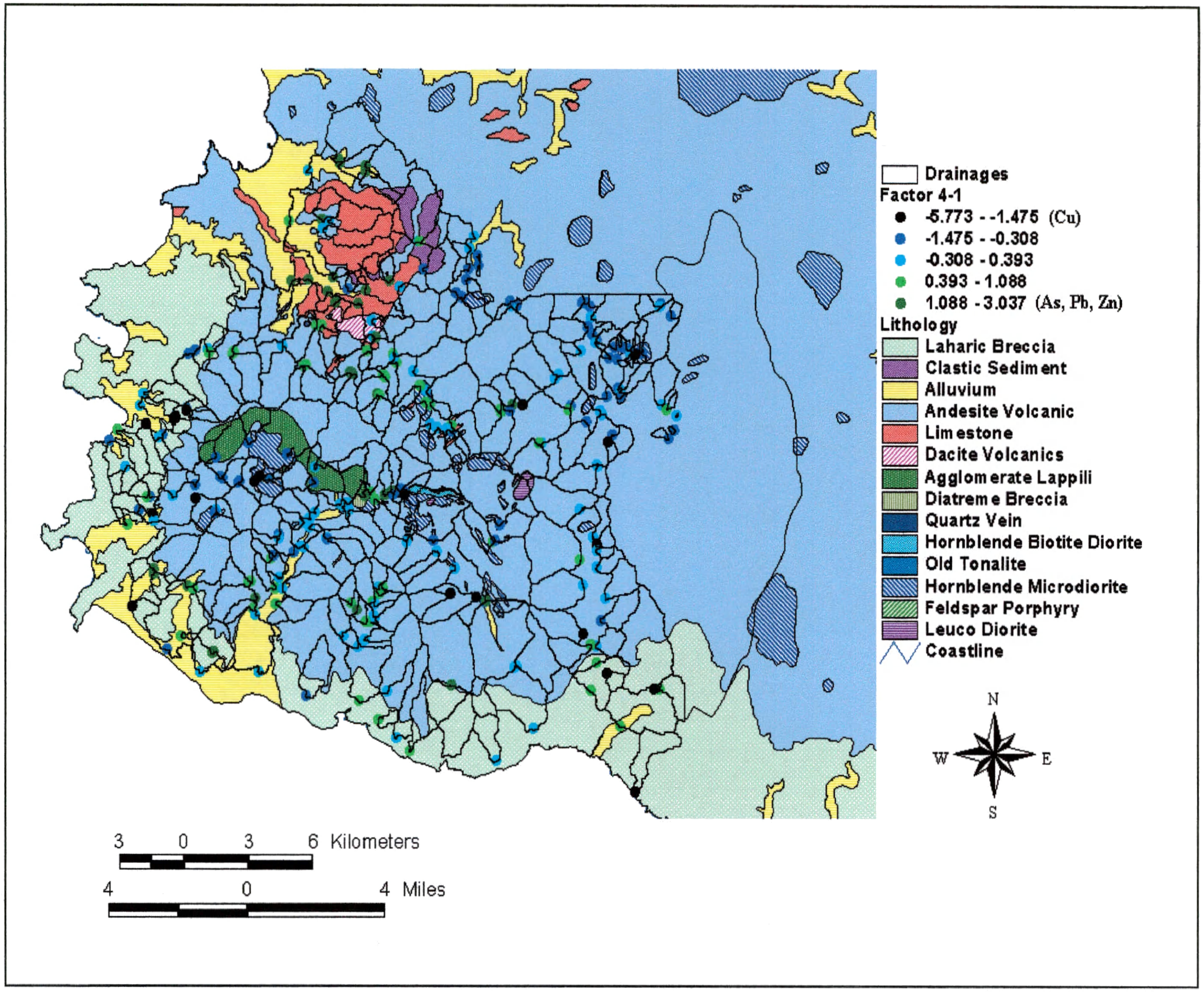

Figure 5.14 Factor one of the four factor model [As, Pb, Zn, -Cu] versus lithology for the reconnaissance survey.

significantly related to lithology, although high positive values occur in drainages with only andesite volcanic rocks or with limestone. High positive values also occur downstream, near the coastal regions, suggesting that perhaps it might be more closely related to element mobility rather than mineralization.

Figure 5.15 is a plot of the factor scores for factor two [As, Au, Cu] of the four factor model by drainage. Factor two appears to correlate well with mineralization as high positive scores correspond to known porphyry copper-gold deposits. Moderate to low scores correspond with low-sulfidation epithermal deposits. Figure 5.16 is a plot of the factor scores for factor two versus lithology. Factor two is not related to lithology as large negative (low) scores are found throughout despite changes in underlying lithology.

Figure 5.17 is a plot of the factor scores for factor three [Cu, -Sb] of the four factor model by drainage. Factor three does not appear to be directly related to mineralization although low scores typically occur in drainages just below porphyry copper-gold and low-sulfidation epithermal gold deposits. Figure 5.18 is a plot of the factor scores for factor three versus lithology. Factor three might be related to mobility since elevated Cu (large positive scores) occurs near the upper areas of drainages and elevated Sb (large negative scores) typically occur near the mouths of the drainages. This follows the mobility of Cu and Sb, as Sb tends to be dispersed further downstream than Cu (see Appendix A and B for discussion on element mobility).

Figure 5.19 is a plot of the factor scores for factor four [As, Cu, Pb] of the four factor model by drainage. Factor four appears to be related to mineralization, as drainages with

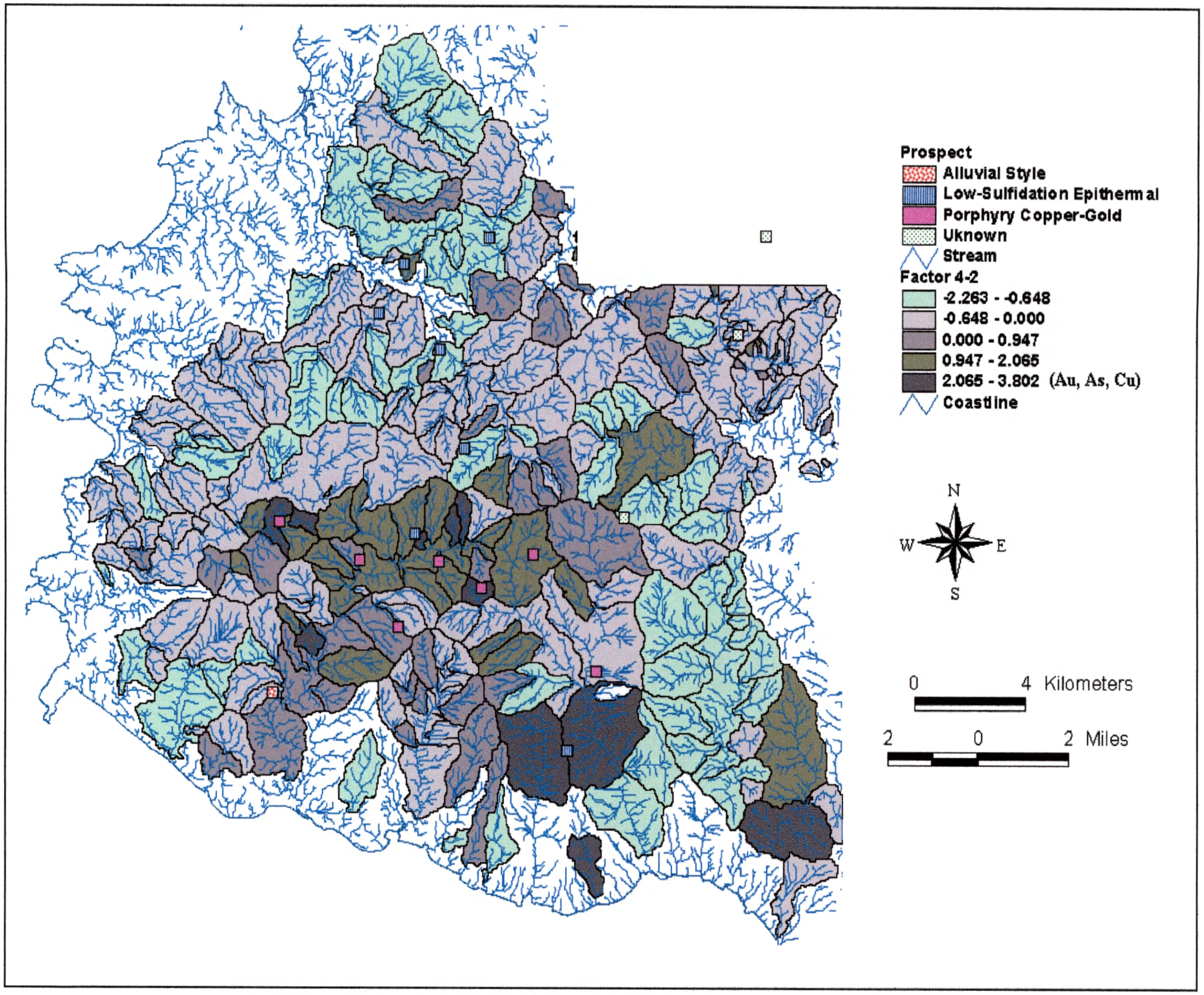

Figure 5.15 Factor two of the four factor model [Au, As, Cu] by drainage for the reconnaissance survey.

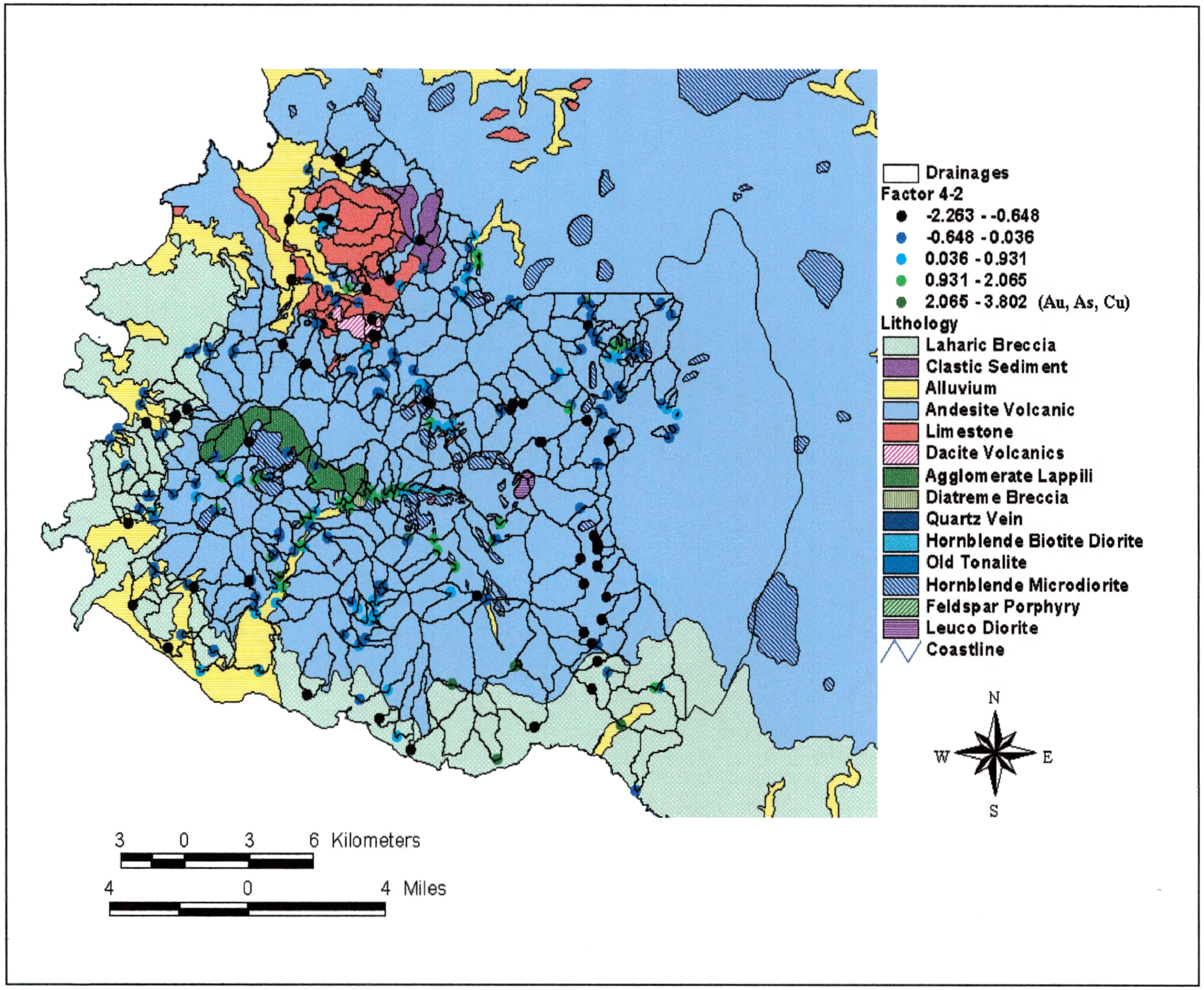

Figure 5.16 Factor two of the four factor model [Au, As, Cu] versus lithology for the reconnaissance survey.

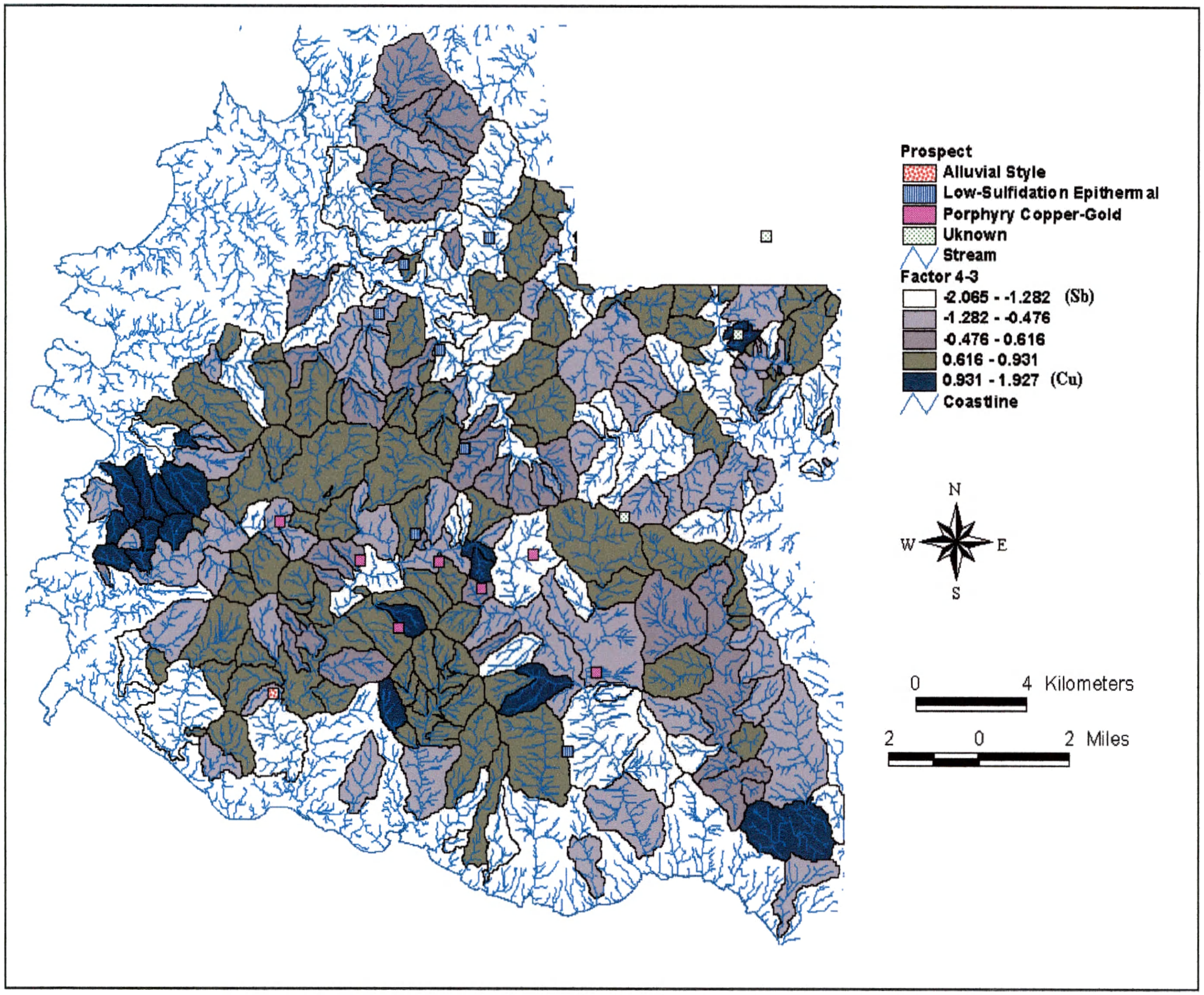

Figure 5.17 Factor three of the four factor model [Cu, -Sb] by drainage for the reconnaissance survey.

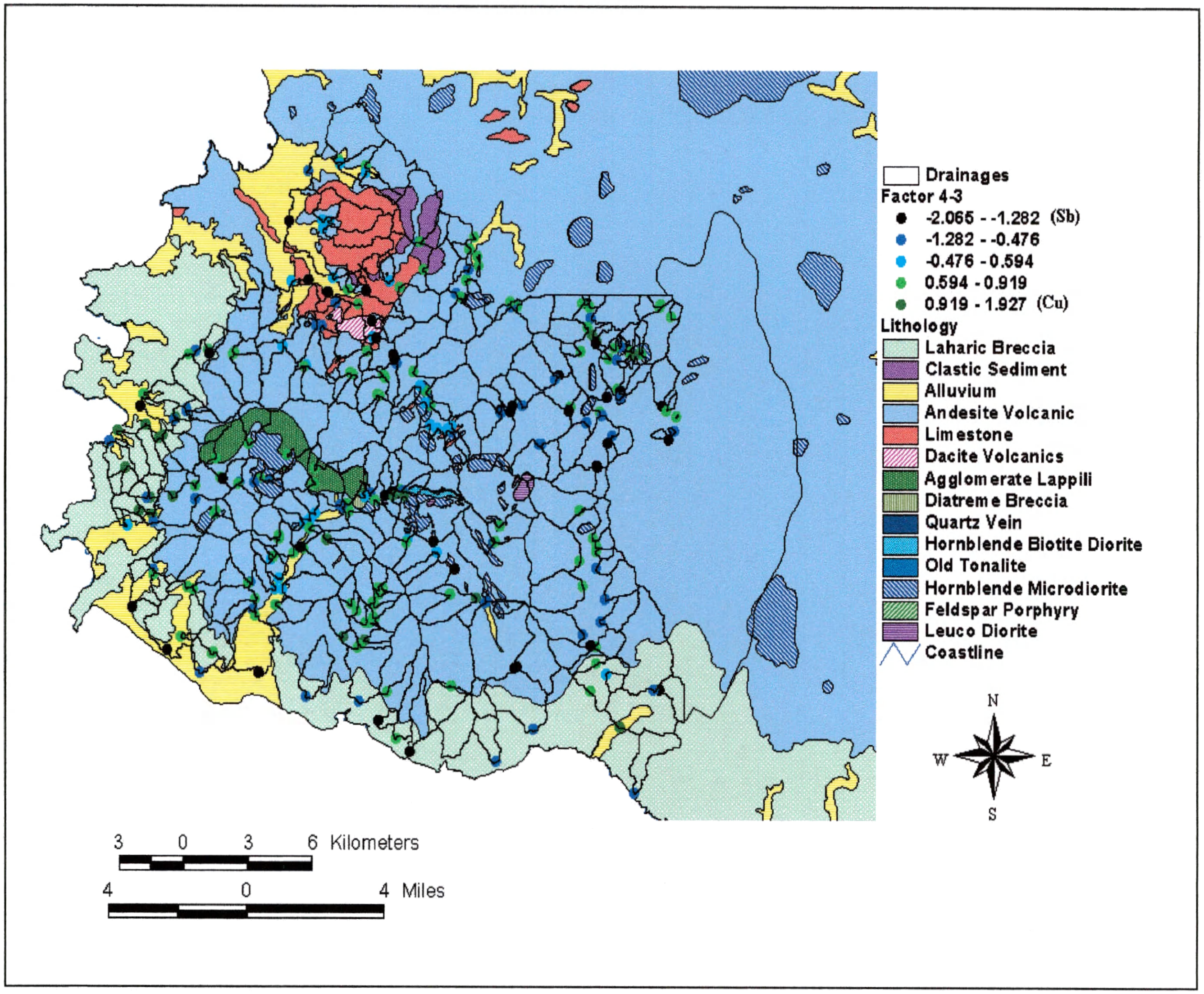

Figure 5.18 Factor three of the four factor model [Cu, -Sb] versus lithology for the reconnaissance survey.

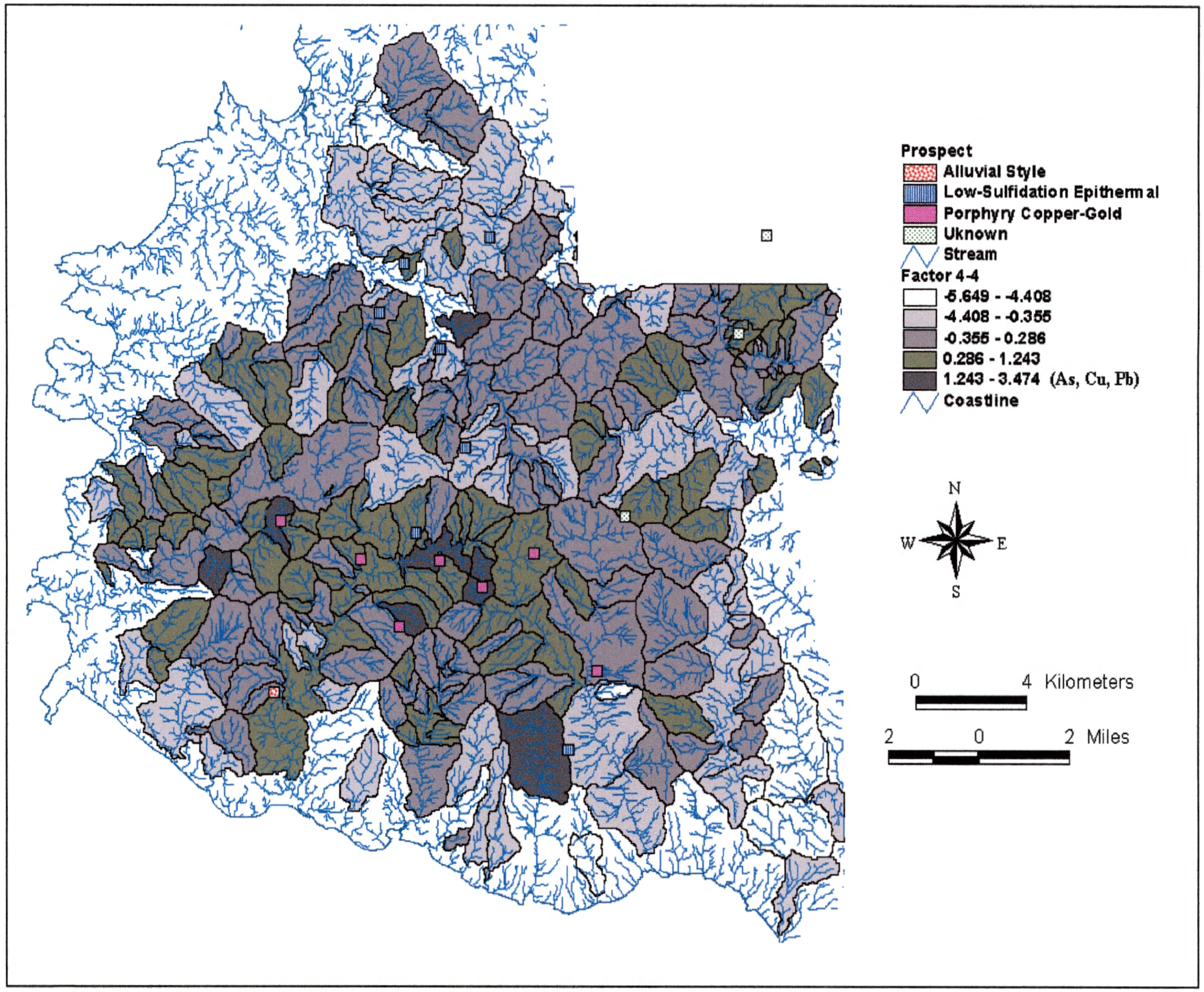

Figure 5.19 Factor four of the four factor model [As, Cu, Pb] by drainage for the reconnaissance survey.

moderate to high positive scores typically occur near porphyry copper-gold deposits. Figure 5.20 is a plot of the factor scores for factor four versus lithology. Factor four does not appear to be related to lithology. An extensive outcrop of limestone in the northern portion of the study area, however, may buffer the stream chemistry and alter the signature that is seen in the south-central portion of the study area near the Batu Hijau deposit.

5.5 Discussion

Factor analysis for both the orientation and reconnaissance surveys was able to locate drainages for further investigation, i.e. potentially mineralized, with adequate reliability. Factor one [As, Zn, -Cu, -Mo] and two [Au, Mo, Zn] of the four factor model for the orientation survey represent mineralization. Factor two [Au, As, Cu] and four [As, Cu, Pb] of the four factor model for the reconnaissance survey represent mineralization.

Factor four [As, Pb, -Mo] of the orientation survey and factors one [As, Pb, Zn, -Cu] and three [Cu, -Sb] of the reconnaissance survey are interpreted to represent surficial geochemical processes in the environment. Factor three of the reconnaissance survey represents the mobility of Cu and Sb in the environment. A specific aspect of the surficial environment, like mobility or adsorption, is not easily identifiable based upon the associations for factor one of the reconnaissance survey and factor four of the orientation survey. Factor three [Sb] of the orientation survey is probably related to lithology.

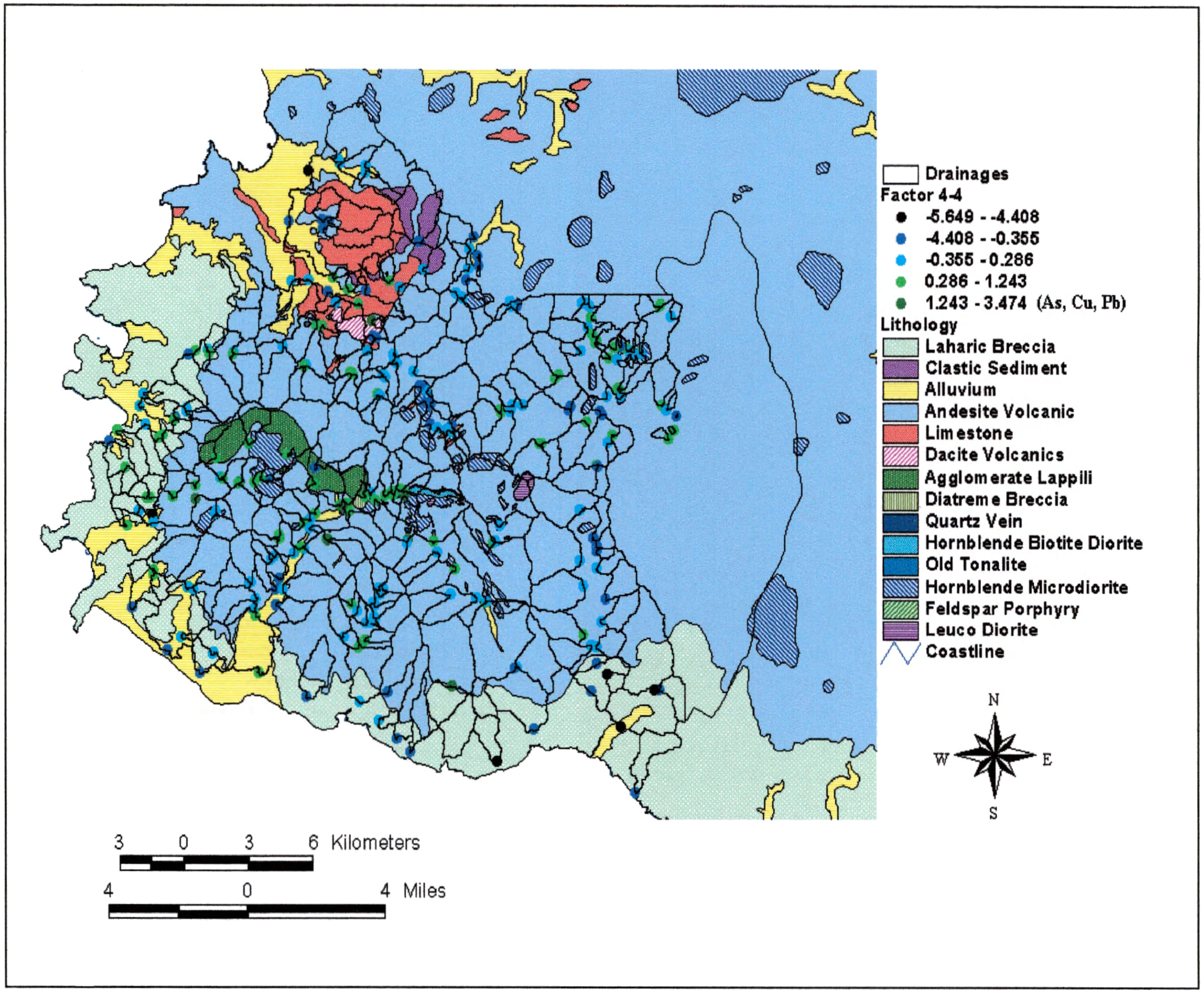

Figure 5.20 Factor four of the four factor model [As, Cu, Pb] versus lithology for the reconnaissance survey.

5.6 Assessment of Technique

The reliability of interpreting factor analysis results hinges upon the interpreter's experience with the problem at hand. The more experienced, the easier and faster the interpretation. The interpretations presented in sections 5.3 and 5.4 are reliable. The reliability of the factors corresponding to surficial geochemical processes would have been dramatically improved if data for Fe and Mn were available. Iron and Mn are elements that can effect the placement of other elements, such as Cu, in the geochemical environment by taking Cu out of solution by adsorption onto Fe- and Mn-particles (Smith and Huyck, 1999). Furthermore, examining the lithologies present and the common minerals in them, such as biotite and plagioclase, along with the occurrence of sulfide minerals in porphyry copper-gold and low-sulfidation epithermal deposits, it might have been helpful to also have data for K, Ca, Na, and S. As the analytical instrument technology advances, making the extra determinations for such elements would only increase the cost of analysis a small amount, but would increase the reliability of the interpretation of the factors immensely as factors related to lithology and geological processes would be easier to identify.

Factor analysis is a technique that is easy to use, especially when utilizing the Statistica factor analysis module. Factor analysis does not require a lot of data pretreatment, and interpretation of the output is fairly straightforward. Training with Statistica and also determining how to display and interpret the results of the analysis took about a day. Once the method is understood, factor analysis results were obtained in

45 minutes of entering the data into Statistica. Mapping the factor analysis results in ArcView took about 3 hours. Interpretation time, which varies with interpreter, depending on experience with the problem and the factor analysis method, took roughly three hours.

Factor analysis is a cost-effective method which does not require a lot of training time to get reliable results. Once a person is trained in using factor analysis, the bulk of cost and time will typically occur during the interpretation and presentation of the results.

CHAPTER 6

DISCRIMINANT ANALYSIS

6.1 Introduction

Discriminant analysis is a classification method that requires *a priori* knowledge to create a function which can be used to then classify unknown samples (Davis, 1986). The strategy behind discriminant analysis is to find the linear relationship between two normally distributed populations that allows for the discrimination between the two populations which might otherwise be indiscernible. Figure 6.1 is a schematic depiction of the relationship and objective of discriminant analysis. A key benefit of discriminant analysis with respect to mineral exploration is the ability, once a function has been obtained, to classify unknown samples as either mineralized or non-mineralized. This method is also statistical and can be tested for statistical significance.

6.2 General Methodology

Discriminant analysis requires a representative set of known samples (i.e. training set) from each population or group in order to create a discriminant function (Rose et al., 1979; Howarth and Sinding-Larsen, 1983). Discriminant functions can be established to discriminate between more than two populations. Once the training set has been selected the data are partitioned into the various groups of deposit types, porphyry copper-gold,

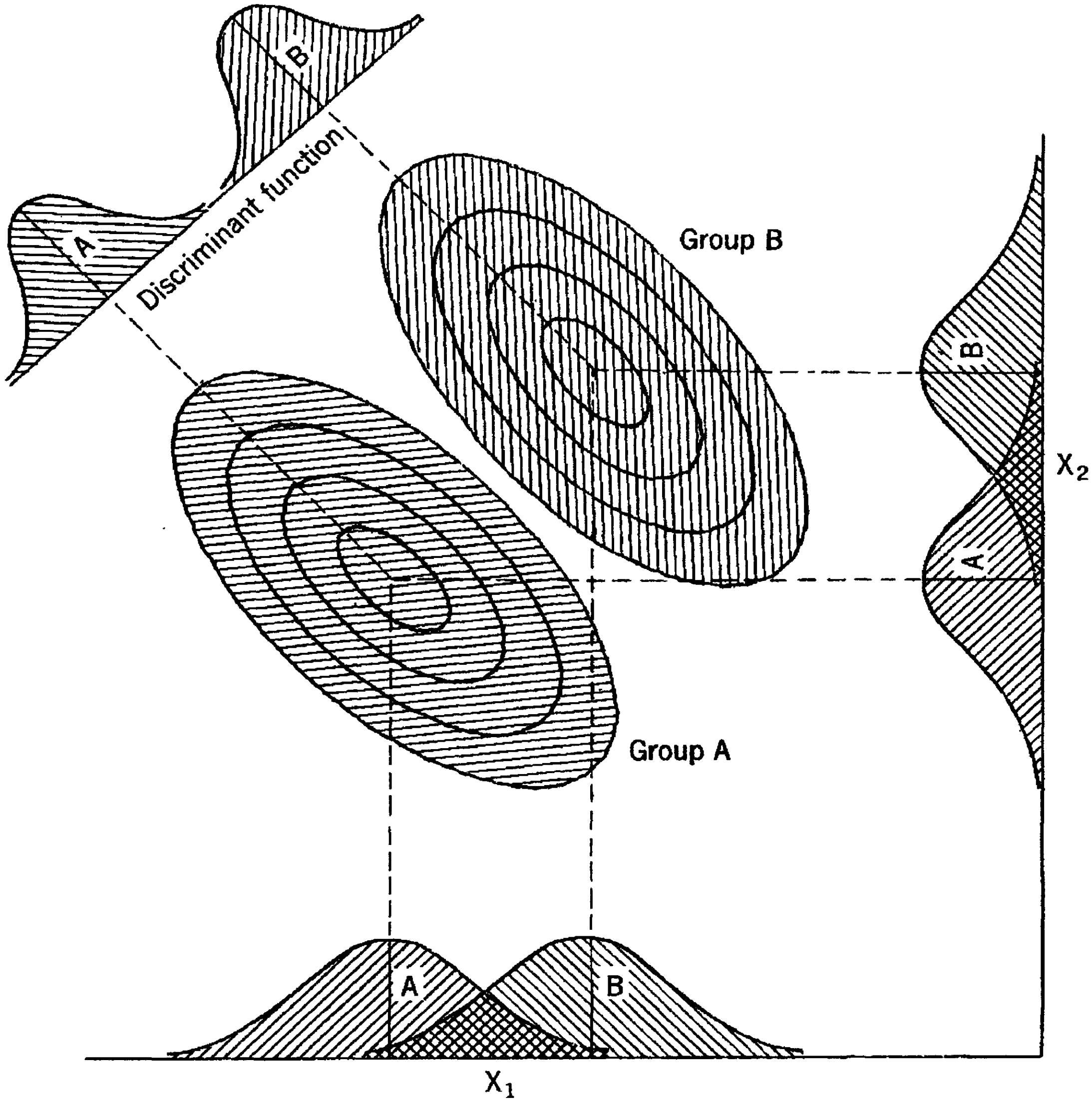

Figure 6.1 Schematic depiction of discriminant analysis. X_1 and X_2 are variables that are common to groups A and B. When X_1 and X_2 are taken together these two variables result in an adequate separation between two groups so that classification of unknown samples can be made. (Davis, 1986)

low-sulfidation epithermal gold, and alluvial style deposits, along with nonmineralized or "barren" drainage basins. This partitioning is based upon the location of known deposits to respective drainage basins. It is critical that the parent populations or groups have sufficiently different means to provide a worthwhile discrimination. This can be tested with the *t*-test such that if the means are not sufficiently different the discrimination will not work (Swan and Sandilands, 1995).

The discriminant function takes the generic form of:

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad \text{(eq. 7.1)}$$

where β_i are the coefficients for X_i independent variables where *i* ranges from 1 to n (Rose et al., 1979). Once the equation has been generated to maximize the separation between the groups, the discriminant scores will be plotted geographically to evaluate the classification spatially with respect to the location of known mineralization.

Some assumptions are required for this method to work. The first assumption is that the covariance matrices are equal (Swan and Sandilands, 1995). Overall these matrices were not equal, and thus the analysis may be slightly more affected by nonnormal distributions. Although the tests of such functions is "not badly affected by unequal covariance matrices" (Swan and Sandilands, 1995, page 360).

The second assumption is that the data come from multivariate normal or near normal distributions (Davis, 1986; Clark et al, 1989; Swan and Sandilands, 1995). Natural log (ln) -transformed As, Au, Cu, Pb, and Zn and stream order data for the reconnaissance surveys were normally distributed, while ln-transformed data for Au, Pb, and Zn for the porphyry copper-gold group in the orientation survey are normal. All other variables for each class for each survey were positively skewed. Swan and Sandilands (1995) noted that if the distributions are significantly nonnormal, the discriminant function may produce spurious results.

The third assumption is that the data are not closed, i.e. does not sum to a constant value (Clark et al, 1989; Swan and Sandilands, 1995). The aerial extents of the lithological data were used in place of percentages which sum to 100, to meet the third assumption.

To use either the forward stepwise or backward stepwise discriminant analysis module in Statistica, the program must calculate a measure of how much a variable contributes to the discrimination between the classes. The application of this calculation results in either the addition (forward stepwise) or the removal (backward stepwise) of variables. Unfortunately, if the training sets fail to meet the three assumptions above such tests will be less reliable (Swan and Sandilands, 1995). If this is the case, the results of *t*-tests and geologic knowledge of the problem at hand will be used to select potential variables for the standard discriminant function.

Statistica also requires that the user set the *a priori* possibilities, the probability that a sample will be in a given group based upon the training data. The *a priori* possibilities were set proportionate to the number of training samples in each class for each group.

Once the final combination of variables is selected (see sections 6.2.1 and 6.2.2 for survey specific discussions of how the variables were selected), the discriminant function is computed for each n-1 classes, e.g. B versus M would have one function. The discriminant scores are calculated and plotted on a simple line graph. For the groups that contain four classes, both a line graph and x-y plot are used to evaluate the discriminant scores and determine group separation. The classification of samples is done by visual examination of the line plots, such that samples which plot within an area defined by a given class, e.g. barren, are classified in that class. Finally, the discriminant function or group of functions which produced the best separation and classification results for the classes used is selected and plotted spatially using ArcView software.

6.2.1 Orientation Survey Training Set

The orientation survey contains 49 sample points, 26 of which have mineralization either in the drainage or within two drainages above the sample point. The training set was established by selecting all drainages which contained alluvial style gold occurrences (two), low-sulfidation epithermal (three), and porphyry copper-gold (ten) either in the drainage or within two drainages upstream of the sample point. Random selection of six of the remaining drainages which did not contain known mineralization within three drainages upstream from the sample point were used for the barren class. This resulted in 21 samples sites for training. A second training set of barren versus mineralized (grouping porphyry copper-gold, low-sulfidation epithermal, and alluvial style occurrences together) was also tested.

The F- and *t*-tests for the comparison of elements by class for each group are presented in Table 6.1. From Table 6.1, the training set for the barren versus mineralized drainages (group 2) will probably not result in a reliable discriminant function, as the two groups do not contain any variables that have statistically different means. Likewise, comparisons between the barren (B) versus low-sulfidation epithermal (L), and barren (B) versus porphyry copper-gold (P) also did not contain any statistically different means, while the comparison between L and P groups contained only four variables with statistically different means. Even though the alluvial style gold occurrences (A) class only contains two points, it appears that comparisons of the B, L, and P groups against this class have a better chance of producing a relatively reliable discriminant function.

6.2.2 Reconnaissance Survey Training Set

The training set for the reconnaissance survey was set up by selecting all of the drainages with known porphyry copper-gold, low-sulfidation epithermal gold, and alluvial style gold occurrences present, or in the immediately preceding drainage. Seventy drainages representing "barren" drainages were randomly selected from the 220 potentially barren drainages, those without any known mineral occurrences within three preceding drainages upstream of the selected drainage. A total of 98 samples were used for the training set, representing roughly 38% of the data.

Table 6.1 List of variables with statistically different means and variances from *t*- and F-tests, respectively, for combinations of the different classes within the two groups for the orientation survey training data. See Figure 2.2 for spatial distribution of lithologic units listed here.

