Large-Scale Mineral Potential Estimation for Blind Precious Metal Ore Bodies

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Conventional evaluation of quantitative mineral potential has focused on target selection at small scales. Mapping at small scales usually results in large-area targets, which may be suitable for grass-roots exploration or regional evaluation of potential. Unfortunately, the estimates in small-scale exploration are commonly associated with large uncertainties. Large-scale estimation is used for optimal in-fill drilling design and step-out drilling target selection. In-fill drilling helps to confirm ore-grade continuities and translate a portion of geological resources into minable reserves, whereas step-out target estimation is useful for finding new orebodies in the vicinity of known ore deposits. Both of these processes are necessary for mine development and production planning. A comprehensive methodology is proposed here, particularly for large-scale mineral exploration. The central information synthesizer is canonical or indicator favorability analysis. A case study is presented to demonstrate the methodology for large-scale target selection. The study involves a gold-mining district where step-out drilling targets are being sought to expand the resource base. Several drilling targets were delineated in the study region. Two of them were tested through surface sampling with positive results.

Key words: Favorability analysis
Large-scale mineral estimation
Target
Gold–silver deposit

Introduction

In the next decade, mineral exploration will likely target blind orebodies by means of optimal data-integration technologies. Mineral potential evaluation commonly involves multiple data sets, or layers, of diverse forms. Multiple layers can be combined either qualitatively (for example, by superposing a single map) or quantitatively (through mathematical optimization). The qualitative methods identify targets as areas where more than one anomaly coincides, whereas the quantitative methods delineate targets by computing probability or favorability of mineral occurrences. Quantitative techniques have been emphasized recently, for several reasons: (1) their superiority in evaluating numerous layers, (2) their ability to evaluate the interrelationships of different layers, (3) their ability to filter and enhance, and (4) their flexibility for reinterpretation as more data is acquired.

With the advent of sophisticated computer technologies in the last decade, numerous quantitative methods have been introduced to optimize the combination of multiple layers of geo-maps. Notable techniques include favorability analysis (Pan and Harris, 1992; Pan, 1993a, b) and probability analysis, for example, weights of evidence modeling (Bonham-Carter and others, 1988; Agterberg, 1992). Other related techniques are derived from artificial intelligence (Bonham-Carter and others, 1990), such as belief function, plausible function, and fuzzy logic membership function (see Shafer, 1986; Moon, 1990; Chung and Moon, 1991). All these methods can be efficiently implemented by means of automated or expert systems based on Geographic Information Systems (GIS). Although each method employs a different algorithm to combine multiple maps, they all produce some unique measures for mineral potential based on a given set of geoscience variables.

Conventionally, mathematical estimation methods have been used mainly to select targets for small-scale (grass-roots or regional) mineral potential. A major characteristic of small-scale estimation is low-level information related to the deposits. In other words, we usually have insufficient information to define targets in evaluating regional mineral potential. Consequently, the estimates of favorability function for regional mineral potential are commonly associated with extremely large uncertainties, which are difficult to quantify. Moreover, most objective methods are based on the principle of analogy: A mathematical model is created from a set of standard samples within a preselected control area; the model is then applied to the entire region. Since detailed information about the control area is frequently lacking, extrapolating the model to a large region can be geologically inappropriate. If this issue is not successfully addressed, quantitative estimates in regional resource evaluation are hardly adequate and reliable. Hence, the results will be less useful for practical exploration and decision-making.

Estimation of large-scale mineral potential has been essentially ignored for several reasons. One major reason is the traditional perception in regard to the nature of large-scale targets. Deposit- or district-scale targets can be reliably selected by resident geologists based on their knowledge of the area and geological models. This implies that exploration programs can be appropriately designed even without using quantitative methods. The second important reason lies with the geomathematicians, who lack confidence in defining precise drilling targets because of technical limitations. These may include ineffective quantitative methods, insufficient practical experience, financial constraints, and lack of support from exploration managers who are unfamiliar with quantitative methods. The difficulty in acquiring sufficient data sets is another reason that large-scale estimation has been ignored. This does not mean that there is insufficient information for quantitative analysis, but rather that we have not fully utilized data generated by past cumulative exploration efforts. In fact, it is quite common in many companies that data are only partially utilized.

Although large-scale targets can be satisfactorily delineated by expert geologists, more rigorous quantitative studies would be useful. In estimation, the goal is the selection of optimal drilling targets; that is, the drill plans must yield the largest discoverability for a given exploration expenditure. Furthermore, in completely covered areas, there rarely exists a single exploration approach sufficient for the most efficient target selection. In other words, objective and quantitative methods should play an important role in large-scale mineral potential prospecting.

In this article, we apply favorability analysis to estimate large-scale potential for epithermal gold deposits in volcanic environments. Canonical favorability analysis is used to yield target maps by integrating geological, geochemical, geophysical, and drill-hole data. The major targets have been appropriately tested by means of surface rock sampling.

The Scope of Large-Scale Estimation

When a mineral potential estimation program is enacted, it is necessary to understand the scale and character of targets to be delineated. This is important because different scales define different types of targets, and targets identified in one area may not be appropriate in other areas. For example, some targets may indicate potential mineral occurrences, whereas others may indicate ore deposits. The type of target will usually influence follow-up exploration. Targets of ore deposits are usually of more interest to mining companies than targets of mineral occurrences.

Estimation of large-scale mineral potential usually refers to mapping orebodies or ore deposits. In concept, large-scale estimation should focus on detailed data integration and selection of drill targets in relatively small areas. Presumably, the size of mapping areas may vary from a few square kilometers to a few hundred square kilometers, depending on the nature of resource distributions and the type of properties. For example, large-scale estimation of iron or coal deposits may deal with areas many times larger than those considered in gold-deposit prospecting.

It is worthwhile to understand the practical values of large-scale evaluation. In general, large-scale estimation is used for identifying in-fill drilling targets and step-out drilling targets.

In-Fill Drilling Targets. When an ore deposit is adequately delineated by sparse exploration drilling in the early phases, the deposit must be carefully evaluated to determine whether further mine development is warranted. In-fill drilling is usually required when initial feasibility studies support the development of economical production. Large-scale evaluation can be conducted to design optimal in-fill drilling patterns by the integration of all data sets, including known drill-hole assays and logs. The goal of in-fill drilling is to confirm ore continuities, better define grades and geometry, and expand the size of orebodies. A portion of geological resources may be translated into minable reserves through in-fill drilling.

Step-Out Drilling Targets. When an orebody is located, explorationists usually try to find new orebodies in the vicinity of established deposits. Large-scale evaluation can help to identify the step-out targets for new orebodies and new deposits. Adding new resources to the reserve base is particularly necessary when known mineral resources are insufficient for mine development or when the mine life is to be prolonged. Many operational mines today require new orebodies to fully utilize existing mining and milling facilities. Exploration for this kind of target clearly falls in the scope of large-scale estimation.

Mapping for in-fill and step-out drilling targets bridges gaps between grass-roots exploration and mine operations. In-fill drilling patterns are designed by means of interpolation, whereas step-out targets are mapped through extrapolation. However, both do share many features associated with general large-scale estimation practices.

A major characteristic of large-scale evaluation is the availability of large data sets, including not only regional surveys (geophysical and geochemical) but also detailed geological models and drill-hole assays. With the known deposits, control areas can be readily selected from the study region. Since the control areas usually contain high-level information, the models established by the control samples are generally reliable and can be readily cross validated.

In large-scale analysis, extrapolation of the models established in control areas is relatively stable and reasonable, since the study region is generally not too large. In other words, the principle of analogy can be more readily observed because there is less heterogeneity within a small study region relative to the size of the control areas. The usefulness of the analysis is maximized if all information is fully extracted and utilized in the selection of targets.

Review of Canonical Favorability Analysis

In favorability analysis, the following model is commonly considered:

$$F = \mathbf{Z}\mathbf{a} = a_1Z_1 + a_2Z_2 + \ldots + a_mZ_m, \tag{1}$$

where F is the favorability function in terms of random variables $Z_1, \ldots, Z_m$, $Z = (Z_1, Z_2, \ldots, Z_m)$, and $\mathbf{a} = (a_1, a_2, \ldots, a_m)^T$. The favorability function F is required to characterize a type of mineralization given a collection of observations. F is sometimes regularized, say, to the interval $[-1, 1]$ with 1 indicating the most favorable for the mineralization of interest and -1 representing the opposite.

In the canonical favorability model (CFA) (see Pan, 1989), favorability function is estimated such that the canonical correlation between explanatory and target variables is maximized. To characterize the largest variability, target variables are transformed into a set of independent principal components.

Let us consider the sample estimates. Suppose that both sets of explanatory and target variables are observed on a control sample of size n. Let $\mathbf{Z} = (\mathbf{z}_1, \ldots, \mathbf{z}_m)$ be an $n \times m$ data matrix for explanatory variables and $\mathbf{Y} = (\mathbf{y}_1, \ldots, \mathbf{y}_t)$ be an $n \times t$ data matrix for target variables. In this sample, let $\mathbf{f} = (f_1, \ldots, f_n)^T$ be the vector of realizations of F given the set of observations on the m explanatory variables. Thus,

$$\mathbf{f} = \mathbf{Z}\mathbf{a}. \tag{2}$$

Furthermore, the first q sample principal components of t target variables are denoted by $\hat{\mathbf{P}} = (\hat{\mathbf{p}}_1, \ldots, \hat{\mathbf{p}}_q) = \mathbf{Y}\hat{\mathbf{U}}$, where $\hat{\mathbf{U}} = (\hat{\mathbf{u}}_1, \ldots, \hat{\mathbf{u}}_q)$ with $\hat{\mathbf{u}}_j$ being the unit eigenvector associated with the jth largest eigenvalue of the sample covariance matrix of the t target variables. Consider

$$\phi_n^2(\mathbf{a}) = \sum_{j=1}^{q} \left[\left(\hat{\mathbf{p}}_j - \frac{1}{n} \mathbf{J} \hat{\mathbf{p}}_j \right)^T \left(\mathbf{f} - \frac{1}{n} \mathbf{J} \mathbf{f} \right) \right]^2 = \mathbf{a}^T \mathbf{S} \mathbf{a},$$

where $\mathbf{Q} = \mathbf{I} - (1/n)\mathbf{J}$ with $\mathbf{J} = (1)_{n \times n}$, and

$$\mathbf{S} = \mathbf{Z}^T \mathbf{Q} \mathbf{Y} \hat{\mathbf{U}} \hat{\mathbf{U}}^T \mathbf{Y}^T \mathbf{Q} \mathbf{Z}. \tag{3}$$

The sample variance of F is

$$\alpha_n^2(\mathbf{a}) = \mathbf{a}^T \mathbf{D} \mathbf{a}$$

with

$$\mathbf{D} = \mathbf{Z}^T \mathbf{Q} \mathbf{Z}. \tag{4}$$

The coefficient vector $\mathbf{a}$ is determined by maximizing ϕ_n^2 subject to the constraint $\alpha_n^2 = 1$, leading to

$$\mathbf{S}\mathbf{a} = \mu \mathbf{D} \mathbf{a}, \qquad \mathbf{a}^T \mathbf{D} \mathbf{a} = 1. \tag{5}$$

Hence, the estimate of equation 1 based on this sample is given by

$$\hat{\mathbf{f}} = \begin{pmatrix} \hat{f}_1 \\ \hat{f}_2 \\ \vdots \\ \hat{f}_n \end{pmatrix} = \mathbf{Z}\mathbf{D}^{-1/2} \hat{\mathbf{e}}, \tag{6}$$

where $\hat{\mathbf{e}}$ is the unit eigenvector associated with the largest eigenvalue of matrix $\mathbf{D}^{-1/2}\mathbf{S}\mathbf{D}^{-1/2}$.