***t*-test**	**F-test**
Group 1	
Class Alluvial Style versus Low-Sulfidation Epithermal	
Cu Agglomerate Lapilli, Alluvium, Limestone	Agglomerate Lapilli, Andesite Volcanic Rocks, Diatreme Breccia, Feldspar Porphyry, Hornblende Biotite Diorite, Hornblende Microdiorite, and Quartz Veins
Class Alluvial Style versus Porphyry Copper-Gold	
As Agglomerate Lapilli, Alluvium, Andesite Volcanic Rocks, Diatreme Breccia, Feldspar Porphyry, Laharic Breccia, Limestone, and Quartz Veins	Agglomerate Lapilli, Andesite Volcanic Rocks, Diatreme Breccia, Feldspar Porphyry, Hornblende Biotite Diorite, Hornblende Microdiorite, Limestone, and Quartz Veins
Class Alluvial Style versus Barren	
Agglomerate Lapilli, Andesite Volcanic Rocks, Limestone, and Quartz Veins	Agglomerate Lapilli, Andesite Volcanic Rocks, Diatreme Breccia, Feldspar Porphyry, Hornblende Biotite Diorite, Hornblende Microdiorite, Limestone, and Quartz Veins
Class Low-Sulfidation Epithermal versus Porphyry Copper-Gold	
Cu Hornblende Microdiorite, and Leuco Diorite	Stream Order, Cu
Class Low-Sulfidation Epithermal versus Barren	
(none)	Alluvium, Hornblende Microdiorite, and Leuco Diorite
Class Porphyry Copper-Gold versus Barren	
(none)	Stream Order Alluvium, Hornblende Microdiorite, and Leuco Diorite
Group 2	
Class Barren versus Mineralized	
(none)	Stream Order, Hornblende microdiorite, Laharic Breccia, and Leuco Diorite

Two groups of classes were selected, the first group contained the classes: porphyry copper-gold (P), low-sulfidation epithermal gold (L), alluvial style gold occurrences (A), and "barren" (B), where the P, L, and A classes all represent drainages which either contain the specific mineral occurrence or are immediately below drainages that do. Class A contains two data points, so the statistical significance of this class is nearly nonexistent compared with the other classes. The second group contained the classes: "barren" (B) and mineralized (M), where the mineral occurrence either occurs within the drainage or within the drainage immediately preceding it.

F- and *t*-tests were run on each group's classes to determine the parameters that might best discriminate between the each group's classes. The results of the F- and *t*-tests are provided in Table 6.2. Several variables have statistically different means for classes in both the first and second groups.

6.3 Orientation Results

The first of the three functions that were determined using the discriminant analysis module of Statistica correctly classifies 71% of the data. The second and the third can correctly classify 48 and 43% of the data, respectively. All three functions, however, failed the chi^2 significance test, meaning that all three functions fail to produce statistically significant discriminations. Table 6.3 provides the three discriminant functions and the statistics for the correct classification percentage. Figures 6.2, 6.3, and

Table 6.2 List of variables with statistically different means and variances from *t*- and F-tests, respectively, for combinations of the different classes within the two groups for the reconnaissance survey. See Figure 2.2 for spatial distribution of lithologic units listed here.

***t*-test**	**F-test**
Group 1	
Class Barren versus Low-Sulfidation Epithermal	
Stream order, As, Sb, Andesite Volcanic Rocks, Diatreme Breccia, Feldspar Porphyry, Hornblende Micro-Diorite, Leuco Diorite, and Quartz Veins	Stream order, Au, Cu, Agglomerate Lapilli, Alluvium, Andesite Volcanic Rocks, Clastic Sediment, Dacite Volcanic Rocks, Hornblende, Biotite Diorite, Hornblende Micro-Diorite, Laharic Breccia, Limestone, and Old Tonalite
Class Barren versus Alluvial Style*	
Sb, Diatreme Breccia, Feldspar Porphyry, Laharic Breccia, and Quartz Veins	Stream order, Agglomerate Lapilli, Alluvium, Andesite Volcanic Rocks, Hornblende Biotite Diorite, Hornblende Micro-Diorite, and Laharic Breccia
Class Barren versus Porphyry Copper-Gold	
Stream order, Au, Cu, Pb, Sb, Diatreme Breccia, Feldspar Porphyry, Hornblende Micro-Diorite, Leuco Diorite, and Quartz Veins	As, Cu, Pb, Agglomerate Lapilli, Andesite Volcanic Rocks, Hornblende Biotite Diorite, Hornblende Micro-Diorite, Limestone, and Old Tonalite
Class Low-Sulfidation Epithermal versus Alluvial Style*	
(none)	Agglomerate Lapilli, Alluvium, Diatreme Breccia, Feldspar Porphyry, and Quartz Veins
Class Low-Sulfidation Epithermal versus Porphyry Copper-Gold	
As, Cu	Pb, Agglomerate Lapilli, Alluvium, Diatreme Breccia, Feldspar Porphyry, Hornblende Micro-Diorite, Limestone, and Old Tonalite
Class Porphyry Copper-Gold versus Alluvial Style*	
Laharic Breccia	Alluvium, Andesite Volcanic Rocks, and Feldspar Porphyry
Group 2	
Class Barren versus Mineralized	
Stream order, Au, As, Sb, Agglomerate Lapilli, Andesite Volcanic Rocks, Diatreme Breccia, Feldspar Porphyry, Hornblende Biotite Diorite, Hornblende Micro-Diorite, Laharic Breccia, Leuco Diorite, Old Tonalite, and Quartz Veins	Stream order, As, Au, Cu, Pb, Dacite Volcanic Rocks, Laharic Breccia, Limestone, Old Tonalite

* Alluvial Style class has two data points

Table 6.3 Discriminant functions for the orientation survey data. The number of samples in each training class is provided immediately below the abbreviation for the class. The percent correctly classified samples are calculated by plotting the discriminant scores for each function from the training data on the line plots of Figures 6.2, 6.3, and 6.4.

Discriminant Functions	**Percent Correctly Classified for Each Class (%)**			
	A *2*	L *3*	B *6*	P *10*
Discriminant Function 1	*Total Correct: 71%*			
-2.87 + 0.64 lnCu + 0.66 Alluvium – 0.47 Andesite Volcanic Rocks + 86.19 Limestone + 2.03 Agglomerate Lapilli – 16.40 Diatreme Breccia + 155.29 Quartz Veins + 2.53 Hornblende Microdiorite + 13.44 Leuco Diorite	100	33	50	90
Discriminant Function 2	*Total Correct: 48%*			
-1.20 + 0.21 lnCu + 0.27 Alluvium – 0.01 Andesite Volcanic Rocks + 13.68 Limestone + 0.48 Agglomerate Lapilli – 3.37 Diatreme Breccia – 63.99 Quartz Veins + 0.84 Hornblende Microdorite – 7.93 Leuco Diorite	100	100	50	20
Discriminant Function 3	*Total Correct: 43%*			
3.48 – 0.61 lnCu +0.87 Alluvium – 0.019 Andesite Volcanic Rocks – 22.59 Limestone + 0.31 Agglomerate Lapilli + 11.70 Diatreme Breccia – 228.25 Quartz Veins + 2.91 Hornblende Microdiorite – 6.03 Leuco Diorite	50	33	100	10

A) alluvial style
L) low-sulfidation epithermal
B) barren
P) porphyry copper-gold

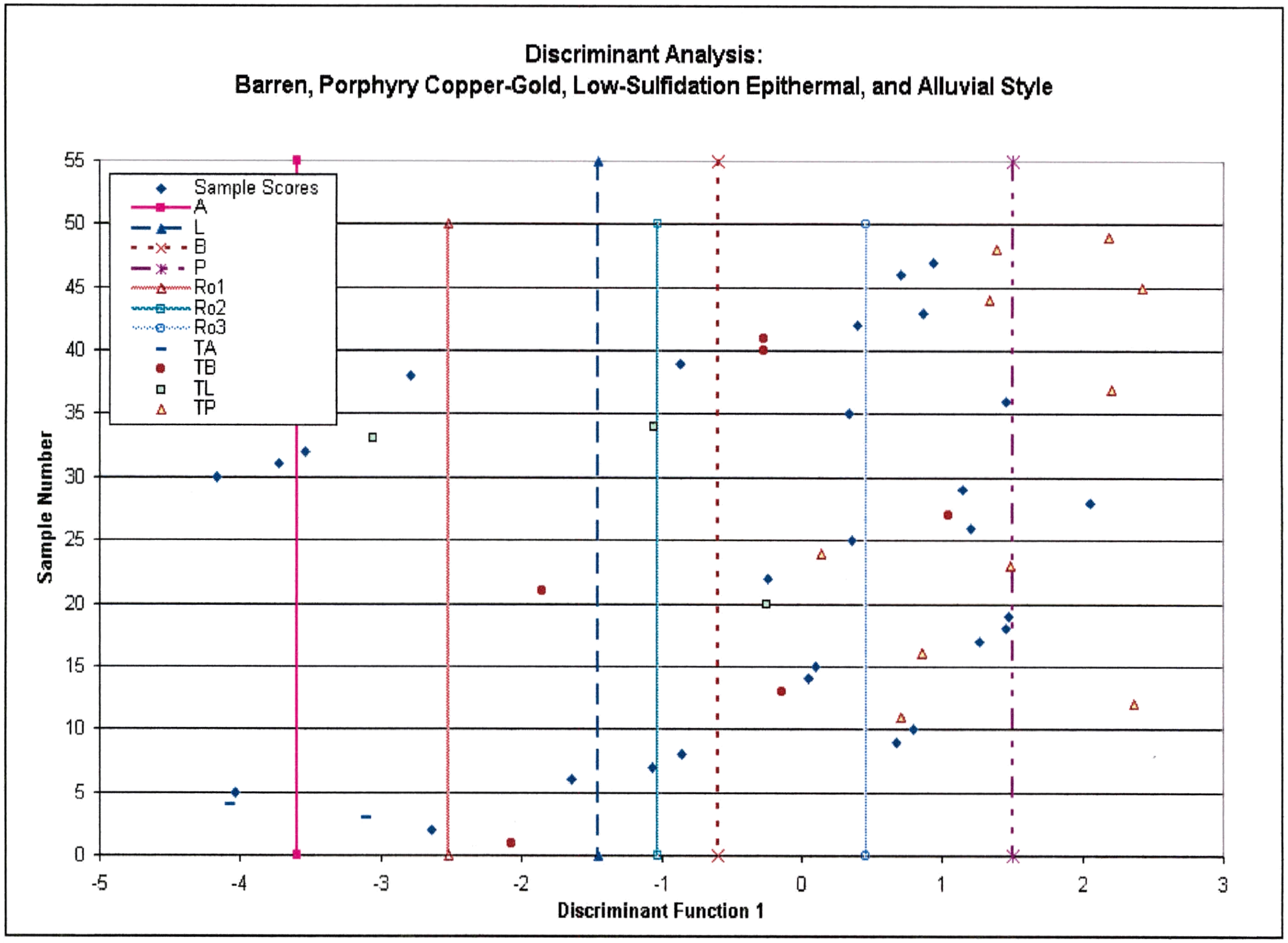

Figure 6.2 Line plot of the first discriminant function sample scores for unknown and training samples from the orientation survey. Ro1 is the median between groups A and L. Ro2 is the median between groups L and B. Ro3 is the median between groups B and P. TA, TB, TL, and TP represent the training data for classes A, B, L, and P, respectively.

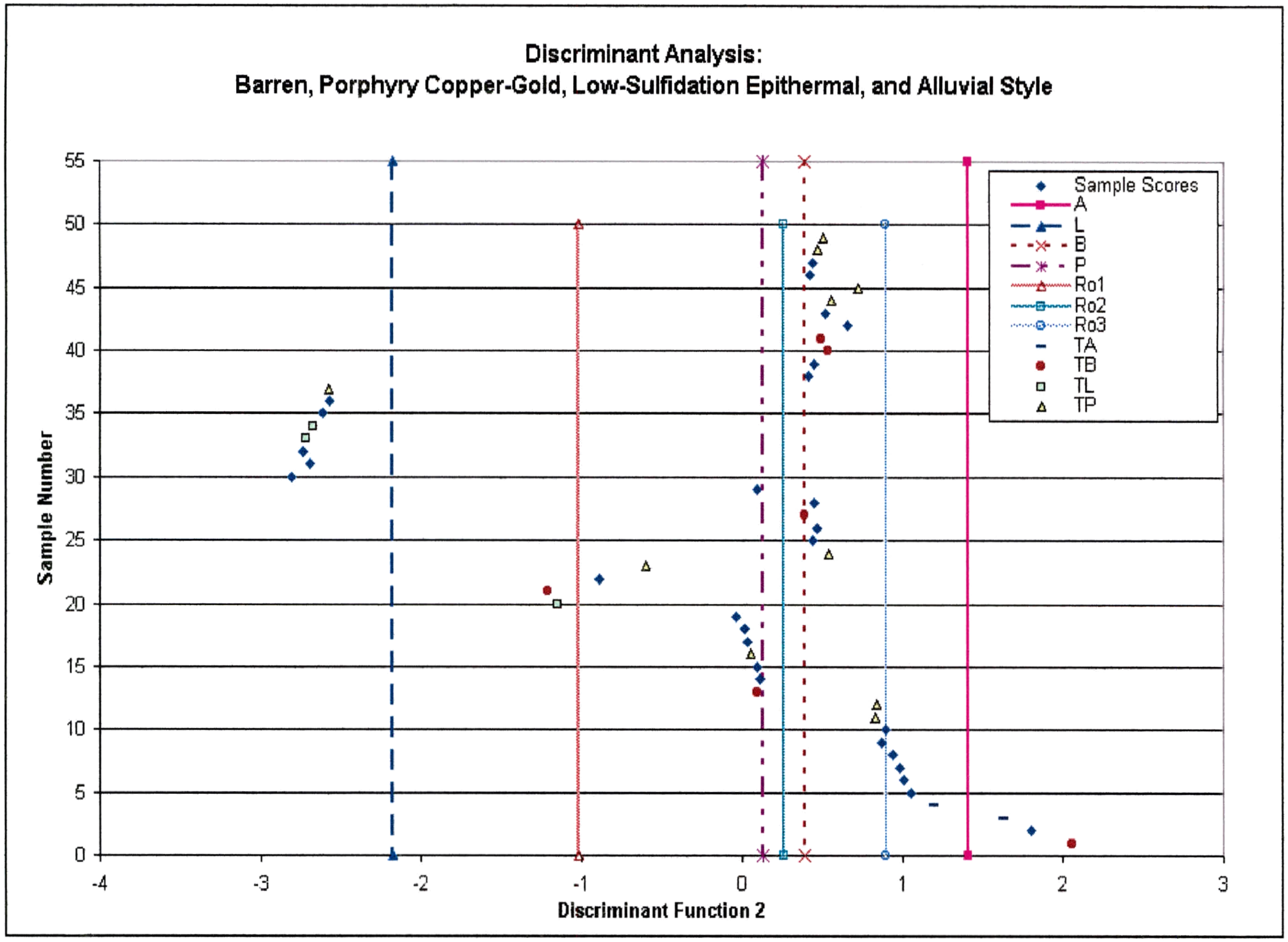

Figure 6.3 Line plot of the second discriminant function sample scores for unknown and training samples for the orientation survey. Ro1 is the median between groups L and P. Ro2 is the median between groups P and B. Ro3 is the median between groups B and A. TA, TB, TL, and TP represent the training data for classes A, B, L, and P, respectively.

6.4 are line plots of the results from the first, second, and third discriminant functions, respectively. Both unknown and training data are plotted to show the accuracy of the classification with each function. The first function (Figure 6.2) provides the best separation of the classes and also the most accurate overall correct classification. The second and third functions have a significant drop in overall correct classification. This is reflected in Figures 6.3 and 6.4 where at least two of the four classes contain similar means.

Figure 6.5 is a plot of the first discriminant function versus the second discriminant function. Figure 6.6 is a plot of the first discriminant function versus the third discriminant function. Figure 6.7 is a plot of the second discriminant function versus the third discriminant function. Plotting the results of one discriminant function against the other is another way of checking the quality of the classifications. If different classes separate into distinctly different regions of the graph, these regions could be used to classify the unknown samples. No distinct separation is visible between the four classes in any of the three plots.

Figures 6.8, 6.9, and 6.10 are the spatial distributions of the results from the first, second, and third discriminant functions, respectively plotted using ArcView software. From these figures it is clear that the classifications specific to each discriminant function are not consistent.

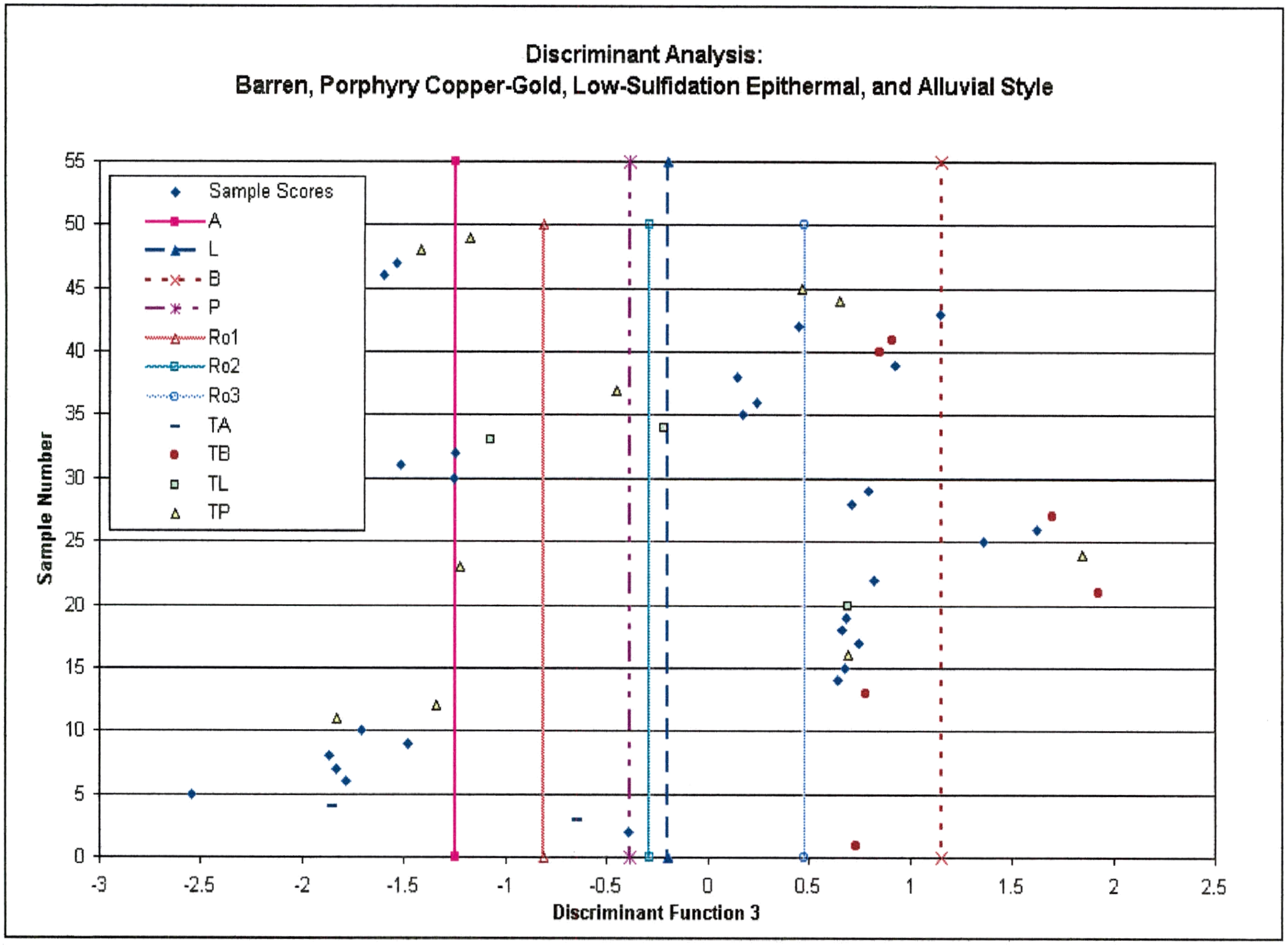

Figure 6.4 Line plot of the third discriminant function sample scores for unknown and training samples for the orientation survey. Ro1 is the median between groups A and P. Ro2 is the median between groups P and L. Ro3 is the median between groups L and B. TA, TB, TL, and TP represent the training data for classes A, B, L, and P, respectively.

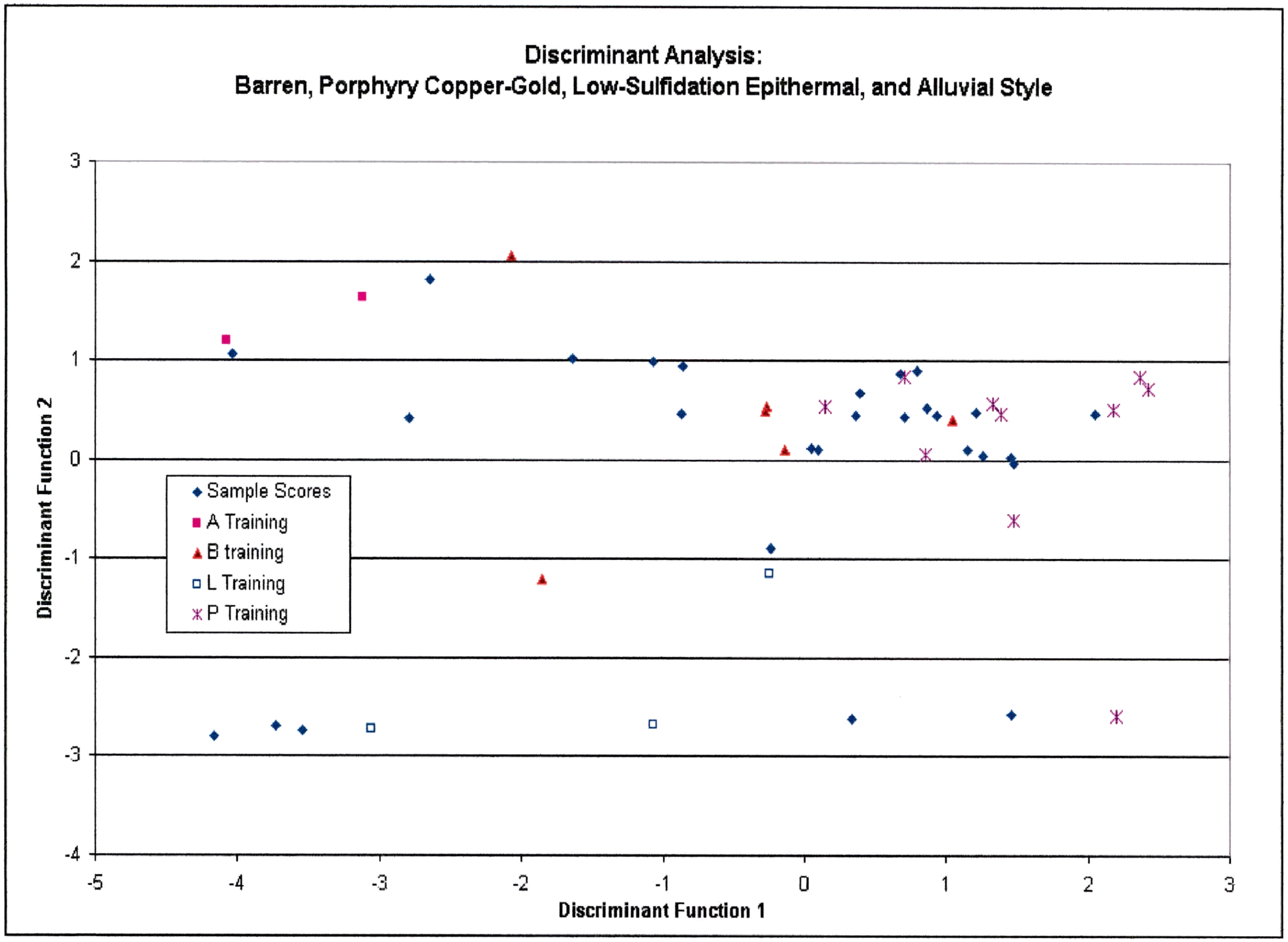

Figure 6.5 Plot of the first versus the second discriminant function for the orientation survey.

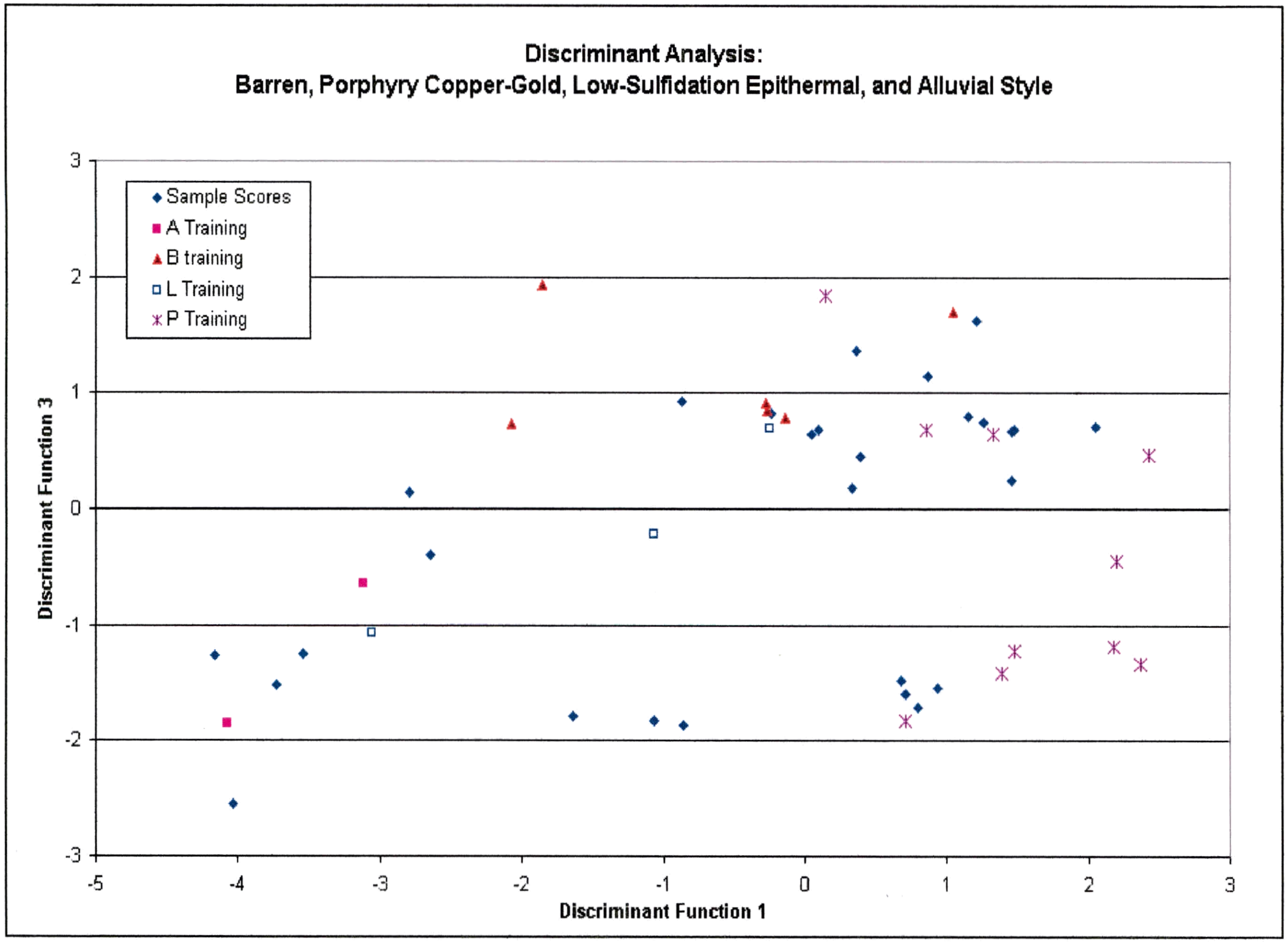

Figure 6.6 Plot of the first versus the third discriminant function for the orientation survey.

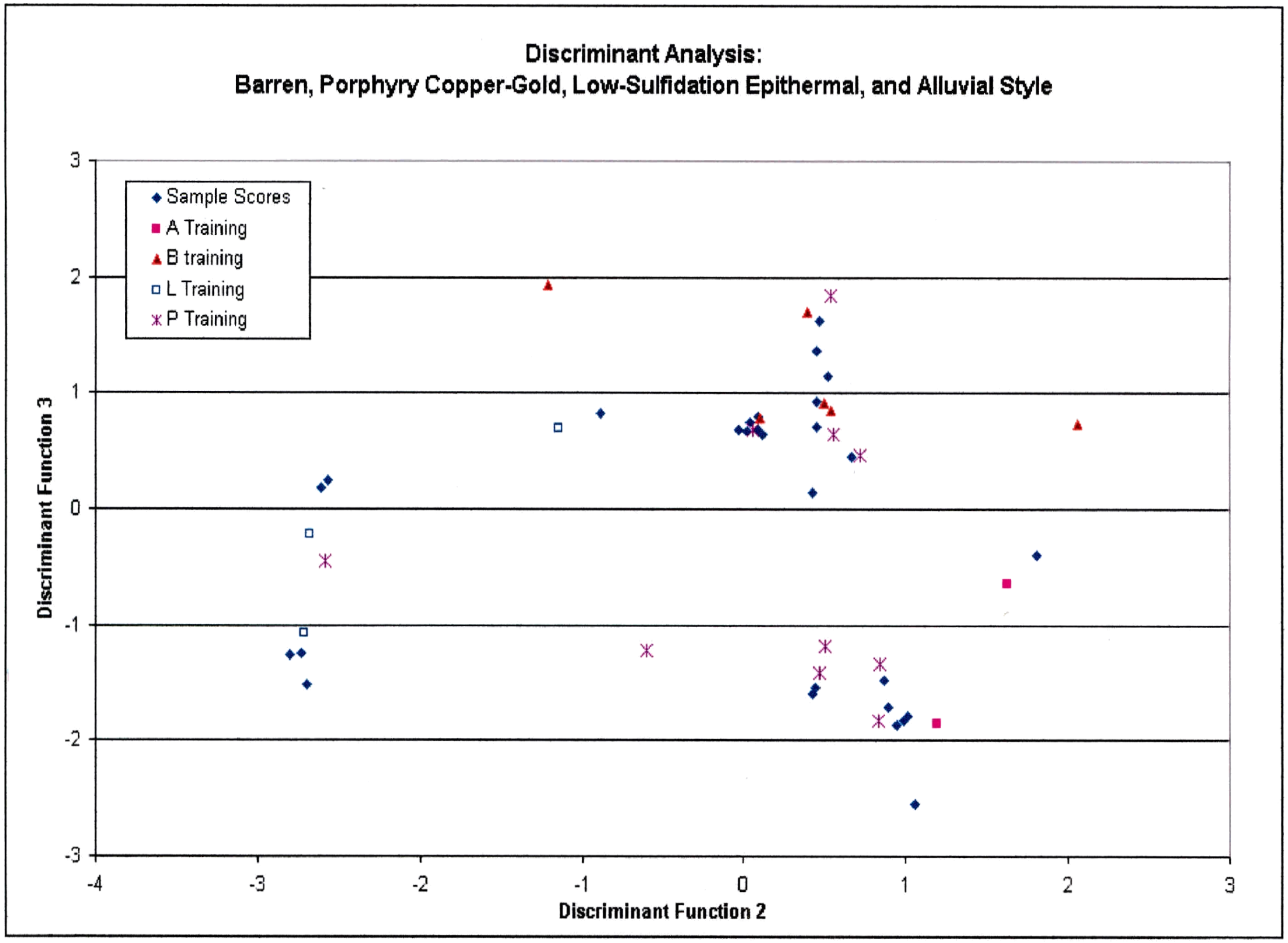

Figure 6.7 Plot of the second versus the third discriminant function for the orientation survey.

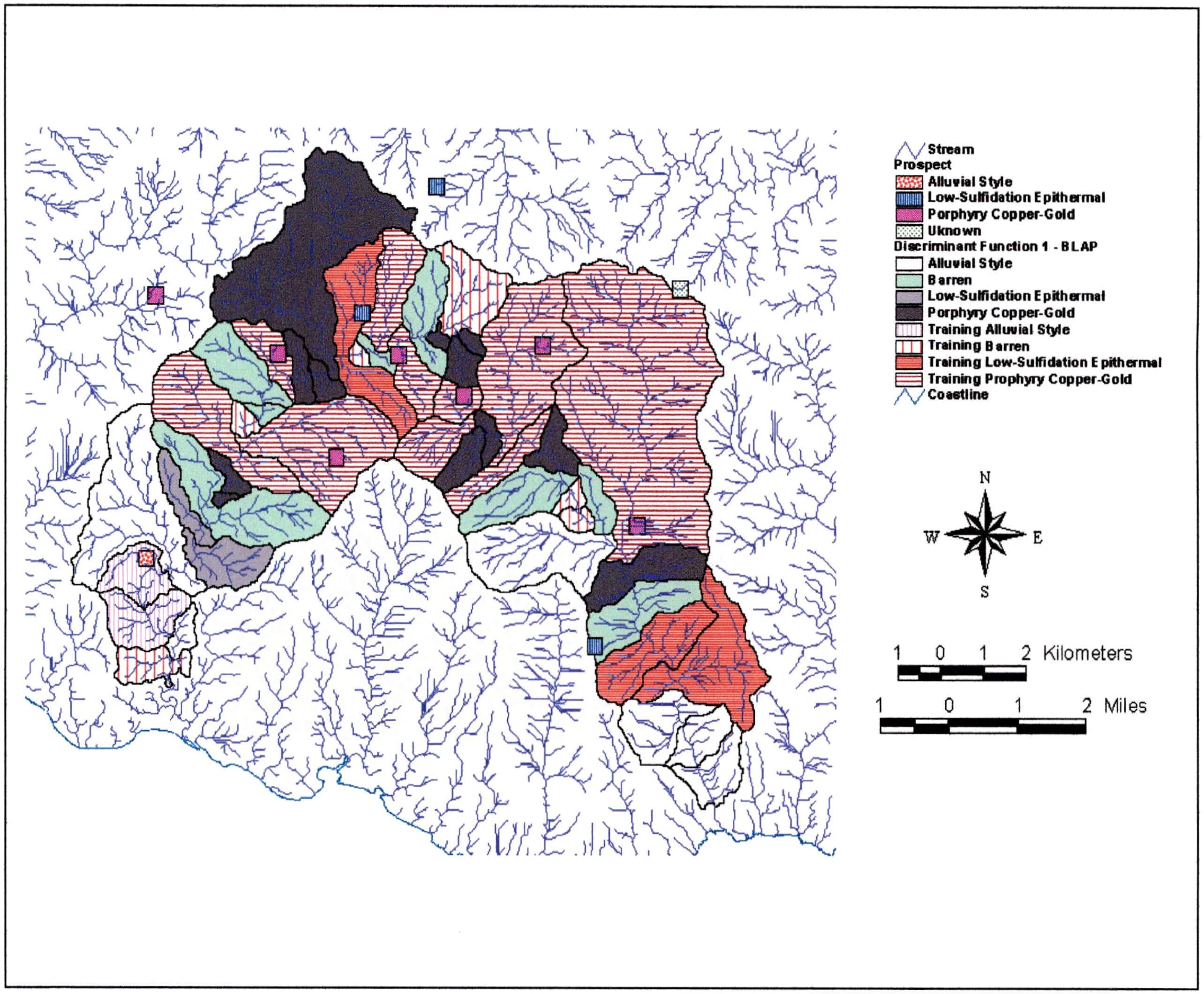

Figure 6.8 Results from the first discriminant function by drainage for the orientation survey.

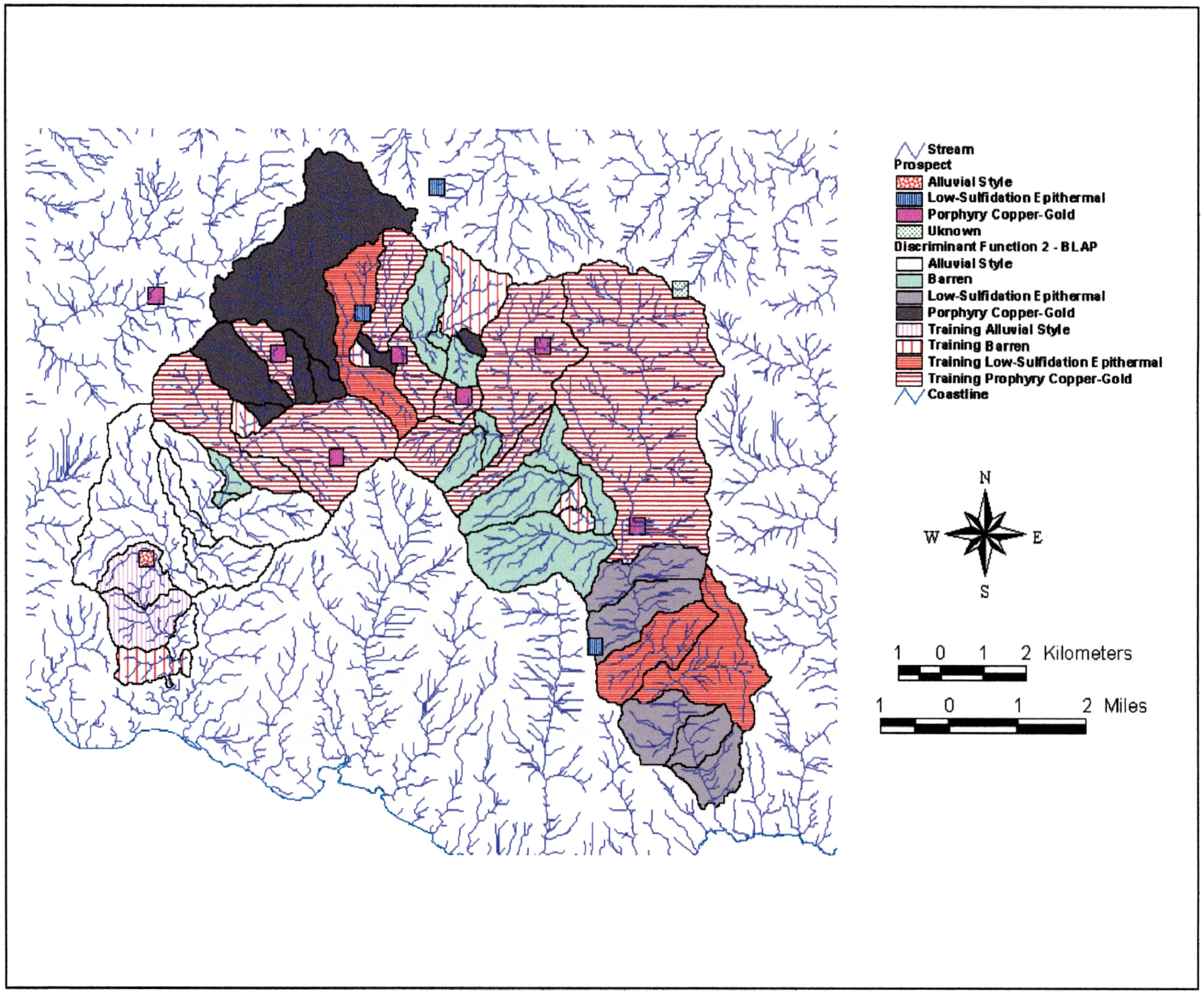

Figure 6.9 Results from the second discriminant function by drainage for the orientation survey.

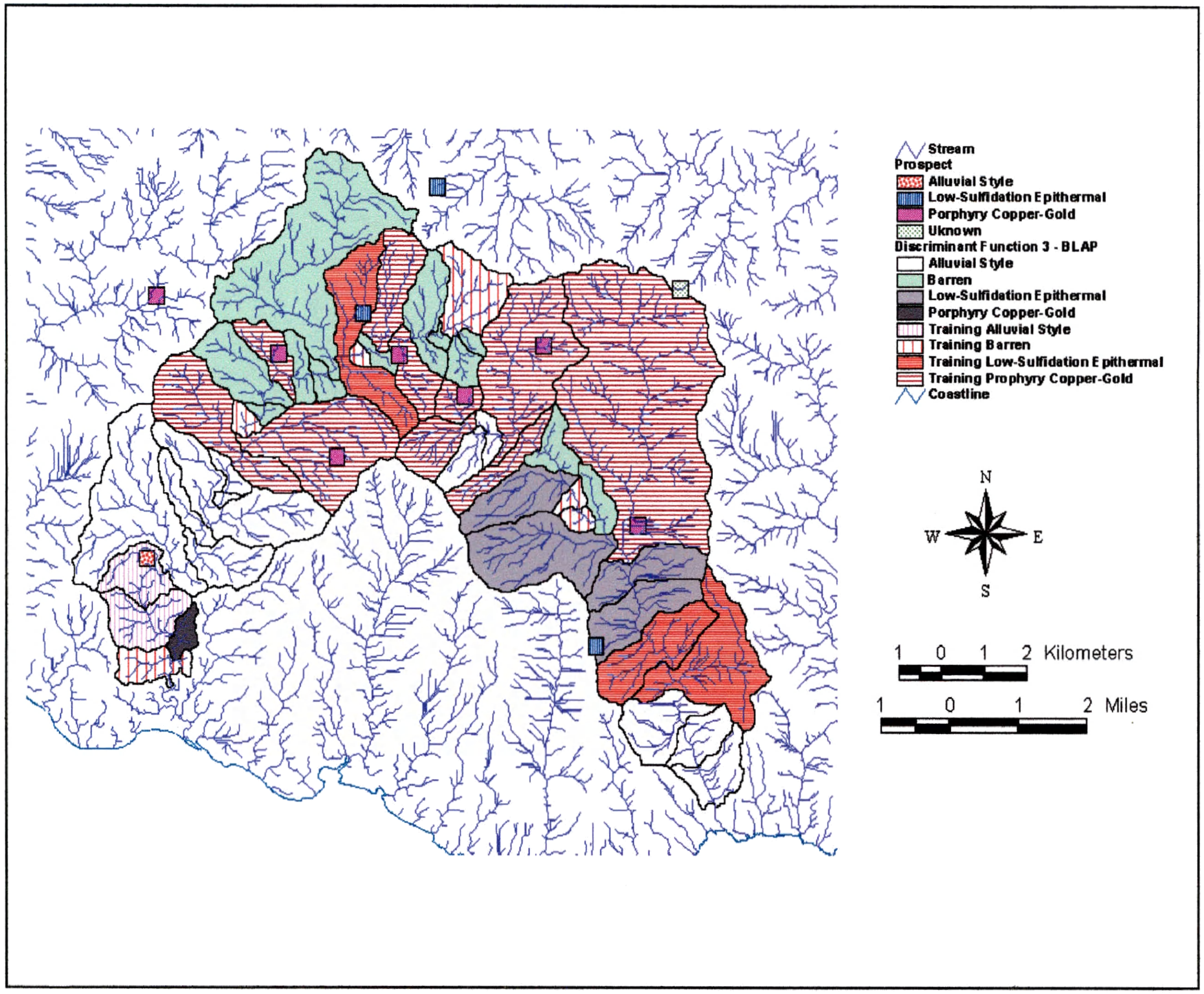

Figure 6.10 Results from the third discriminant function by drainage for the orientation survey.

6.4 Reconnaissance Results

The first of the three functions for the first group (B, L, A, and P classes) that were determined using the discriminant analysis module of Statistica correctly classified 70% of the data. The second and third functions each correctly classified 56% of the data. All three functions passed the chi^2 significant test, meaning that all three functions produce statistically significant discriminations. Table 6.4 provides the discriminant functions and the statistics for the correct classification percentage for each class in both the first and the second groups.

Figures 6.11, 6.12, and 6.13 are line plots of the results from the first, second, and third discriminant functions, respectively, for the first group of classes. Similar to the results from the orientation survey, the first discriminant function provided the best separation between the groups compared to the second and third functions.

Figure 6.14 is a plot of the first discriminant function versus the second discriminant function. Figure 6.15 is a plot of the first discriminant function versus the third discriminant function. Figure 6.16 is a plot of the second discriminant function versus the third discriminant function. Figure 6.14 provides the best possible discrimination between the classes using an x-y plot based upon the training data. The barren samples are neatly clustered together, while the other three groups spread outward about the barren cluster. Unfortunately, due to the number of data points and the slight overlap between the groups, the separation is not significant enough to use to classify all of the unknown samples.

Table 6.4 Discriminant functions for the reconnaissance survey data. The number of samples in each training class is provided immediately below the abbreviation for the class. The percent correctly classified samples are calculated by plotting the discriminant scores for each function from the training data on the line plots of Figures 6.11, 6.12, 6.13, and 6.18.

<table>
<tr><th>Discriminant Functions</th><th colspan="4">Percent Correctly Classified for Each Class (%)</th></tr>
<tr><td>Group 1 (classes B, L, A, P)</td><td>A
2</td><td>L
13</td><td>B
70</td><td>P
13</td></tr>
<tr><td>*Discriminant Function 1*</td><td colspan="4">*Total Correct: 70%*</td></tr>
<tr><td>2.83 – 0.29 lnAu – 0.16 lnCu – 0.18 lnPb – 0.23 lnAs + 0.03 lnSb – 664.27 Quartz Veins – 1.38 Limestone + 1.21 Alluvium – 0.13 Andesite Volcanic Rocks + 4.43 Hornblende Biotite Diorite – 0.70 Hornblende Microdiorite + 1.58 Old Tonalite + 192.85 Diatreme Breccia</td><td>50</td><td>38</td><td>80</td><td>54</td></tr>
<tr><td></td><td colspan="4"></td></tr>
<tr><td>*Discriminant Function 2*</td><td colspan="4">*Total Correct: 56%*</td></tr>
<tr><td>-2.80 – 0.11 lnAu + 0.67 lnCu + 0.04 lnPb + 0.11 lnAs + 0.15 lnSb – 299.09 Quartz Veins + 0.22 Limestone – 0.48 Alluvium – 0.01 Andesite Volcanic Rocks + 1.73 Hornblende Biotite Diorite – 0.09 Hornblende Microdiorite + 14.52 Old Tonalite + 110.20 Diatreme Breccia</td><td>50</td><td>31</td><td>69</td><td>15</td></tr>
<tr><td></td><td colspan="4"></td></tr>
<tr><td>*Discriminant Function 3*</td><td colspan="4">*Total Correct: 56%*</td></tr>
<tr><td>-1.77 – 0.14 lnAu + 0.49 lnCu + 0.03 lnPb – 0.01 lnAs – 0.11 lnSb + 43.98 Quartz Veins + 0.31 Limestone – 2.17 Alluvium – 0.11 Andesite Volcanic Rocks + 3.19 Hornblende Biotite Diorite + 0.66 Hornblende Microdiorite + 13.04 Old Tonalite – 3.87 Diatreme Breccia</td><td>50</td><td>31</td><td>60</td><td>62</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td>Group 2 (classes B and M)</td><td colspan="2">B
70</td><td colspan="2">M
28</td></tr>
<tr><td>*Discriminant Function 1*</td><td colspan="4">*Total Correct: 90%*</td></tr>
<tr><td>3.91 + 0.14 lnAu + 0.57 lnCu + 0.15 lnPb + 0.22 lnAs + 0.10 lnSb + 302.21 Quartz Veins + 1.01 Limestone + 0.08 Andesite Volcanic Rocks – 2.12 Hornblende Biotite Diorite + 0.49 Hornblende Micro Diorite + 8.55 Old Tonalite – 73.65 Diatreme Breccia</td><td colspan="2">97</td><td colspan="2">71</td></tr>
</table>

A) alluvial style
B) barren
M) mineralized
L) low-sulfidation epithermal
P) porphyry copper-gold

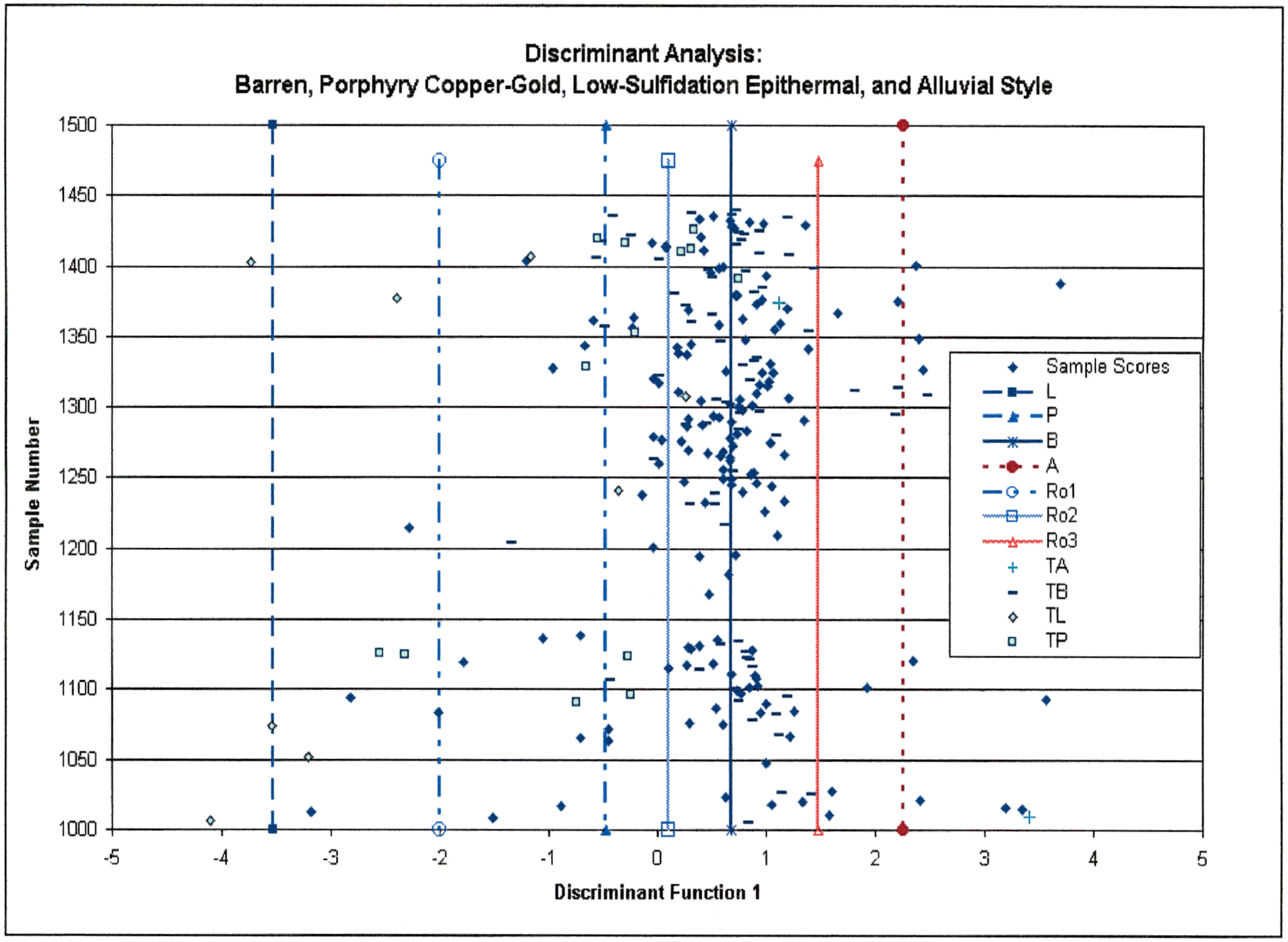

Figure 6.11 Line plot of the results from the first discriminant function for the first group on unknown and training samples from the reconnaissance survey. Ro1 is the median between classes L and P. Ro2 is the median between classes P and B. Ro3 is the median between classes B and A. TA, TB, TL, and TP denote the training data.

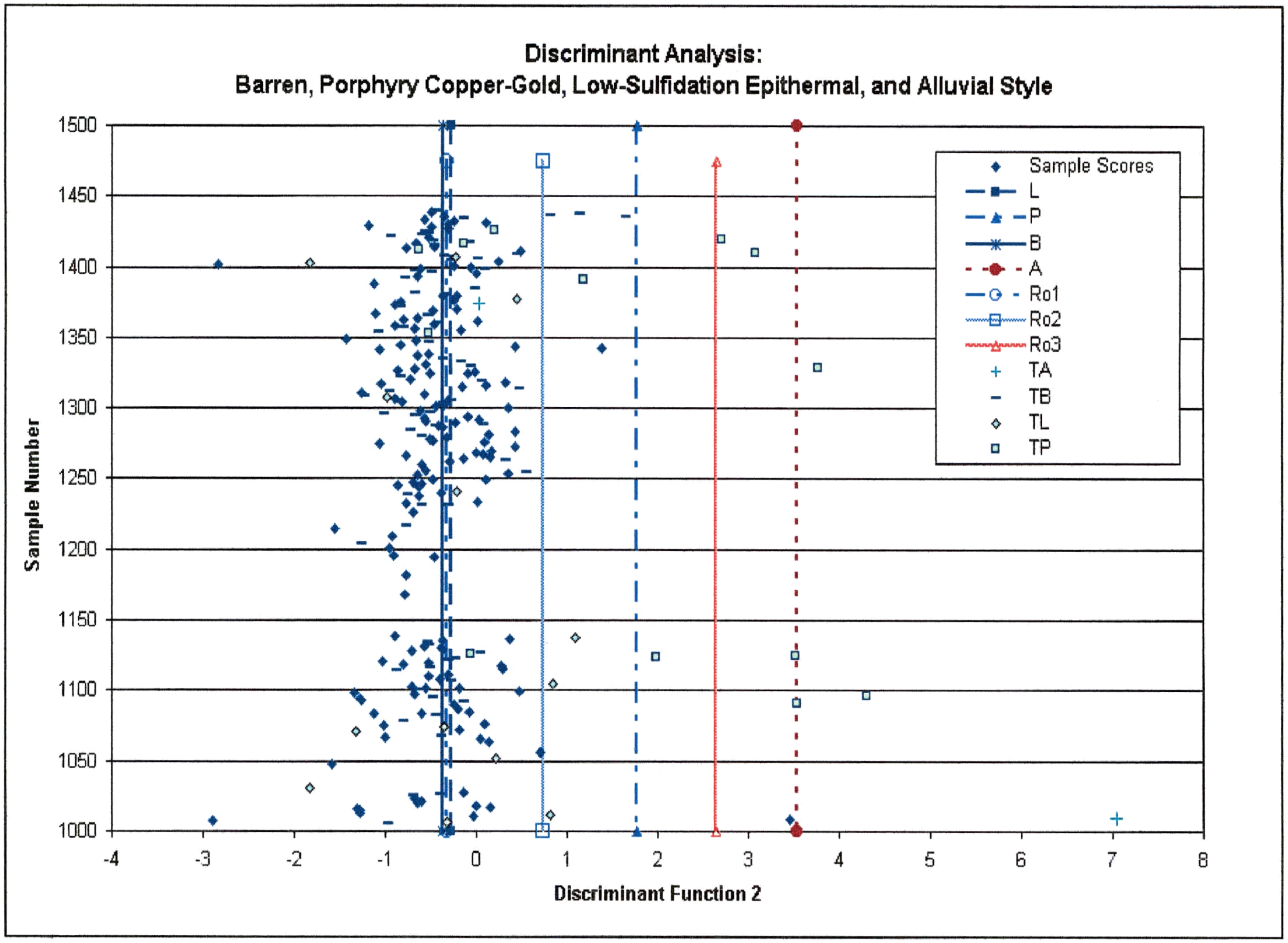

Figure 6.12 Line plot of the results from the second discriminant function for the first group on unknown and training samples from the reconnaissance survey. Ro1 is the median between classes B and L. Ro2 is the median between classes L and P. Ro3 is the median between classes P and A. TA, TB, TL, and TP denote the training data.

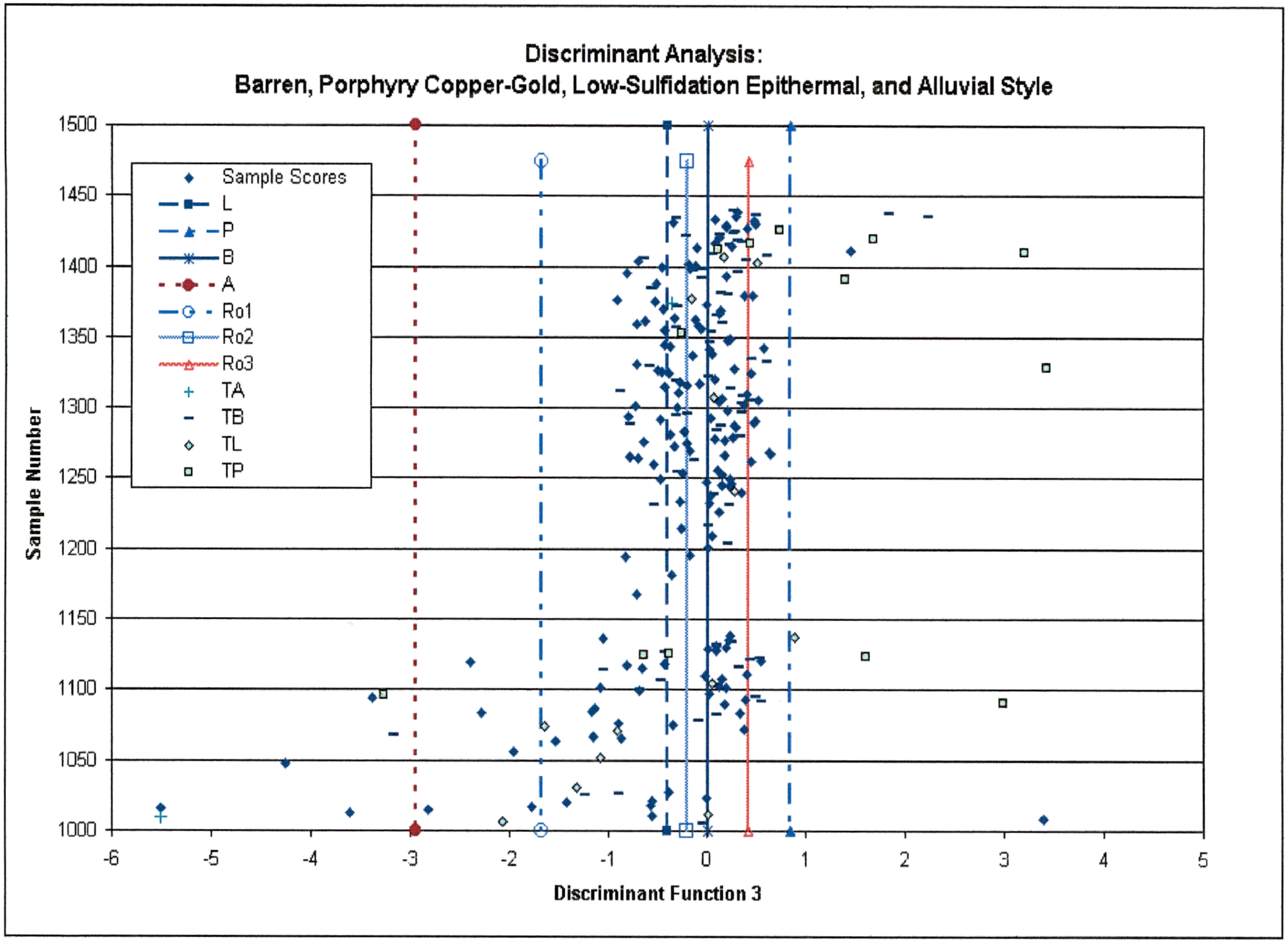

Figure 6.13 Line plot of the results from the third discriminant function for the first group on unknown and training samples from the reconnaissance survey. Ro1 is the median between classes A and L. Ro2 is the median between classes L and B. Ro3 is the median between classes B and P. TA, TB, TL, and TP denote the training data.

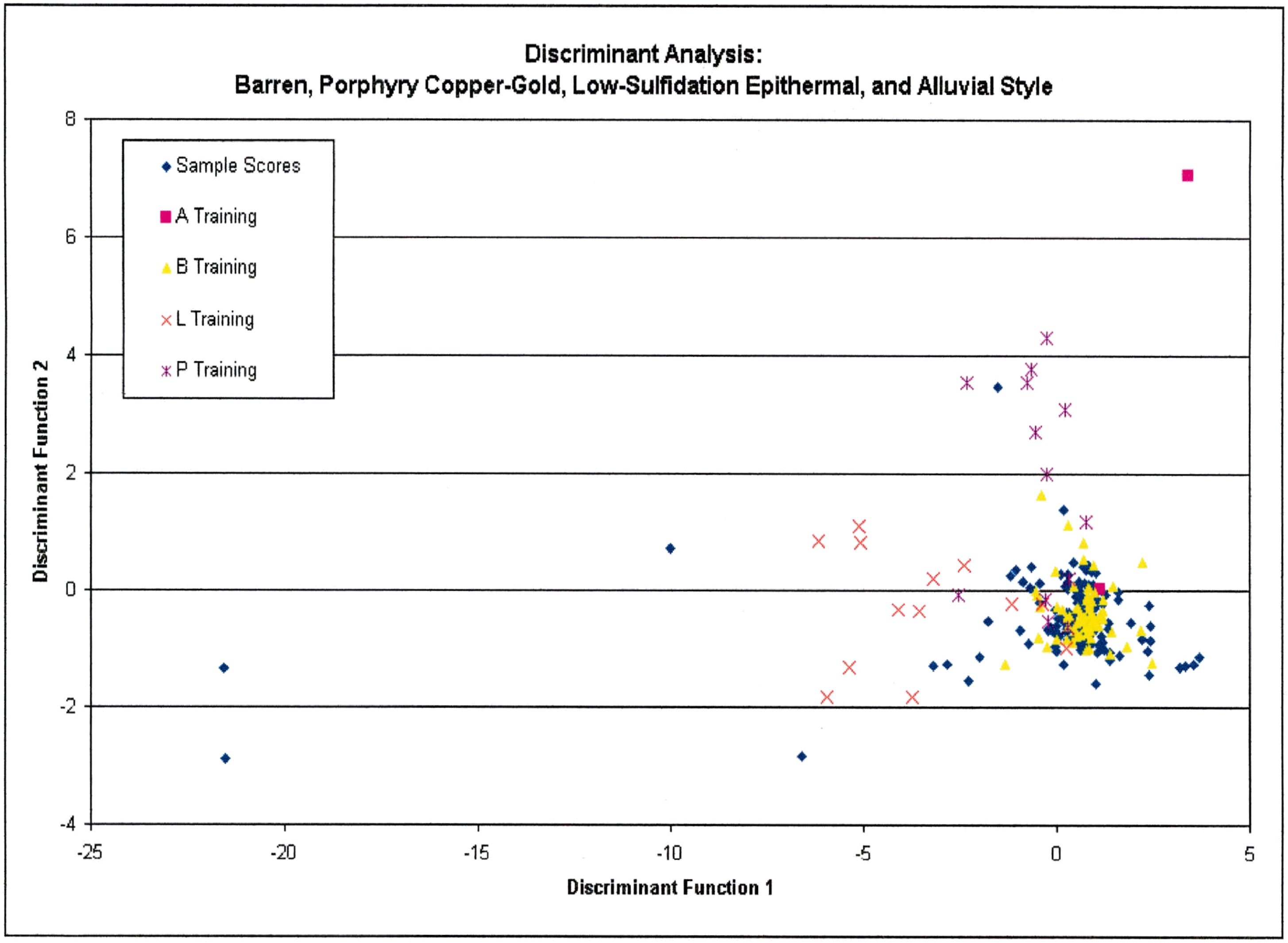

Figure 6.14 First discriminant function versus second discriminant function for the first group from the reconnaissance survey.

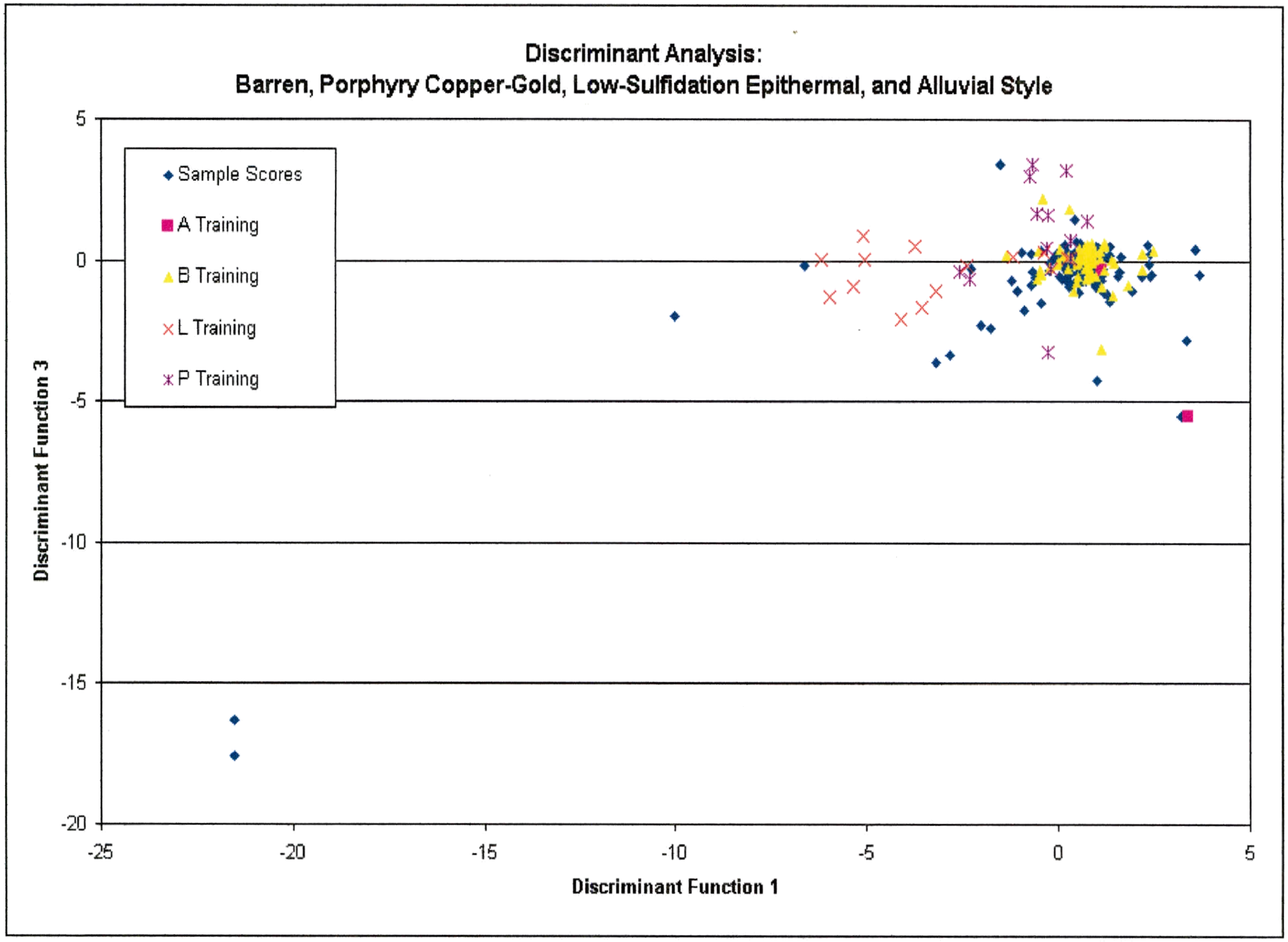

Figure 6.15 First discriminant function versus third discriminant function for the first group from the reconnaissance survey.

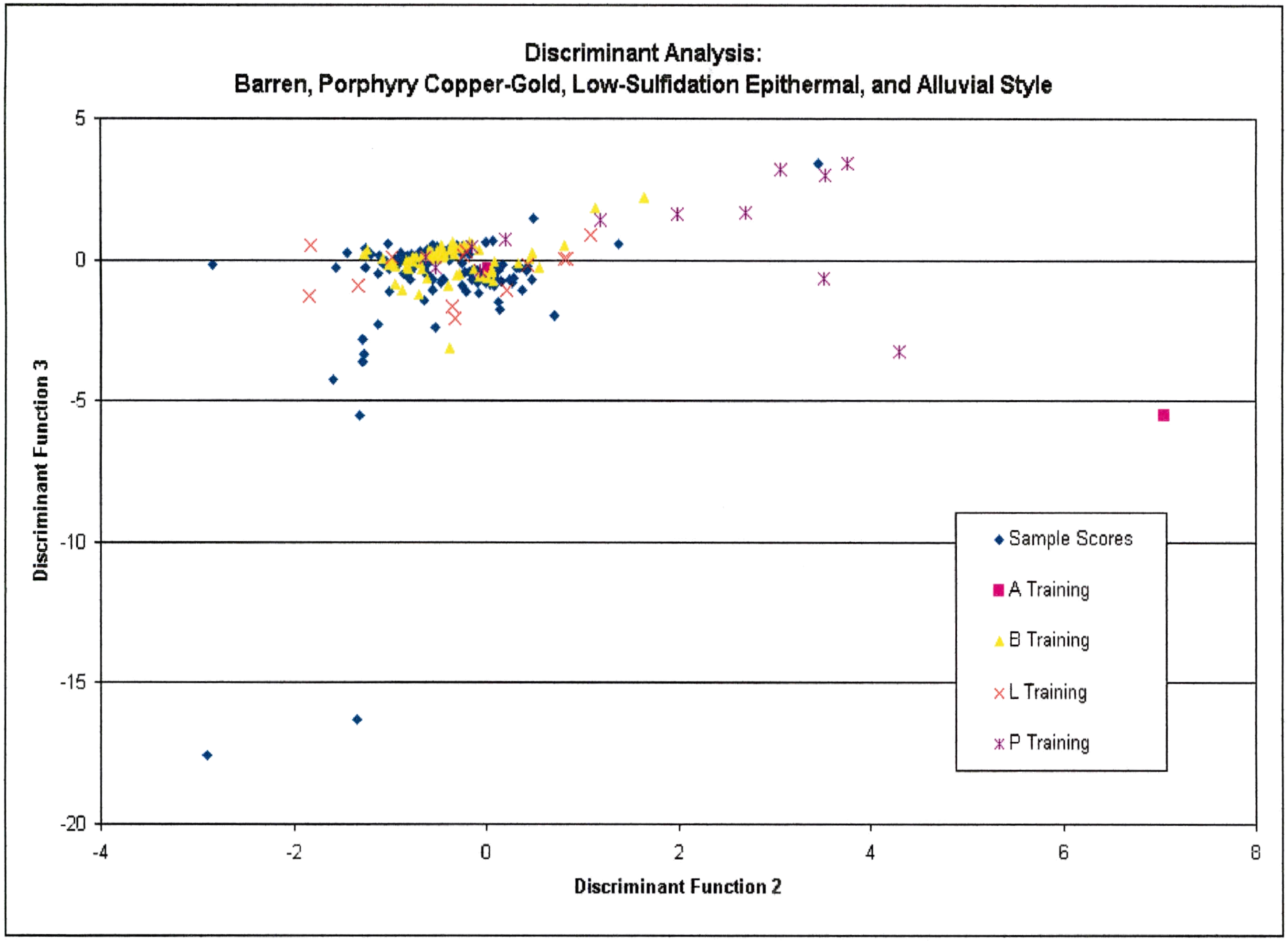

Figure 6.16 Second discriminant function versus third discriminant function for the first group from the reconnaissance survey.

Figure 6.17 is the spatial distribution of the results from the first discriminant function. The results of the second and third discriminant functions were not plotted spatially because these functions did not show good separation between the classes (Figures 6.12 and 6.13).

The discriminant function for the second group, B and M classes, correctly classified 90% of the training data and passed the chi^2 significance test. Figure 6.18 is the line plot of the results from the unknown and known samples. Figure 6.19 is the spatial distribution of the results from the discriminant function. Approximately seven of the unknown drainages classified as mineralized by group two were also classified as a mineralization type in group one. Group two contained fewer drainages classified as mineralized, compared with group one, and also failed to classify the two unknown mineralizations in the northwestern portion of the study area. This could be due to "weak" geochemical signatures of the two mineral occurrences, resulting in the barren classification from group two.

6.5 Discussion

The spatial distribution of the results from the first discriminant function for the orientation study are in agreement with existing mineral occurrences in the upper part of the two drainage basins, but disagree in the middle to lower portions. The disagreement may be due to the similarity of the signatures between the A, B, and L classes and the small number of training samples for each of those classes relative to the P class.

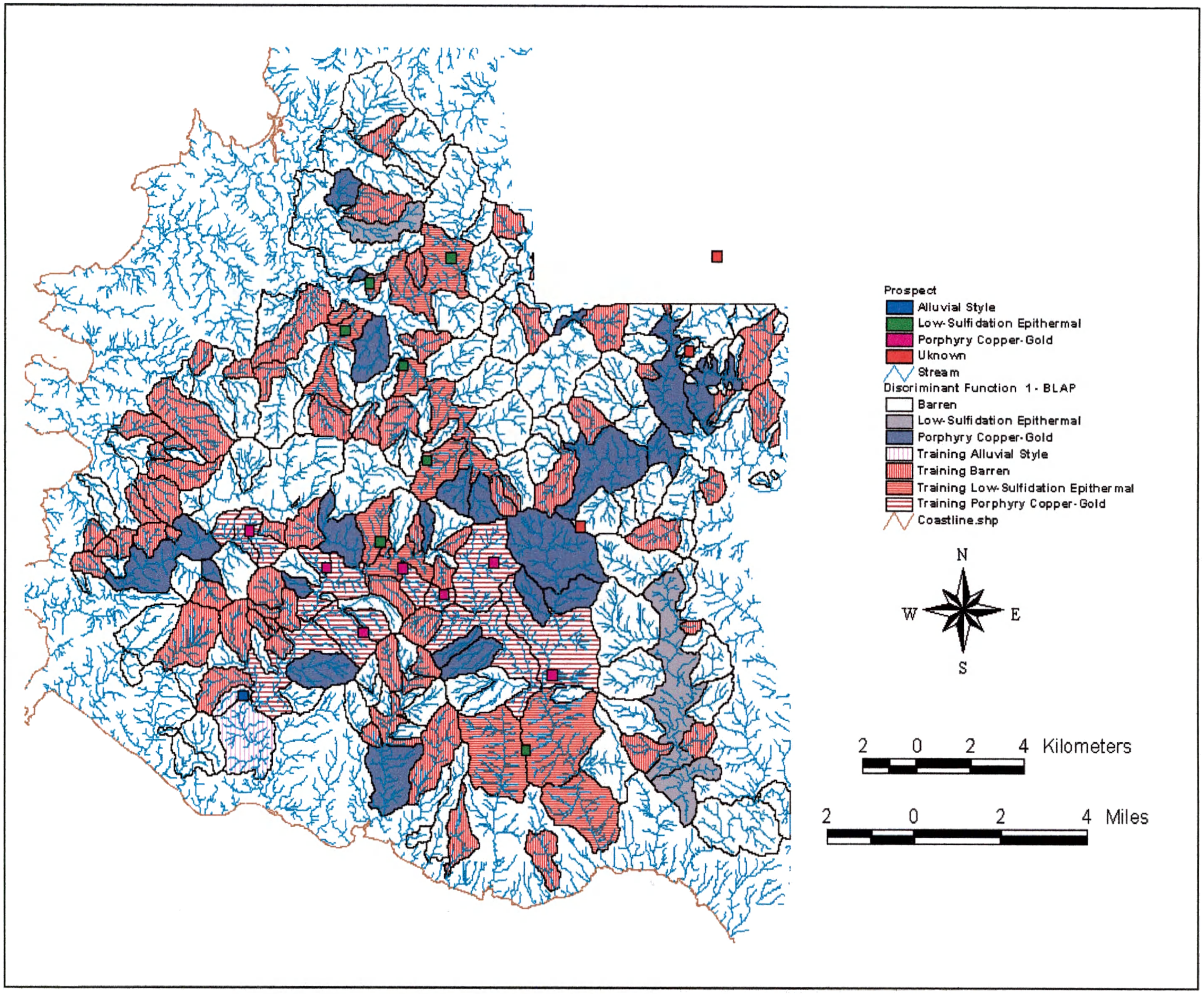

Figure 6.17 Spatial distribution of results from the first discriminant function for the first group from the reconnaissance survey.

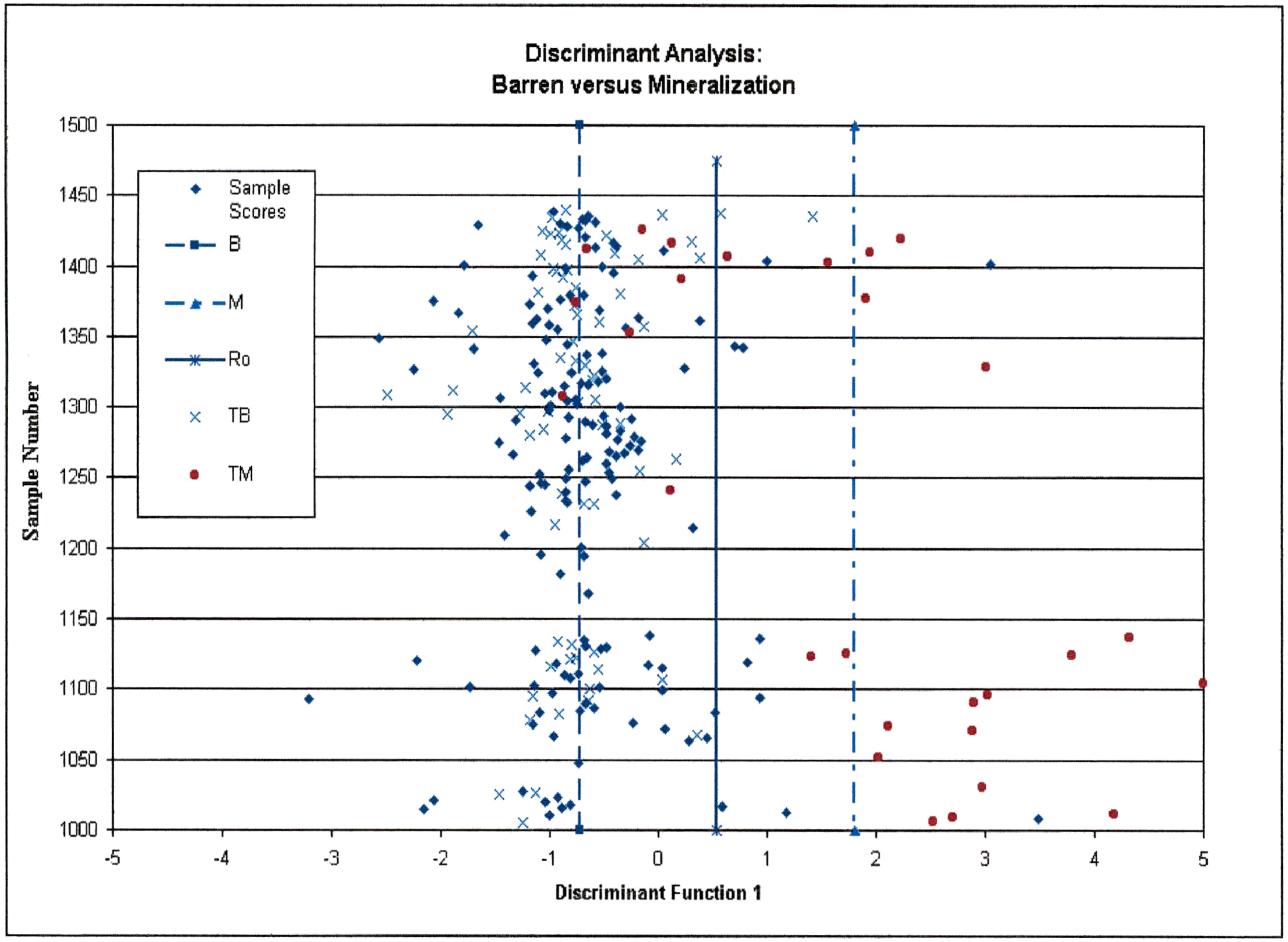

Figure 6.18 Line plot of results of unknown and training data from first discriminant function for second group for reconnaissance survey. Ro is the median between classes B and M. TB and TM indicate training samples.

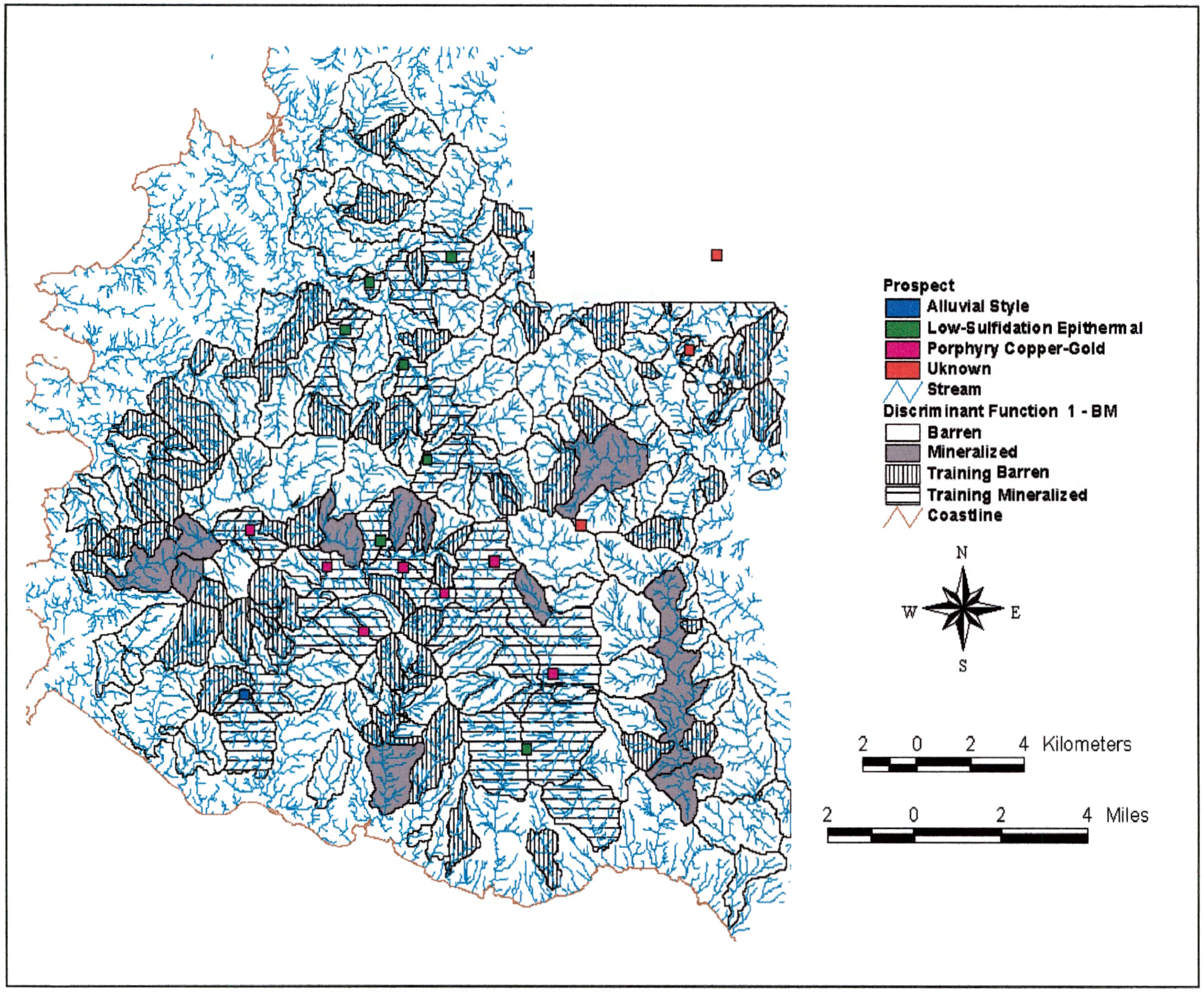

Figure 6.19 Spatial distribution of the discriminant function scores from second group for reconnaissance survey.