Sample correlations between F and Z, Y, or P can be computed on the basis of the sample estimates. The sample estimates of the correlation coefficients between F and Z are computed by

$$\hat{\mathbf{r}}_{f,z} = \hat{\mathbf{C}}^{-1/2} \mathbf{D}^{1/2} \hat{\mathbf{e}}, \tag{7}$$

where $\hat{\mathbf{C}}$ is the sample estimate of $\mathbf{C} = \mathrm{Diag}(\sigma_1^2, \ldots, \sigma_m^2)$ with $\sigma_j^2 = \mathrm{var}\,(Z_j)$.

Similarly, the sample estimates of the correlation coefficients between F and Y are given by

$$\hat{\mathbf{r}}_{f,y} = \hat{\Gamma}^{-1/2} \hat{\Sigma}_{YZ} \mathbf{D}^{-1/2} \hat{\mathbf{e}}, \tag{8}$$

where $\hat{\Gamma}$ and $\hat{\Sigma}_{YZ}$ are the sample estimates of Γ (diagonal matrix with elements being the variances of target variables) and Σ_{YZ} (covariance matrix between explanatory and target variables), respectively. In the same fashion, the sample estimates of the correlation coefficients between F and $\hat{\mathbf{P}}$ are given by

$$\mathbf{r}_{f,p} = \hat{\Lambda}^{-1/2} \hat{\mathbf{U}}^T \Sigma^{YZ} \mathbf{D}^{-1/2} \hat{\mathbf{e}}, \tag{9}$$

where $\hat{\Lambda}$ is the sample estimate of Λ (a diagonal matrix with the elements being the variances of the principal components of target variables).

In general, correlation coefficients between F and Z can be used to justify the significance of each explanatory variable in terms of favorability estimates. Higher correlation coefficients suggest that the explanatory variables are important in estimation. Low values suggest that the variables should be removed from the favorability equation.

Correlation coefficients between F and Y characterize how close favorability estimates are to each of the target variables. Practically, some target variables are more substantial than others in terms of the objective of estimation, for example, gold concentrate in gold deposits. Thus, the correlation value of F with the most essential target variable(s) should be most informative with respect to the quality of favorability estimates.

Correlation coefficients between F and P provide information on the eligibility of favorability estimates in representing the major variabilities of the target variable space. It is expected that the correlation between F and the first principal component is usually the greatest, the correlation between F and the second principal component is the second largest, and so forth.

Methodology for Large-Scale Estimation

The favorability methodology proposed in this section is an integrated approach for the search, based on diverse geodata, for blind orebodies on a large scale. Data involved in this analysis may include geophysical, geochemical, and geological observations. The approach has the following characteristics:

- The method emphasizes information synthesis (that is, optimal spatial integration) of multiple geodata sets of all forms, for instance, qualitative, nominal, and quantitative. We know a priori that geological features are differentiated with respect to their roles in mineral potential estimation.
- The method creates a unique criterion for identification and delineation of mineral targets, whose credibility can be quantitatively assessed. The favorability function provides a useful ruler for the relative possibilities of mineral occurrences given a set of observations.
- The method uses geophysical fields as the core information for the estimates of favorability function and the synthesis of multiple geofields. Geophysical sur-

veys are crucial for revealing blind targets, but they are ambiguous in defining the targets. The effective use of such data sets makes it necessary to maximize the correlation between geophysical observations and some direct target evidence in three-dimensional space.

The methodology aims to extract the maximum amount of information relevant to the deposits of interest. Favorability analysis is the core information synthesizer that combines multiple geofields. Since exploration efforts are directed toward unexplored areas and covered terrain where surface evidence of mineralization is rare, geophysical data become increasingly important as the core information for target definition. Figure 1 presents a flowchart for the methodology. The major steps in the methodology are preprocessing, interpolation and enhancement, variable classification, establishment of information criteria, favorability function estimation, target delineation, and target evaluation.

Preprocessing

All relevant information (digital or map) for the deposit type of interest is compiled and unified. In most cases, geodata collected in different survey campaigns may have inconsistent spatial distributions, different sampling densities, and uneven measurement precisions. This stage includes three treatments: quantification, transformation, and prescreening.

Quantification. Information is diverse in both form and nature. For example, geochemical data are numerical and quantitative, whereas rock type is nominal and quantitative. Nonnumerical geological features must be appropriately expressed as a quantity. For example, rock type is assigned a meaningful numerical value according to presence or absence or according to favorability for the presence of deposits. This step may also generate composite variables, such as grade-thickness, which provide additional information.

Transformation. Appropriate data transformation helps to unify different data sets with diverse scales and contrasts. Common methods include regularization, standardization, and logarithm transformation. Regularization converts a variable into a limited numerical range, for example, [0, 1], [−1, 1], or [0, 100]. Standardization transforms a variable into a new variable that has a zero mean and unit variance. Logarithm transformation is used to suppress the effects of large numerical contrasts or nonsymmetric distributions.

Prescreening. Data bases usually contain numerous geological maps or quantified features for large exploration projects. Only some of the data are relevant; other data are either less interesting or statistically redundant. Therefore, prescreening of the data helps to focus on the most important features with minimal processing costs. For example, if both drill-hole assays and rock geochemical data are available in a control area, it is desirable to compress the geochemical data set by either deleting less important elements or converting them into fewer composite factors.

Interpolation and Enhancement

Original geodata sets are converted into a standard XYZ file and interpolated into a regular grid, which is then subjected to filtering and enhancement. An equal-area grid should be designed to suit the densities and distributions of samples.

Interpolation. Prior to filtering, all geodata sets are converted into raster formats on a common grid on which the layers are integrated. Different interpolation methods are used for different types of data. For example, the minimum curvature method may be employed for geophysical data, whereas kriging may be best suited for drill-hole assays. It is important to make sure that the operation is interpolation and not extrapolation.

Enhancement. The grid is usually filtered first to remove possible noise and then enhanced in various ways, depending on the objectives and the characteristics of data sets. Since mineral exploration is usually directed at shallow deposits, the enhancement of local and shallow anomalies is a common practice for the interpretation of geophysical data. Similar treatments may also be applied to digital elevation models and quantified structural data.

Variable Classification.

Relevant geofields are classified into two categories according to their roles: explanatory variables and target variables.

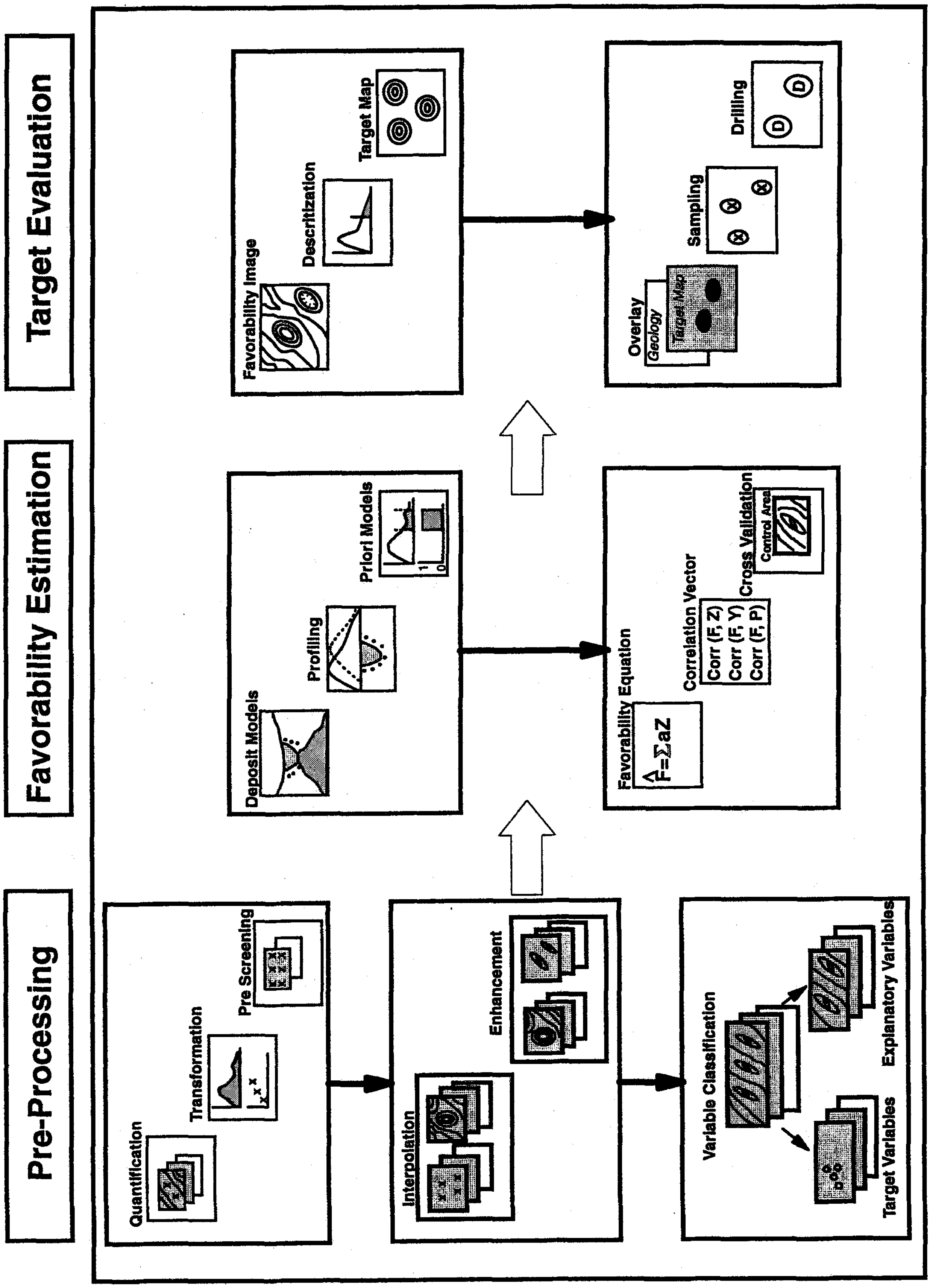
Explanatory Variables. Explanatory variables are those that quantify physical and chemical characteristics of geological objects hosting or adjacent to mineral deposits. These data can be obtained for the entire study region at a relatively low cost, for example, with a magnetic survey. This type of variable provides indirect evidence of the existence of mineral deposits.

Target Variables. Target variables are those that provide firm, direct, and definite information for the mineral occurrence of interest. This type of information is usually available in the best-explored subregions; the data can be very costly to obtain.

Establishment of Information Criteria

This is a critical step in establishing a set of necessary criteria that guide the conversion of diverse data into the information in terms of mineral deposits.

Deposit Model. One or more control areas containing


Pre-Processing
Favorability Estimation
Target Evaluation
Quantification
Transformation
Pre Screening
Interpolation
Enhancement
Variable Classification
Target Variables
Explanatory Variables
Deposit Models
Profiling
Priori Models
Favorability Equation
$\hat{F}=\sum aZ$
Correlation Vector
Corr (F, Z)
Corr (F, Y)
Corr (F, P)
Cross Validation
Control Area
Favorability Image
Descritization
Target Map
Overlay
Geology
Target Map
Sampling
Drilling

known deposits or mineral occurrences are required for large-scale estimation to establish reliable deposit models as the basis of target identification in unexplored regions. In the control areas, target variables can be collected and quantified by utilizing all data accumulated in the past. Undiscovered deposits of the same type as those occurring in control areas are sought in noncontrol areas.