The spatial distribution of the results from the second and third functions show even less agreement with the first discriminant function. The line plots of the second and third discriminant functions (Figures 6.3 and 6.4) do not show good separation between the P and B classes, and P and L classes, respectively.

The first discriminant function for the first group of the reconnaissance survey has fairly good separation between the classes (Figure 6.11). The line plot for the second and third discriminant functions (Figures 6.12 and 6.13, respectively) and the x-y plots of the discriminant functions (Figures 6.14, 6.15, and 6.16) were not very helpful in discriminating between the classes.

The results of the second training group for the reconnaissance survey were much easier to interpret. The line plot (Figure 6.18) showed good separation between the two classes. The only drawback is that information on the type of mineral occurrence is missing from the second group's classification scheme.

6.6 Assessment of Technique

Overall, the discriminant analysis worked fairly well, with a minimum of 78% to 90% correct classification when the training set was run through the equations. While this is a biased estimate of the correct classification as it uses the same data that was used to create the functions, for areas where all of the known drainages have been used for training, it is difficult to assess the percent correct for the regular data set.

Considerable time was required to set up the training sets and interpreting the results. It took roughly three hours to set up the training and corresponding unknown data sets for both surveys. The functions were obtained using Statistica in about three hours, after trying different combinations of variables. Calculations, line plots, and x-y plots for the unknown data sets took another two hours. The interpretation of the plots and subsequent spatial plotting of the results in ArcView took approximately five hours.

The discriminant analysis method seems to work better when only discriminating between two classes and when there is adequate training data for each class. As such the results from the orientation survey were not as promising as the results from the reconnaissance survey. This is probably due to the small number of training data points for the barren, low-sulfidation epithermal, and alluvial style mineralization relative to the porphyry copper-gold class. For the reconnaissance survey, the first group (B versus M) was a better choice of classes than the second group (B, L, A, and P). This is probably due to the significant number of training data points for each class in the B versus the M group, relative to the B, L, A, and P classes. The breakdown of the M class into the respective types of mineralizations, L, A, and P, reduces the overall training points for the mineralized (M) class into three individual classes.

Perhaps a better way to use discriminant analysis is to break the outcomes into two classes each so that several two class functions can be developed that would provide all of the information that the investigator needs. For example, the first function could look at barren versus mineralized. Then for those drainages that were mineralized, look at porphyry copper-gold versus low-sulfidation epithermal gold deposits. Additionally, having equal, and subsequently more, training samples would have aided in both the accuracy and interpretation of the results.

CHAPTER 7

CLUSTER ANALYSIS

7.1 Introduction

Cluster analysis is a classification technique that, ideally, forms separate relatively homogeneous groups from an originally heterogeneous data set (Davis, 1986). The principle behind cluster analysis is that the similarities or dissimilarities between samples or variables can be used to group together samples or variables that are the most similar thereby forming clusters. Like factor analysis, cluster analysis has two basic modes: R-mode and Q-mode. In R-mode cluster analysis examines the similarities and interrelationships between the variables, whereas Q-mode cluster analysis looks at the similarities between samples. Cluster analysis is most commonly used in Q-mode as the interpreter is looking for clusters of objects, sample sites, drainage characteristics, etc. This study employs Q-mode cluster analysis. The characteristics of the samples within each cluster can then be examined for potential indications of the target mineralization.

Cluster analysis is useful for large sets of multivariate data. Howarth and Sinding-Larsen (1983) proposed a method of cluster analysis whereby a random subset of data is run first. The clusters so generated can then be used to classify the remaining samples by similarity to the groups or discriminant analysis. Sjoekri (1997) utilized a method similar to this in that he used the orientation survey data to develop clusters representing three classes of potential mineralization. Once these classes were established, he used the same parameters to interpret the reconnaissance data. Howarth and Sinding-Larsen (1983) also warned that two underlying problems exist with cluster analysis: 1) there are many different ways of defining similarity between samples; and 2) there are no universally agreed statistical or nonstatistical criteria for what constitutes a valid cluster. As a result the interpreter's judgment and experience with the type of problem at hand are very important factors in the interpretation of the results.

7.2 General Methodology

Q-mode cluster analysis is a type of data analysis technique used to classify samples into homogenous groups. Four types of cluster analysis techniques exist and are based upon: 1) partitioning methods; 2) arbitrary origin methods; 3) mutual similarity; and 4) hierarchical clustering (Davis, 1986). Hierarchical clustering techniques are the most commonly used techniques in the geosciences (Davis, 1986; Sjoekri, 1997).

First, similarity or dissimilarity measures such as the Pearson Product-Moment Coefficient (R^2) (similarity) or Euclidean distances (dissimilarity) must be selected based upon the problem at hand (Swan and Sandilands, 1995). For example, the Euclidean distance measures the "distance" or similarity between two points or a point and a cluster or two clusters. The similarity between the two objects increases as the distance between the two objects decreases and the similarity is greatest when the distance between to points is zero. In contrast, the Pearson Product-Moment Coefficient increases to one as the similarity between two objects increases.

Second the linkage method is selected. Nearest neighbors (single linkages) and furthest neighbors (complete linkages) are the two most commonly used techniques (Davis, 1986; Swan and Sandilands, 1995; Sjoekri, 1997). Nearest neighbor linkage involves joining the closest points, recalculating the matrix and then linking the next closest point to the cluster and so on (Jackson, 1983). The furthest neighbor linkage involves the initial linkage of the two closest points, followed by the recalculation of the distance between the initial cluster and the remaining points and the joining of two points that are closest together. This process is repeated iteratively until all points or clusters are joined (Jackson, 1983). Swan and Sandilands (1995) recommend the furthest neighbors technique for producing robust dendrograms with a minimum degree of chaining. Chaining refers to the connection of points to the ends of elongated clusters where the opposite ends of the clusters could be significantly different, thus producing more heterogeneous clusters.

Third, dendrograms are produced. Dendrograms are tree-shaped graphical representations of the relationships between the samples and their associated clusters (Davis, 1986; Swan and Sandilands, 1995). In order to interpret a dendrogram, the investigator must place a phenon line (a line at a given similarity or dissimilarity level) to define a set of clusters. The placement of the phenon line is subjective. It is typically based upon the investigator's best judgment and previous experience with the problem at hand (Swan and Sandilands, 1995). "Natural breaks" in the linkages of the clusters, may assist in the placement of the phenon line (Swan and Sandilands, 1995). In addition, the number of clusters selected may vary with the detail required by the project. Cluster analysis is not a statistical procedure (Swan and Sandilands, 1995) and, as such, ordinary tests for the statistical significance between clusters do not apply.

7.3 Cluster Analysis from Sjoekri (1997)

Sjoekri (1997) used a Q-mode hierarchical clustering technique, experimenting with the Pearson Product-Moment Coefficient (R^2) and Euclidean distance measure and with nearest neighbor and furthest neighbor (complete) linkages. Sjoekri (1997) used the MultiVariate Statistical Package (MVSP 2.0) for the orientation survey as it only contained 49 sample points. The MVSP software, however, was unable to handle the 262 sample points for the reconnaissance survey, thus the cluster analysis module in Statistica 5.0 was utilized for this phase of the analysis. The orientation survey was used to establish parameters that were then used to interpret the reconnaissance survey. The results from each step in the cluster analysis were plotted using the ArcView and Arc/Info software packages to examine the spatial relationships with known mineral occurrences. This aided in the selection of the final clusters and interpretation of the results.

7.3.1 Methodology for the Orientation Survey

Sjoekri (1997) used eight steps in order to incorporate the geochemical, airborne geophysical, and lithological data into the final dendrogram for cluster analysis (Figure 7.1). Initially, Sjoekri (1997) produced dendrograms for stream sediment geochemistry, bedrock lithology, and airborne radiometric data separately. Then four more dendrograms were produced with combinations of the variables: 1) combined airborne radiometric and magnetic data; 2) lithology and geochemistry; 3) lithology, geochemistry, and airborne magnetic; and 4) lithology, geochemistry, and airborne radiometric data (Sjoekri, 1997). The dendrogram for each step helped guide the interpretation of the results for each subsequent step.

The placement of the phenon line for the final dendrogram was done using several iterations and map displays of the resulting clusters. Each resulting cluster was evaluated with respect to *a priori* knowledge of the study area and known mineral occurrences (Sjoekri, 1997). The final dendrogram for the orientation survey was classified into eight groups. Sjoekri (1997) noted that "the final classification…was selected based on several subjective criteria, since there is no quantitative statistical basis for choosing the 'best' classification. The criteria used included the number of distinct groups – between five and ten seemed optimal – and their spatial distribution" (page 135).

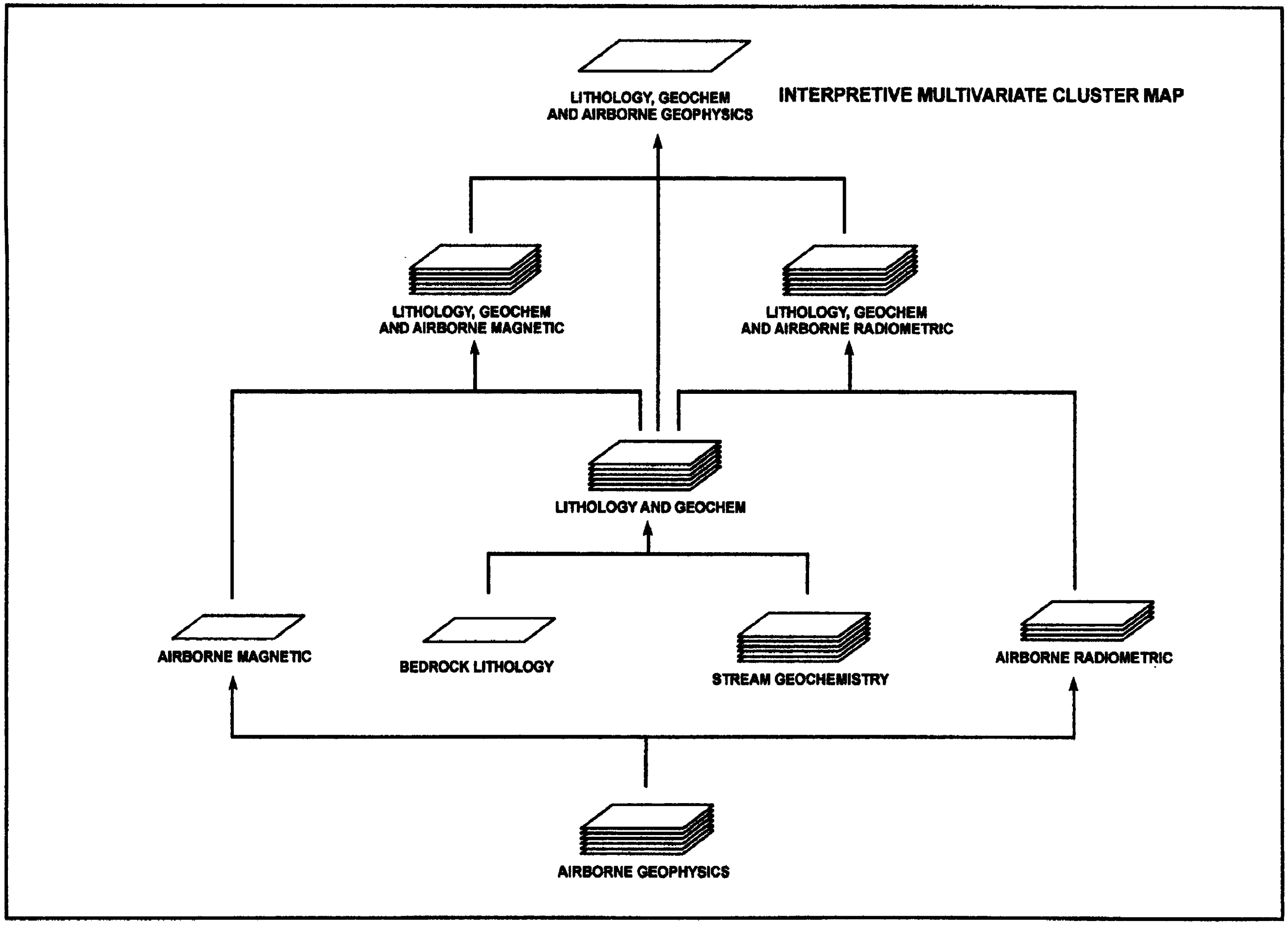

Figure 7.1 Flowchart for the steps used to produce the final dendrogram from the cluster analysis for the orientation survey. (Sjoekri, 1997)

7.3.2 Methodology for the Reconnaissance Survey

Sjoekri (1997) used both the –40# BLEG and –80# silt samples in the cluster analysis; however, only approximately 67% of the sample sites have –40# BLEG data while 99% of the sample sites have –80# silt data. This resulted in "gaps" in the multivariate data set which had to be "filled" prior to cluster analysis (Sjoekri, 1997). To fill the "gaps" three dendrograms were produced, one for the –40# BLEG, one for the –80# silt, and another for the samples with both –40# BLEG and –80# silt data, which provided multiple classifications for most samples (Sjoekri, 1997). Cross-tabulation of individual –40# BLEG and –80# silt classifications with "corresponding classification based upon both size fractions allowed for those samples lacking one or the other fraction to be assigned to the most similar classification based on both fractions" (Sjoekri, 1997, page 144). This provided all sample locations with a uniform geochemical classification code, which was then used for the subsequent cluster analyses to produce the final classification.

Figure 7.2 provides a flow chart for the cluster analysis used on the reconnaissance survey data. Both standardized and nonstandardized Euclidean distances were used with furthest neighbor linkage (Sjoekri, 1997). The standardized Euclidean distance produced a "straggly, chained set of clusters, which [are] difficult to explain," thus non-standardized Euclidean distances were used for the subsequent hierarchical cluster analysis (Sjoekri, 1997, page 146). The final dendrogram for the reconnaissance survey was separated into ten clusters.

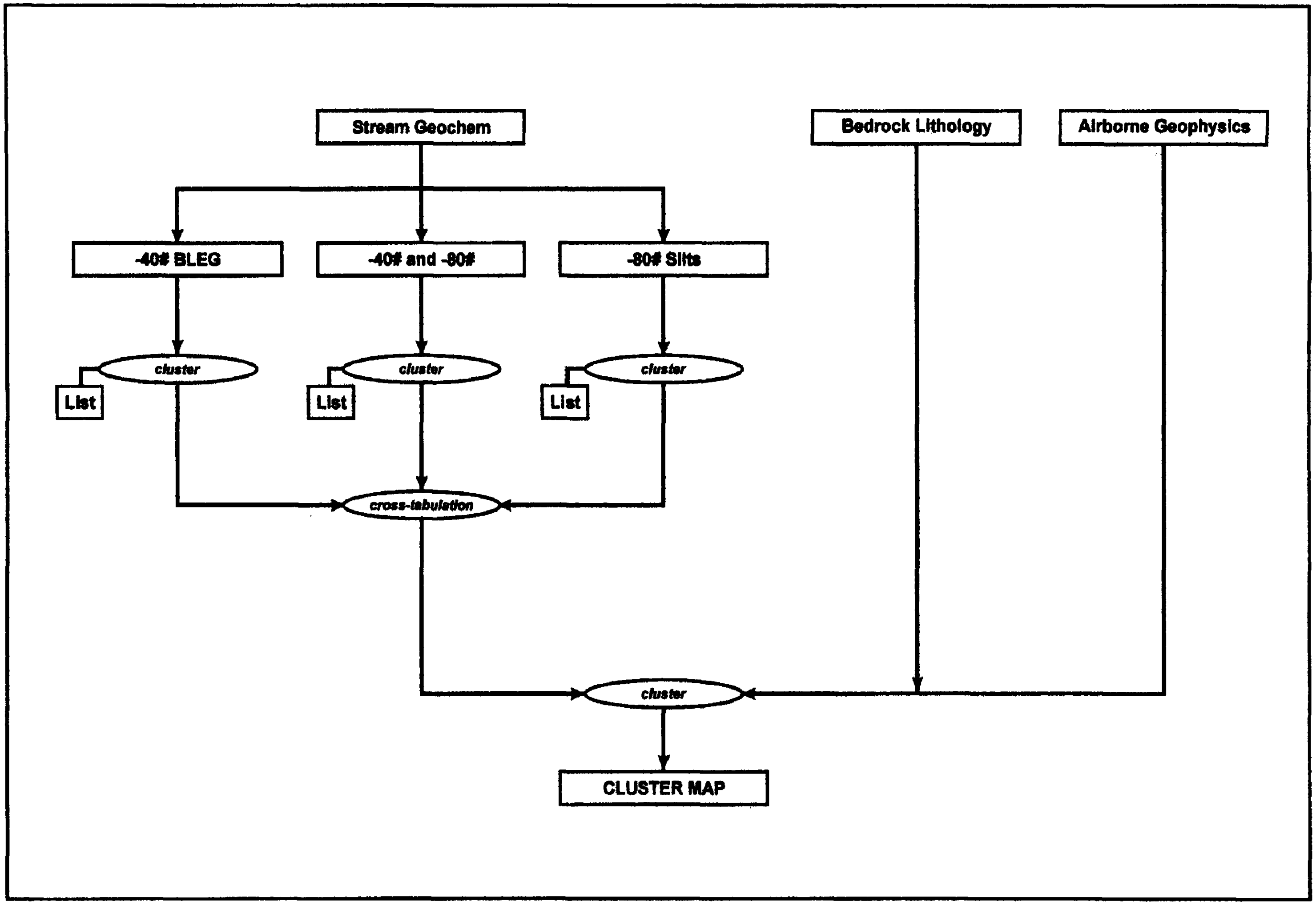

Figure 7.2 Flowchart for data treatment and steps to produce the final dendrogram from the cluster analysis on the reconnaissance survey data. (Sjoekri, 1997)

7.4 Results

The final dendrogram and resulting clusters for each survey were plotted using ArcView software. The clusters were examined for common characteristics that might be related to mineralization as well as their spatial relationship to known mineral occurrences in the area.

7.4.1 Orientation Survey

The final dendrogram and corresponding map of the clusters from Sjoekri (1997) are provided as Figure 7.3 and Figure 7.4, respectively. The separation between groups 1 to 4 and 5 to 8 is representative of the different drainages, where groups 1 to 4 represent the Sejorang drainage, while groups 5 to 8 represent the Tongoloka drainage (Sjoekri, 1997). Groups 6 and 8 are associated with porphyry copper-gold mineralization in the area, specifically the Batu Hijau deposit and the weakly developed Katala prospect (Sjoekri, 1997). Table 7.1 contains the characteristics of each group.

The groups that contained mineralization were assigned to one of three mineral exploration target classes (Table 7.2) (Sjoekri, 1997). The target classes were established to provide a "possible guidance for … further mineral exploration in the area" (Sjoekri, 1997, page 133). Target class A samples reflect high volume low-grade porphyry copper-gold deposits and diorite and intrusive rocks associated with Batu Hijau and Katala (Sjoekri, 1997). Target class B reflects low-sulfidation epithermal gold mineralization with moderate to high Au values and weakly developed porphyry copper-

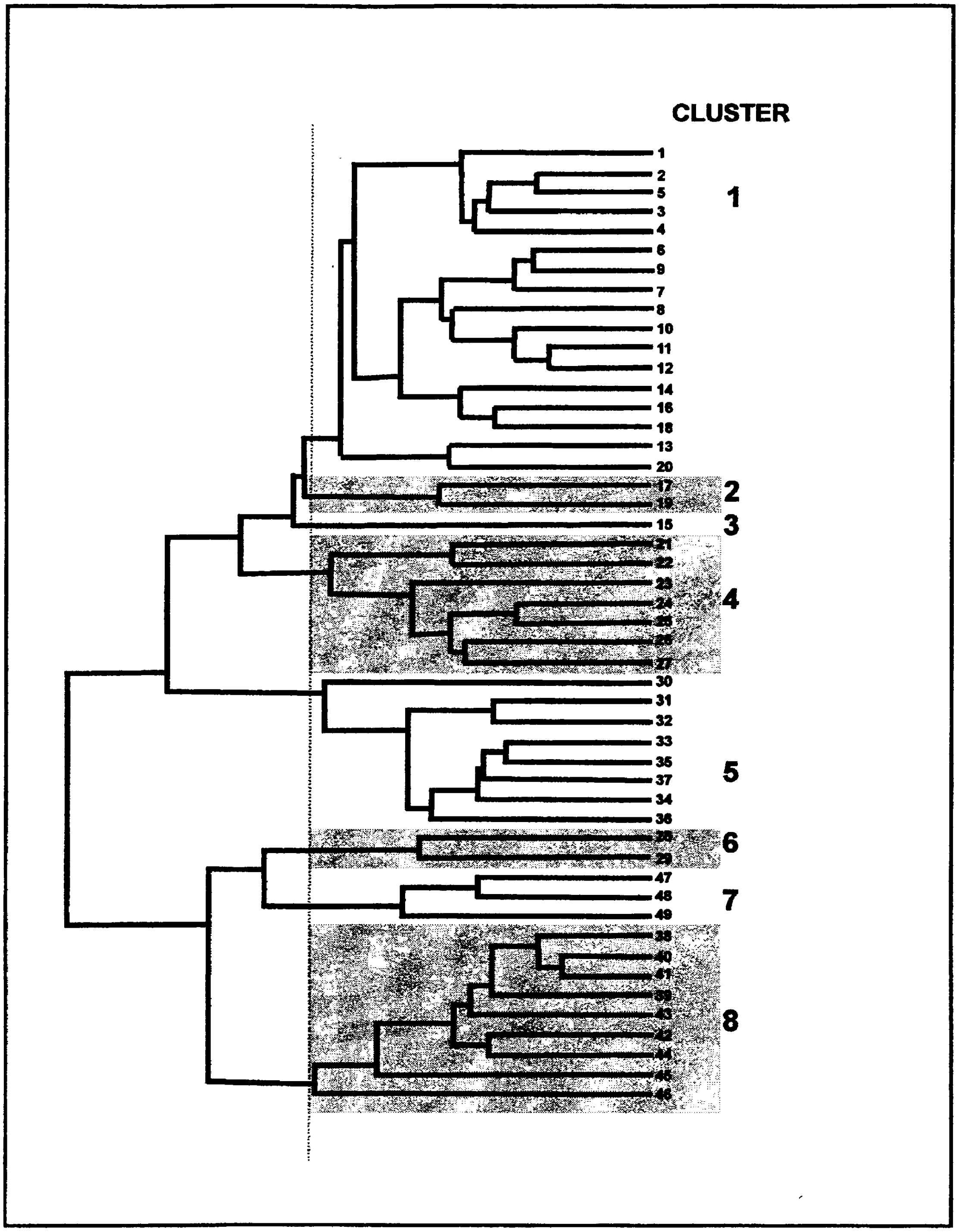

Figure 7.3 Final dendrogram from cluster analysis on the orientation survey (Sjoekri, 1997).

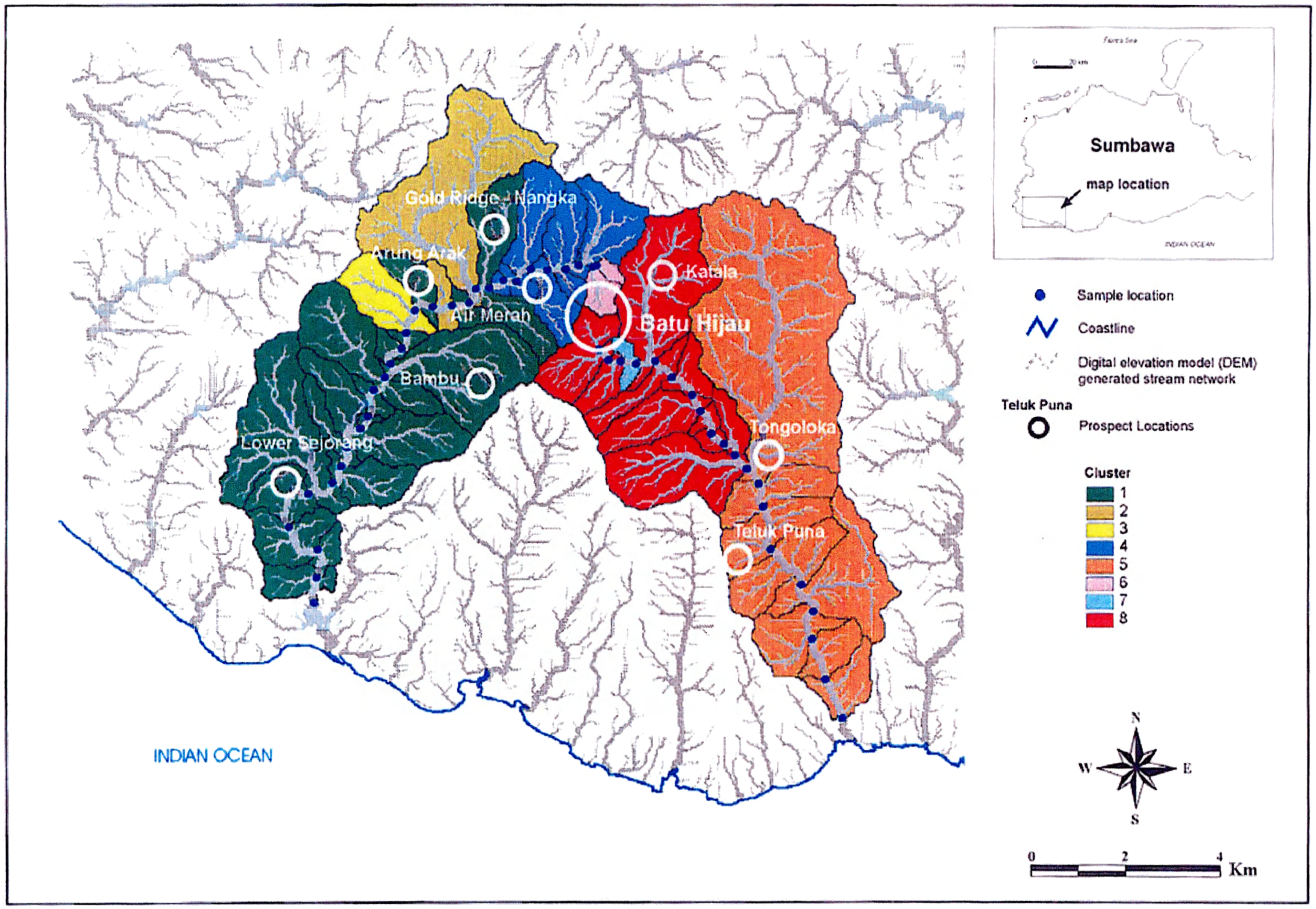

Figure 7.4 Map of the final clusters from the orientation survey data. (Sjoekri, 1997)

Table 7.1 Characteristics of Sjoekri's (1997) final clusters for the orientation survey data. (Sjoekri, 1997)

CLUSTER	TARGET	LITHOLOGY	GEOCHEM		GEOPHYSICS		PROSPECTS	
ID	CLASS Table 7-9		Gold	Copper	Magnetic	Radiometric	Epithermal	Porphyry
1	C	Andesite, agg.lapilli, diorite, alluvium, diatreme breccia, limestone, felds, porphyry, qtz.vein, laharic breccia	high	low	background	background	Bambu, Gold Ridge	Arung Arak **Alluvial Style:** Lower Sejorang
2	B	Andesite, Aggl.Lapilli, Diorite, diatreme breccia, alluvium, felds. Porphyry, qtz.vein	mod	low	background	background		Air Merah
3	-	Andesite, agg.lapilli, diorite, alluvium, diatreme breccia, felds.porphyry, qtz.vein	mod	low	background	background		
4	-	Andesite, diorite, agg.lapilli, diatreme breccia, feldspar porphyry, qtz.vein	low	low	background	background		
			mod	low	background	background		
5	B	Andesitic, diorite, alluvium, laharic breccia, old tonalite	high	low	background	background	Teluk Puna	
			low	low	background	background		Tongoloka
6	A	Diorite, andesite	low	mod	high	high		Batu Hijau - north
7	A	Andesite, diorite, old tonalite	mod	high	high	background		
8	A	Andesite, diorite, old tonalite, alluvium	mod	mod	background	background		Batu Hijau - south
			mod	high	background	background		Katala

Table 7.2 Sjoekri's (1997) exploration target class descriptions. (Sjoekri, 1997)

TARGET CLASS	DESCRIPTION
A	Porphyry Copper-Gold mineralization style, with diorite and tonalite intrusive association, and significant magnetic and radiometric response.
B	Epithermal vein mineralization style with some indication of weak porphyry mineralization, moderate to high gold geochemistry.
C	Epithermal vein mineralization style with possible occurrence of secondary enrichment alluvial style. Results showed high gold geochemistry

gold, such as Teluk Puna (Sjoekri, 1997). Target class C reflects other low-sulfidation epithermal gold mineral occurrences and possibly alluvial style occurrences, such as that at the Lower Sejorang prospect (Sjoekri, 1997).

7.4.2 Reconnaissance Survey

Figure 7.5 and 7.6 contain Sjoekri's (1997) final dendrograms and cluster distribution map selected for the reconnaissance data. Table 7.3 contains the characteristics for each of the ten final clusters for the reconnaissance survey. These clusters for the reconnaissance survey were then compared with the eight clusters and the exploration target classes previously defined for the orientation survey (Sjoekri, 1997). Three clusters in the reconnaissance data (clusters 1, 3, and 9 in Table 7.3) did not match characteristics for the groups established using the orientation data. Sjoekri (1997) did not explain why this might have happened, however, it may be due to the occurrence of "barren drainages" or larger proportions of some lithologies in the reconnaissance survey compared with the orientation survey. For example, limestone represents a maximum of 15% in drainages from the orientation survey, compared with a high of 94% in the reconnaissance survey.

Figure 7.7 is a map of the exploration target classification for the reconnaissance survey. Drainages were classified into one of the three exploration target classes based upon their similarity to the target class (Sjoekri, 1997).

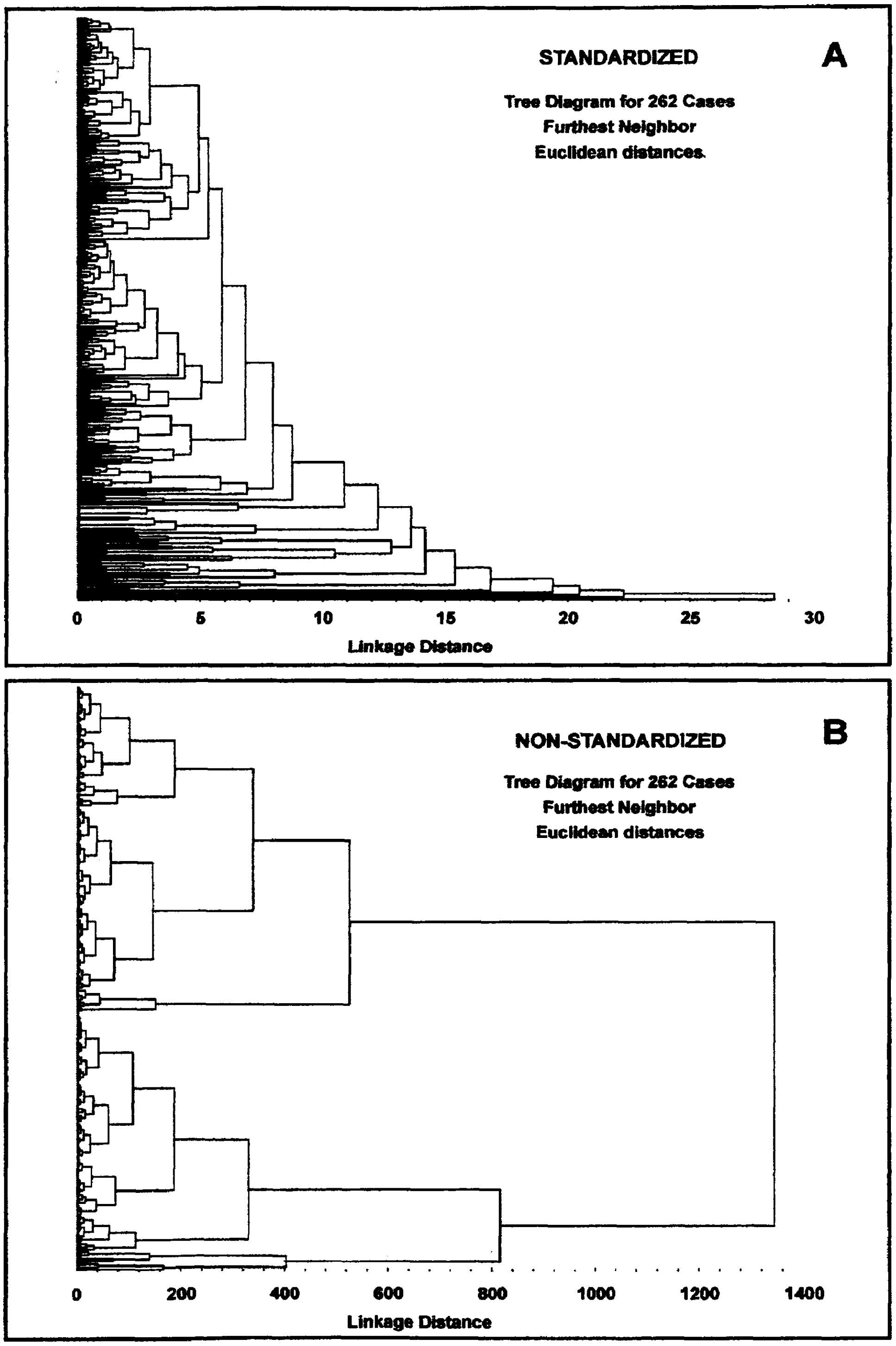

Figure 7.3 Final dendrogram from cluster analysis on the reconnaissance survey (Sjoekri, 1997).

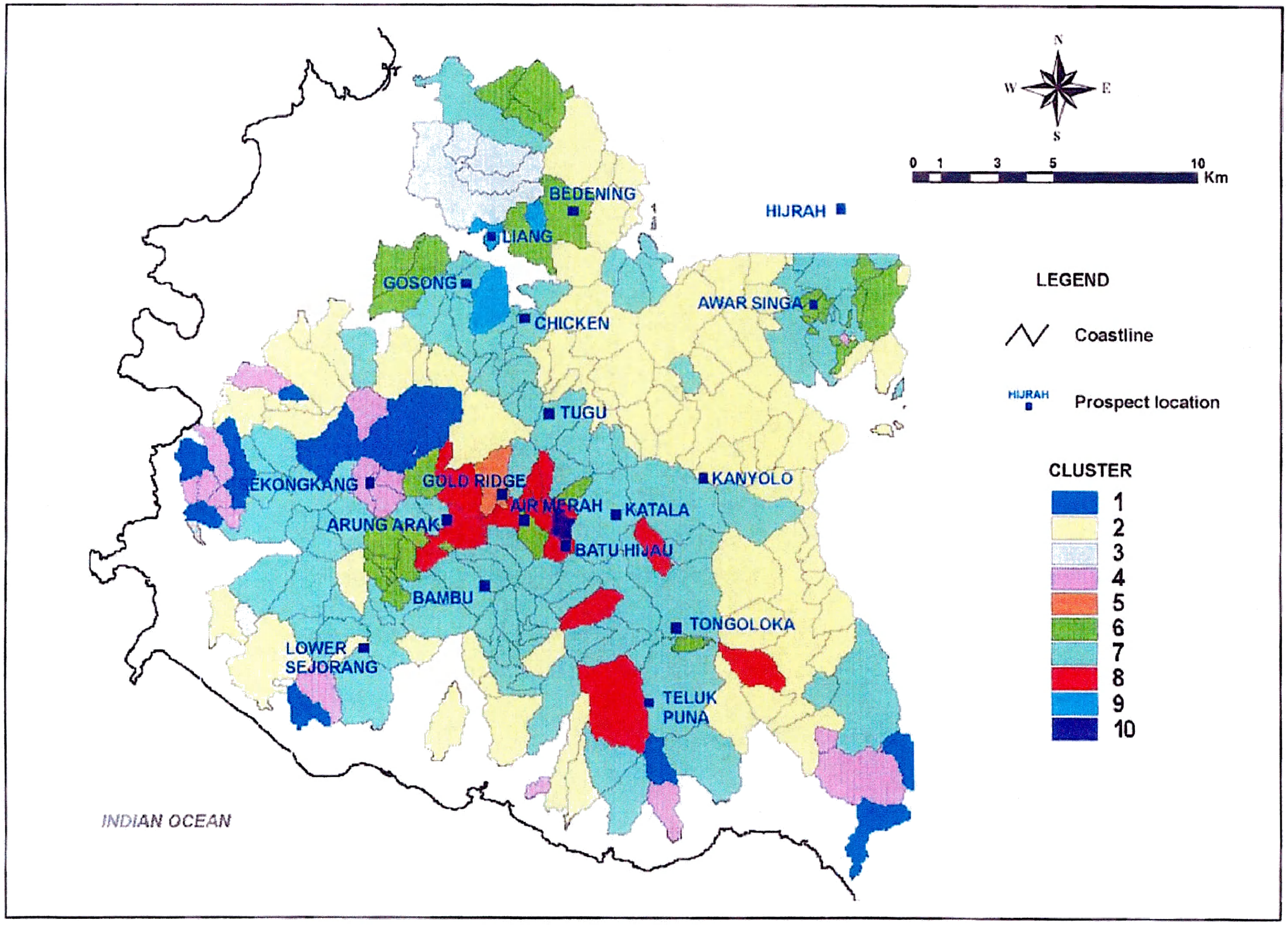

Figure 7.6 Map of final clusters for reconnaissance survey. (Sjoekri, 1997)

Table 7.3 Characteristics for Sjoekri's (1997) final clusters for the reconnaissance survey. (Sjoekri, 1997)

CLUSTER ID	CLUSTER ID Table 7-8 TARGET CLASS	LITHOLOGY	GEOCHEM		GEOPHYSICS		PROSPECTS
			Gold	Copper	Magnetic	Radiometric	
1	-	Laharic breccia, agg. Lapilli, andesite, diorite, alluvium	low	low	background	background	
2	1 TARGET C	Andesite, laharic breccia, clastic sed., alluvium, diorite, agg.lapilli, limestone	low	low	background	background	Lower Sejorang (Alluvial style) Kanyolo (Epithermal)
3	-	Limestone, laharic breccia, alluvium, andesite, clastic sed.	low	low	low	high	
4	5 TARGET A	Laharic breccia, diorite, andesite, agg.lapilli, old tonalite, alluvium	mod	low	mod	background	Sekongkang (Porphyry)
5	1 TARGET C	Agg.lapilli, andesite, diatreme breccia, qtz.vein,	high	low	background	background	Gold Ridge (Epithermal)
6	2 TARGET B	Andesite, diorite, alluvium, clastic sed., limestone, agg.lapilli,	mod	mod	mod	background	Bedening, Awar Singa (Epithermal) Air Merah (Porphyry)
7	3, 4, 5 TARGET B	Andesite, diorite, laharic breccia, limestone, alluvium, agg.lapilli, dacite, old tonalite, clast sed., diatreme breccia, qtz.vein	mod	low	background	background	Teluk Puna, Bambu, Tugu, Vein, Chicken Vein, and Gosong Vein (Epithermal) Katala, Tongoloka, Arung Arak (Porphyry)
8	6, 7, 8 TARGET A	Andesite, diorite, agg.lapilli, old tonalite, alluvium, diatreme breccia, laharic breccia, felds.porphyry, qtz.vein	high	high	high	high	Batu Hijau - north (Porphyry)
9	-	Andesite, Limestone, Dacite, Clastic Seds., Alluvium, diorite, agg.lapilli,	mod	low	low	background	Liang (Epithermal)
10	8 TARGET A	Andesite, Diorite	high	high	high	background	Batu Hijau - south (Porphyry)

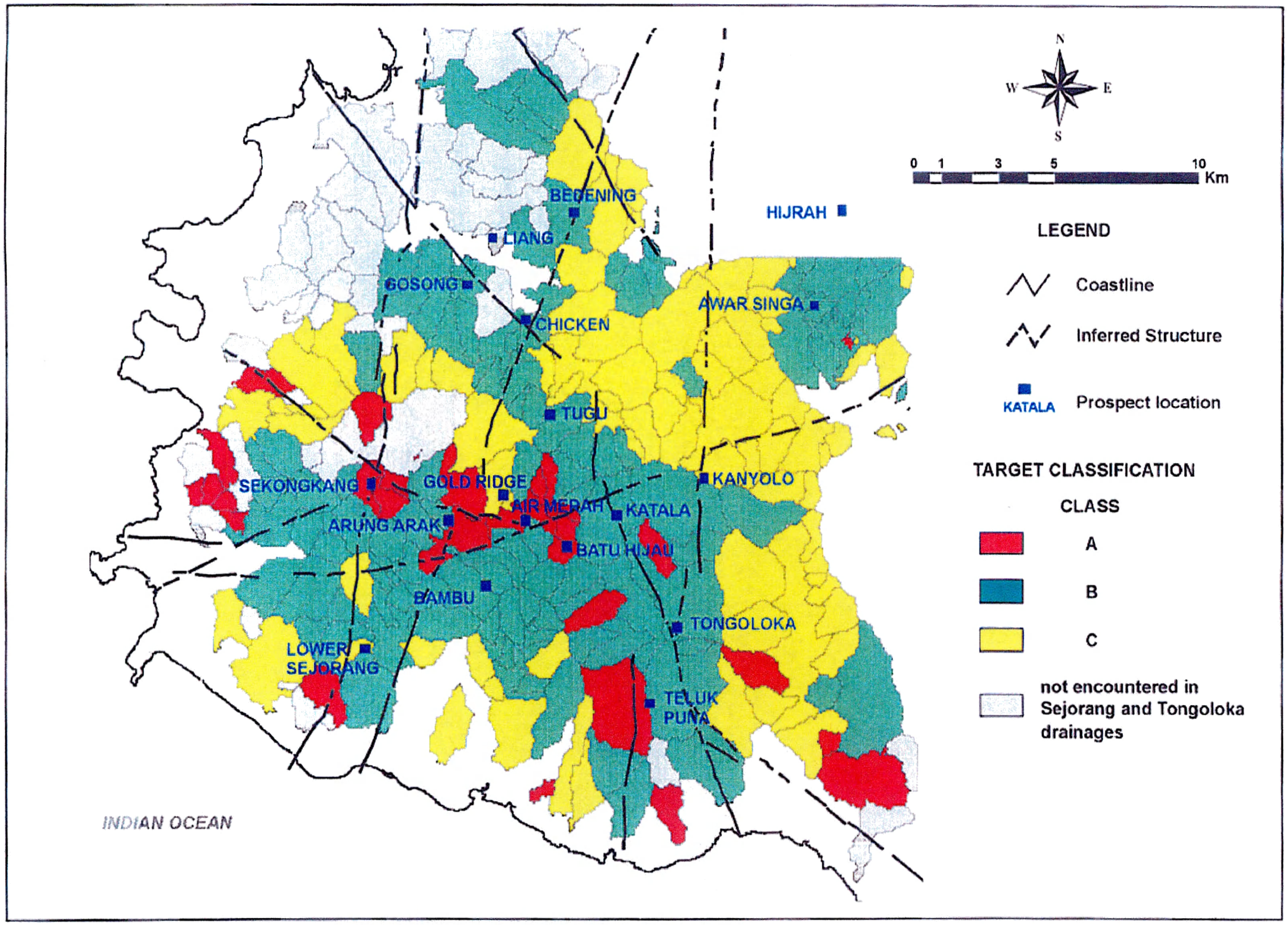

Figure 7.7 Map of the exploration target classification for the reconnaissance survey. (Sjoekri, 1997)

Exploration target class A drainages (clusters 4, 8, and 10 in Table 7.3) are characterized by large proportions of andesite, diorite, agglomerate lapilli, and laharic breccia, as well as more localized areas of alluvium, diatreme breccia, quartz veins, and old tonalite (Sjoekri, 1997, page 151). Exploration target class A also corresponds spatially with the Batu Hijau deposit and with elevated Au and Cu values in the stream sediments. The west-northwest trend of drainages of target class A is consistent with the alignment of porphyry copper-gold occurrences in the area and their inferred regional structural control (Sjoekri, 1997). Sjoekri (1997, page 152) suggested that this trend may represent a corridor of potential exploration targets having some similarity to Batu Hijau (Sjoekri, 1997, page 152). He also states that "by experience with mineral prospecting in southwest Sumbawa, it can be interpreted that target class A, representing porphyry style mineralization, is the most economically important class."