Profiling. For geophysical data, profiling is necessary to establish geological–geophysical models. Known geology should be maximally utilized in the construction of typical profiles within the control areas and possibly the study region. Modeling is necessary when known information is insufficient. Profiling will help us understand the relations between subsurface geology and geophysical anomalies.

A Priori Model. This is a summary of the relations from the profiling and statistical analysis of control data sets, including a priori weights of the fields, thresholds, and value assignment strategies. Prior weights are determined from the relations of each explanatory field to target variables and possibly to the opinions of expert geologists. Thresholds are determined from geological–geophysical relations and statistical analysis of explanatory data. These values serve as cutoffs to convert original data into discrete numbers. Value assignment provides a strategy to explicitly define favorability levels between the pairs of threshold values.

Favorability Function Estimation

Based on the control data sets, one or more of the following favorability functions may be estimated to optimally combine the multiple explanatory fields.

Target Principal Components. Target variables are usually multiple and highly intercorrelated because they represent the same targeting features (for example, copper mineralization). It is desirable to convert them into orthogonal principal components and retain only the major components.

Estimation of Weights. The optimal weights are determined by maximizing the correlation between explanatory and target variables. The favorability equation is defined as the weighted sum of explanatory variables.

Cross Validation. The quality of the favorability functions may be validated in the control areas by computing the favorability estimates and known target principal component values. A set of correlation coefficients should be computed between the favorability functions and explanatory, target, and the target principal components variables.

Favorability Regularization. Favorability estimates can have any numerical range. For interpretation, it is usually helpful to regularize the favorability estimates into a limited range, for example, [0, 1] or [−1, 1].

Target Delineation

The favorability grids generated by the favorability functions can be further converted into color images, which are then enhanced in different ways to emphasize trends and highly favorable areas.

Trend Correlation. Prior to delineating targets, it is important to examine the correlations between favorable trends and the known structural or geological zones that are relevant to the formation of ore.

Boundary Definition. Although the favorability images may reveal a large contrast between highly favorable areas and the surrounding background, it is still desirable to precisely define the boundaries of targets. This can be done simply on the basis of a contour line or by using more complicated approaches, such as optimal discretization (Pan and Harris, 1990).

Target Evaluation

The final stage in the methodology is to evaluate the identified targets through field work and sampling. If the favorability of a target is supported by field work and surface sampling results, a small drill plan (for example, a couple of drill holes) may be designed on the targets. The drill-hole information is carefully examined to determine whether further work is warranted. If the results are positive, the plan continues. Otherwise, the model is redone by incorporating the new data into the analysis.

Case Study

The favorability methodology for large-scale estimation described here is applied to the target definition for hydrothermal gold–silver deposits within a known mining district. The gold–silver deposits in the mine region are association with middle Miocene silicic volcanic flow domes, which vented along north- to northwest-trending fault zones. The deposits are characterized by a high silver-to-gold ratio, low amounts of sulfides and base metals, and the occurrence of silver selenides. The mineralization is associated with strong silicification and argillization of the host rocks.

Geodata used in this study include a exploration drill-

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Figure 1. Flowchart for the methodology of large-scale mineral potential evaluation.

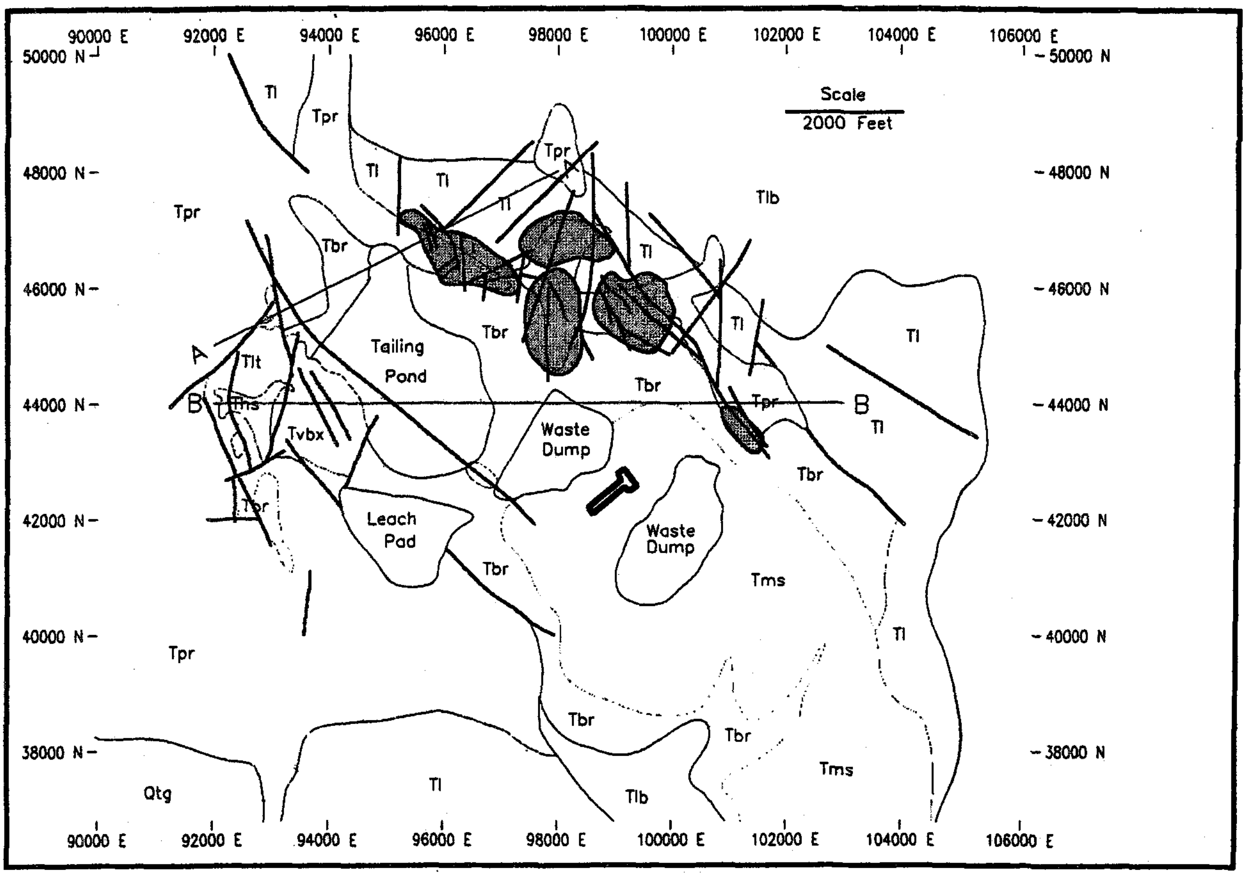


Figure 2. Generalized geological map of the study region: Tpr, Teriary porphyritic rhyolite; Tl, Tertiary latites; Tbr, Tertiary banded rhyolite; Tlb, Tertiary lower basalt; Tms, Teritary millsite rhyolite; Tvbx, vent breccia; Tlt, Tertiary latite tuff; Ths, hot spring center; Qtg, gravel cover.

hole assays (gold, silver), geology, high-resolution electromagnetic measurements, and soil geochemical samples. All geophysical fields (total magnetic, resistivity fields at three different frequency bands) were filtered to enhance the signals for local and relatively shallow geological objects. Results of drill-hole assays of the mine area were used as target variables. Various images were created to assist the interpretation of geophysical anomalies. A target map was generated to show the potentials of undiscovered gold–silver deposits in the study region.

The results from this study include multiple targets, some of which have been field-checked and are permissible for hosting ore deposits. Two of the targets have revealed trends of mineralization from chip, rock grab, and soil samples. Postmineral cover in other target areas precludes surface verification and will require drill confirmation.

Review of Geology

A generalized geological map is shown in figure 2. The region contains four major premineral rock units: granite, silicic volcanic rocks, volcanic sediments, and basalt. Granitic rocks occur in the eastern portion of the district and form the basement beneath the volcanic units elsewhere in the district. Basalt flows overlay the granite in the lower elevations and are widely exposed in the northeast portion of the district. Silicic volcanic rocks form most of the topographic highs and overlay the basalt in the western portion of the district (Porterfield, 1993).

Volcanic rocks that postdate the main period of mineralization include rhyolite, vitrophyres, tuffs, and basalt. Up to 500 feet of postmineral rhyolite flows occur directly south of the district. Vitrophyre flows cover the area in the northeastern part of the district. The lower section of the sediments are clastics derived from the granitic and volcanic units, whereas the upper section consists of greenish tuffaceous sediments that filled topographic lows. Black siliceous hot spring sinter containing abundant fossil plant material is common in these sediments.

Several fault sets are pronounced, including north-to-northwest-striking high-angle normal faults with small to moderate dip-slip displacement. Northeast-striking structures are rare in the volcanic rocks but are much more common in the granites. These faults may be related to an older structural system because some are cut off by northwest-trending faults. The most important fault is the northwest one, which is in a zone of northwest to east–west faults.

Most of the gold and silver mineralization in this region is related to flow vents of silicic volcanism. Exogenous dome complexes, which include a tuff breccia event between quartz latite and rhyolite flows, host the major bulk-minable ore deposits. These domes are formed from a series of coalescing flows vented from the major northwest-trending faults. Disseminated gold–silver mineralization in favorable lithologies and structurally prepared breccias composes much of the bulk-minable deposits. A porphyritic rhyolite unit has been the major ore host in the district. A basal clay-altered vitrophyre of an overlaying banded rhyolite exerted important stratigraphic control on the mineralization. Ore mineralogy consists primarily of gold and electrum, the silver selenides, naumanite, and aguilarite.

Strong hydrothermal alteration is associated with gold and silver mineralization in the district. The extent and character of alteration is strongly dependent on host lithology. The alteration in granitic rocks is usually limited to less than an inch of silicification and argillization next to veins. The lower basalt is usually chloritized near hydrothermal conduits, but rarely exhibits silicification or argillization. The silicic volcanic rocks generally exhibit strong quartz-sericite alteration associated with the mineralization. Strong silicification is common, and clay minerals, including illite, smectite, and kaolinite, are locally abundant, particularly in structural conduits. Propylitic alteration, including strong silicification, can extend outward from mineralization over 100 feet in the latites and quartz latites. Argillic alteration characterized by kaolinite and montmorillonite commonly extends many hundreds of feet above and outward from the core of mineralization systems.

Figures 3 and 4 each present a geological section and a geophysical profile; locations are indicated in figure 2. Both sections reveal that the orebodies are hosted in Tertiary porphyritic rhyolite and latite. The sections show that the occurrence of ore is closely associated with faults—probably the contact between rhyolite and latite. The geophysical fields exhibit the following features:

1. The host environments, including porphyritic rhyolites and latites, are characterized by local and complex resistivity lows and magnetic lows. These lows represent extensively altered lithological settings. Relatively unaltered rocks, such as millsite rhyolites and lower basalts, correspond to high resistivity fields and high magnetic residuals.
2. The high gradients in both magnetic and resistivity fields indicate high-angle structures (faults). The adjacent high-gradient fields clearly define the downdropping of blocks favorable for the localization of ore. Both strikes and dips of faults may be reasonably inferred from geophysical fields.
3. Mineralization is generally associated with local resistivity lows and the transitional zones of magnetic residuals. The distinction, however, is not unique because of the extensively faulted environment and the complexity of alteration. The hot spring center in figure 4 is clearly indicated by a local geophysical low.

Selection of Geofields

Each exploration datum carries two attributes: spatial location and geological typicality (Pan, 1993b). Some measurements, for example, geophysical surveys, reveal general physical properties, whereas others characterize rare events, such as mineralization. The search for mineral deposits generally requires prediction of rare spatial phenomena through chemical and physical measurements. Target and explanatory variables (Pan and Harris, 1992) have been introduced to describe the different roles of geodata. Target variables, associated with exploration completeness, provide direct and firm evidence for mineral deposits. They are usually available only in the most thoroughly explored part of the study region. Explanatory variables, observable through the entire region at relatively low costs, describe indirect evidence for mineralization.

Geophysical surveys generate explanatory data about the physical properties of geological objects in three-dimensional space. Detailed geological and deposit investigations, including drilling and mine development, usually create target variables, such as mineral occurrence, alteration, ore grade, and genetic process. Geochemical surveys provide information on both explanatory and target variables. For instance, assays on ore elements (for example, gold) from rock samples indicate direct evidence of mineralization. Local ore-control structures (faults) are used as important explanatory variables.

Data involved in this analysis include airborne electromagnetic (EM) geophysical surveys, geological structures, favorable rock types, and digital topographic data. The geophysical data set was obtained from a high-resolution airborne EM survey conducted through a multicoil, multifrequency electromagnetic system hooked to a helicopter through Dighem, a Canadian geophysical service company. The flight line was north–south, with a line spacing of about a quarter mile. The flight altitude was approximately a hundred feet above ground. The data include total magnetic and apparent resistivity fields

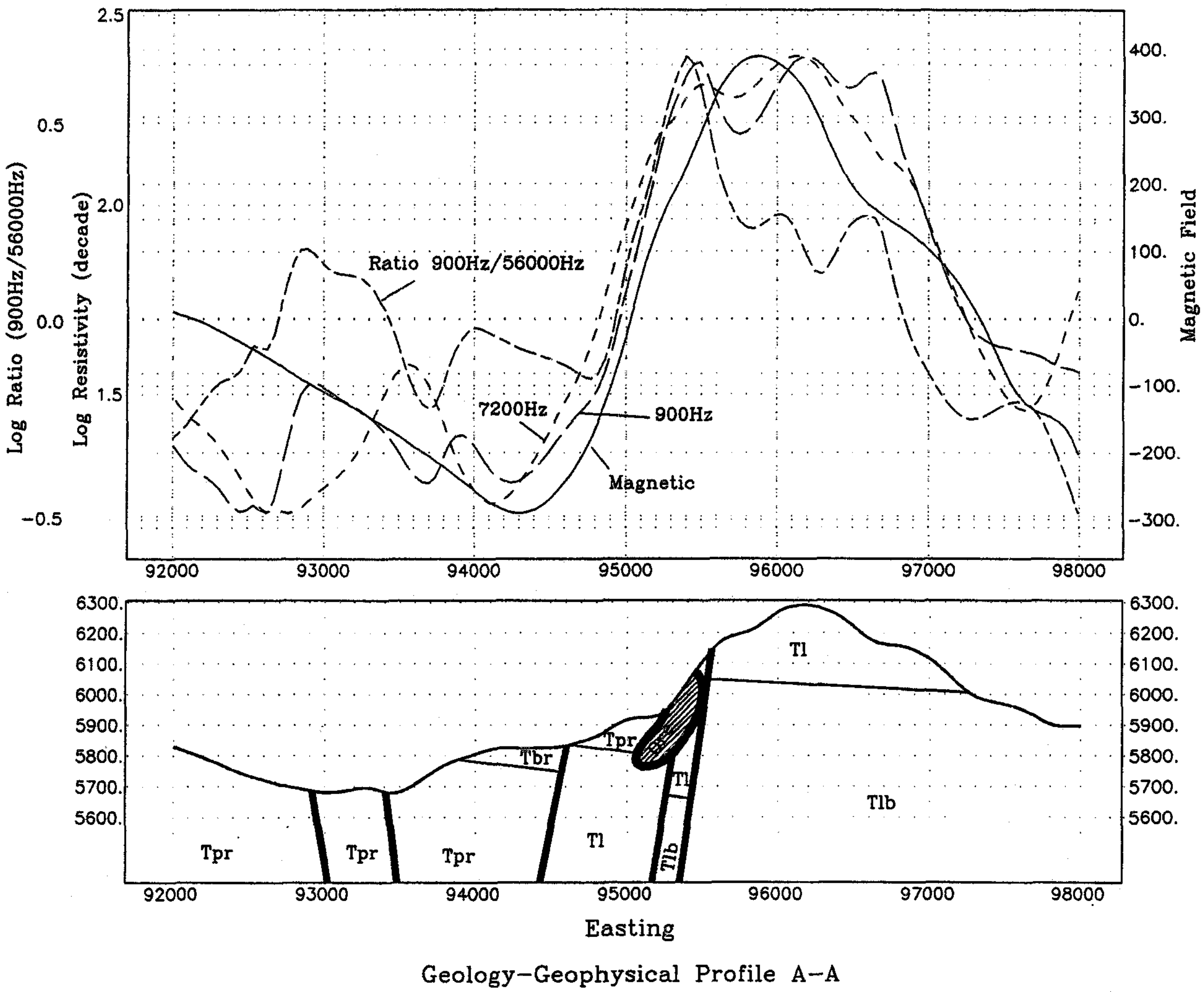


Figure 3. Geological–geophysical section, whose location is indicated on the geological map (profile AA). The legend is explained in figure 2.

at three frequency bands. Filtered total magnetic fields and three apparent resistivities at 900; 7,200; and 56,000 hz were employed in this analysis. The data were processed by various filtering and enhancing techniques for noise removal and enhancement of local anomalies.

In this study, we selected the following three target variables:

Y_1: *Drill-hole Gold Assay.* This variable is defined by the average gold assays along each drill-hole within the intercepts of orebodies

Y_2: *Drillhold Silver Assay.* This variable is defined by the average silver assays along each drill-hole within the intercepts of orebodies

Y_3: *Grade-Thickness.* This variable is defined by the cumulated product of gold grade and thickness within the intercepted orebodies for each drill-hole.

To estimate favorability functions, we used the following six explanatory variables:

Z_1: *High-Passed Magnetic Field.* This field was derived from an airborne EM survey. The data were filtered for noise. A second-order polynomial trend was removed from the grid. The local residuals were then filtered again to emphasize local anomalies.

Z_2: *Resistivity at* 900 *Hz.* This field was derived from the apparent resistivity measurements at 900 Hz by an EM helicopter survey. The apparent resistivity was computed from a two-layer half-space model. The field was first low-passed to suppress some single-point anomalies. The regional trend of second order was then removed from the data. The data were finally transformed by logarithm.

Z_3: *Resistivity at* 7,200 *Hz.* This field was obtained in a manner similar to that of Z_2.

Z_4: *Resistivity Ratio of* 900 *Hz over* 56,000 *Hz.* This variable was defined as the ratio of the two resistivity fields at 900 Hz and 56,000 Hz: $Z = [\ln(R_{900}) - \ln(R_{56000})]/\ln(R_{900})$. The ratio helps to reveal the sig-

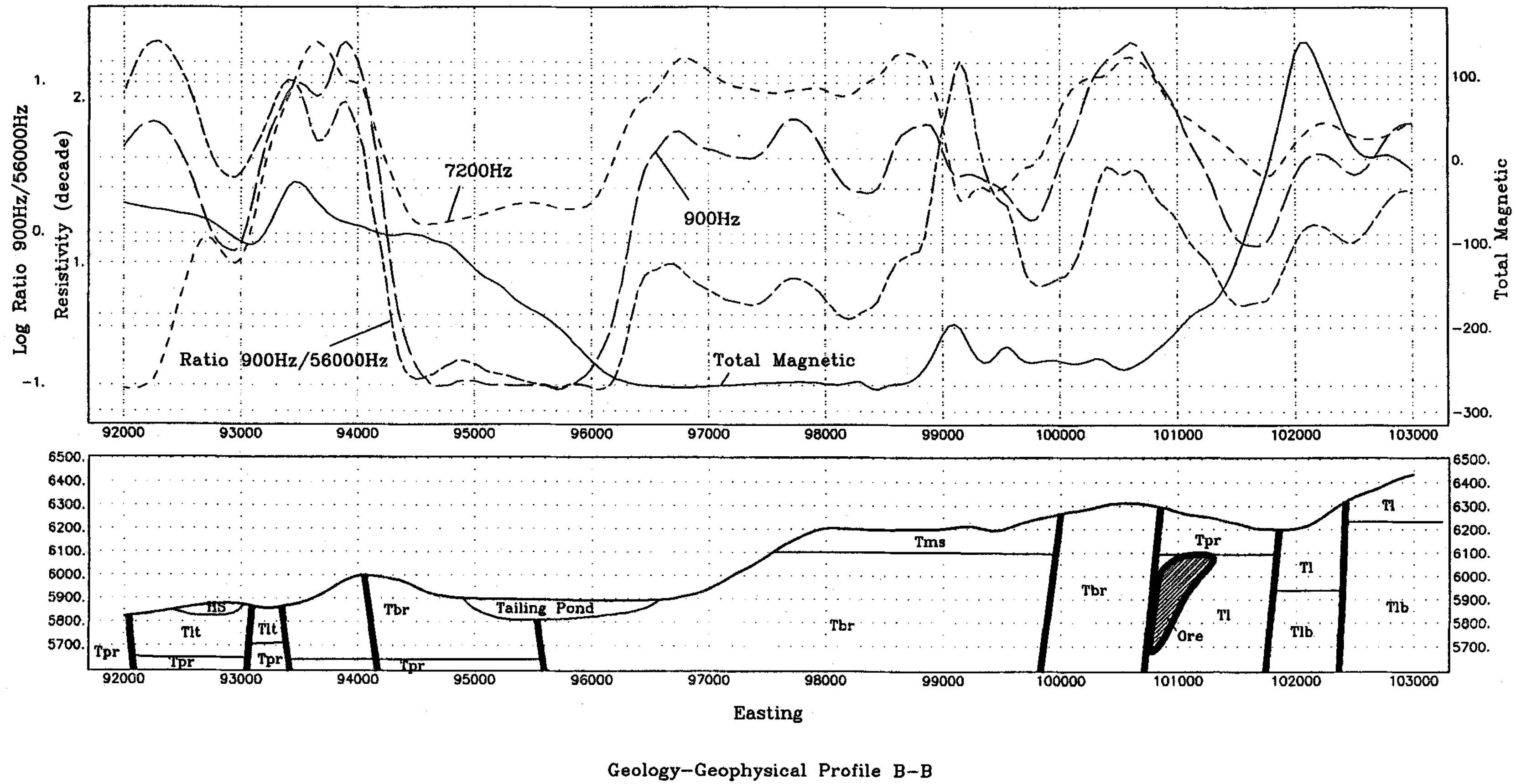


Figure 4. Geological-geophysical section, whose location is indicated on the geological map (profile BB). The legend is explained in figure 2.