Exploration target class B drainages (clusters 6 and 7 in Table 7.3) include several known localities of low-sulfidation epithermal gold mineralization, along with weakly developed porphyry copper-gold deposits (Sjoekri, 1997). Class B drainages are also characterized by predominantly andesite volcanic rocks and diorite intrusives with minor dacite and limestone. Class B drainages are typically located peripheral to target class A and represent the second most important drainages for follow-up exploration (Sjoekri, 1997).

Exploration target class C (clusters 2 and 5 in Table 7.3) includes some areas of low-sulfidation epithermal gold and alluvial-style mineralization. Class C is predominantly andesite volcanic rocks, agglomerate lapilli, laharic breccia, and alluvium, with localized diorite and diatreme breccia (Sjoekri, 1997, page 151). Class C represents the lowest ranking exploration target class and is given low priority for follow-up exploration programs (Sjoekri, 1997).

7.5 Assessment of Technique

The highly subjective nature of cluster analysis is both an asset and a detriment. It is an asset for those familiar with the technique and the problem at hand as it allows the investigator a wide variety of possibilities for interpreting the results. It is a detriment for those not as familiar with the technique, or the problem at hand, as there are so many options to choose from when selecting dissimilarity versus similarity measures, linkage procedures and the placement of the phenon line. The options can be overwhelming and confusing as there are no set guidelines or recommendations for the procedures (Howarth and Sinding-Larsen, 1983).

Cluster analysis can be a reliable method. The reliability of the interpretation is largely reliant upon the experience of the interpreter. Sjoekri (1997) was able to select clusters which correctly identified the known mineral occurrences in the area.

Cluster analysis becomes easier to use with experience, both with the technique and the geological problem at hand. This is largely due to the many options, such as similarity versus dissimilarity measures, that must be selected. The selection of the various parameters becomes easier as the interpreter gains experience with which parameter works best for a given problem.

Cost-effectiveness of cluster analysis, again, is largely based upon the experience of the interpreter. For example, someone with little experience with the technique will take much longer than someone who has used the technique several times. An estimate of the time it took Sjoekri (1997) to perform the cluster analysis is not available. It is estimated that he took one, probably two, days to complete the cluster analysis, due to the number of steps and iterations that were performed to arrive at the final interpretation.

The cluster analysis did result in extracting valuable information from the original data and in the selection of potentially mineralized drainages in the reconnaissance survey. A key benefit of cluster analysis is to be able to examine the properties of the clusters and then group them into categories to fit the problem at hand, such as the selection of target classes above. To adequately use the method, the interpreter needs some experience with the cluster analysis technique and the problem at hand to aid in the placement of the phenon line and subsequent selection of clusters. A benefit is that no prior knowledge, i.e. training data, is needed to use the method.

CHAPTER 8

NEURAL NETWORK TECHNIQUES

8.1 Introduction

Neural networks, also called artificial neural networks (ANN), consist of a group of computer programs which look for patterns in data sets to classify objects. Neural networks, modeled after the human brain, consist of a set of nodes, also known as neurons, interconnected by weighted linkages (Brown et al., 2000). The weights of the linkages can be adjusted so that the underlying patterns in the data can be seen. Most supervised neural networks techniques are similar to discriminant analysis, requiring *a priori* knowledge of the survey area and data at hand to select training data. However, in contrast, neural networks look for patterns in the data rather than computing a linear relationship within the variables, and thus neural networks do not require normalized data. Unsupervised neural networks do not require *a priori* knowledge and result in clustering the unknown data into similar groups (Mehrotra et al., 1997).

The use of neural networks techniques in the geosciences is fairly recent, and its application in mineral exploration has only developed within the last decade (Pan and Harris, 2000). Several varieties of neural networks exist; however, the feedforward back-propagating and probabilistic neural networks (PNN) techniques seem to have been used more frequently within the mining and mineral exploration geosciences (Singer and

Kouda, 1997; Brown et al., 2000). Back-propagating neural networks are supervised neural networks where the interpreter adjusts the weights on the links between nodes so as to reduce the error between the expected outcome (training set) and network output. The PNN is also supervised neural networks in that training data is required. In contrast, PNN's can have any number of categorical outputs.

8.2 General Methodology

Supervised neural network techniques require a training set that typically consists of preselected samples used in a training session or a randomly selected subset of the target area data used in an unsupervised training method. The training set should contain an equal number of patterns for each outcome and the total number of patterns should be ten times the number of inputs (Ward, 1996). Redundant variables should be avoided as they increase the training time and can, in some cases, decrease the reliability (Ward, 1996). Also, if the ratio of two variables contains more information than the two individual variables, the ratio should be used instead of the original two variables as it increases the accuracy of the network (Ward, 1996).

The training data sets for the orientation and reconnaissance data set consist of natural log (ln)-transformed geochemical data, drainage area, lithology (in percents), and stream order for each survey. While normally distributed data are not required for this technique, Ward (1996) suggests using ln-transformed data for variables with large ranges, such as Cu in the reconnaissance survey (which ranges from 8 to 1400 ppm), to make training the network faster.

The most common structure for neural network applications is a three layer system which includes input, hidden, and output layers (Dowd and Saraç, 1994). Each layer consists of nodes or neurons. Each node may have more than one input, but only one output and can perform calculations. The nodes are connected and weights are applied to the connections during the training portion of the procedure so that the network "learns" the pattern of the target mineral deposit (Dowd and Saraç, 1994; Ward, 1996).

Dr. K. J. Voorhees, Chemistry and Geochemistry Department, Colorado School of Mines, gave the author permission to use the NeuroShell 2 (Ward, 1996) software for this evaluation of the neural networks technique. NeuroShell2 software is produced by Ward Systems, Inc. A probabilistic neural network (PNN) algorithm is used for this analysis as it allows for the several categorical outputs (Ward, 1996).

8.2.1 Orientation Survey Training Set

The training set initially included all of the variables with the exception of Sb as it didn't have any variance within the training set. Subsequent training sets were made as variables were removed due to smoothing factor adjustments below 0.1 (see section 8.3 for discussion on smoothing factors). A total of three training sets were set up to classify samples based upon barren (B), low-sulfidation epithermal (L), alluvial style occurrences (A), and porphyry copper-gold (P) classes. One training set was set up to classify samples based upon B, L, and P categories. It is important to note that the A category only contained two data points while B, L, and P all contained 9 to 11 data points.

8.2.2 Reconnaissance Survey Training Set

Two training data sets were developed for two groups of categorical outputs, i.e. classes. The first categorical output contained the barren (B) and mineralized (M) classes. The first group contained 28 samples in both the B and M classes. The samples used for the B training patterns were selected randomly from all of the drainages which were more than four drainages removed from known mineralization. The second group of categorical outputs contained the barren (B), low-sulfidation epithermal (L), and porphyry copper-gold (P) classes. The alluvial style occurrences category was not used in the second group as it only contained two sample points while the other categories contained nine sample points each. The samples used for the B training patterns in the second group consisted of nine randomly chosen samples from the B training samples for the first group.

Initially the training data set for the first group contained all variables except Mo, dacite volcanic rocks, and feldspar porphyry. Molybdenum was not included as the network needs to have a variable input for each pattern, thus patterns with no data for a variable could not be considered. Dacite volcanic rocks and feldspar porphyry were not included as the data in the corresponding unknown data set did not contain any nonzero values for these two lithologies. NeuroShell 2 will not accept variables if the minimum and maximum values are the same. A total of four training sets were tested for the first group: BM1, BM4, BM5a, and BM6.

Initially the training data for the second group contained all variables except Mo. Variables were removed if the smoothing factor adjustment was below 0.1. A total of three training sets were tested for this group: BLP1a, BLP2, and BLP3a.

8.3 PNN Architecture

Several steps were needed to set up the neural networks. First, the training data were selected (see discussion in sections 8.2.1 and 8.2.2) and loaded into the program. Since this was a supervised network, the columns from the training set were denoted as either input or output. This told the network the number of input variables, the number of output variables, and allowed the network to adjust the weights on the linkages so that the network outputs more closely match the "actual" outputs.

Second, the test set, or validation set, was extracted from the training set. The test set is used by the network to test itself during training for calibration. For the orientation survey, 30% of the data in the training set was used as the test set. The reconnaissance survey used 25% of the training set as the test set.

Third, the network was set up (Figure 8.1). The PNN has three "slabs" or layers. The first, or input, layer is the collection of nodes for the input variables. The second, or "hidden," layer assembles different combinations of the variables based upon their

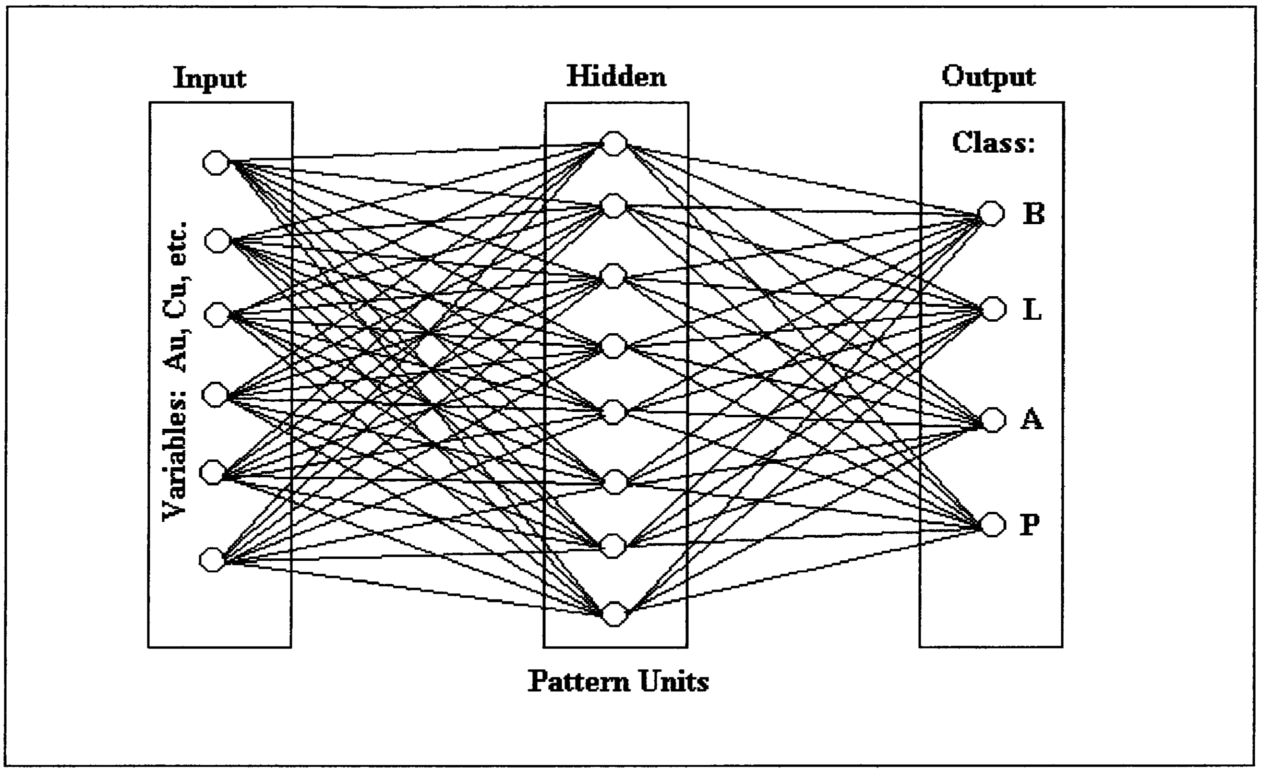

Figure 8.1 An example of probabilistic neural networks architecture. Open circles are nodes. Input, hidden, and output represent layers in a three layer network. Classes are barren (B), low-sulfidation epithermal (L), alluvial style (A), and porphyry copper-gold (P). The nodes in the hidden layer assemble different combinations of the variables based upon the their individual smoothing factor. Nodes with similar patterns are then grouped together, using Euclidean distance measure. These patterns are then compared with the actual output for each corresponding sample in the training data set and are assigned to a categorical output.

individual smoothing factor. Nodes with similar patterns are then grouped together. The hidden layer typically has many more nodes than the input layer. The third, or output, layer contains the nodes for the network output. The number of nodes for each layer varies with the training set and the number of categorical outputs. For example, if all variables were used for the reconnaissance survey, the input layer would have 20 nodes. The hidden layer would have 98 nodes. The output layer, if the B and M classification is desired, would have two nodes.

The initial smoothing factor was set to 0.6. The smoothing factor ranges from 0 to 1 with 1 being the most smooth. "High smoothing factors cause more relaxed surface fits through the data" (Ward, 1996; online Help).

Fourth, the training criteria were set. For this, the Euclidean distance was used, much like in cluster analysis, to compare patterns based upon their distance to each other (Ward, 1996). The genetic adaptive calibration was selected. The genetic adaptive calibration finds smoothing factors for each input as well as an overall smoothing factor for the network (Ward, 1996). First, the network is trained with the training set. Then the network uses the calibration to test a wide range of smoothing factors that work best with the test (or validation set). The individual smoothing factor adjustments that result are multipliers for each input which can be used to adjust the overall smoothing factor established for the network. Thus, inputs with large smoothing factor adjustments are more valuable to the network than those with smaller adjustments (Ward, 1996). Input variables with smoothing factor adjustments of less than 0.1 were subsequently discarded and a new network trained.

The network was also set to notify the author if any inputs had missing data. This option was selected as all variables should have had numerical values. This also meant that Mo for the reconnaissance survey could not be used. Other options were available, such as using the average value in place of missing data for an input; however, Mo data were so sparse, this option did not seem feasible.

Each network was trained by running the training and test data through once to attempt to avoid over-training since the training sets were so small. Once the network had been trained, the unknown data set corresponding to the training data set, must have exactly the same variables, was run through the network. The results were then mapped spatially using ArcView.

8.4 Orientation Survey Results

Table 8.1 contains a list of the variables which were retained for each network and the percent of training samples correctly classified by the trained network. A variable was removed if it had a smoothing factor adjustment of less than 0.1, with the exception of stream order. Stream order was removed because it is strongly correlated with drainage area (Figure 4.1) and thus is probably redundant.

The unknown data were run through each network several times, in order to get outcomes where nearly all the samples were classified. Each time the unknown data

Table 8.1 List of variables retained for each network trained for the orientation survey and statistics on the number of correctly classified training samples.

	Set 1a	Set 2	Set 3	Set 4
Variables Retained	Stream Order Au, Cu, Pb, Zn, As, Mo All Lithology Drainage Area	Stream Order Au, Cu, Pb, Zn, As, Mo All Lithology Drainage Area	Au, Cu, Pb, Mo Alluvium, Andesite Volcanic Rocks, Limestone, Diatreme Breccia, Quartz Veins, Hornblende Biotite Diorite, Old Tonalite, Hornblende Microdiorite, Drainage Area	Au, Cu, Pb, Mo Alluvium, Limestone, Diatreme Breccia, Quartz Veins, Hornblende Biotite Diorite, Old Tonalite, Hornblende Microdiorite
Variables Not Retained	Sb	Sb	Stream Order As, Sb, Zn, Agglomerate Lapilli, Laharic Breccia, Feldspar Porphyry, Leuco Diorite	Stream Order As, Sb, Zn, Agglomerate Lapilli, Laharic Breccia, Feldspar Porphyry, Leuco Diorite, Andesite Volcanic Rocks Drainage Area
% Correct of Training Data				
B	100	100	60	100
L	100	100	100	100
A	100	---	100	100
P	100	100	60	100

B = barren
L = low-sulfidation epithermal mineralization
A = alluvial-style mineralization
P = porphyry copper-gold mineralization

were run through its corresponding network, a different outcome was obtained, which indicated that the networks that were produced during training were unstable. Figures 8.2, 8.3, 8.4, and 8.5 are the spatial plots of the classifications for each network, i.e. set. From examining Figures 8.2, 8.3, 8.4, and 8.5, it is clear that several drainages which contain known mineral occurrences have been misclassified. For example, many of the drainages with known porphyry copper-gold deposits were classified as either barren or low-sulfidation epithermal. This is probably due to inadequate training data.

8.5 Reconnaissance Survey Results

Table 8.2 contains a list of the variables retained and the percent correct classification for the four networks produced with the first group of classes: BM1, BM4, BM5a, and BM6. Table 8.3 contains a list of the variables retained and the percent correct classification for the three networks produced with the second group of classes: BLP1a, BLP2, and BLP3a.

Figures 8.6, 8.7, 8.8, and 8.9 are spatial plots of the results for networks for the first group. The only network which recognized the two unknown mineralization sites, or types of mineralization, was BM1 (Figure 8.6). Both networks BM4 and BM6 are probably unstable as: (1) they didn't recognize the two unknown mineralized drainages as mineralized; and (2) a significant number of drainages were not classified at all. The BM5a network (Figure 8.8) was able to classify all drainages but was unable to recognize the two unknown mineral occurrences as mineralized drainages.

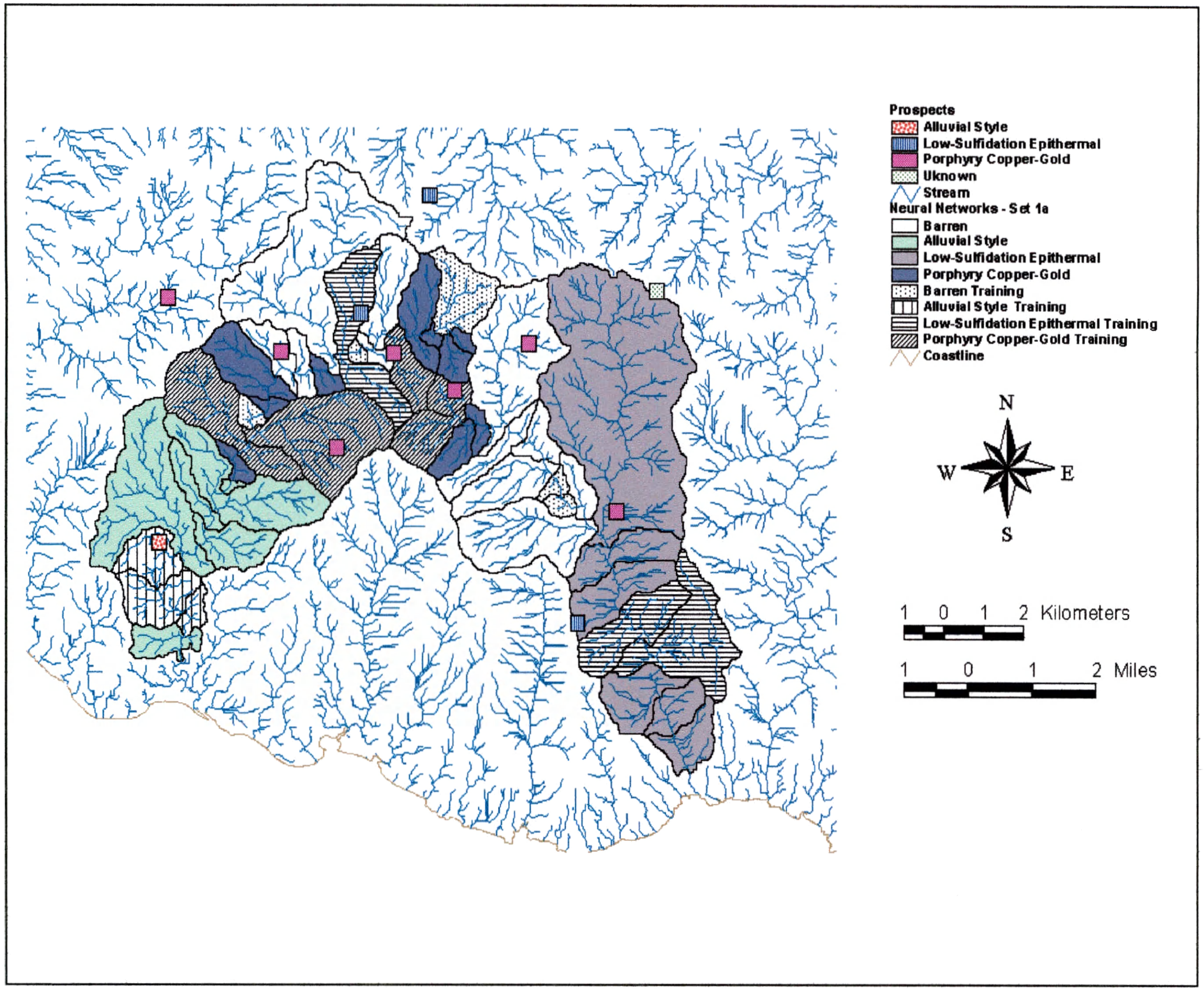

Figure 8.2 Spatial distribution of the neural networks classifications for Set 1a of the orientation survey. Set 1a retained all variables, except Sb, for the barren, low-sulfidation epithermal, alluvial style gold, and porphyry copper-gold classes.

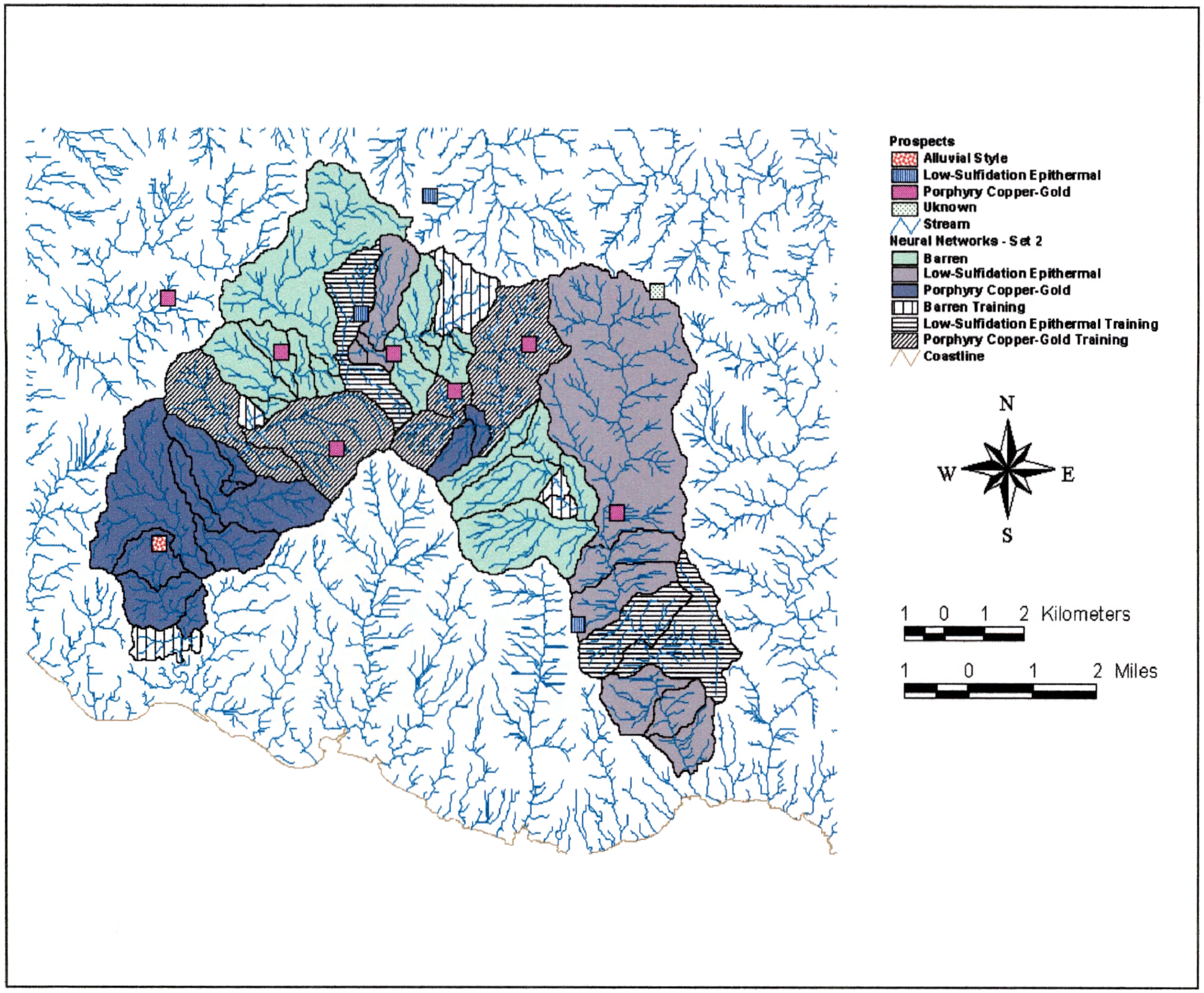

Figure 8.3 Spatial distribution of the neural networks classifications for Set 2 of the orientation survey. Set 2 retained all variables, except Sb, using the barren, low-sulfidation epithermal, and porphyry copper-gold classes.

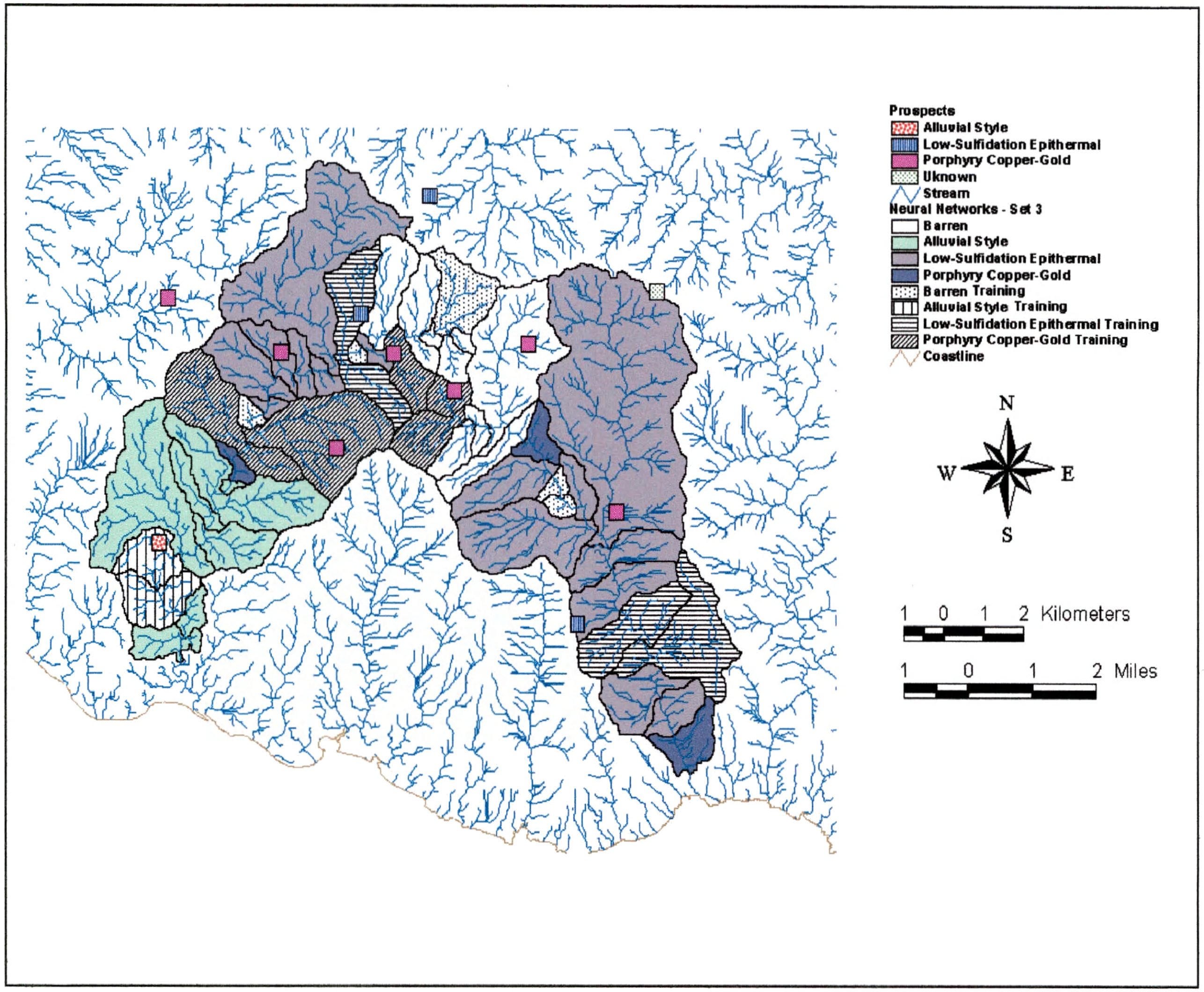

Figure 8.4 Spatial distribution of the neural networks classifications for Set 3 of the orientation survey. Set 3 retained all variables except stream order, As, Sb, Zn, agglomerate lapilli, laharic breccia, feldspar porphyry, and leuco diorite for the barren, low-sulfidation epithermal, alluvial style gold, and porphyry copper-gold classes.

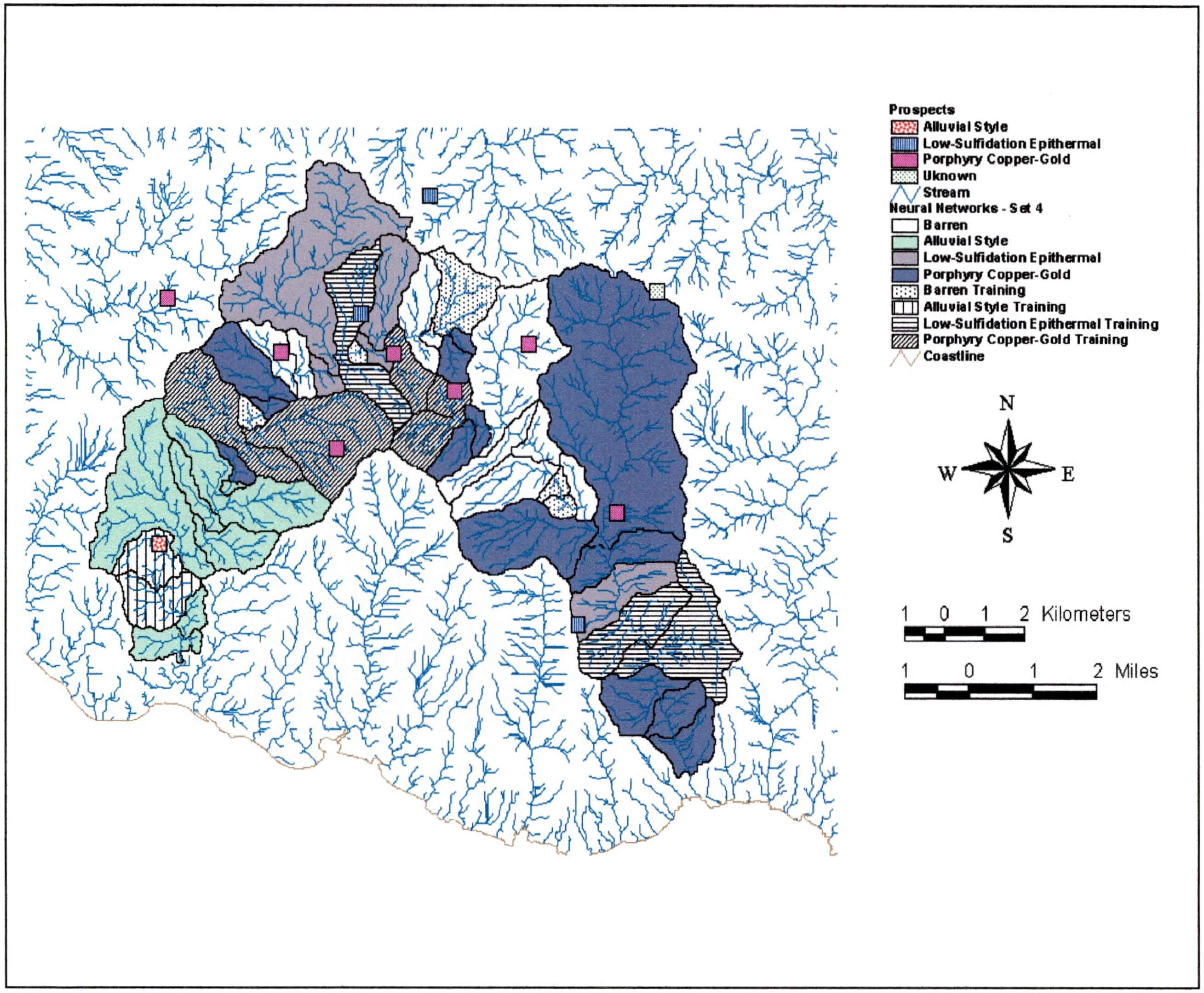

Figure 8.5 Spatial distribution of the neural networks classifications for Set 4 of the orientation survey. Set 4 retained Au, Cu, Pb, Mo, alluvium, limestone, diatreme breccia, quartz veins, hornblende biotite diorite, old tonalite, and hornblende microdiorite for the barren, low-sulfidation epithermal, alluvial style gold, and porphyry copper-gold classes.

Table 8.2 List of variables retained for each network from the first group of classes for the reconnaissance survey and statistics on the number of correctly classified training samples.

	BM1	BM4	BM5a	BM6
Variables Retained	Au, Cu, Pb, Zn, As, Sb Quartz Veins, Limestone, Andesite Volcanic Rocks, Hornblende Biotite Diorite, Hornblende Microdiorite, Old Tonalite, Alluvium, Laharic Breccia, Clastic Sediment, Agglomerate Lapilli, Leuco Diorite, Diatreme Breccia Drainage Area	Au, Cu, Pb, As, Sb Quartz Veins, Limestone, Andesite Volcanic Rocks, Hornblende Biotite Diorite, Hornblende Microdiorite, Old Tonalite Drainage Area	Au, Cu, Pb, Zn, As, Sb Quartz Veins, Limestone, Andesite Volcanic Rocks, Hornblende Biotite Diorite, Hornblende Microdiorite, Old Tonalite Drainage Area	Au, Cu, Pb, Zn, As, Sb Quartz Veins, Limestone, Andesite Volcanic Rocks, Hornblende Biotite Diorite, Hornblende Microdiorite, Old Tonalite
Variables Not Retained	Mo Dacite Volcanic Rocks, Feldspar Porphyry	Mo, Zn Dacite Volcanic Rocks, Feldspar Porphyry, Alluvium, Laharic Breccia, Clastic Sediment, Agglomerate Lapilli, Leuco Diorite, Diatreme Breccia	Mo Dacite Volcanic Rocks, Feldspar Porphyry, Alluvium, Laharic Breccia, Clastic Sediment, Agglomerate Lapilli, Leuco Diorite, Diatreme Breccia	Mo Dacite Volcanic Rocks, Feldspar Porphyry, Alluvium, Laharic Breccia, Clastic Sediment, Agglomerate Lapilli, Leuco Diorite, Diatreme Breccia, Drainage Area
% Correct of Training Data				
B	93	100	89	100
M	79	100	71	100

B = barren M = mineralized

Table 8.3 List of variables retained for each network from the second group of classes for the reconnaissance survey and statistics on the number of correctly classified training samples.

	BLP1a	BLP2	BLP3a
Variables Retained	Stream Order Au, Cu, Pb, Zn, As, Sb All Lithology Drainage Area	Stream Order Au, Cu, Pb, Zn, As, Mo All Lithology Drainage Area	Au, Cu, Pb, As, Sb Alluvium, Andesite Volcanic Rocks, Quartz Veins, Limestone, Hornblende Biotite Diorite, Hornblende Microdiorite, Old Tonalite, Diatreme Breccia, Drainage Area
Variables Not Retained	Mo	Mo, Zn	Stream Order Mo, Zn, Feldspar Porphyry, Agglomerate Lapilli, Laharic Breccia, Clastic Sediment, Leuco Diorite, Dacite Volcanic Rocks
% Correct of Training Data			
B	78	78	78
L	89	89	78
P	100	100	100

B = barren
L = low-sulfidation epithermal mineralization
P = porphyry copper-gold mineralization

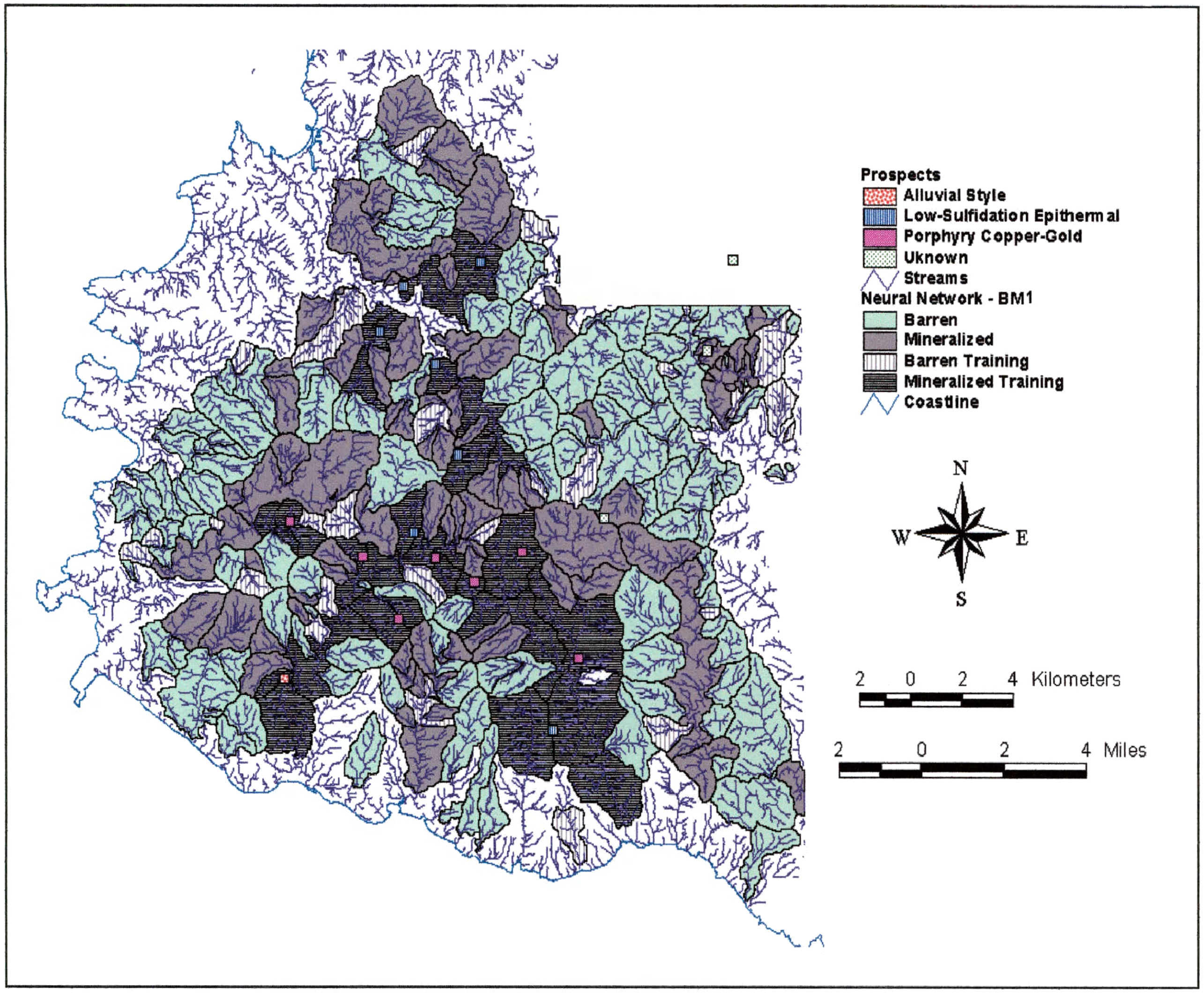

Figure 8.6 Spatial distribution of the neural networks classifications for BM1 network of the reconnaissance survey. Set BM1 retained all variables except Mo, dacite volcanic rocks, and feldspar porphyry, for the barren and mineralized classes.

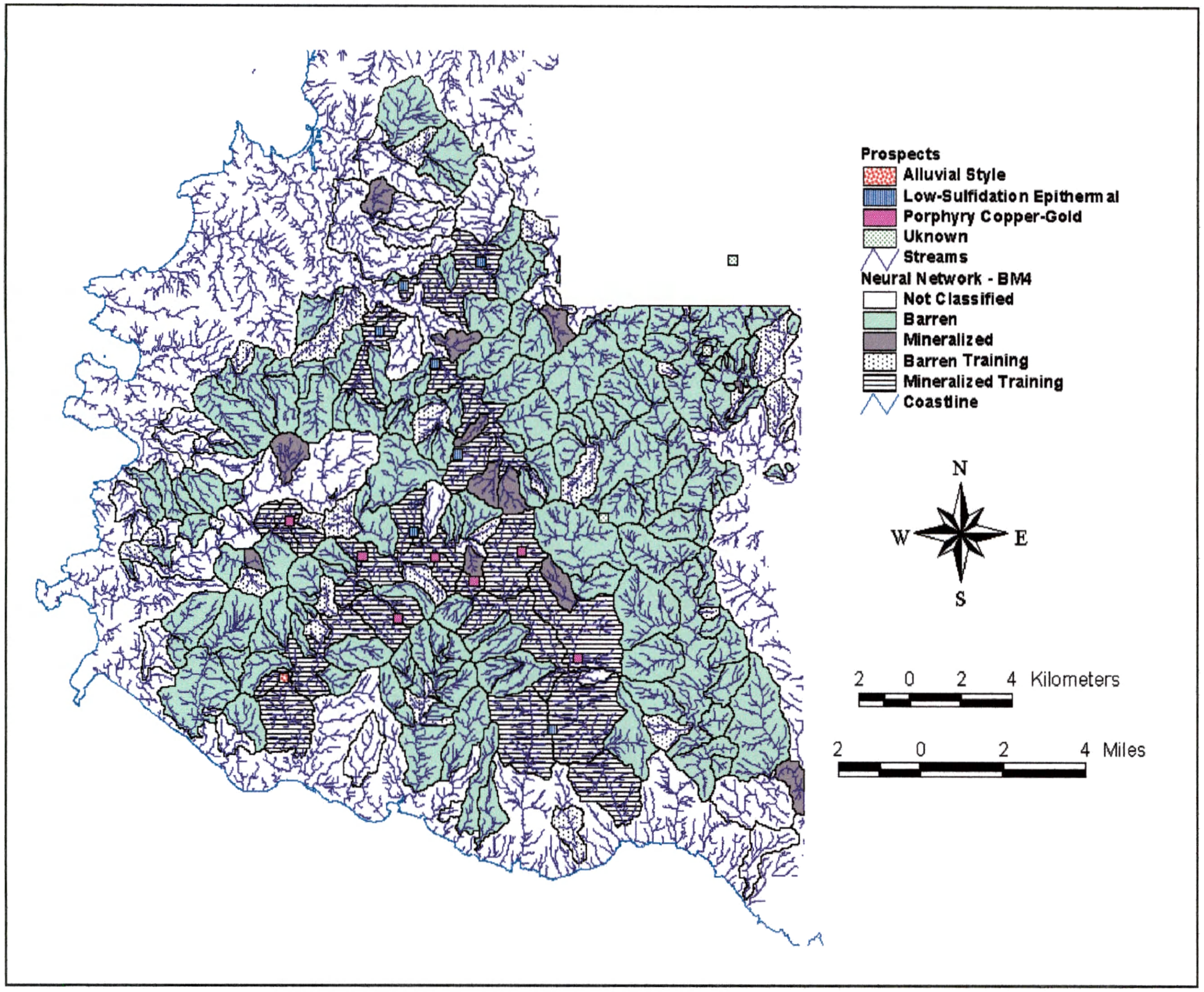

Figure 8.7 Spatial distribution of the neural networks classification for BM4 network of the reconnaissance survey. Set BM4 retained Au, Cu, Pb, As, Sb, quartz veins, limestone, alluvium, hornblende biotite diorite, hornblende microdiorite, old tonalite, and drainage area for the barren and mineralized classes.

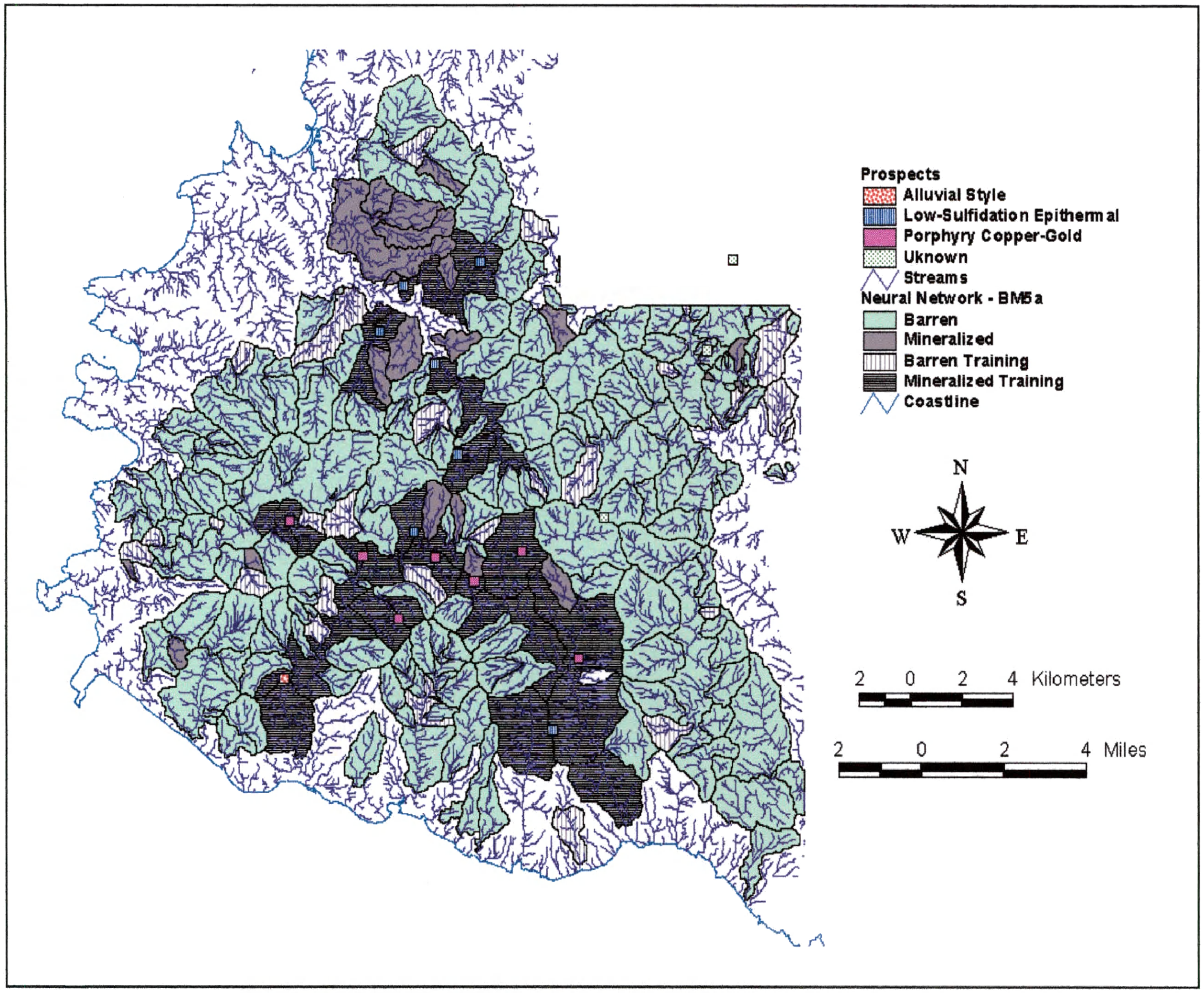

Figure 8.8 Spatial distribution of the neural networks classification for BM5a network of the reconnaissance survey. Set BM5a retained Au, Cu, Pb, Zn, As, Sb, quartz veins, limestone, andesite volcanic rocks, hornblende biotite diorite, hornblende microdiorite, old tonalite, and drainage area for barren and mineralized classes.

be attainable. This technique was attempted for both the orientation survey and the reconnaissance survey; however, the results were very poor. For the reconnaissance survey, only 10% of the unknown data was even classified. It is important to note, however, that Clare and Cohen (2001) were using a data set of 1670 stream sediment sample points, as opposed to the 255 sample points in the reconnaissance survey.

8.7 Assessment of Technique

The reliability of this technique with this data is poor. Singer and Kouda (1997), Brown et al. (2000), and Clare and Cohen (2001) have all been able to develop much more reliable networks, chiefly due to: (1) larger data sets; (2) more experience with the technique; and (3) better training data sets, where applicable.

Neural networks, once trained, are easy to use. The method itself is much less easy to use as it requires several parameters be set and can require a lot of training time. Training time consists of both learning how to use the method and to train the network. In contrast though, the NeuroShell 2 software itself was very user-friendly.

It took approximately eight hours to train to use the neural networks software. Most of this time was used to learn about the different parameters that needed to be selected while setting up the network. The time it took to create the training and corresponding unknown data sets was roughly four hours, based upon trial and error. The time to setup and train each network took on the order of minutes, with actual training time on the order a few seconds. Only a few permutations of variables and outcomes were tested in this study as the results were pretty clear that more training data were needed for more precise outcomes.

In contrast, Clare and Cohen (2001) compared an unsupervised neural network (UNN) technique to k-means clustering. The authors state that "analytical time taken to define clusters and anomalous catchments from presentation of the raw data to the UNN was in the order of minutes. The k-means clustering required some hours of data manipulation and preprocessing prior to running the models" (page 133). Thus, neural networks methods can be cost-effective if: (1) that method is planned for many future projects; and (2) there are enough data for the method to be reliable. This allows the initial set up and training costs to be recovered in later projects.

Overall, neural networks techniques are a promising new approach to data interpretation. Future investigations should continue to look at the limitations and benefits of this technique. The interested reader is referred to Singer and Kouda (1997), Brown et al. (2000), and Clare and Cohen (2001) for more information about neural network techniques in mineral exploration.

CHAPTER 9

COMPARISON OF TECHNIQUES

9.1 Comparisons of the Techniques

The basis of comparison of the techniques, as outlined in section 1.1, will be by reliability, ease-of-use and cost effectiveness. A technique is deemed reliable if it correctly identifies nearly all of the drainages with known mineral occurrences. Ease of use criteria includes the time and experience required to prepare for and run each technique and interpret the results. Cost-effective techniques are those with a small overall run and interpretation time, matched by a reliable output and low overhead cost, such as purchase of software or purchase of experience.

In comparing each technique used in this study it is important to note the limitations that the orientation and reconnaissance data sets imparted. First, the reconnaissance survey was conducted in 1987 and the orientation survey was conducted in 1993, both before the widespread ability of large volume multielement low cost ICP analyses. As such, the number of elements determined for each survey was restricted to those which would best represent porphyry copper-gold and low-sulfidation epithermal mineralization. In contrast, many of today's data sets include a wide variety of elements which provide the interpreter with access to elements that might help to identify other geochemical processes such as adsorption. For example, it is common to analyze for Fe and Mn today; however, in 1987, the justification of the added expense to analyze these two elements might not be recognized by the investor.

9.1.1 Reliability

Reliability is probably one of the most important factors when deciding which multivariate data interpretive method to use, especially in relation to mineral exploration programs. For the methods used here, the two most reliable methods were factor analysis and cluster analysis because each method was able to identify potential areas of mineral occurrences that had similar characteristics. Discriminant analysis was reliable if the discrimination was between barren and mineralized classes, but became less reliable if the discrimination was between barren, porphyry copper-gold, low-sulfidation epithermal, and alluvial style mineralization. This is probably due to insignificant number of training samples per class and failing to meet two out of the three criteria.

The results from the neural network analysis for the barren versus mineralized classes of the reconnaissance survey, with all the variables retained, was the most reliable of all of the networks tested. As with the discriminant analysis, neural networks analysis was not as reliable due to the insignificant number of training patterns compared to variables.

9.1.2 Ease of Use

The ease of use is another important criteria when selecting a multivariate interpretive method, as it can affect the cost-effectiveness of the method. For example, if a method is harder to use or require more training, it will probably be more expensive to use either in time or experience. Another factor effecting ease of use is the degree of *a priori* knowledge available for a given study area and data set.

Each method was relatively easy to train for and easy to implement. Factor analysis was the easiest to train for and implement, although the interpretation of the resulting factors required knowledge of the common geochemical associations for the target mineral occurrences, surrounding lithologies, and geochemical environment. Discriminant analysis was also easy to use as it didn't take long to learn the Statistica software package and to run the analysis. Interpretation of the results was also fairly straightforward, as a drainage was either in one class or another. Cluster analysis was probably a little more difficult to use as it requires several iterations with different placements of the phenon line to get clusters which made sense geologically (Sjoekri, 1997). The neural network technique was a little more difficult to use since each network to test different combinations of variables required different training sets. Like discriminant analysis, however, the neural network interpretation was straightforward. The time to learn the NeuroShell 2 software was comparable to learning the Statistica discriminant analysis and factor analysis modules.

9.1.3 Cost-effectiveness

A key component for mineral exploration programs is the issue of cost-effectiveness. Cost-effectiveness is a combination of the reliability of a method, the ease of use, and the cost of running the method in both time and expertise. As previously mentioned, stream sediment sampling can be a cost-effective means of obtaining broad aerial coverage. This has been made possible due to instrumental capability, particularly that of ICP-MS, increasing each year with respect to sensitivity, suite of elements determined, and volume, without significant overall cost increases.

Currently the base price for the Statistica program with the multivariate exploratory techniques module which includes factor analysis, discriminant analysis and cluster analysis is $1,190.00. The new neural network module for Statistica is also available, however, the cost has increased to $1,495.00 at the time this study was published. The price for NeuroShell 2 at the time this study was published was $595.00. If the programs that are used to run the selected interpretive techniques have already been acquired, as was the case in this study, then the initial purchase cost and set up time do not need to be considered.

Another factor is the training time required to use a method. In some cases it is more cost-effective in the long run to train someone to use a method that is expected to be used for many future projects. In this way the initial time and money spent on training is recovered later. In some instances where a method is only expected to be used once, it may be more cost-effective to hire someone who already has experience with the method.

Another factor is the time needed for interpreting the results. A person's experience with the method and the problem will largely dictate the time and reliability of the interpretation.

For the methods compared in this study, factor analysis was reliable, took the least amount of time to prepare the data, run, and interpret the results compared with all of the methods examined. Cluster analysis and discriminant analysis were both slightly less cost-effective than factor analysis. Cluster analysis was less cost-effective than factor analysis due to the estimated time it took Sjoekri (1997) to prepare the data and go through the several steps to arrive at the final dendrogram and subsequent interpretation; however, the results were reliable. Discriminant analysis is probably as cost-effective as cluster analysis; however, in this study it was not as reliable even though it is believed that it took less time to use. The neural network method was the least cost-effective method in this study because the results were not reliable and it took longer to learn how to use compared with the other methods.

9.2 Recommendations for Future Study

The selection of the multivariate approach to use for interpreting drainage survey data must keep in mind the following:

a) what type of *a priori* knowledge is available for the study area
b) what type of information would be most useful, i.e. geochemical associations or classifications
c) what is the time frame in which the study will need to be completed
d) what method is the user most familiar with or prepared to learn
e) what kinds of data have been or will be collected

The answers to these questions will aid in the selection of the most useful method. If no *a priori* knowledge or training data exists for a survey, perhaps factor analysis or cluster analysis would be the most appropriate. Unsupervised neural networks might also work if enough data are collected. The evaluation of geochemical associations might be useful to better understand not only the barren versus mineralization relationship, but also other factors such as adsorption or downstream dilution which might be masking mineralization signatures.

Short time frames, indicating little time for training on a new technique, might result in the investigator picking the technique that he or she is most familiar with. Finally the types of data that are available, if the surveys have already been conducted prior to selecting the method, will also aid in selecting the method to use. All methods can use geochemical data. Discriminant analysis, cluster analysis, and neural network analysis were able to use lithology, stream order and drainage area data as well. Factor analysis worked well with only the geochemical data; however, it would also work well with stream orders and drainage area data. If the survey has not been conducted, selecting the multivariate statistical technique during the design of the survey would be helpful also selecting the appropriate variables for the method.

The author agrees with Wong et al. (1995)'s suggestion that neural network techniques should be used in conjunction with standard statistical techniques, especially if the predictions from the standard techniques are unsatisfactory due to violations of the required assumptions for that technique. However, it is also important for more work to be done with different data sets, comparing discriminant analysis and neural network techniques, along with factor analysis and cluster analysis and other multivariate statistical techniques.

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APPENDIX A

DRAINAGE GEOCHEMISTRY

A.1 Introduction

The general behavior of chemical components within the environment, and specifically with relation to stream sediment, is an important part of interpreting the results of the multivariate statistical techniques that are compared in this study. Macro-environmental factors such as topology, climate (which includes temperature and rainfall), vegetation, and anthropogenic processes must be kept in mind when interpreting results as these factors affect the degree and predominant type of weathering. Intermediate environmental factors affecting an element's geoavailability in the stream environment include the physical and chemical weathering characteristics of the source material and how that material moves downstream. At the micro-environmental level, the interactions between water and stream sediments are dominated by changes in pH and Eh of the water and the overall content of clays, Fe- and Mn-oxides, and organic matter. Geochemical barriers represent significant changes in the micro-environment over short distances and can be used to better understand where an element might be placed within the system and why it got there. All these factors, when taken together, can be used to explore for ore deposits since ore deposits can significantly change the micro-environment when compared with the surrounding lithology.

A.2 Macro-Environmental Factors

The topography of southwestern Sumbawa ranges from coastal lowlands to high mountainous areas. Church et al. (1989) found that mechanical weathering is more prominent in mountainous terrain; however, the authors were studying dispersion in the cool temperate climate of the Alaskan Aleutian Island Chain. In contrast southwestern Sumbawa is a humid tropical climate, especially in the high mountain areas where rainfall can reach 85 inches (220 cm) per year. In addition to the high average rainfall, the average temperature ranges between 68° to 86° F (20° to 30° C). With increased temperature and moisture, chemical weathering becomes more prominent.

Vegetation also plays an important role in affecting the location of elements in the environment (Smith and Huyck, 1999). Vegetation, including trees and shrubs, can take up certain elements, thus removing them from soil and sediment either temporarily or permanently. Bioactivity in humid tropical climates can be intense, resulting in the uptake of elements and subsequent loss of information that might otherwise be in the stream sediment. For example, Au can be concentrated in plants as a cyanide complex (Rose et al., 1979), thus removing it from stream sediment and potentially reducing what might ordinarily be an anomaly to background levels.

Contributions from human activity, such as runoff from roadways or leaching from mine tailings, could also contribute to the composition of drainage sediments. Few roads existed in the survey areas at the time the two surveys were conducted and construction of mining facilities at Batu Hijau did not begin until 1996, well after the two surveys had been completed (DeMull et al., 2001). Thus anthropogenic factors are not considered to be significant in interpretation of the survey data.

A.3 Intermediate Environmental Factors

The geoavailability of an element, its tendency of an element to be released from its source mineral into the surficial environment, is a function of physical and chemical weathering (Smith and Huyck, 1999). Physical weathering is the mechanical, non-chemical, breakdown and movement of material. Insoluble minerals, those that are stable in normal surface conditions, tend to move downstream by saltation or in the suspended load. Chemical weathering is the chemical breakdown of rocks and minerals into more stable substances. Highly soluble minerals, such as calcite, will readily breakdown into its chemical components under certain surficial conditions. Once an element is in solution it moves downstream until the aqueous conditions change so that it precipitates, complexes, or becomes adsorbed and thus taken out of solution.

Geochemical conditions can change significantly throughout a drainage. Hobday and Fletcher (2001) found that for first and second order streams, the dominant factor in the composition of stream sediments is lithologically controlled under normal conditions. As more tributaries merge and the stream order increases, a shift in composition of stream sediment from control by source rocks to aqueous geochemical processes occurs. Thus, in larger streams and rivers feed by several tributaries, the dominant geochemical signature will be affected more by chemical processes in the aqueous environment (Hobday and Fletcher, 2001).

As previously mentioned, the proportions of lithologies within the drainage area that are represented at a sample site depend upon the individual lithologies' susceptibility to weathering (Stallard and Edmond, 1987). As a result lithologies which are more readily weathered than their counterparts in the catchment will make up a proportionally greater percentage of the stream sediment composition. The exception to this is if the lithologic unit as a whole is more readily chemically weathered or dissolved. In this case the more resistant lithology, and probably more mechanically transported material, will represent a greater proportion of the stream sediment composition.

A.4 Micro-Environmental Factors

Interactions between the aqueous environment, source minerals, and stream sediment are predominantly affected by changes in pH and Eh, and adsorption on clays, Fe- and Mn-oxides, and organic matter (Rose et al., 1979; Perel'man, 1986; Horowitz, 1991; Plumlee and Nash, 1995; Smith and Huyck, 1999). The degree of acidity or alkalinity, the pH, is a measure of the H^+ ion activity present in water. Eh is a measure of the free oxygen content in the system, with oxidating waters being rich in free oxygen and reducing waters being absent of free oxygen. Both pH and Eh can affect the location of elements in the environment. For example, under highly oxidative and strongly acidic conditions Au is somewhat mobile in solution, but otherwise it is generally chemically inert, i.e. immobile (Smith and Huyck, 1999). Horowitz (1991) notes that Sb typically is the most soluble of the elements collected for this study, traveling on average 50% in the soluble phase under normal conditions. Roughly 20 to 30% As travels in solution, Cu between 8 and 10%, Pb roughly 0.8% and Zn roughly 0.2%.

Once an element is in solution, the ionic potential, the ratio of oxidation number to ionic radius, predicts whether an element will by mobile as a simple cation, e.g. Na^+ which has a low ionic potential, or form compounds with oxygen, e.g. S^{6+} as SO_4^{2-} which has a high ionic potential (Smith and Huyck, 1999; Rose et al., 1979). Appendix B contains selected geochemical parameters for elements used in this study, including ionic potential and mobility in solution. Elements with moderate ionic potential are fairly immobile because they have a tendency to strongly adsorb or hydrolyze (Smith and Huyck, 1999; Rose et al., 1979). It is important to note that changes in valence state, i.e. oxidation number, will change the ionic potential and subsequently change the element's mobility in a given environment (Rose et al., 1979).

Adsorption is the process by which elements in solution, either as simple cations or as oxyanions, attach to the surface of hydrous Fe- and Mn-oxides, clays, or organic matter (Rose et al., 1979; Perel'man, 1986; Horowitz, 1991). Fine grained sediments or organic molecules with large charged surface areas and high cation exchange capacity are the best receptors for ions in solution. Hydrous Fe- and Mn-oxides are excellent candidates for adsorbing ions due to the fine-grained, poorly crystallized habit with large surface area and high cation exchange (Horowitz, 1991).

Clay minerals are also extremely fine-grained, have large surface areas, expandable lattices, and moderate to high cation exchange capacity with high negative surface charge principally due to broken bonds on mineral edges and substitution of Al^{3+} for Si^{4+} within the lattice structure (Plant and Hale, 1994; Horowitz, 1991). As a result, the fine-grained clay-sized particles have some of the highest metal concentrations (Smith and Huyck, 1999).

Organic matter, or humus, can concentrate substantial amounts of Co, Cu, Fe, Pb, Mo, Ag, and Zn, due to the large surface area, high cation exchange capacity, high negative surface charge and physical trapping (Horowitz, 1991). Three of the ways organic matter can affect the mobility of ions in solution include complexing with trace elements thereby increasing their mobility, forming organic compounds that result in immobilization of the element, or reducing the element to a lower valence state which changes the chemical properties of the element as reflected by a change in ionic potential (Rose et al., 1979).

The affects of the above factors on the location of elements in the surficial environment can be predicted by understanding the concept of geochemical barriers. Geochemical barriers result from significant and mostly abrupt changes in the physical or chemical properties of a stream which result in the precipitation of certain elements (Smith and Huyck, 1999; Perel'man, 1986). The most significant physio-chemical barriers in the southwestern Sumbawa region are oxidizing, reducing hydrogen sulfide, acidic, alkaline and adsorption (Perel'man, 1986, Rose et al., 1979). Table A.1 contains a synopsis of the geochemical barriers most common in the southwestern Sumbawa region. It is important to understand that more than one geochemical barrier can exist at a location, such as the complex oxidizing-adsorption barrier, where the precipitation of hydrous Fe- and Mn-oxides (oxidizing) is accompanied by the adsorption of Cu, Zn and Pb (adsorption) on the hydrous oxides (Perel'man, 1986).

A.5 Application to Mineral Exploration

The design of mineral exploration drainage surveys and selection of elements for analysis should include careful consideration of the aforementioned factors. For example, the elements that are used in this study may occur in primary ore minerals that travel with the heavy mineral fraction (concentrated in coarser-sized particles), secondary ore minerals which become finer grained downstream from the source, precipitates, adsorbed ions on Fe-Mn oxides, organic matter, or clay, or taken up by vegetation along the stream bank (Rose et al., 1979).

Rose et al. (1979) note that normal surface waters are typically between a pH of 5 and 8, however, near a sulfide ore body the pH can drop significantly, which can significantly affect an elements mobility as described in section A.4. Typically immobile elements tend to create a "halo" about the deposit, moving mostly with the clastic, solid particles by saltation (Rose et al., 1979), whereas the mobile elements move into solution and are carried much further from the deposit. The size of halos about pyrite-rich orebodies tend to be reduced, while the

Table A.1 Synopsis of geochemical barriers commonly found in southwestern Sumbawa. Compiled from Rose et al. (1979), Perel'man (1986), Plumlee and Nash (1995), and Smith and Huyck (1999).

Geochemical Barrier	**Occurrence**	**Results**
Oxidizing	When reducing waters come into contact with free oxygen	Precipitation of hydrous Fe- and Mn- oxides, which lead to adsorption of Cu, Ni, Ag, Zn, and Pb from solution
Reducing Hydrogen Sulfide	When oxidizing or reducing gley waters come into contact with hydrogen sulfide or sulfide minerals, such as in the vicinity of sulfide deposits in humid climates	Precipitation of sulfides such as pyrite and galena, and concentration of Fe, Cu, Zn, Pb, and Ni
Acidic	Acidic barriers occur when neutral or alkaline waters come into contact with acidic waters	Silica minerals and Mo- and Ti-minerals can be precipitated; cause anionic elements to become less mobile and cationic elements to become more mobile
Alkaline barriers	Occur where acidic conditions are replaced by alkaline conditions, such as at the oxidation zones about a sulfide ore deposit surrounded by limestone; presence of carbonate, which can buffer acidic conditions	Carbonates, phosphates, and hydroxides can be precipitated; cause elements that migrate easily under acidic conditions, such as Fe, Al, Ca, Mg, Cu and Pb to precipitate as hydroxides or carbonates
Adsorption	Commonly occur in connection with any of the above barriers, where ions are taken out of solution by adsorbing onto a precipitating hydrous Fe- or Mn-oxide, clay or existing organic molecule	Elevated concentrations of elements, such as Cu, Pb, and Zn, that readily adsorb onto precipitating or fine-grained particulates

magnitude increases because of the large amounts of iron oxides that form during weathering, since these iron oxides tend to adsorb ions readily (Plant and Hale, 1994). Rose et al. (1979) note that Mo is commonly used as a pathfinder element for porphyry copper deposits as it has a larger dispersion pattern than Cu due to its increased mobility in more neutral to alkaline conditions. The authors also note that As in stream sediment is also used as a pathfinder for vein-type Au ore because it has a greater dispersion pattern due to increased mobility.

Chastain and Fletcher (2001) examined the Pascua-Lama high sulfidation epithermal gold deposit in the High Andes of Argentina-Chile. The authors noted that mobile elements, e.g. Cu and Zn, tend to be leached near the deposit due to highly acidic conditions and increased concentrations of these are seen further from the deposit, mostly controlled by changes in pH. In contrast, the largely immobile elements, e.g. Au, As, Sb, Hg, and Mo, tend to stay out of solution and rely mostly on mechanical transport, thus anomalous halos tend to stay near the site of origin (Chastain and Fletcher, 2001).

APPENDIX B

Selected geochemical characteristics of As, Au, Cu, Mo, Pb, Sb, and Zn.

Table B.1 Selected geochemical characteristics for elements used in this study. Compiled from Rose et al. (1979), Klein and Hurlbut (1993), Krauskopf and Bird (1995), Plumlee and Nash (1995), Ottonello (1997), Reimann and de Caritat, (1998), and Smith and Huyck (1999).

Characteristic	**As**	**Au**
Geochemical Affiliation[1]	Chalcophile	Dominantly Siderophile, sometimes chalcophile as it is often found in sulfide veins
Common Valence states, corresponding ionic radii (Å) (Coordination Number); Ionic Potential[2]	As^{3+}, 0.58 (VI); 5.2 As^{5+}, 0.34 (IV); 14.7 As^{5+}, 0.46 (VI); 6.5	Au^{+} , 1.37 (VI); 0.7 Au^{3+}, 0.68 (IV); 4.4 Au^{3+}, 0.85 (VI); 3.5
Anionic vs. Cationic[3]	Anionic	Anionic
Common Aqueous species	$H_2AsO_4^-$ $HAsO_4^{2-}$ $HAsO_2$	H_3AuO_3 $H_2AuO_3^-$ $HAuO_3^{2-}$
Redox Sensitivity[4]	Sensitive	Probably sensitive only under extreme conditions
Mobility Strongly acidic: pH < 3 Weakly acidic: pH 5 to 6.5 Neutral to Weakly alkaline: pH 6.5 to 8.5 Strongly alkaline: pH > 8.5	*Mobile* under oxidizing, strongly acidic conditions; *Somewhat mobile* under oxidizing, weakly acidic to weakly alkaline and reducing gley conditions; *Immobile* in strongly alkaline and reducing hydrogen sulfide conditions	*Somewhat mobile* under oxidizing, strongly acidic conditions; *Immobile* otherwise
Factors affecting mobility	Presence of sulfide to form arsenic-rich sulfides; Adhesion and coprecipitation with Fe-hydroxides and clays; Some plants readily take out of solution	-

Table B.1 (Continued)

Characteristic	Cu	Mo
Geochemical Affiliation[1]	Chalcophile	Siderophile
Common Valence states, corresponding ionic radii (Å) (Coordination Number); Ionic Potential[2]	Cu^{+} , 0.46 (II); 2.2 Cu^{+} , 0.77 (VI); 1.1 Cu^{2+}, 0.57 (IV); 3.5 Cu^{2+}, 0.65 (V); 3.1 Cu^{2+}, 0.73 (VI); 2.7	Mo^{4+}, 0.65 (VI); 6.2 Mo^{6+}, 0.41 (IV); 14.6 Mo^{6+}, 0.59 (VI); 10.2
Anionic vs. Cationic[3]	Cationic	Anionic
Common Aqueous species	Cu^{2+} $Cu(OH)_2$ $CuHCO_3^{+}$ $CuCl_3^{2-}$ $CuCl_2$	MoO_4^{2-} $HMoO_2^{-}$
Redox Sensitivity[4]	Sensitive	Sensitive
Mobility Strongly acidic: pH < 3 Weakly acidic: pH 5 to 6.5 Neutral to Weakly alkaline: pH 6.5 to 8.5 Strongly alkaline: pH > 8.5	*Very mobile* under oxidizing, strongly acidic conditions; *Mobile* under reducing gley, weakly acidic conditions; *Somewhat mobile* under oxidizing, weakly acidic conditions; *Immobile* under reducing hydrogen sulfide and alkaline conditions	*Mobile* under oxidizing weakly acidic to weakly alkaline conditions; *Somewhat mobile* under oxidizing, strongly acidic conditions; *Immobile* under reducing conditions
Factors affecting mobility	Presence of sulfides, adsorption to Fe- and Mn-oxides, organic matter and hydrolysis effect placement in environment; Elevated chloride decreases adsorption on sediment, due to complexing with chloride to form more mobile complexes	Presence of sulfides, reducing conditions, adsorption, presence of Pb, Fe, and carbonate ions effect placement in environment; Adsorption on clays, precipitation in carbonate rich environs is common

Table B.1 (Continued)

Characteristic	**Pb**	**Sb**
Geochemical Affiliation[1]	Chalcophile	Chalcophile
Common Valence states, corresponding ionic radii (Å) (Coordination Number); Ionic Potential[2]	Pb^{2+}, 1.19 (VI); 1.7 Pb^{2+}, 1.29 (VIII); 1.6 Pb^{2+}, 1.35 (IX); 1.5 Pb^{2+}, 1.40 (X); 1.4	Sb^{3+}, 0.76 (VI); 3.9 Sb^{5+}, 0.60 (VI); 8.3
Anionic vs. Cationic[3]	Cationic	Anionic
Common Aqueous species	Pb^{2+} $PbCO_3$ $Pb(OH)^+$ $Pb(OH)_2$ $PbCl_2$	SbO_2^- $HSbO_2$ SbS_3^{2-}
Redox Sensitivity[4]	Sensitive only under extreme conditions	Sensitive
Mobility Strongly acidic: pH < 3 Weakly acidic: pH 5 to 6.5 Neutral to Weakly alkaline: pH 6.5 to 8.5 Strongly alkaline: pH > 8.5	*Mobile* under reducing gley, weakly acidic conditions; *Somewhat mobile* under oxidizing, strongly to weakly acidic conditions; *Immobile* under reducing hydrogen sulfide and alkaline conditions	*Somewhat mobile* under oxidizing conditions regardless of pH; *Immobile* under reducing conditions regardless of pH
Factors affecting mobility	Controlled by adsorption on Mn- and Fe-oxides and insoluble organic matter. Presence of sulfate, sulfide, adsorption effect placement in environment; Most Pb bound in carbonates and Fe-Mn oxides	Presence of sulfide, adsorption onto Fe-Mn oxides affect placement in environment

Table B.1 (Continued)

Characteristic	**Zn**
Geochemical Affiliation[1]	Chalcophile
Common Valence states, corresponding ionic radii (Å) (Coordination Number); Ionic Potential[2]	Zn^{2+}, 0.60 (IV); 3.3 Zn^{2+}, 0.74 (VI); 2.7 Zn^{2+}, 0.90 (VIII); 2.2
Anionic vs. Cationic[3]	Cationic
Common Aqueous species	Zn^{2+} $Zn(OH)_2$ $Zn(NH_3)_4^{2+}$ $HZnO_2^-$
Redox Sensitivity[4]	Not Sensitive
Mobility Strongly acidic: pH < 3 Weakly acidic: pH 5 to 6.5 Neutral to Weakly alkaline: pH 6.5 to 8.5 Strongly alkaline: pH > 8.5	*Very mobile* under oxidizing, strongly to weakly acidic conditions; *Mobile* under reducing gley, weakly acidic conditions; *Immobile* under reducing hydrogen sulfide and alkaline conditions
Factors affecting mobility	Tends to be adsorbed by MnO_2 and insoluble organic matter; scavenged by non-detrital carbonates, organic matter, and oxide minerals; elevated chloride causes Zn to complex with chloride molecules resulting in decreased adsorption on sediment

Footnotes:

1. Geochemical Affiliation: Denotes Goldschmidt's classification of elements based upon the element's preference to be concentrated with sulfur in sulfides (chalcophile), occur with native iron (siderophile), or occur in silicate minerals (lithophile) (Krauskopf and Brid, 1995).
2. Ionic potential: ratio of valence state (oxidation number) to ionic radii. Low ionic potential typically indicates greater mobility as single cations in aqueous environments, while high ionic potential indicates greater mobility as oxyanions (Smith and Huyck, 1999).
3. Anionic vs. cationic: Denotes the general ionic behavior in aqueous solutions, where cationic means that the element travels as cations and anionic means the element travels as anions, typically oxyanions (Smith and Huyck, 1999).
4. Redox sensitivity: An element is sensitive if it responds to changes in redox state by changing oxidation number (valence state), which can result in changes in geochemical behavior (Smith and Huyck, 1999).

APPENDIX C

Histograms and cumulative frequency plots for the orientation and reconnaissance survey data.

Figure C.1a	Histogram for gold from the orientation survey.
Figure C.1b	Cumulative frequency plot for gold from the orientation survey.
Figure C.1c	Histogram for copper from the orientation survey.
Figure C.1d	Cumulative frequency plot for copper from the orientation survey.
Figure C.2a	Histogram for lead from the orientation survey.
Figure C.2b	Cumulative frequency plot for lead from the orientation survey.
Figure C.2c	Histogram for zinc from the orientation survey.
Figure C.2d	Cumulative frequency plot for zinc from the orientation survey.
Figure C.3a	Histogram for arsenic from the orientation survey.
Figure C.3b	Cumulative frequency plot for arsenic from the orientation survey.
Figure C.3c	Histogram for antimony from the orientation survey.
Figure C.3d	Cumulative frequency plot for antimony from the orientation survey.
Figure C.4a	Histogram for molybdenum from the orientation survey.
Figure C.4b	Cumulative frequency plot for molybdenum from the orientation survey.
Figure C.4c	Histogram for gold from the reconnaissance survey.
Figure C.4d	Cumulative frequency plot for gold from the reconnaissance survey.
Figure C.5a	Histogram for copper from the reconnaissance survey.
Figure C.5b	Cumulative frequency plot for copper from the reconnaissance survey.
Figure C.5c	Histogram for lead from the reconnaissance survey.
Figure C.5d	Cumulative frequency plot for lead from the reconnaissance survey.
Figure C.6a	Histogram for zinc from the reconnaissance survey.
Figure C.6b	Cumulative frequency plot for zinc from the reconnaissance survey.
Figure C.6c	Histogram for arsenic from the reconnaissance survey.
Figure C.6d	Cumulative frequency plot for arsenic from the reconnaissance survey.
Figure C.7a	Histogram for antimony from the reconnaissance survey.
Figure C.7b	Cumulative frequency plot for antimony from the reconnaissance survey.
Figure C.7c	Histogram for molybdenum from the reconnaissance survey.
Figure C.7d	Cumulative frequency plot for molybdenum from the reconnaissance survey.

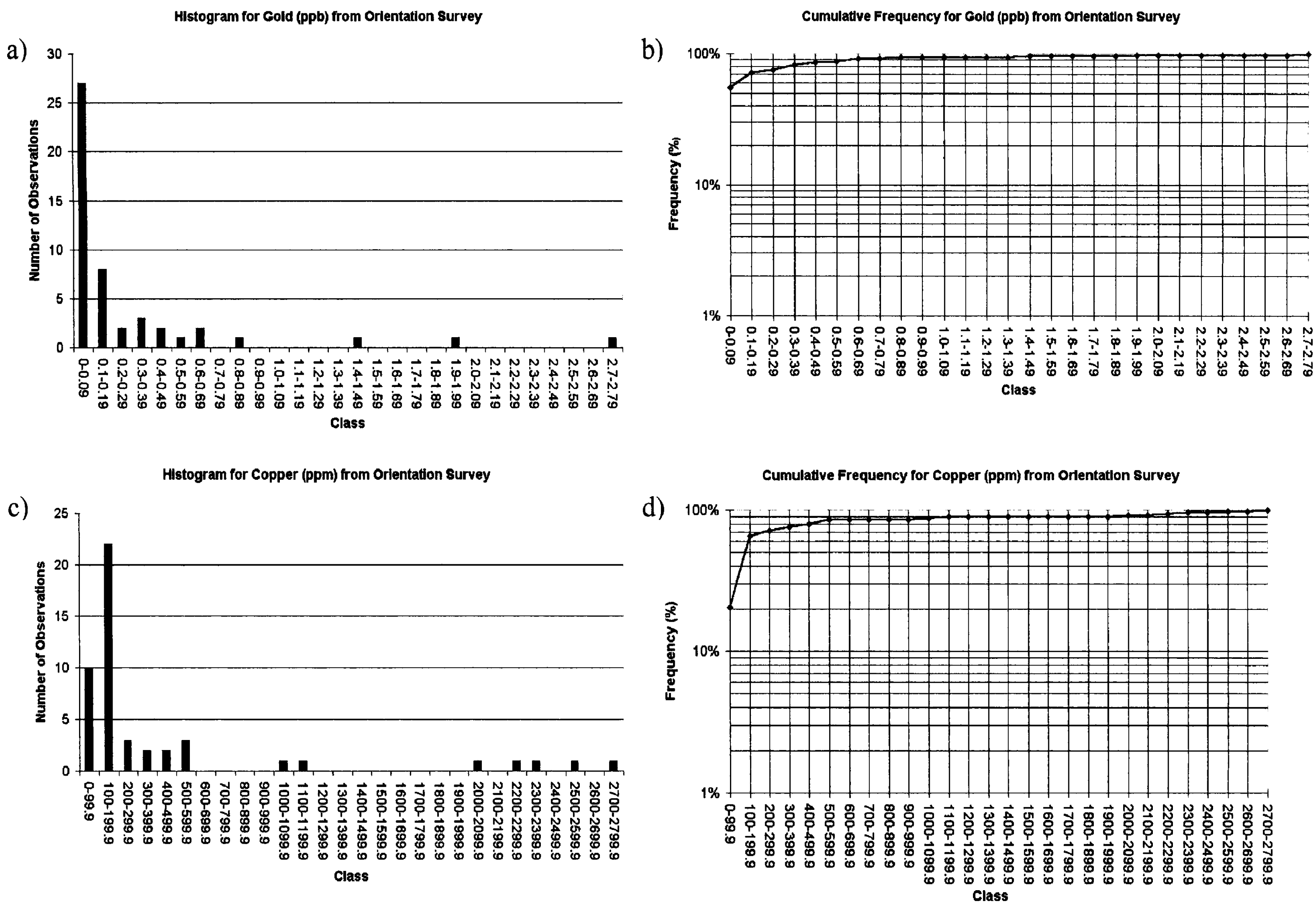

Figure C.1 a) histogram for gold from the orientation survey; b) cumulative frequency plot for gold from the orientation survey; c) histogram for copper from the orientation survey; d) cumulative frequency plot for copper from the orientation survey.