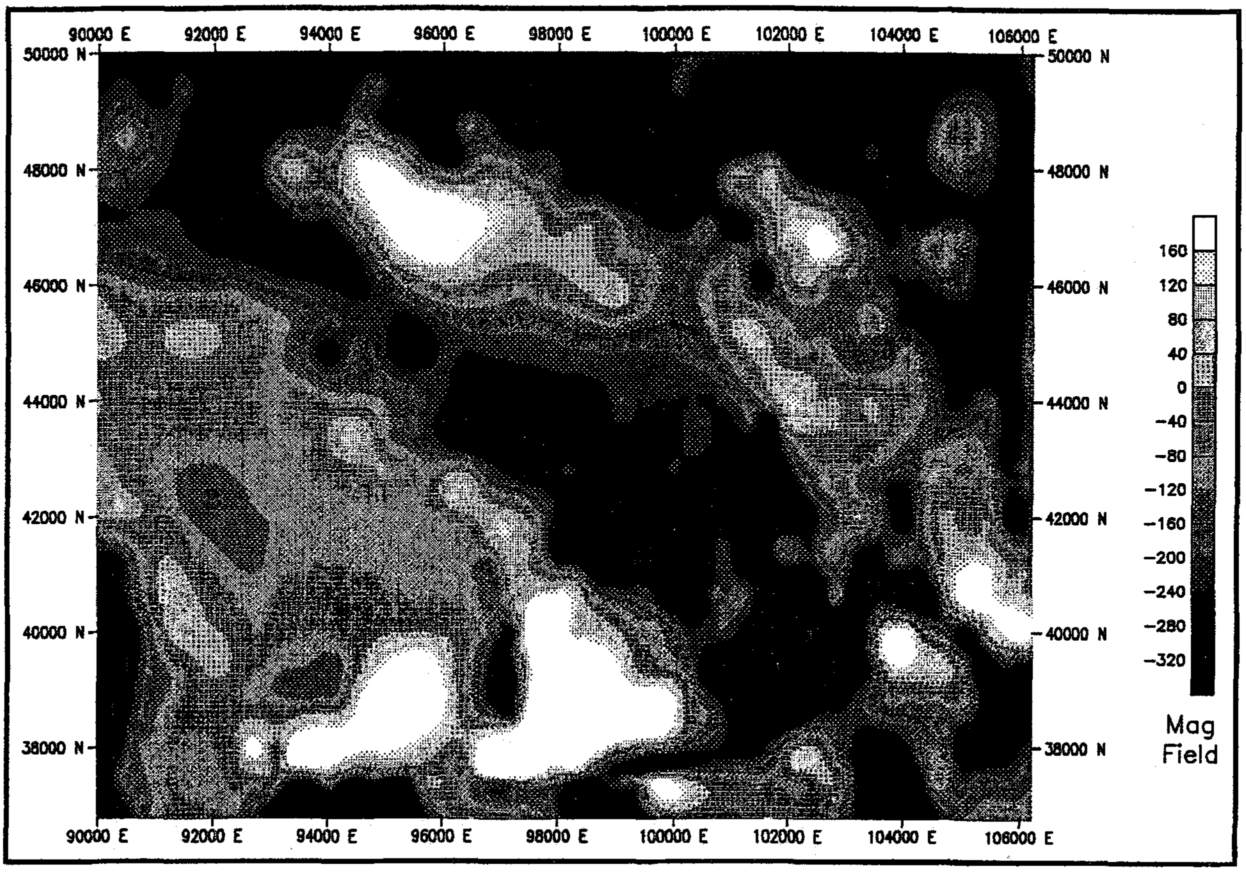


Figure 5. Image of high-passed magnetic fields.

nals from the sources of different depths. It is particularly useful to show local resistors (or conductors) at depth.

Z_5: *Structural Scores.* This feature was created to exhibit the extensiveness and spatial distribution of structures. Lineaments were identified from geophysical and topographic images. They were then reconciliated with known faults relevant to mineralization. The vector file was converted to raster format by quantifying and synthesizing the structural variables.

Z_6: *Digital Elevation Model.* This variable was made of elevation filtered for local features. It is incorporated mainly because some explanatory variables are related to topographic features.

Geological Interpretation

Each of the explanatory fields was carefully examined and interpreted to reveal the maximum amount of information relevant to the targets of interest. Geological interpretation of the explanatory fields has been detailed with reference to known geological background.

According to the characteristics of fields, the magnetic field and apparent resistivity fields were partitioned into five domains, each of which bears internal similarities. Figure 5 is the image of the filtered magnetic fields. Figures 6, 7, and 8 show the resistivity fields and the resistivity ratio image. Figure 9 shows the partitioned domains of the geophysical fields. Clearly, the partitioned magnetic domains correlate well with different geological formations in the region. The five magnetic field domains are as follows:

I. This type of field is not common in the region. It characterizes quiet and local anomalies, indicating local heterogeneities within the basaltic formation in the northeastern corner.

II. This type occurs widely in the northeast and northwest quarters. The major features are magnetic highs with large internal variabilities, which may be related to strong silicification and argillization. The fields, trending N. 60° W., are spatially consistent with the distribution of silicic volcanic rocks, such as porphyritic rhyolite and latite, the major host rocks of the gold–silver deposits. The high anomalies are probably the result of the reversed polar-

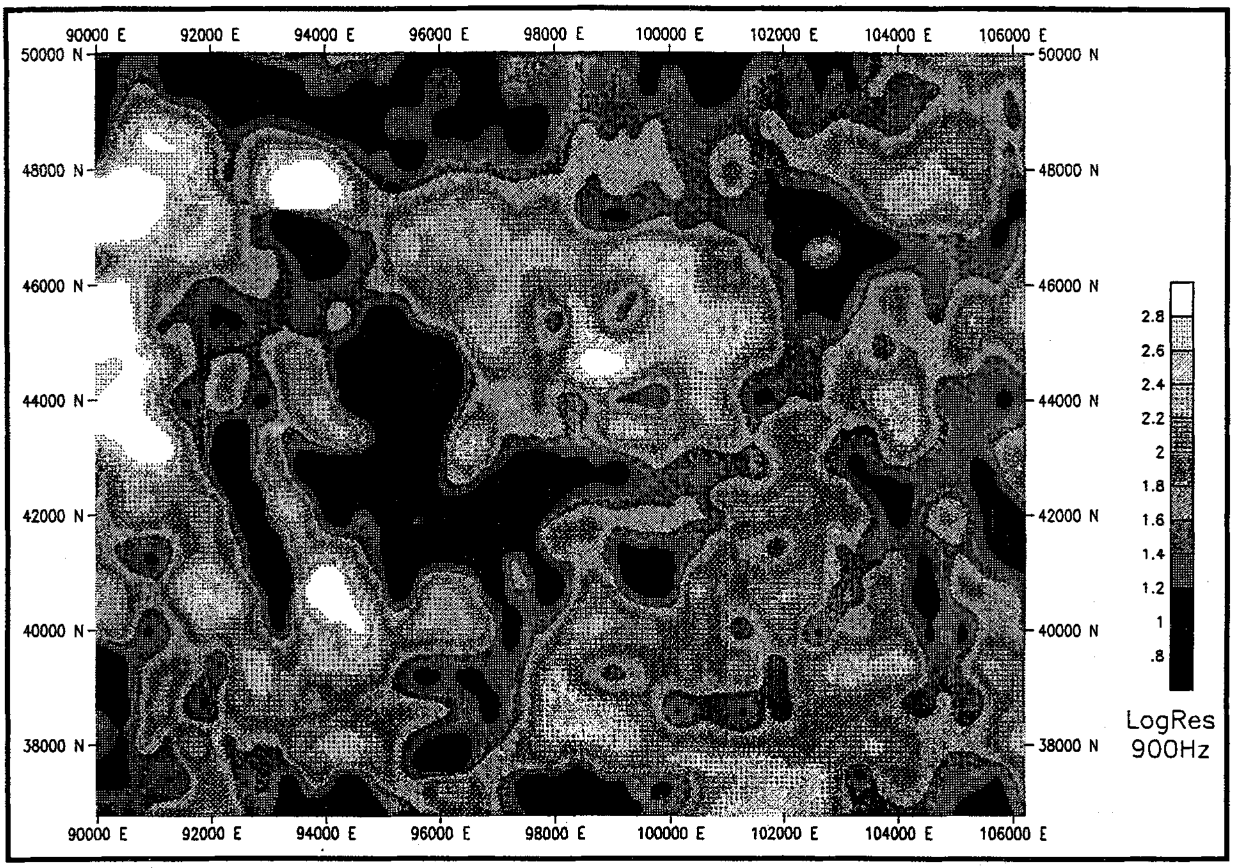


Figure 6. Image of filtered apparent resistivity fields at 900 Hz.

ization of the volcanic rocks, since the rocks are not magnetic.

III. The third type of magnetic field is recognized in several areas, trending N. 60° W. These areas, which are extremely quiet and low, are geologically associated with Tertiary volcanic sediments. They appear to have no relation to the occurrence of ore deposits in the region.

IV. The fourth type characterizes "magnetic basins" with intermediate magnetic anomalies. These fields are relatively quiet but have certain internal magnetic variabilities, which correlate to some surficial features, such as waste dumps and leach ponds. Therefore, this type will not play a role in the selection of targets.

V. The last type includes the areas with quiet and low magnetic anomalies. Surprisingly, these fields occur with premineral basalt rocks. One interpretation is that reversed polarization caused the extremely low anomalies. Clearly, this type has little relation to the formation of ore deposits in this region.

In similar fashion, the resistivity fields of 900 Hz and 7,200 Hz, as well as the ratio fields of 900 Hz and 56,000 Hz, were also partitioned in terms of their spatial characteristics (see fig. 9). The resistivity fields of 900 Hz and 7,200 Hz bear a lot of similarities in spatial distributions. The following is a summary of the major features of the partitioned resistivity anomalies:

I. This type of field contains variable and relatively low anomalies distributed throughout the region. The anomalies are mainly associated with porphyritic rhyolites and Tertiary latites, the major host rocks of ore deposits. The anomalies inside the basalt area might reflect the effect of fracturing and local hydrothermal alteration.

II. The second type of field includes the highest anomalies that correlate well with the occurrence of ore deposits. The main rock type is latite. The high resistivity anomalies are clearly associated with the strong silicification in latites and porphyritic rhyolites in the mine areas.

III. The third type contains those anomalies with intermediate magnitudes of resistivity values. These anomalies are localized along with some structures, which may be related to the conduits of mineral-

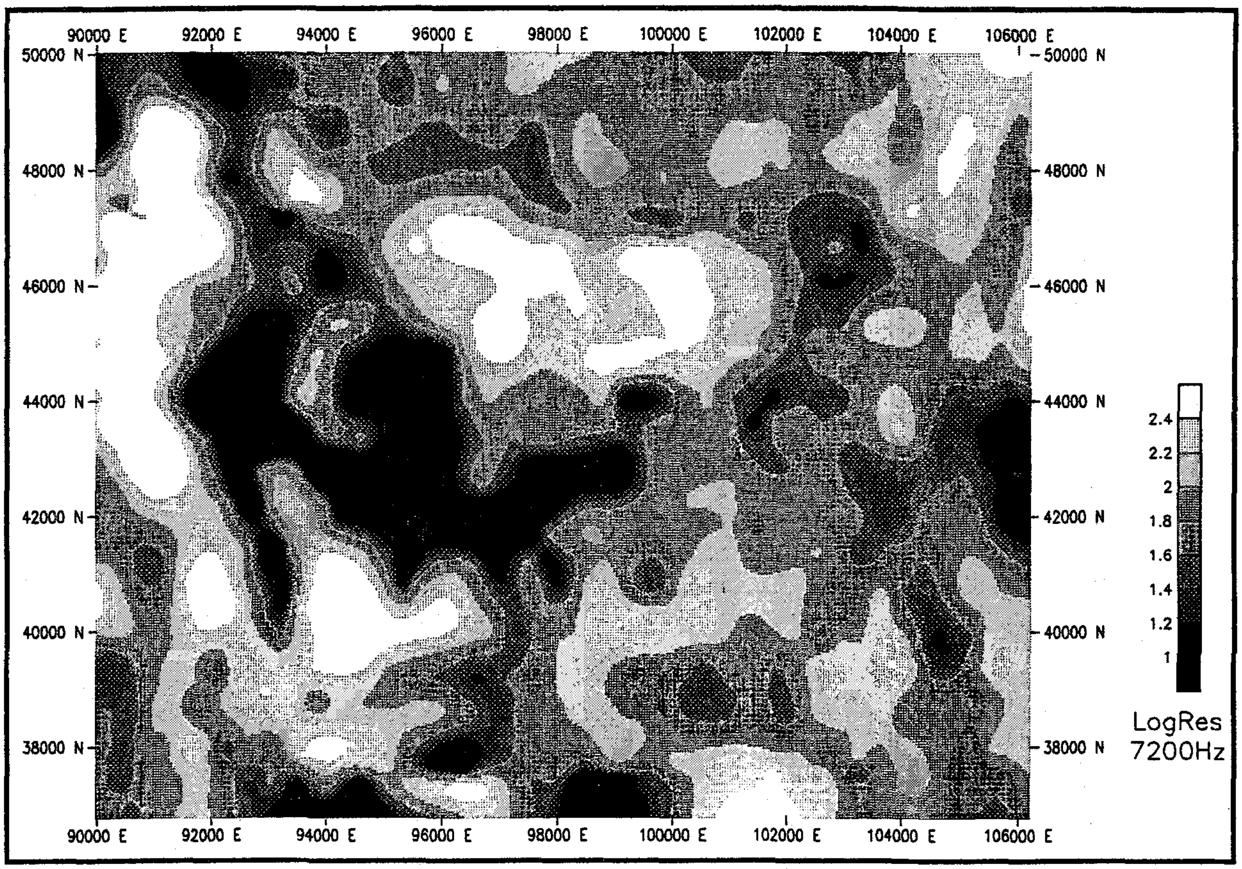


Figure 7. Image of filtered apparent resistivity fields at 7,200 Hz.

ization. Overall, this type is minor relative to other types of anomalies.

IV. The fourth type includes those anomalies that are caused by surficial features, such as tailing ponds and waste dumps.

V. The last type of field corresponds to the premineralization basalt.

The fields of resistivity ratios (fig. 8) exhibit strong structural trends. Geologically observed trends, such as northwest and northeast faults, are clearly shown in the ratio fields. Moreover, the image also reveals some east–west structural trends, which appear to correlate with the localization of orebodies. Rationing of resistivity fields at different frequencies is effective in discerning subsurface conductors or resistors. The subsurface becomes more conductive with depth when the ratio is negative, and the opposite holds when the ratio is positive.

Geological structural data were obtained from lineament interpretation and digitized regional faults going through the study region and local fractures related to gold–silver mineral occurrence (fig. 10). Seven structural variables were quantified on a regular grid by a moving window technique with a window size of 300 by 300 feet. The structural variables generated are as follows:

X_1: Number of regional faults;
X_2: Number of local faults;
X_3: Total length of local faults;
X_4: Number of north–east local faults;
X_5: Number of north–west local faults;
X_6: Number of east–west local faults;
X_7: Number of intersections between faults.

These structural features were then combined into a structural score at the center of each window by means of principal component analysis. The structural score, S, is given by:

$$S = -0.20X_1 + 0.44X_2 + 0.12X_3 - 0.08X_4 + 0.25X_5 + 0.14X_6 + 0.45X_7, \qquad (10)$$

where the coefficients were obtained from the standardized eigenvector associated with the largest eigenvalue of

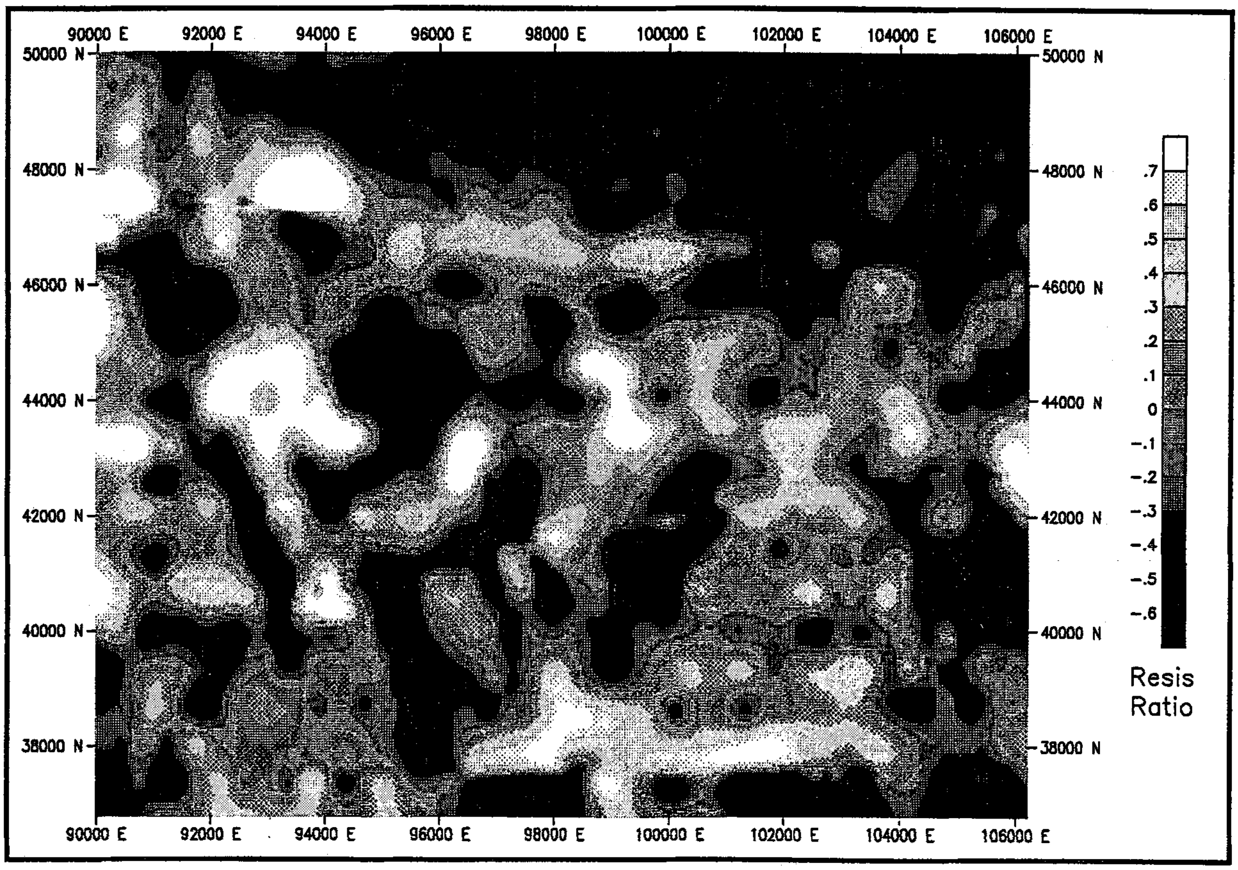


Figure 8. Image of filtered apparent resistivity fields at 56,000 Hz.

the correlation matrix of the seven features. Finally, a set of structural scores was obtained by applying equation 10 to all blocks in the study region. The image of the structural scores is given in figure 11.

The digital topographic data were obtained at the mine site. The model was established by removal of trends and by other filtering techniques. Figure 12 shows the image of the topographic relief in the study region.

Favorability Equation

Before applying canonical favorability analysis, we used principal component analysis to convert the target variables into orthogonal components. The first component loadings indicate that all three target variables are quite important, although variable Y_1 (gold assay) is relatively more weighted. The first component accounts for more than 65 percent of the total variability in the data set, whereas the first two components account for almost 90 percent of the total variations. Thus, the first two components were used in the subsequent analysis.

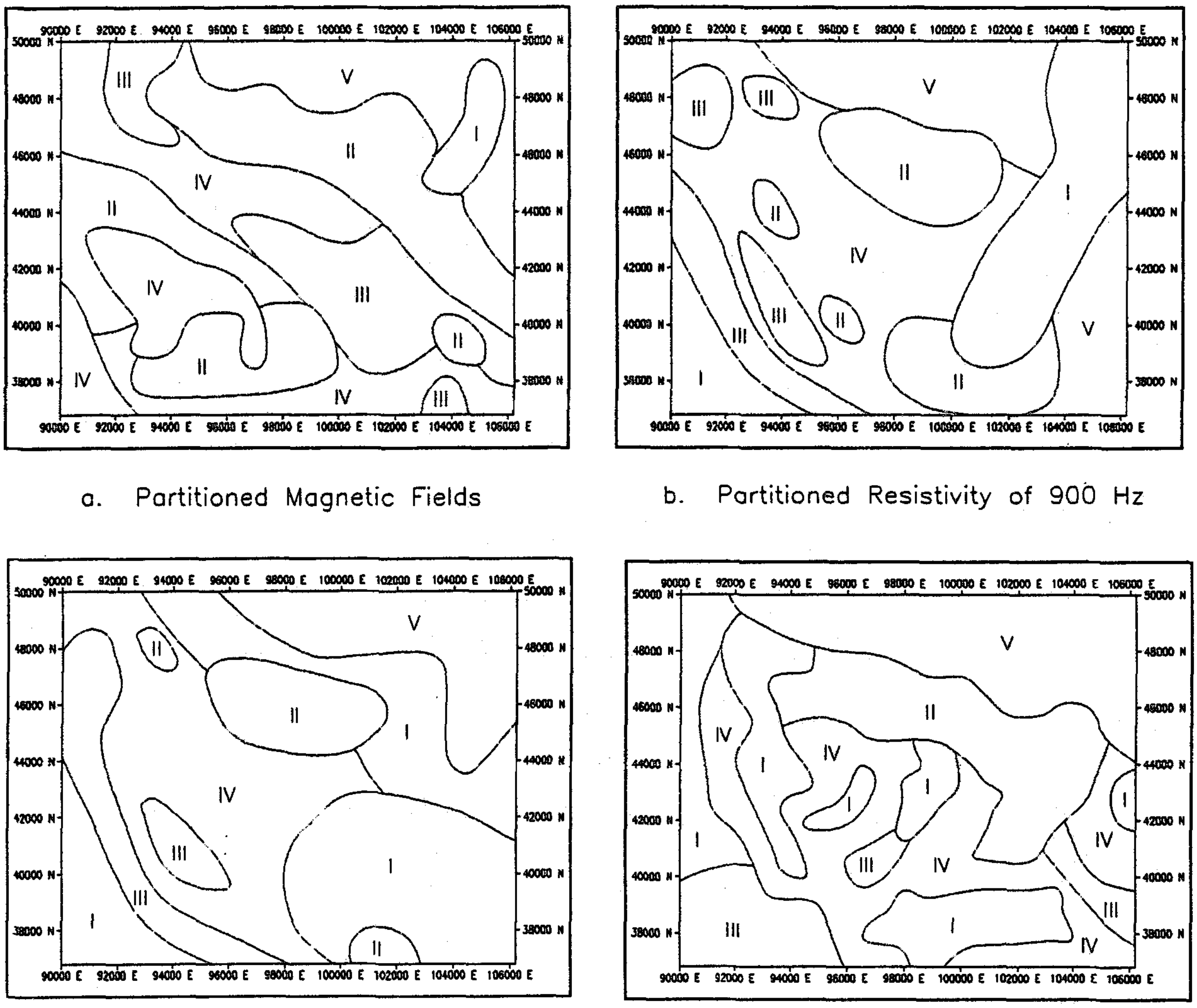
Based on six explanatory variables and two principal components of the target variables, an optimal favorability equation is estimated as:

$$\hat{F} = 0.341Z_1 + 0.416Z_2 - 0.081Z_3 - 0.502Z_4 + 0.411Z_5 - 0.233Z_6. \quad (11)$$

According to the eigenvalues, this estimate accounts for over 95 percent of the total variability related to the covariances between exploratory variables and two principal components of the target variables.