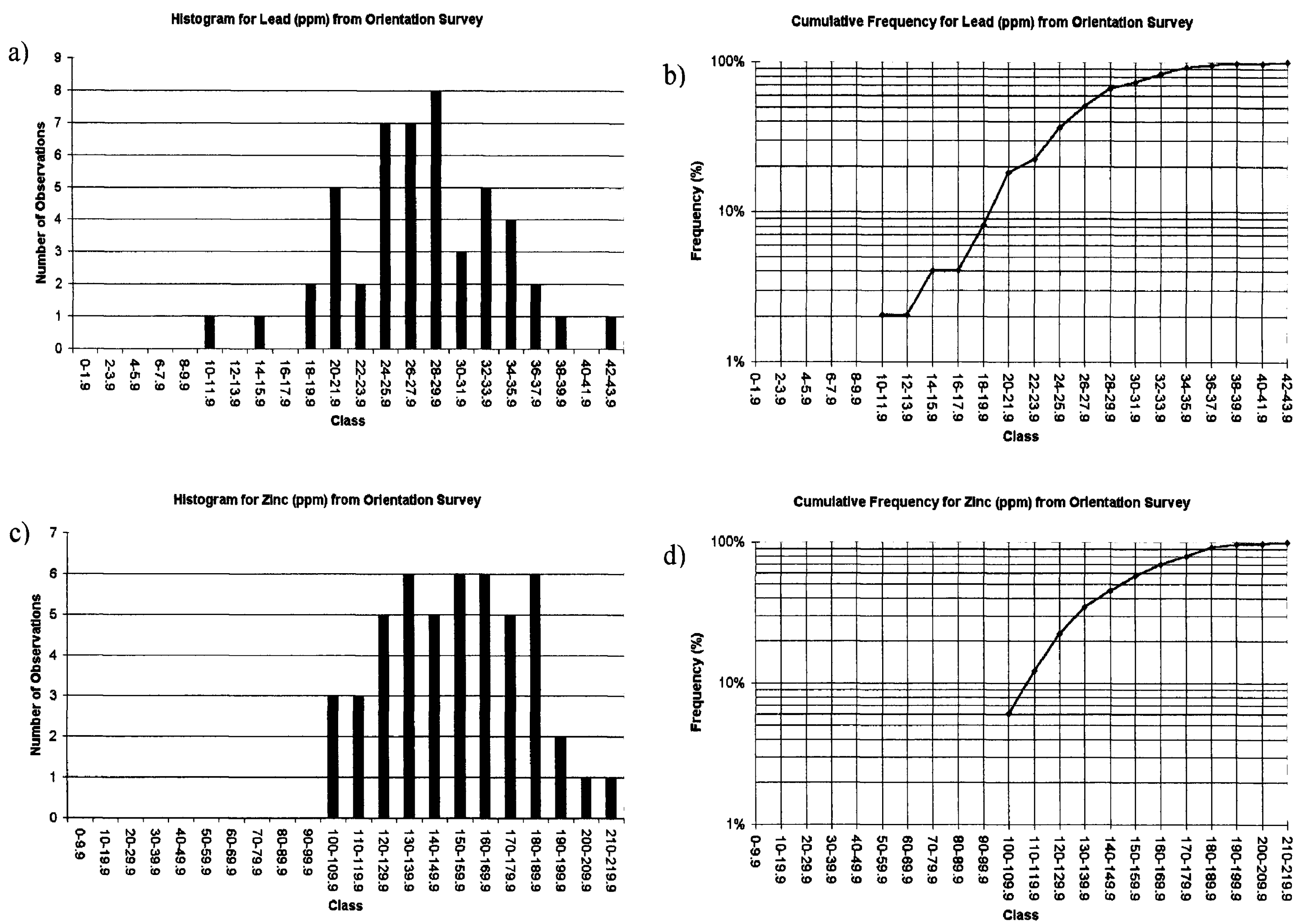

Figure C.2 a) histogram for lead from the orientation survey; b) cumulative frequency plot for lead from the orientation survey; c) histogram for zinc from the orientation survey; d) cumulative frequency plot for zinc from the orientation survey.

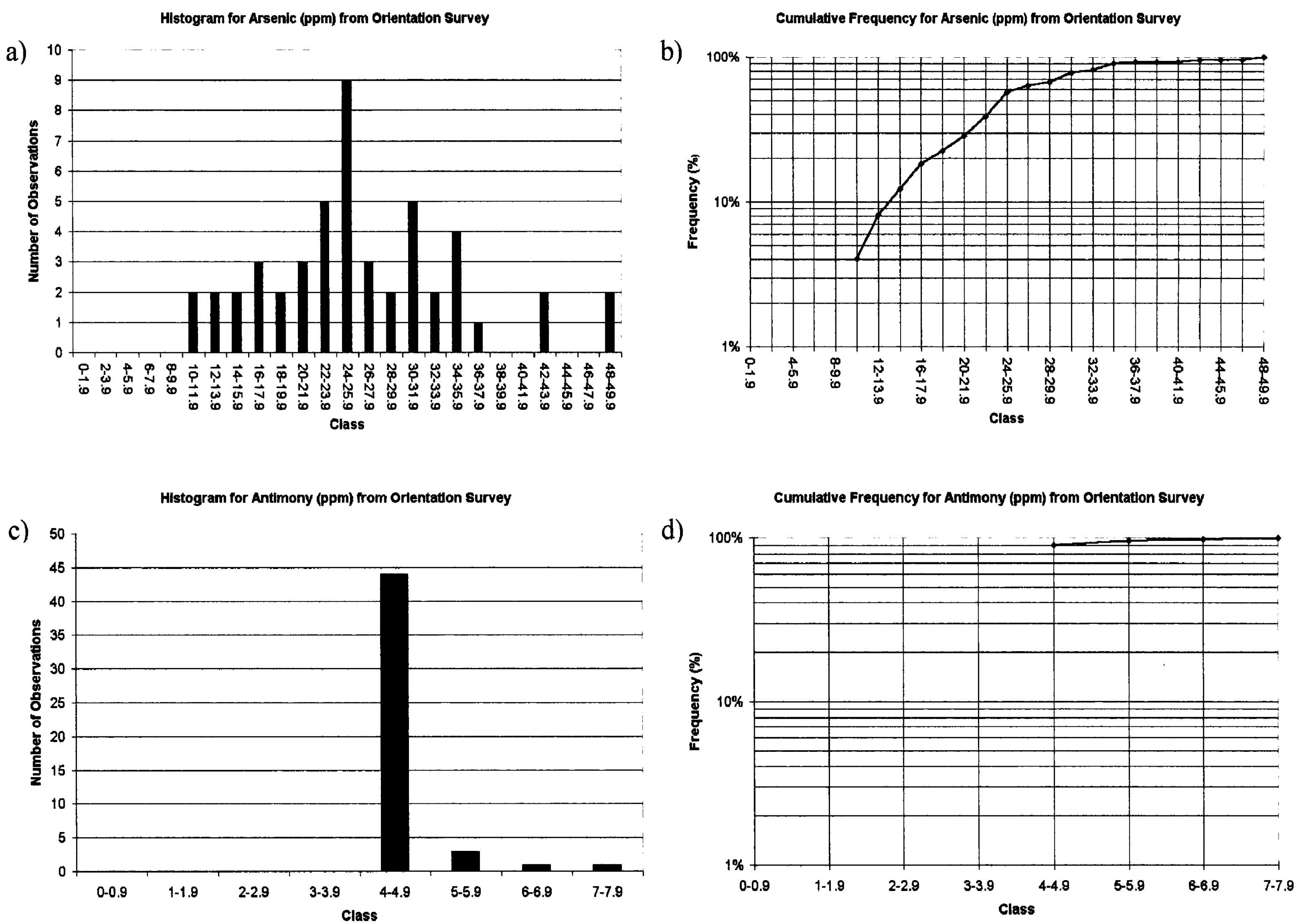

Figure C.3 a) histogram for arsenic from the orientation survey; b) cumulative frequency plot for arsenic from the orientation survey; c) histogram for antimony from the orientation survey; d) cumulative frequency plot for antimony from the orientation survey.

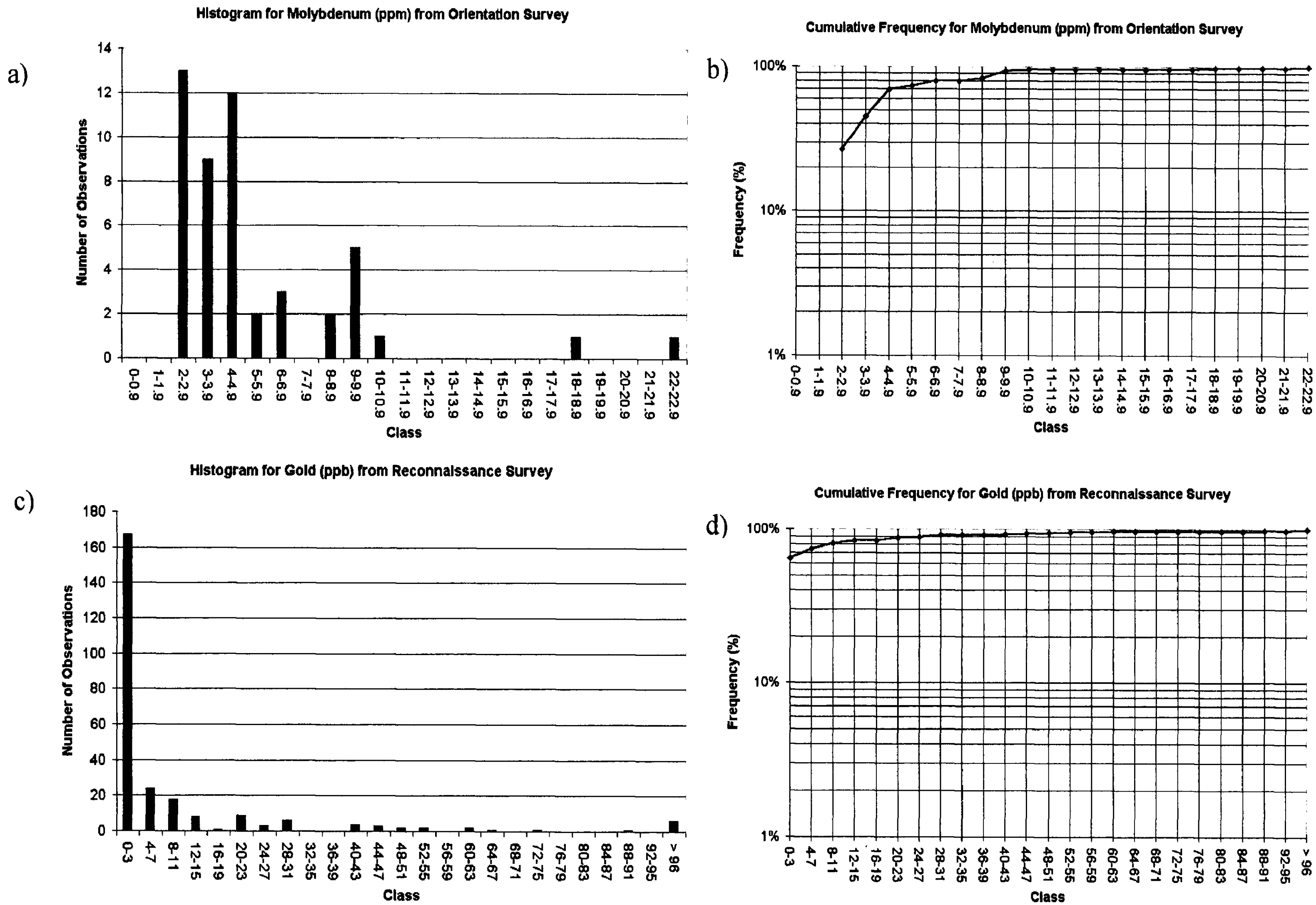

Figure C.4 a) histogram for molybdenum from the orientation survey; b) cumulative frequency plot for molybdenum from the orientation survey; c) histogram for gold from the reconnaissance survey; d) cumulative frequency plot for gold from the reconnaissance survey.

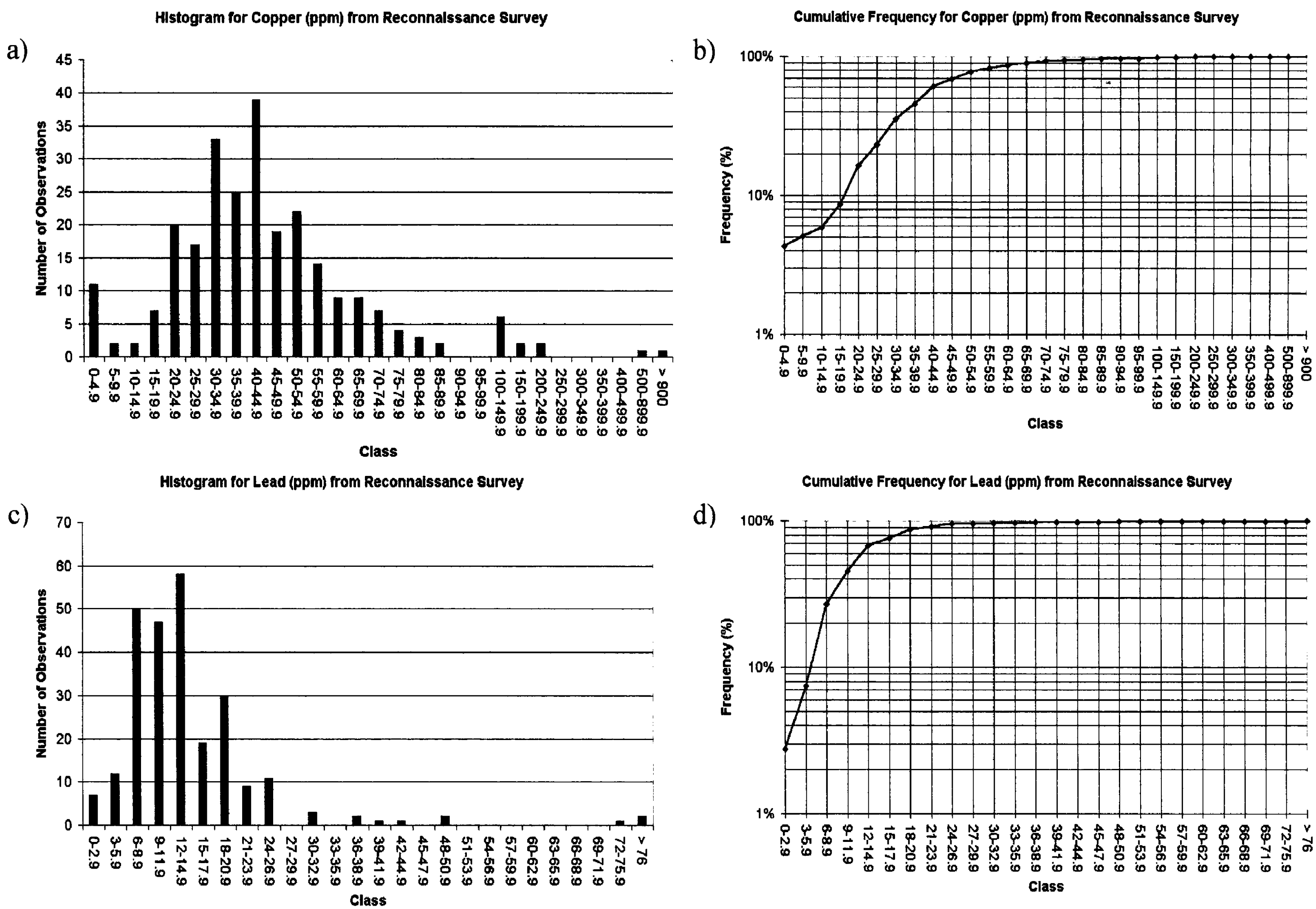

Figure C.5 a) histogram for copper from the reconnaissance survey; b) cumulative frequency plot for copper from the reconnaissance survey; c) histogram for lead from the reconnaissance survey; d) cumulative frequency plot for lead from the reconnaissance survey.

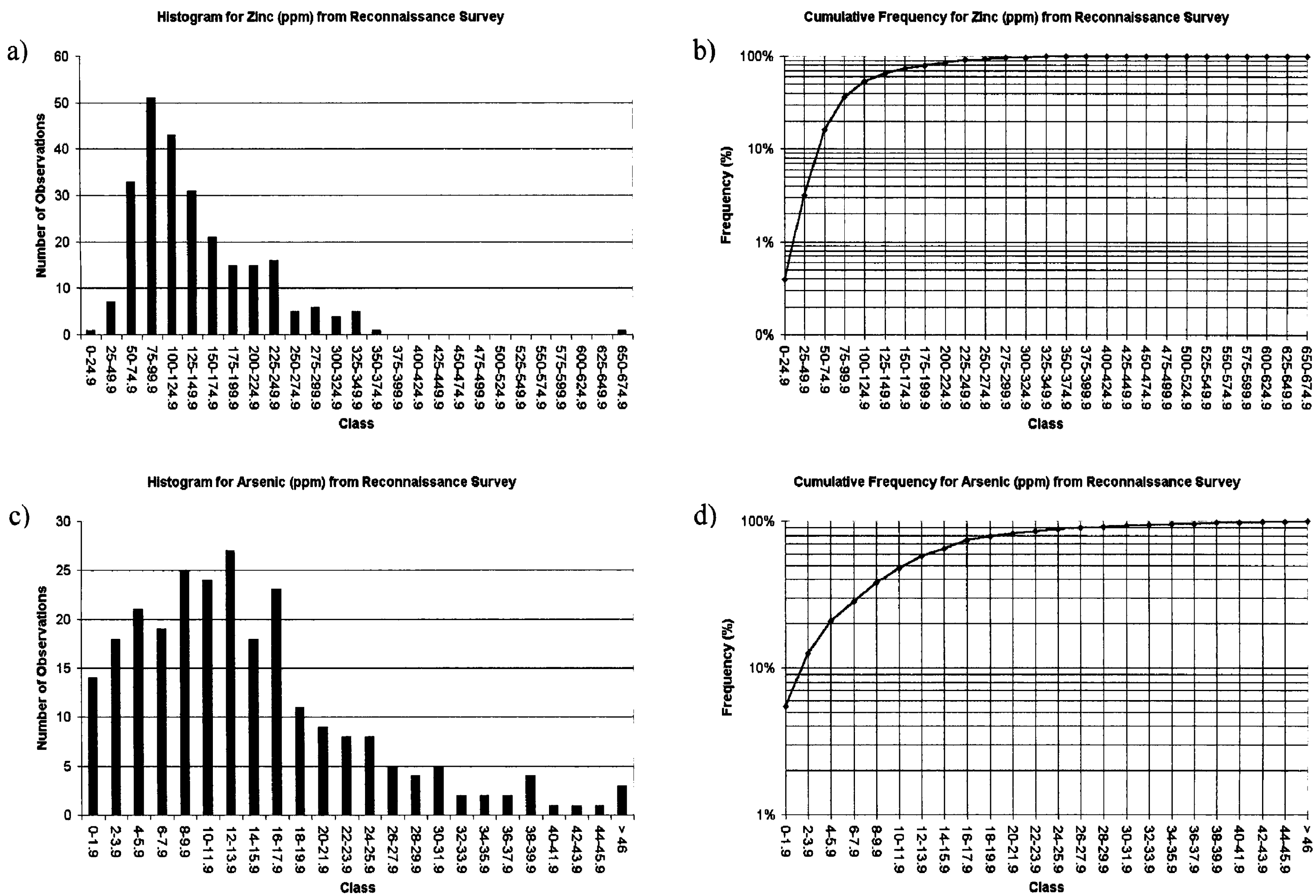

Figure C.6 a) histogram for zinc from the reconnaissance survey; b) cumulative frequency plot for zinc from the reconnaissance survey; c) histogram for arsenic from the reconnaissance survey; d) cumulative frequency plot for arsenic from the reconnaissance survey.

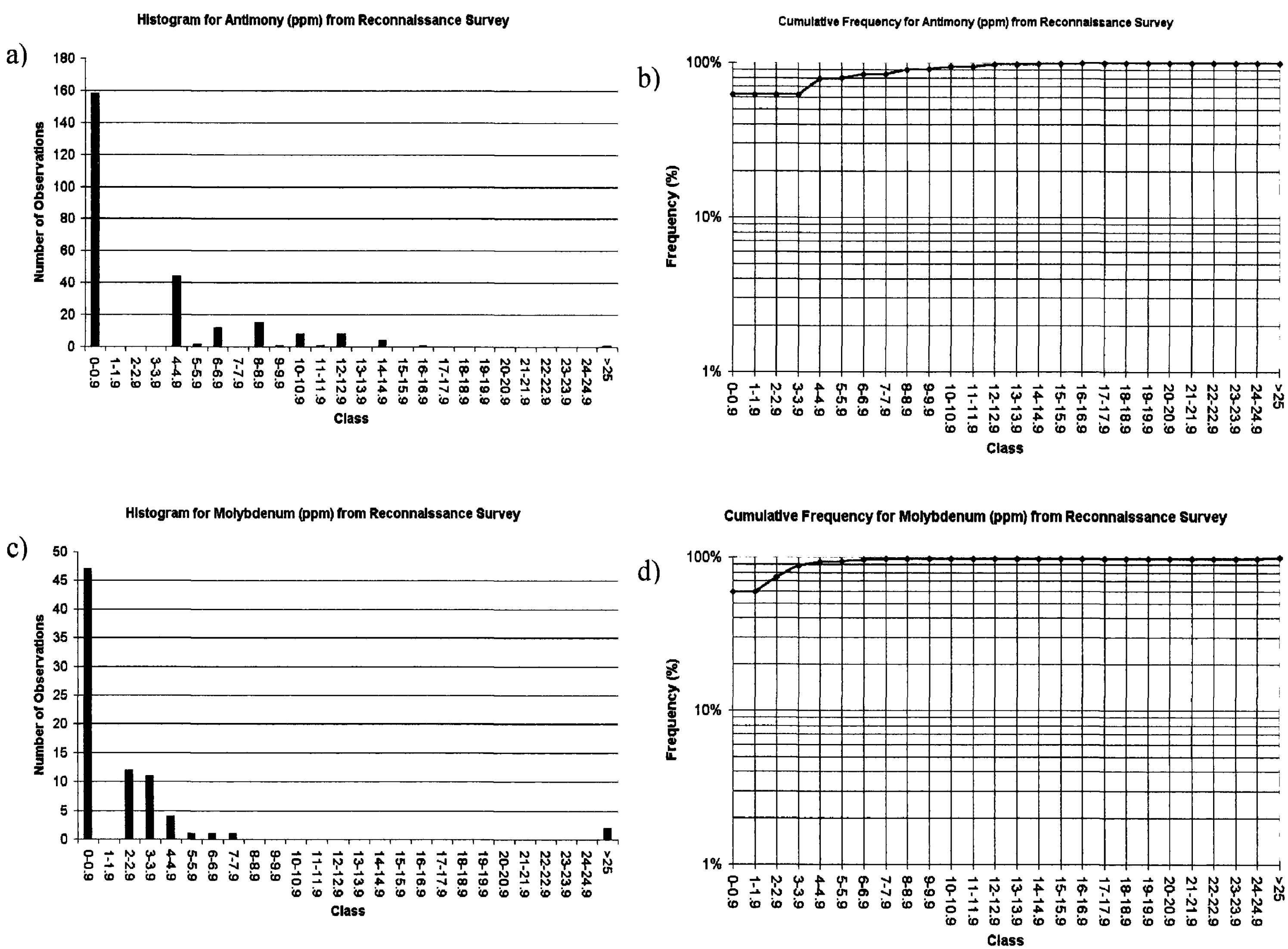

Figure C.7 a) histogram for antimony from the reconnaissance survey; b) cumulative frequency plot for antimony from the reconnaissance survey; c) histogram for molybdenum from the reconnaissance survey; d) cumulative frequency plot for molybdenum from the reconnaissance survey.

APPENDIX D

THE CARRANZA AND HALE (1997) METHOD

D.1 Introduction

The Carranza and Hale (1997) method of estimating the background contribution of lithology for a drainage basin involves taking into consideration the area being drained by the stream at the point it is being sampled, the different lithologies present in the upstream drainage area, and corresponding aerial extent in the upstream drainage area.

As with many techniques of this nature a few assumptions need to be addressed first. The first assumption is that the stream sediment samples do not contain any contributions from alluvial river bank material, which is probably the case as the area contains dense vegetation which would probably result in more stable river banks. The second assumption is that once the elements are removed from solution they remain in the sediment. The second assumption is probably met best in higher order streams, say third order or higher. The third assumption is that erosion is uniform within each drainage. The topography in southwest Sumbawa changes significantly from low coastal lands to high mountainous terrain, which suggests that the third assumption is probably not met, especially for the reconnaissance survey which covers a large more varied area. The fourth assumption is that the area of exposed mineralization is very small, roughly 10 to 200 times smaller, relative to the drainage basin. In most cases this assumption is true, especially for the low-sulfidation epithermal gold mineralizations in the area. The fifth, and final, assumption is that all anomalous values are due to mineralization (Carranza and Hale, 1997). The final assumption is also probably met, however, it is expected that background concentrations will be elevated in this region due to the numerous known mineral occurrences.

D.2 Methodology

The Carranza and Hale (1997) method involves the multiple linear regression. For the regression technique, the aerial extents of the lithology (j) are regressed against the ln-transformed element data to estimate the regression coefficients for each lithologic unit (b_j). By forcing b_o through the origin (zero) the investigator is able to estimate the mean element concentration of the j^{th} rock unit. The aerial extents of lithology are used instead of the percents to avoid introducing negative correlations and to provide the regression with an open data set (Swan and Sandilands, 1995). The regression is done according to equation D.1.

$$\hat{Y}_i = b_o + \sum_{j=1}^{m} b_j X_{ij} \qquad \text{(D.1)}$$

Where: $\hat{Y}_i$ = stream sediment element contents due to lithology
X_{ij} = aerial proportions of the j^{th} rock unit (j = 1, 2, …, m) in the i^{th} sample catchment basin (i=1, 2, …, n)

$\sum_{j=1}^{m} X_{ij} = 1.0$ for j=1, 2, …, m rock units in sample catchment basin i

b_o and b_j = regression coefficients

Once the regression is complete and the regression coefficients are obtained. The $\hat{Y}_i$ values are calculated according to equation D.2 for each sample site:

$$\hat{Y}_i = b_1 X_1 + b_2 X_2 + \ldots + b_n X_n \qquad \text{(D.2)}$$

Where $b_1, b_2, \ldots, b_n$ = regression coefficients for lithologies X=1, 2, …, n
$X_1, X_2, \ldots, X_n$ = aerial extent of lithologies X = 1, 2, …, n

Then the $\hat{Y}_i$ values are converted from ln-transformed data to regular element concentrations using the $e^{\hat{Y}i}$ function. Finally, the average $\hat{Y}_i$ values for each element are then taken to represent the average lithologic contribution to background concentrations for each element.

APPENDIX E

Figures of element concentrations by drainage for each survey. In each figure the data was subdivided into groups that (1) best reflect the actual spread of the data, and (2) produce a number of subdivisions small enough to make the figure easier to read.

Figure E.1 Gold concentrations for orientation survey
Figure E.2 Copper concentrations for orientation survey
Figure E.3 Lead concentrations for orientation survey
Figure E.4 Zinc concentrations for orientation survey
Figure E.5 Arsenic concentrations for orientation survey
Figure E.6 Antimony concentrations for orientation survey
Figure E.7 Molybdenum concentrations for orientation survey
Figure E.8 Gold concentrations for reconnaissance survey
Figure E.9 Copper concentrations for reconnaissance survey
Figure E.10 Lead concentrations for reconnaissance survey
Figure E.11 Zinc concentrations for reconnaissance survey
Figure E.12 Arsenic concentrations for reconnaissance survey
Figure E.13 Antimony concentrations for reconnaissance survey
Figure E.14 Molybdenum concentrations for reconnaissance survey

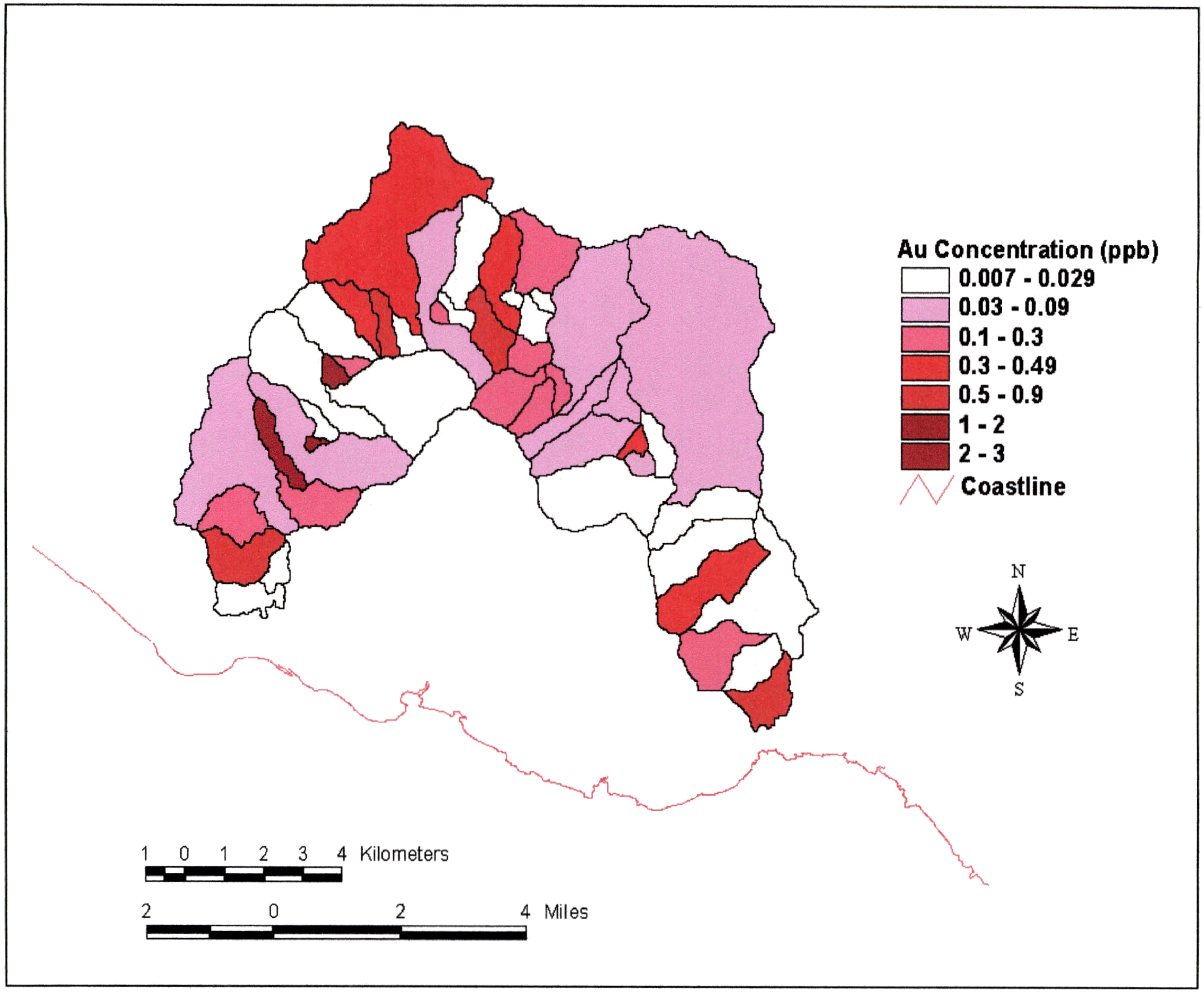

Figure E.1 Gold concentrations for orientation survey.

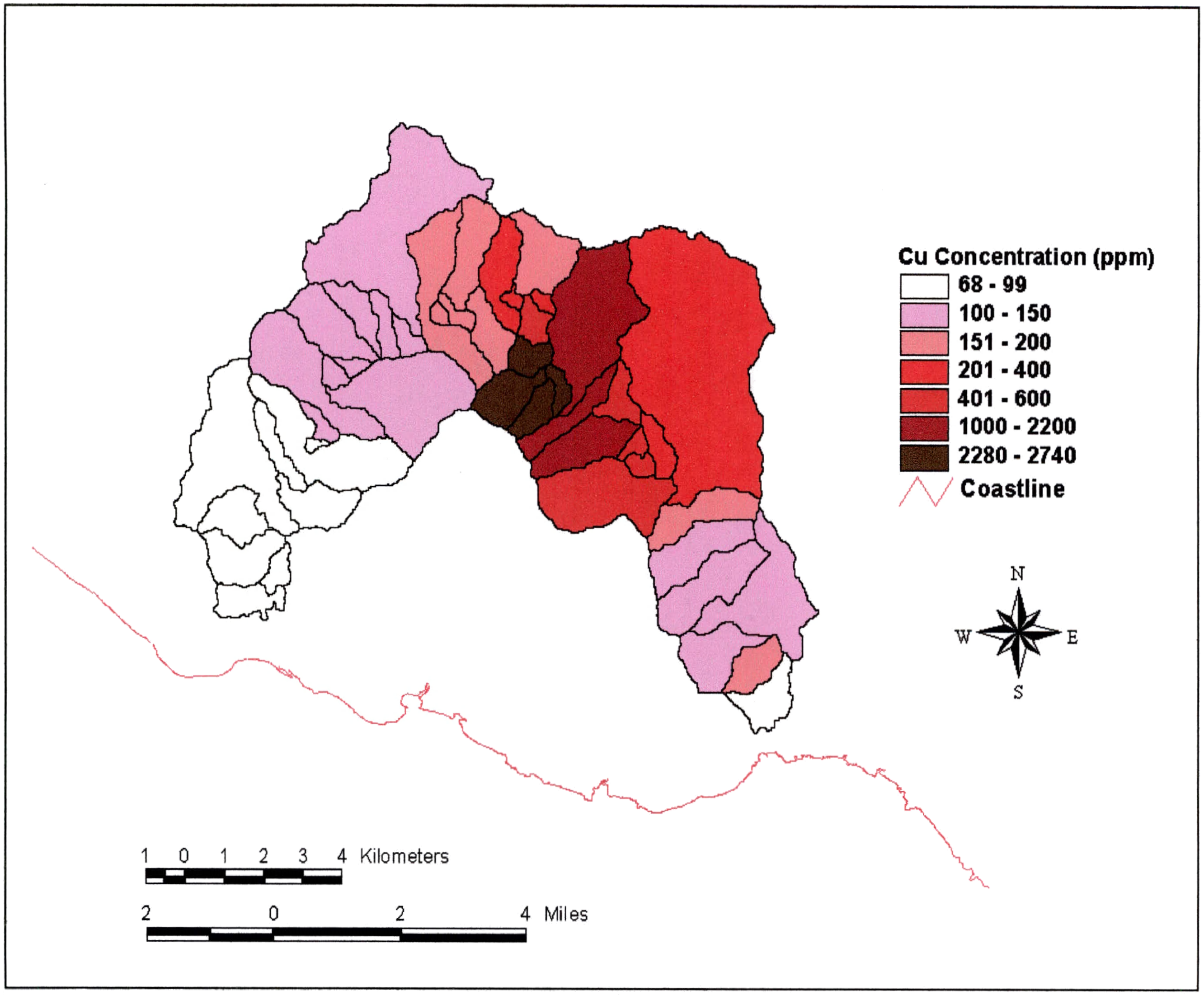

Figure E.2 Copper concentration for orientations survey.

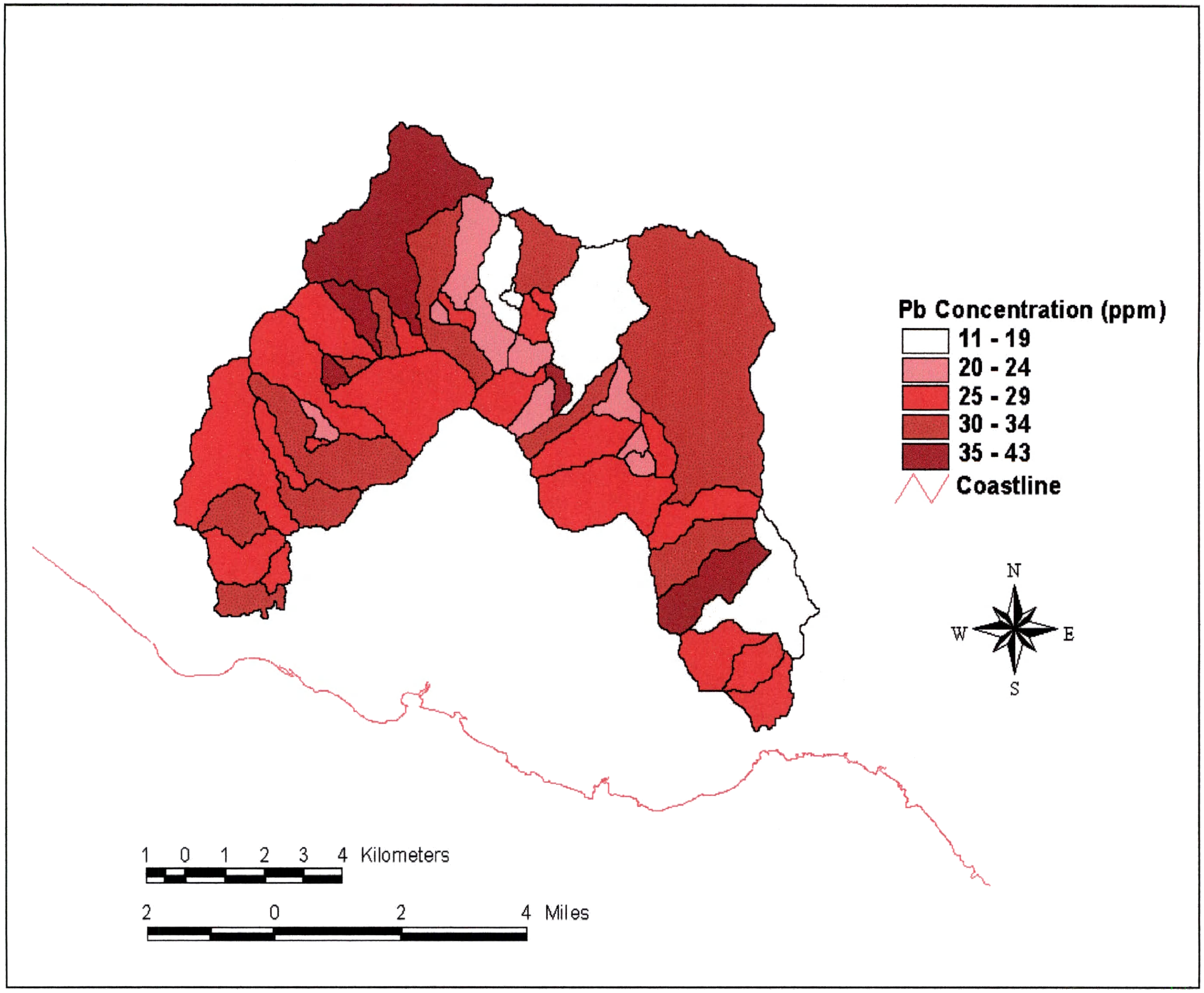

Figure E.3 Lead concentration for orientations survey.