To confirm the validity of the favorability function, several correlation vectors were computed. As expected, the estimated favorability function is most strongly correlated with structural fields (Z_5) and resistivity ratio fields (Z_4), indicating that these two exploratory variables are critical in determining the favorability of a sample unit with respect to the variabilities of the target variables (see table 1).

Furthermore, the estimated favorability function is highly correlated with all three target variables. The correlation of $\hat{F}$ with Y_1 (gold assay) is particularly high (0.78). Interestingly, $\hat{F}$ is strongly correlated with the first principal component of the target variables (0.84) and



a. Partitioned Magnetic Fields

b. Partitioned Resistivity of 900 Hz

c. Patitioned Resistivity of 7200 Hz

d. Partitioned Ratio 900Hz / 56000Hz

Figure 9. Map showing partitioned domains for geophysical fields.

moderately correlated with the second principal component (0.62).

The estimated favorability value at each grid is evaluated from equation 11. Figure 13 is the image of the favorability estimates in the region, showing that all known ore deposits are associated with the highest favorability values. Using the optimum discretization approach as described in Pan and Harris (1990), the value 0.62 was obtained as the best threshold for target delineation. Using this cutoff, the favorability values discretized into a binary pattern. With some appropriate modifications, the delineated potential targets are sketched in figure 14.

Target Evaluation

Based on spatial characteristics, the targets are classified into three categories, each of which represents a level of favorability for the occurrence of ore deposits.

A: Targets that occur along known mineralization trends and are supported by favorable geological settings and significant geochemical anomalies

B: Targets that are supported by favorable geological settings, including silicic domes and major faults

C: Targets that occur in areas of favorable geological settings, including silicic domes.

According to this classification, the targets labeled "A" would receive the top priority for follow-up exploration, including surface check and drilling. Two of the most promising targets are described here.

Target A1: TR. The target "TR" occurs southwest of a tailings dam. This anomaly has a northwest linear trend that is parallel to the Northwest Fault and may be reflecting a graben boundary fault. The anomaly is covered for the most part with rhyolite, banded rhyolite, a vitro-

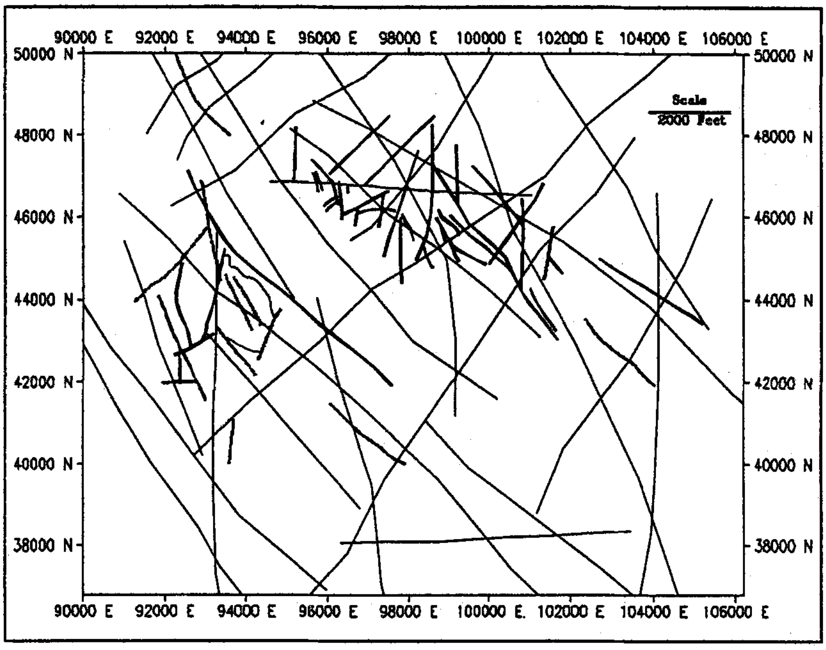


Figure 10. Lineament set interpreted from geophysical and topographic images and known faults in the study region.

phyre flow dome, and volcanic clays, which are all post-mineralization. Immediately west of the tailings dam is a flat hill of bedded lithic tuff, which is capped with hot spring sinter composed of opaline and chalcedonic quartz. The sinter is up to 50 feet thick and covers an area 700 by 1,400 feet. A pyritic zone occurs in the bottom 15 to 30 feet of the sinter and extends about 10 feet into the lithic tuff. Assays of 100 to over 1,000 parts per billion

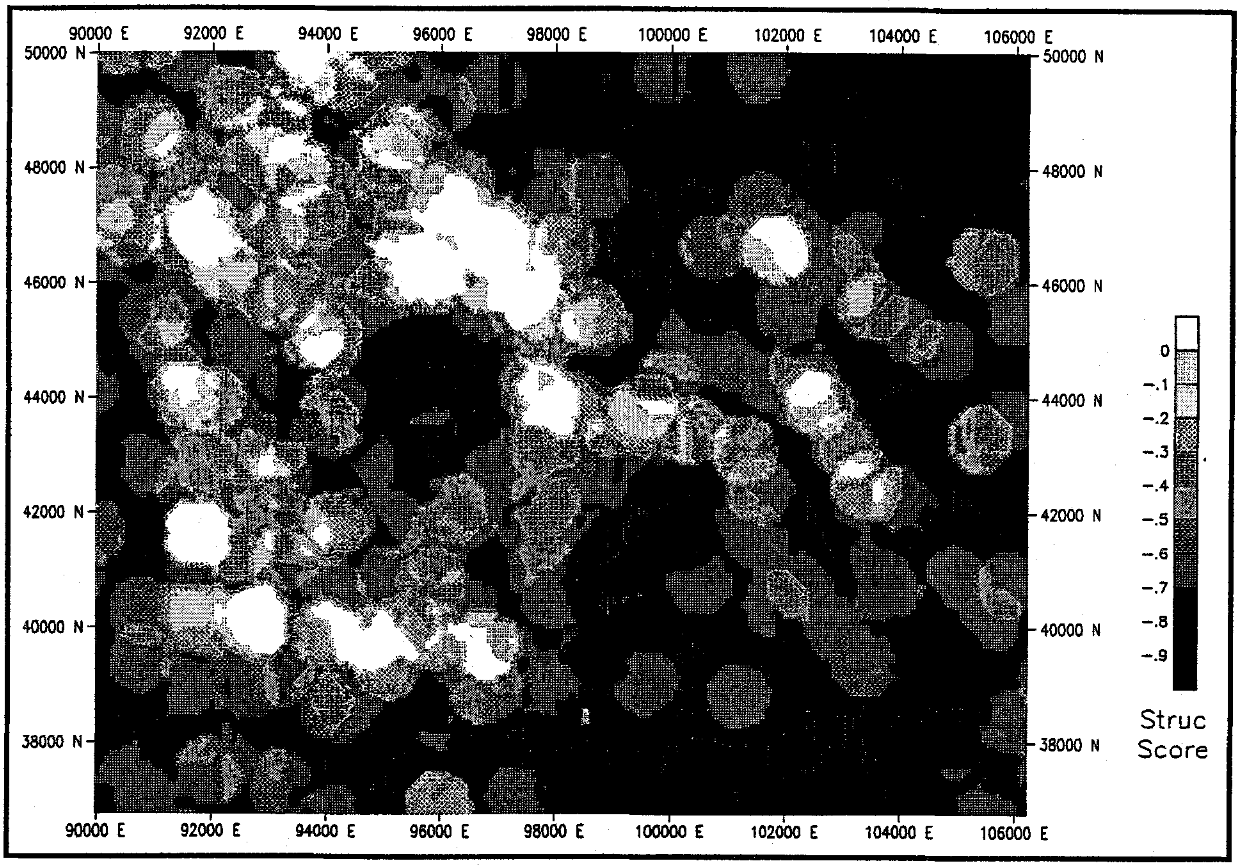


Figure 11. Image of structural scores created from lineaments and faults.

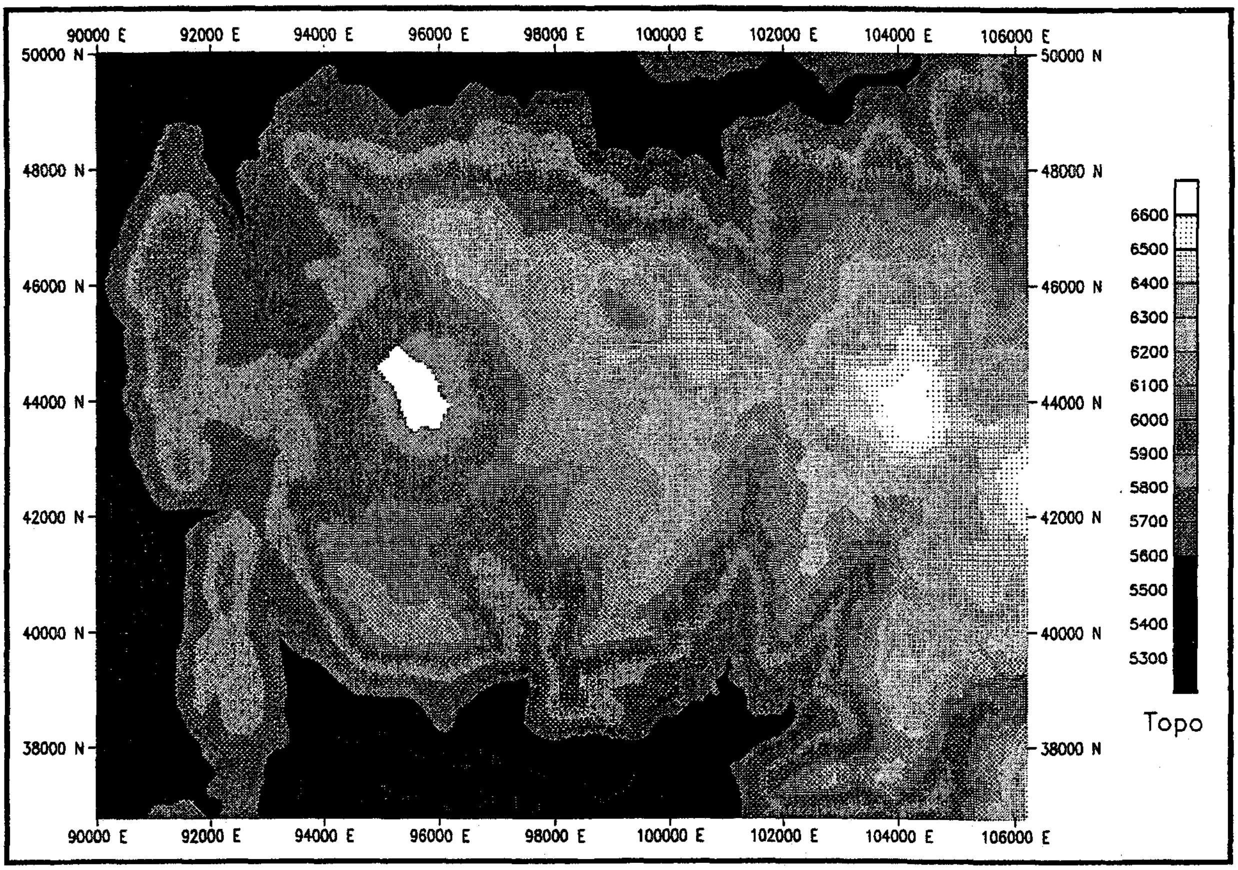


Figure 12. Image of topographic relief.

gold and 12–75 parts per million (ppm) mercury occur within this pyritic zone.