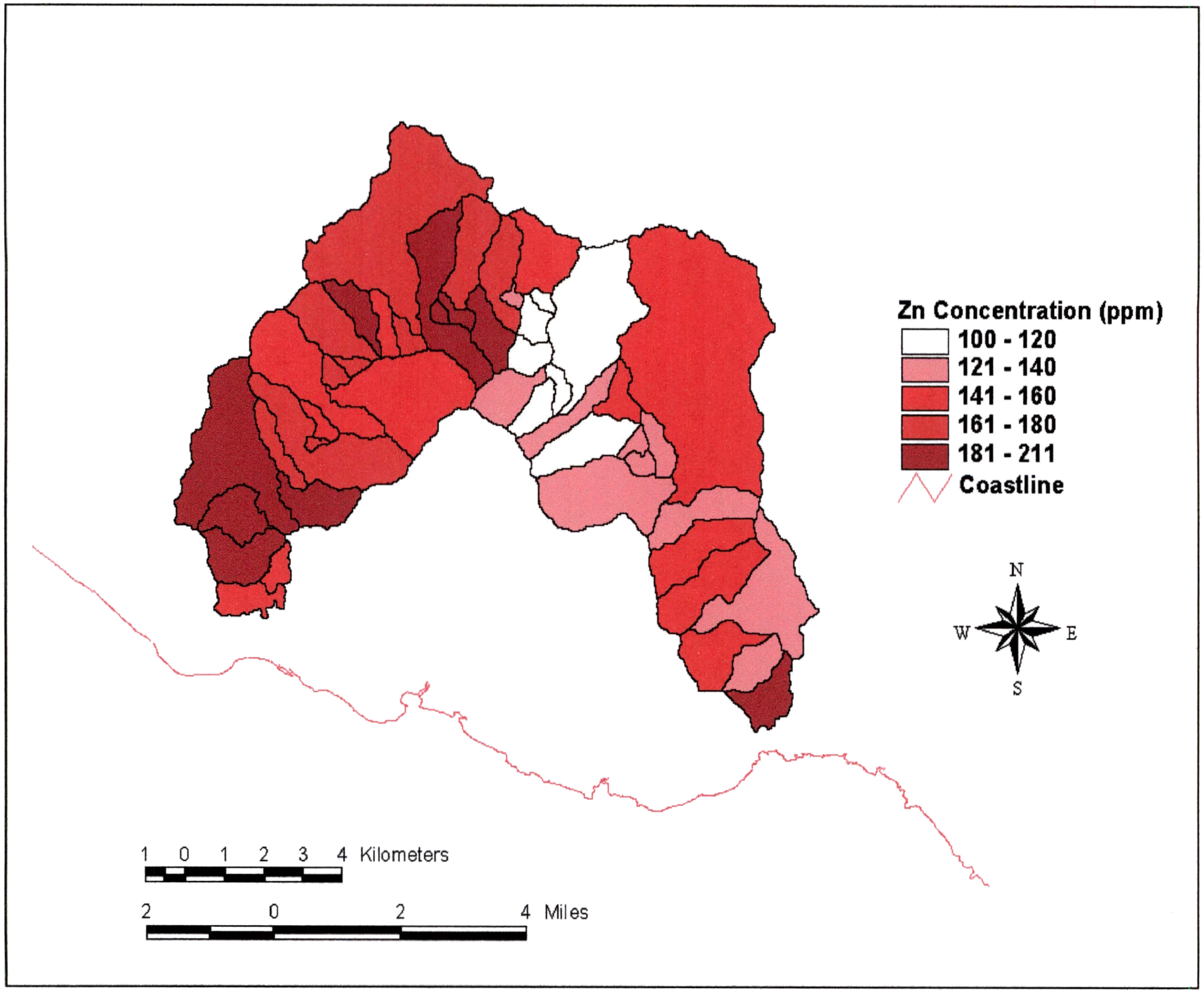

Figure E.4 Zinc concentration for orientations survey.

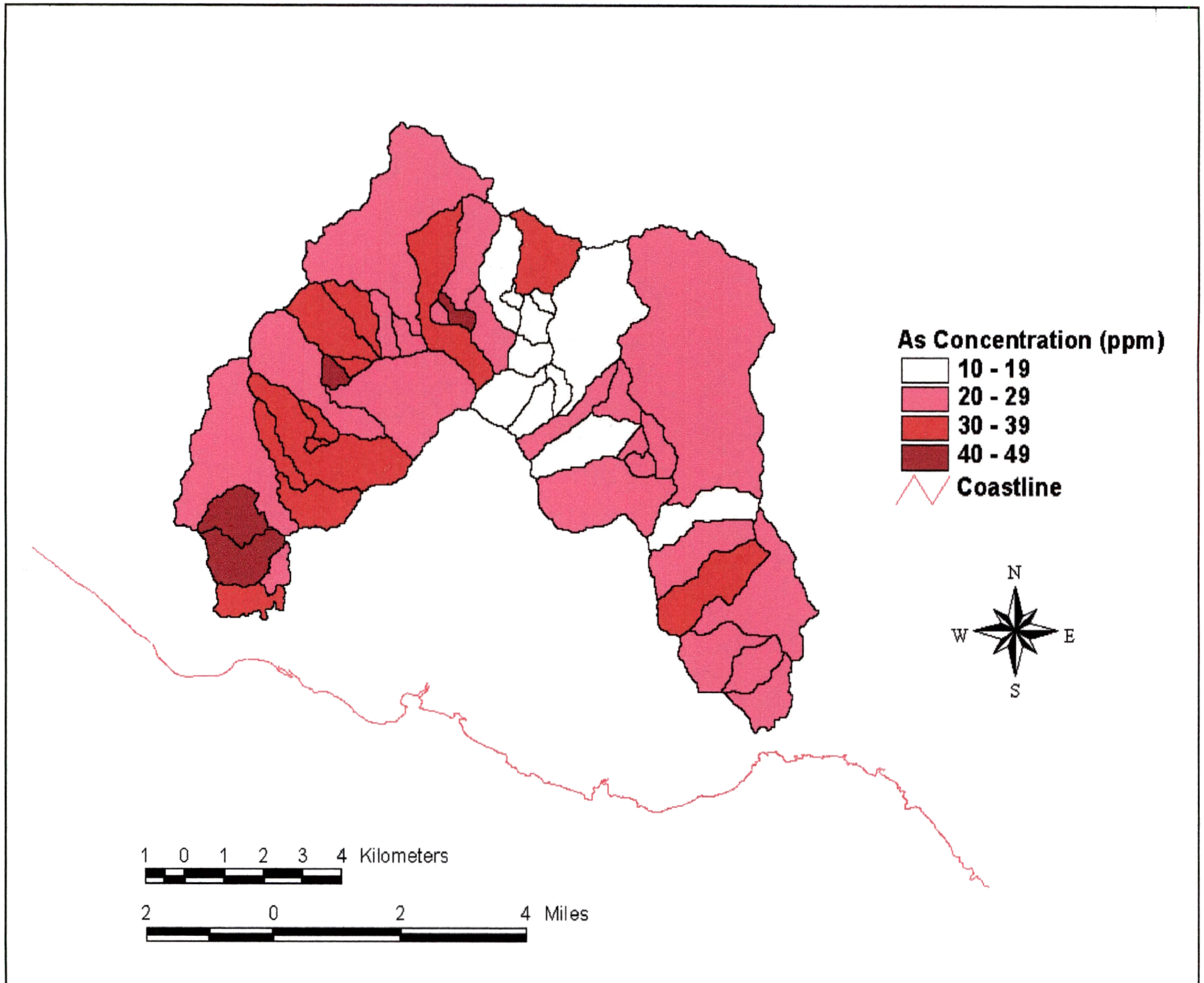

Figure E.5 Arsenic concentrations for orientation survey.

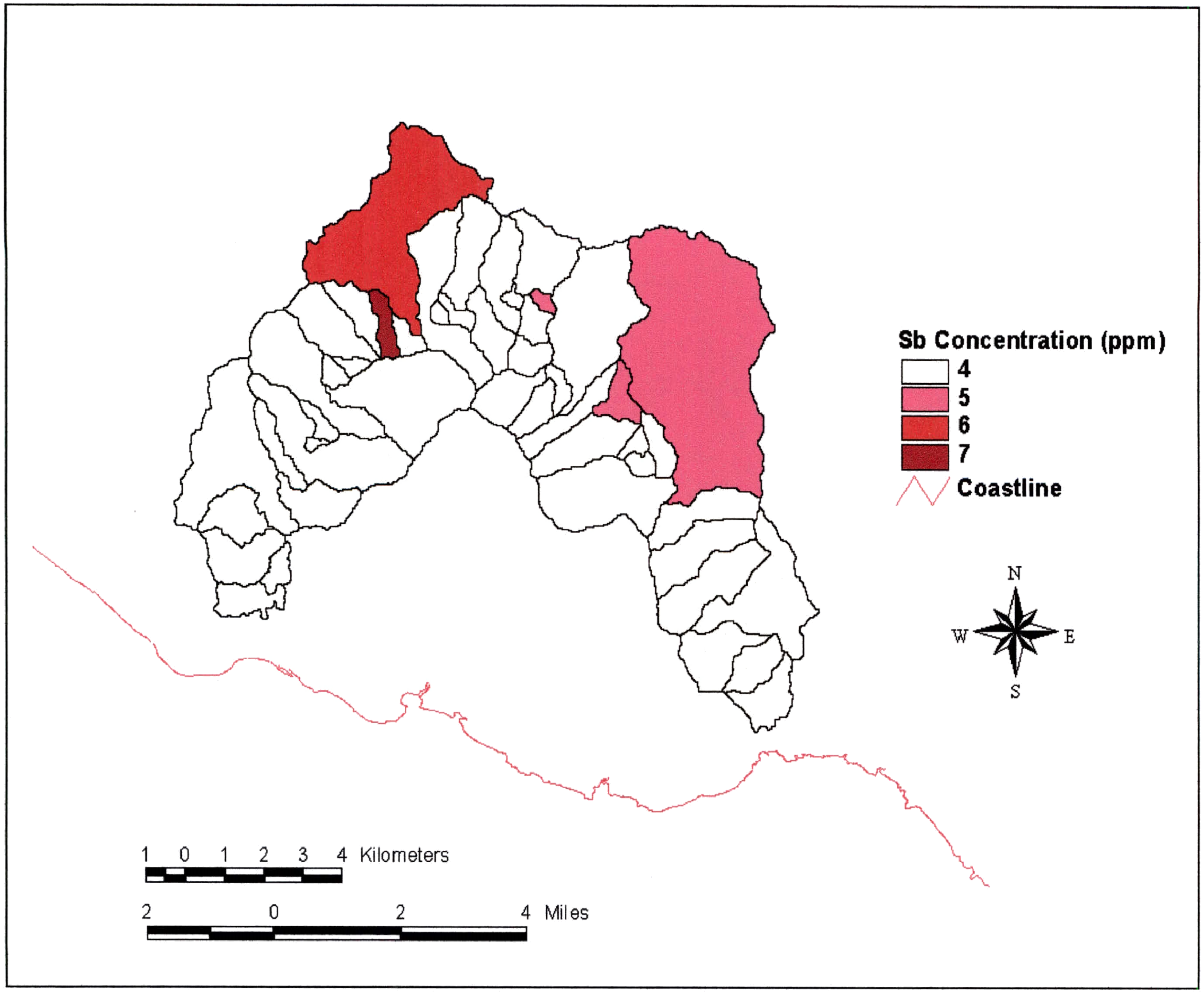

Figure E.6 Antimony concentrations for orientation survey.

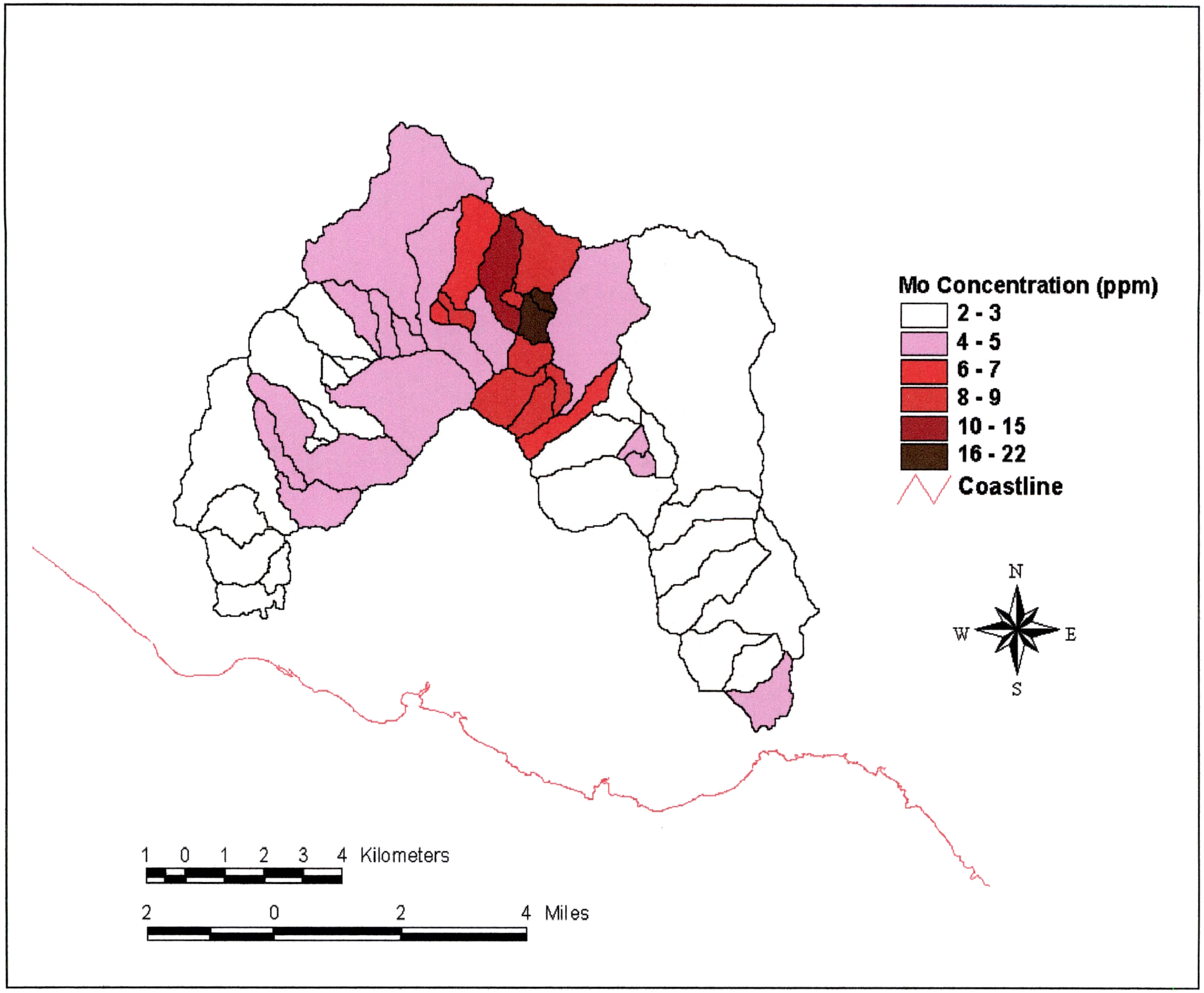

Figure E.7 Molybdenum concentrations for orientation survey.

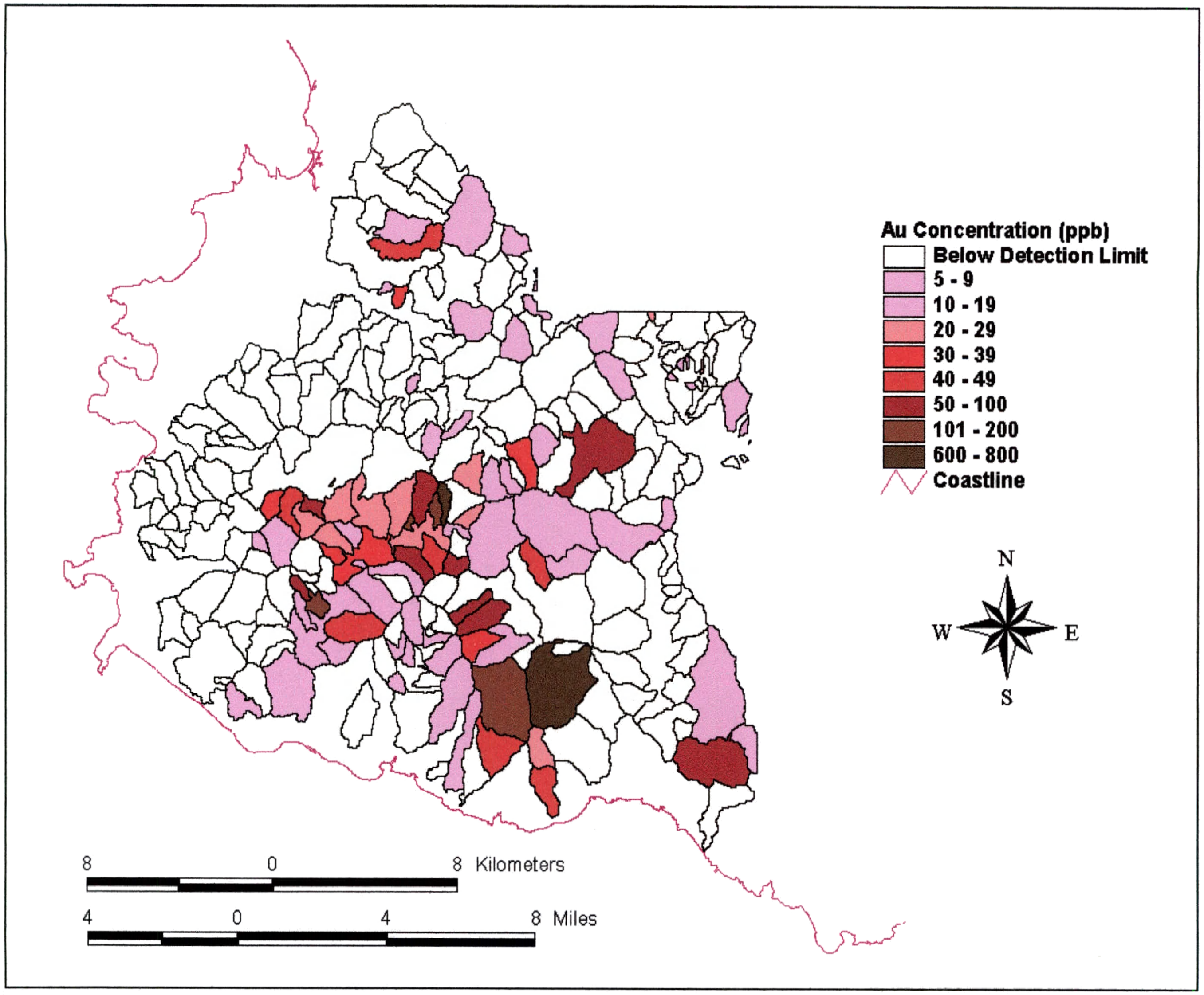

Figure E.8 Gold concentrations for reconnaissance survey.

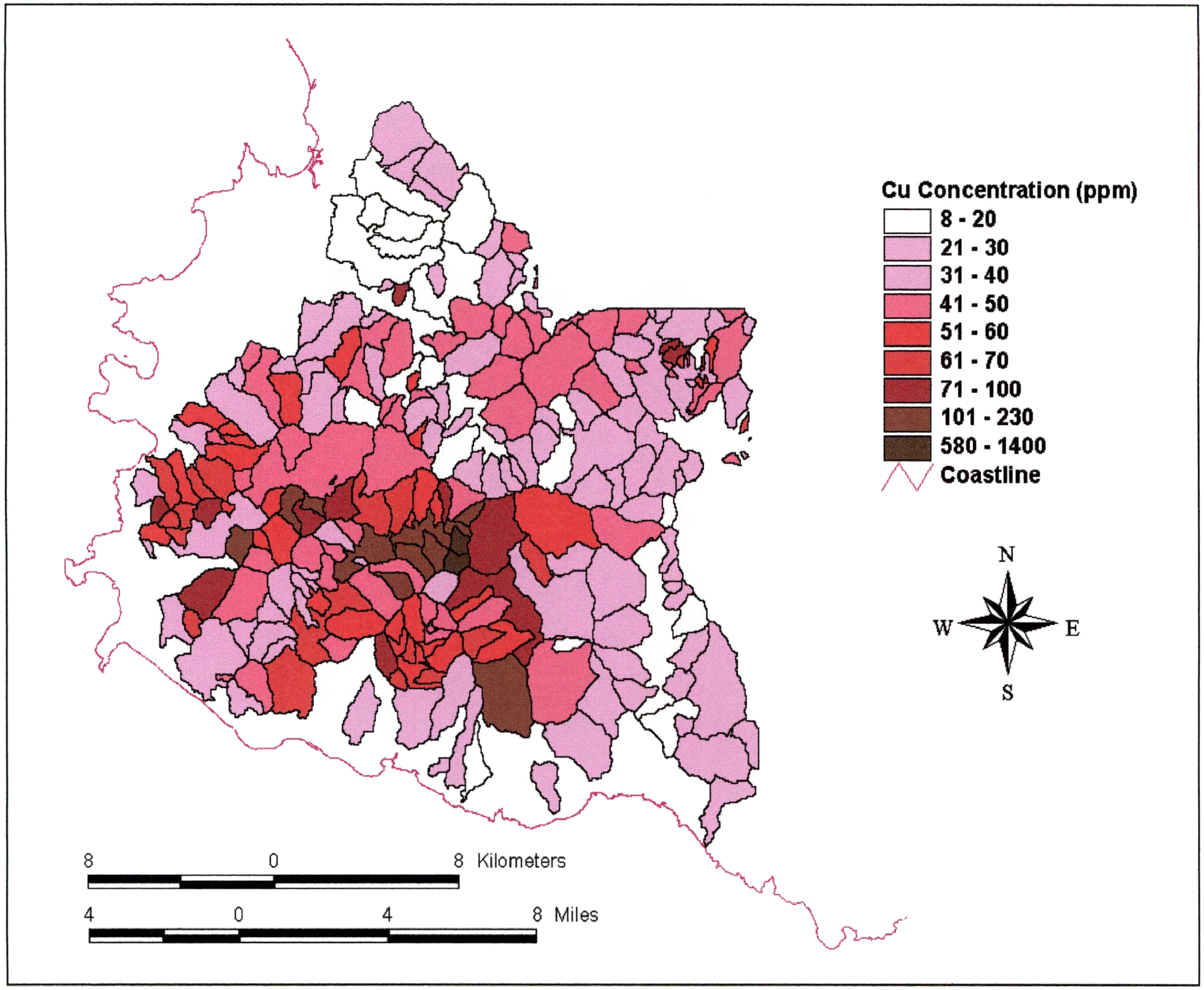

Figure E.9 Copper concentrations for reconnaissance survey.

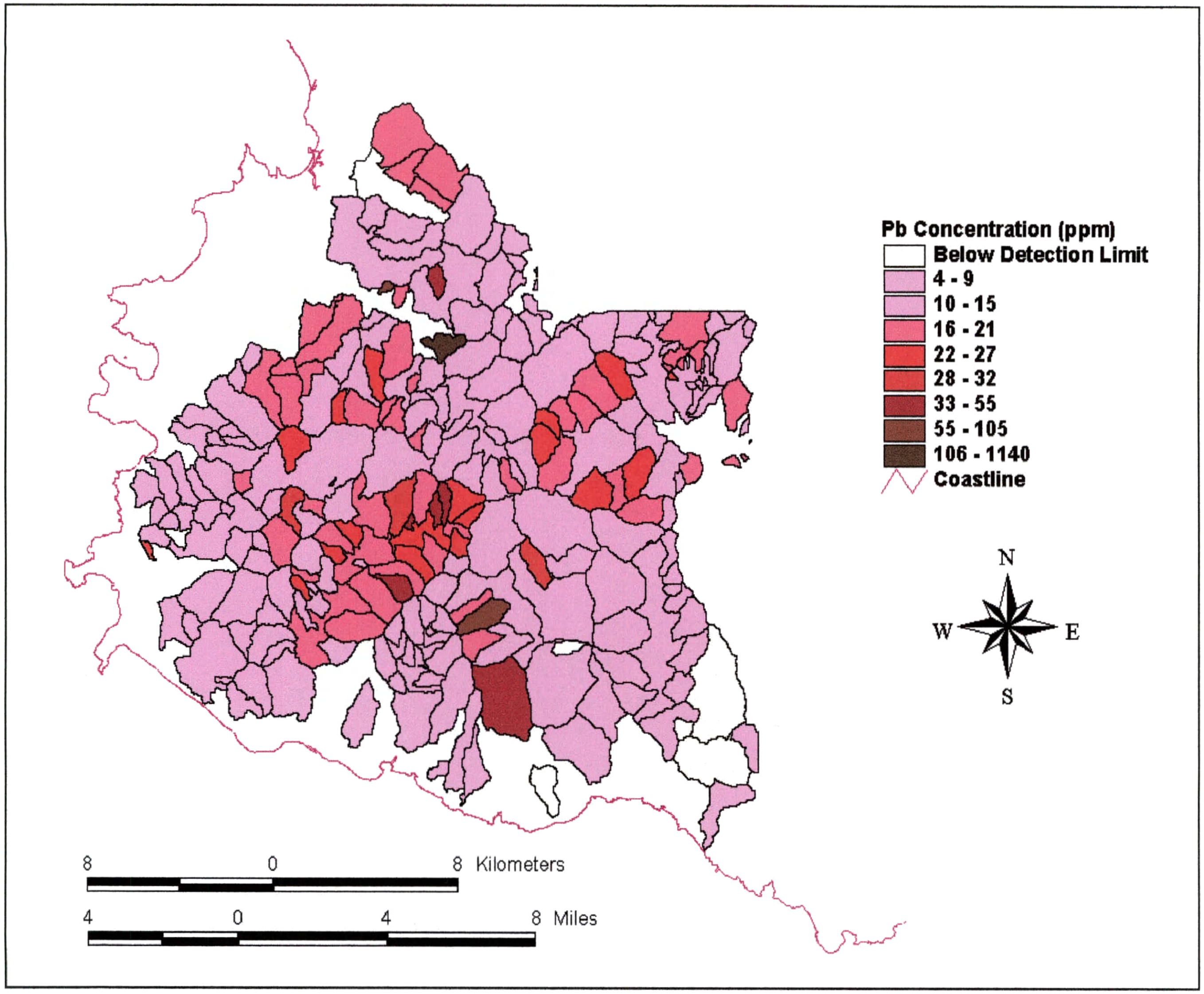

Figure E.10 Lead concentrations for reconnaissance survey.

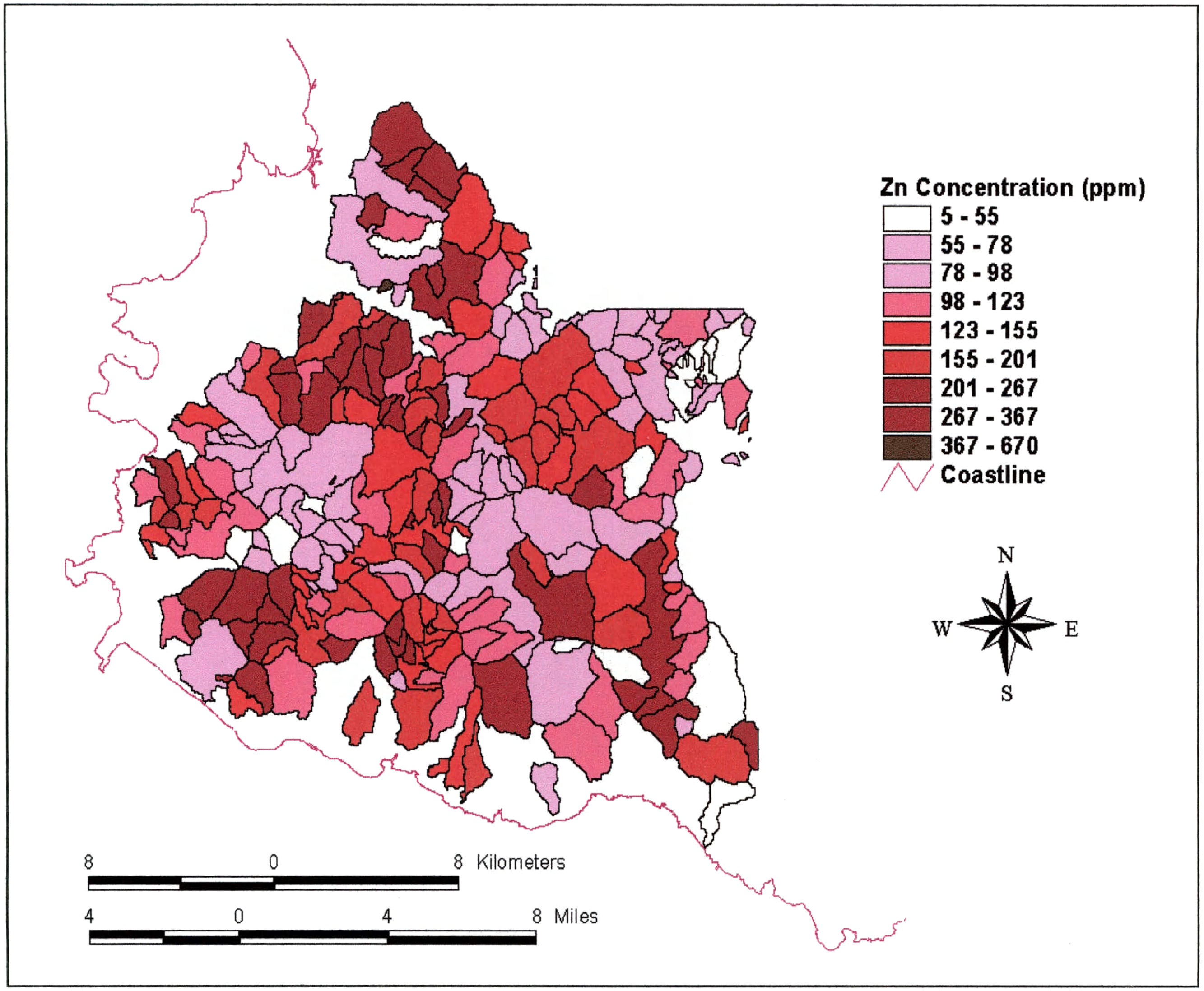

Figure E.11 Zinc concentrations for reconnaissance survey.

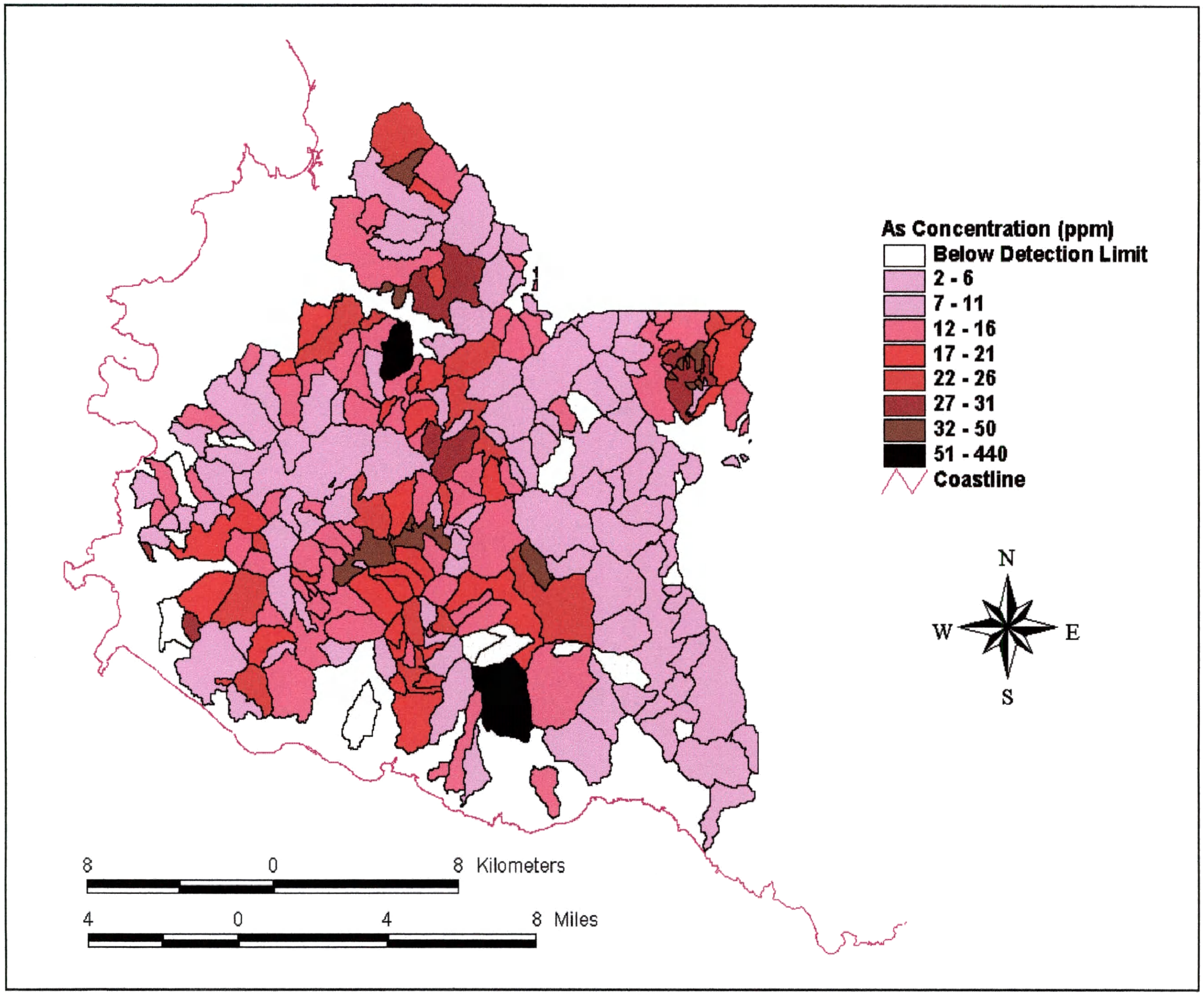

Figure E.12 Arsenic concentrations for reconnaissance survey.

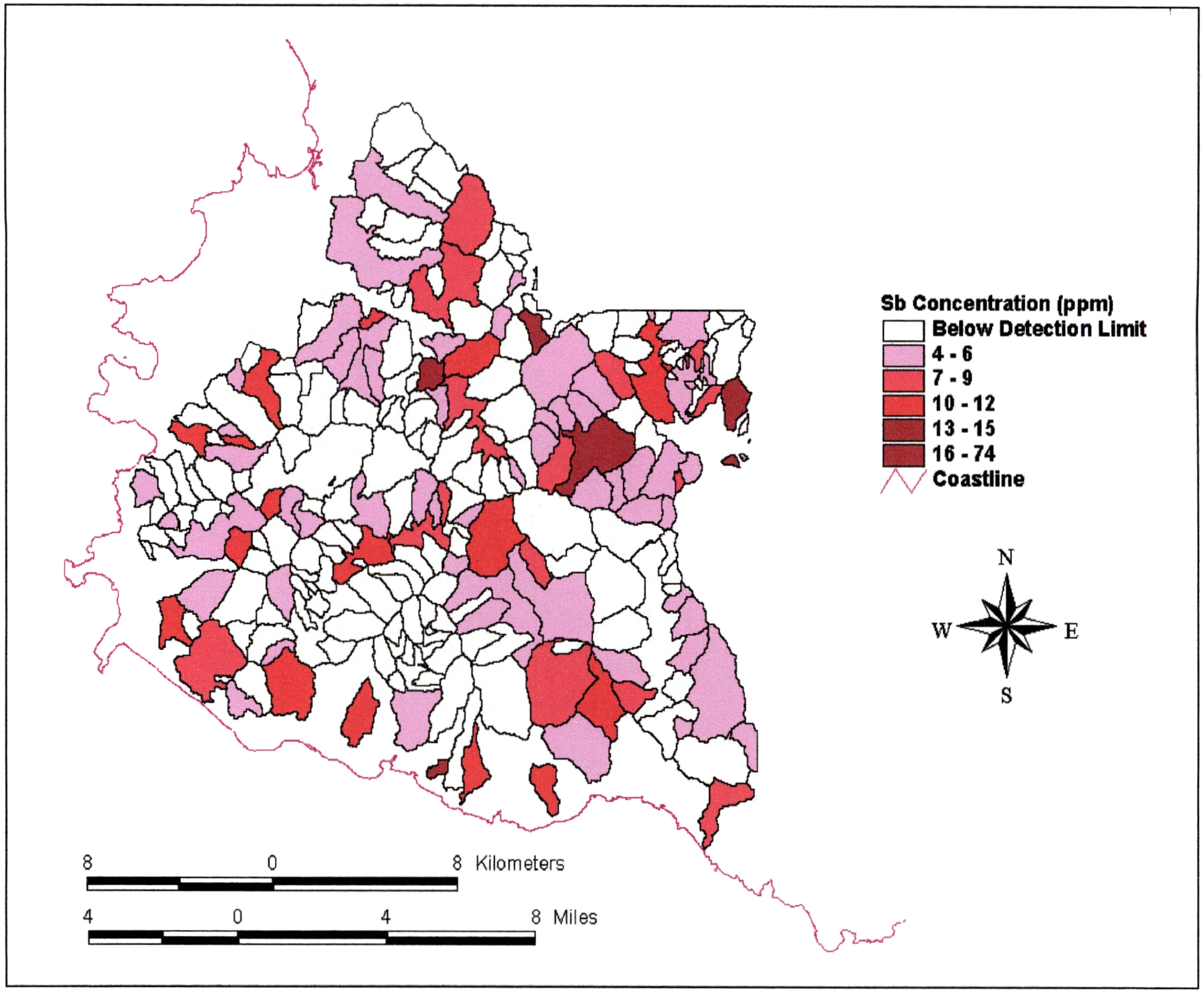

Figure E.13 Antimony concentrations for reconnaissance survey.

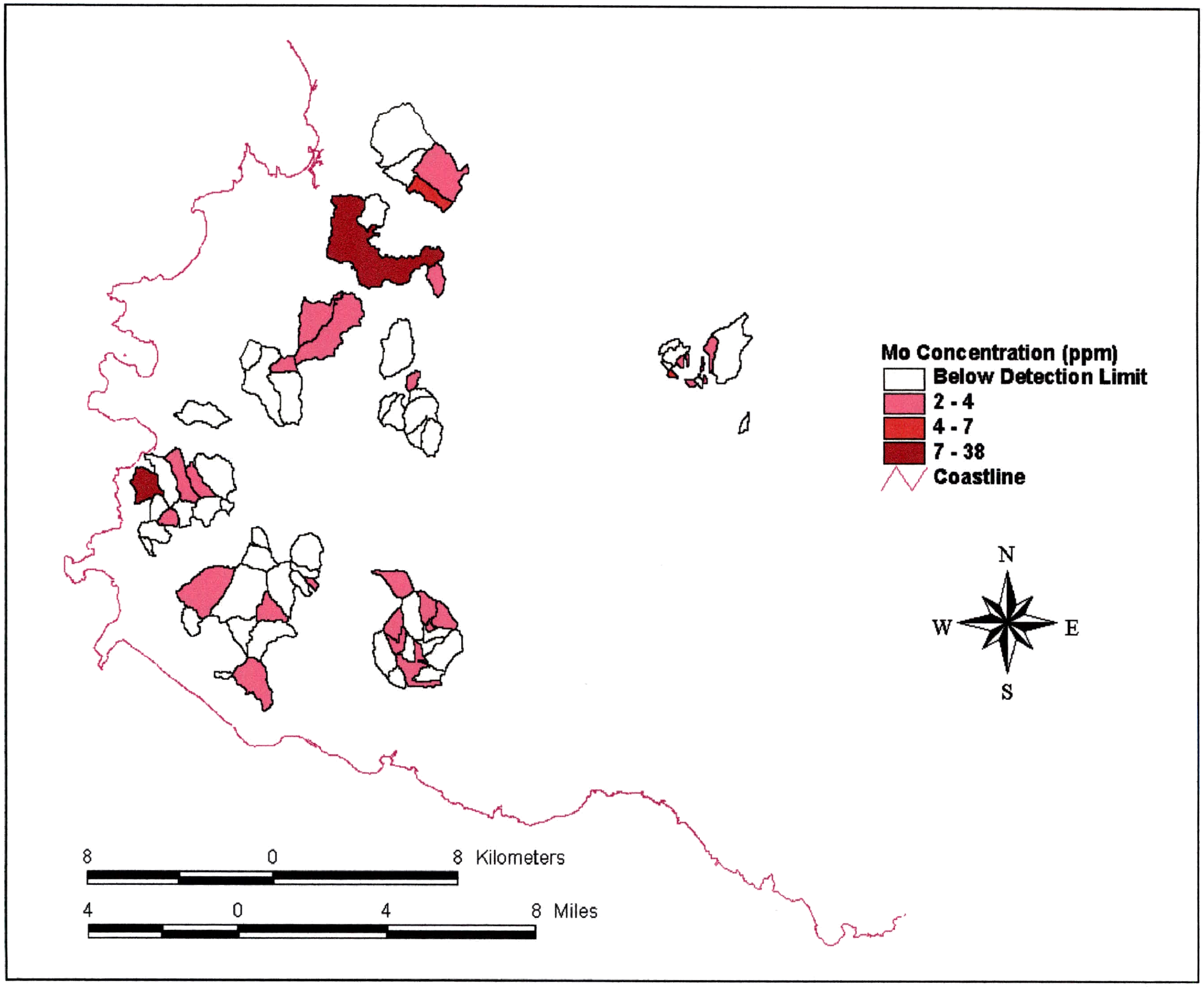

Figure E.14 Molybdenum concentrations for reconnaissance survey.

APPENDIX F

Contents of CD-ROM in the back pocket. The document (*.doc) files are in Microsoft Word 2000 format. The spreadsheet (*.xls) files are in Microsoft Excel 2000 format.

- Plate I.doc
- Plate II.doc
- Plate III.doc
- Plate IV.doc
- Plate V.doc
- Orientation Survey.xls[1]
- Reconnaissance Survey.xls[2]

1. Contains all of the orientation survey data used for this study. Column headings are self-explanatory.
2. Contains all of the reconnaissance survey data used for this study. Column headings are self-explanatory.