An area with abundant pseudomorphic, banded and massive quartz vein float occurs between the sinter and the tailings dam. Fire assays of the float yield values of 0.03 to 0.17 opt (oz per ton) gold and up to .50 opt silver. Twelve shallow rotary holes were drilled in this area in late 1992. These holes failed to locate a conduit for the sinter or a source for the quartz vein float but did establish that porphyritic rhyolite, a favorable ore host, underlies the lithic tuff, which is 170 to over 300 feet thick.

A hot spring system with sinter, mercury, and gold at the surface would be expected to host significant gold and silver mineralization at depth. The thickness of the lithic tuff and the proximity of the tailings pond weigh against the potential for open pit reserves in this area, but an underground target is possible if the conduit(s) of these sinters can be located. The three most likely conduits are as follows:

1. A fault along the west flank of the vitrophyre breccia dome. The mineralized quartz vein float occurs along this trend and positive geophysical anomalies (EM and magnetic profiles) indicate a structure at this location.
2. The fault contact between the vitrophyre breccia flows and the lithic tuff. This fault has the same orientation as structures exposed by trenches in the sinter beds.
3. A north-trending normal fault cutting through the saddle west of the target.

Since this target is favorable from both integrated measures and geological environments, it should be drilled to find out the details of subsurface geology. The target

Table 1. The coefficients of favorability estimates.

	Explanatory variables			Target variables
	Coefficient	Correlation to F		Correlation to F
Z_1	0.341	0.455	Y_1	0.781
Z_2	0.416	0.561	Y_2	0.234
Z_3	−0.081	−0.105	Y_3	0.356
Z_4	−0.502	−0.799	P_1	0.842
Z_5	0.411	0.811	P_2	0.619
Z_6	−0.233	−0.332	P_3	N/A

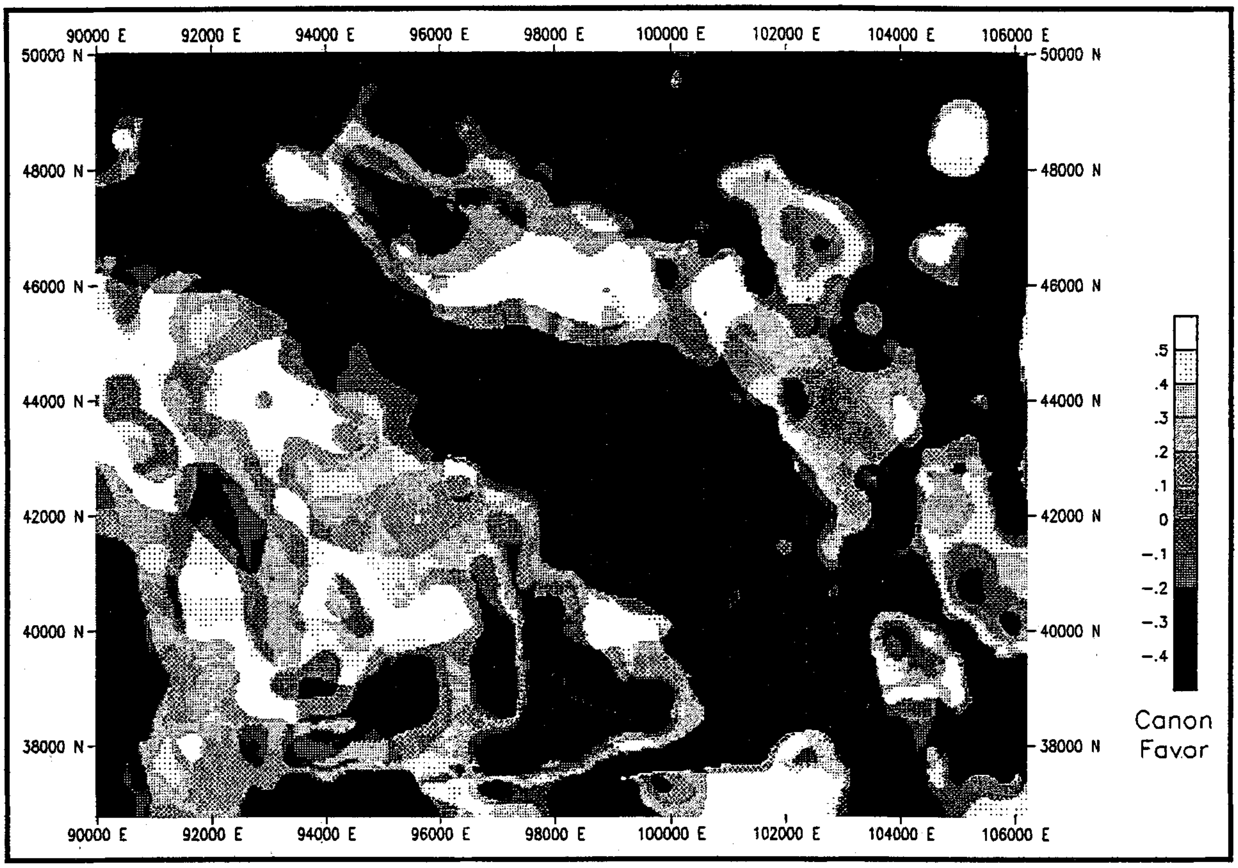


Figure 13. Image of favorability estimates for target evaluation.

likely contains structural hydrothermal conduits that could be mineralized.

Target A2: SO. The target SO is in a fault wedge composed primarily of quartz latite. The wedge is 2,400 feet long and averages several hundred feet wide. This wedge is exposed between a porphyritic rhyolite ridge and the lower basalt to the east. Over 60 drill holes in the north end of the area have defined several high-grade silver–

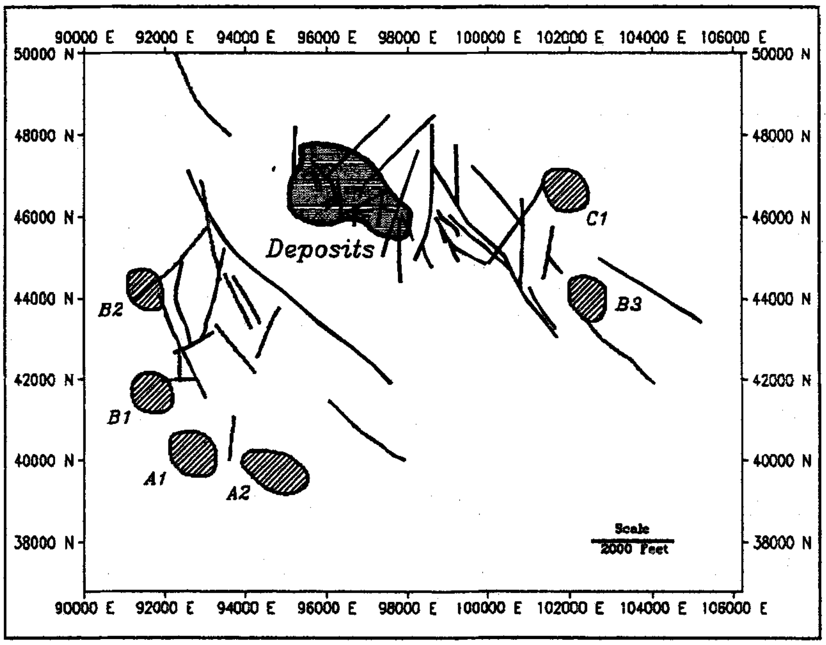


Figure 14. Map showing known ore deposits and predicted targets.

gold shoots and numerous intercepts of low-grade (around 0.015 opt) gold mineralization. The south end has had limited drilling despite the occurrence of a strong north-trending geochemical anomaly (greater than 0.4 ppm Hg, 0.10 oz Ag, and 0.01 oz Au in soils).

Drill targets include updip low-grade gold mineralization east of a west dipping orebody, which is buried under the porphyritic rhyolite ridge. There is a lack of drilling east and north of the existing drill holes (470 ft of 0.015 opt) and (240 ft of 0.012 opt). The east side of a generally barren porphyritic rhyolite intrusive that occurs between the north areas and the major fault in this area is poorly tested. An adjacent lone drill hole to the northeast of the target has an intercept of anomalous gold from 55 ft to 230 ft including 60 ft of 0.009 opt.

Another adjacent drill hole located northwest of the target has assays over 100 ft of 0.020 opt gold and 1.40 opt silver. The third adjacent hole located northwest of the target has anomalous assays down to 375 ft, including 65 ft of 0.015 opt gold.

The SO target should be drilled because of the potential large tonnages of low grade, the possibility of high-grade shoots, and the fact that mineralization in this area could significantly reduce the stripping ratio on the buried orebody. The targets include updip extensions of the west-dipping Sullivan Gulch orebody, the numerous untested faults in this area, and disseminated mineralization in quartz latite near the contact with overlying tuff breccia.

Concluding Comments

To date, major efforts in mineral resources evaluation have emphasized mineral potential evaluation at small scales vis-à-vis regional or grass-roots type exploration. The results are usually the target maps that contain exploration targets with large areal extent. Because of the large uncertainties associated with each individual geofield, the quantification of targets is no doubt highly uncertain. Therefore, the results from the statistical prediction of targets have not been considered to be practical among some geologists and mineral explorationists.

In this article, we present a methodology for mineral potential estimation at a large scale. The method is designed on the basis of favorability analysis in general and canonical favorability analysis in particular. Mapping at large scales is extremely valuable in mineral exploration and the design of drilling programs. The goal of large-scale estimation is to maximize the discoverability of ore and minimize the cost of drilling (and other sampling). From the standpoint of resources, large-scale evaluation will help to translate a portion of geological resources into minable reserves and find new orebodies adjacent to a known deposit.

We presented a detailed case study to demonstrate the use of our methodology for large-scale mineral potential estimation. The case involved geological, geophysical, and drill-hole data. Two major targets were identified and delineated. Some tests have been conducted, with positive results. The two targets are localized within an area where all known information is positive for the occurrence of a gold–silver ore deposit.

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