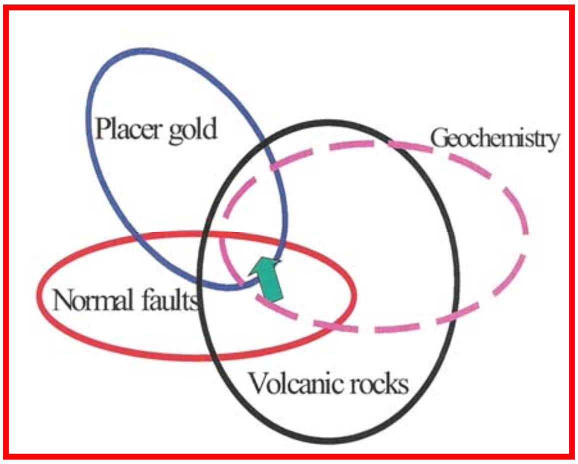
King Fahd University of Petroleum and Minerals
College of Environmental Design
City and Regional Planning Department

A GIS-Based Analysis Using Weight of Evidence

(TERM PAPER)

CRP-514



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I. ABSTRACT

It is important that risks of developing mineral resources are known as accurately as possible. This process starts at the pre-discovery exploration stage and should continue through feasibility to the development stage. Until recently, this type of analysis has been carried out manually, leading to spontaneous judgments. With GIS and resource estimation software now available on personal computers, probabilistic models can now be generated. A program of digital data compilation has recently been undertaken to allow the use of more probabilistic data analysis techniques, moving away from the traditional expert-system methods.

The distribution of 2,690 gold-silver-bearing occurrences in the Nevada Great Basin was examined in terms of spatial association with various geological phenomena. Analysis of these relationships, using GIS and weights of evidence modeling techniques, has predicted areas of high mineral potential where little or no mining activity exists. Mineral potential maps for sedimentary and volcanic rock-hosted gold-silver mineralization revealed two distinct patterns that highlight two sets of crustal-scale geologic features that likely control the regional distribution of these deposit types.

The weights-of-evidence method is a probability-based technique for mapping mineral potential using the spatial distribution of known mineral occurrences. Mineral potential maps predicting the distribution of gold-silver-bearing occurrences were generated from structural, geochemical, geomagnetic, gravimetric, lithologic, and lithotectonic-related deposit-indicator factors. The maps successfully predicted nearly 70% of the total number of known occurrences, including ~83% of sedimentary and ~60% of volcanic rock-hosted types. Sedimentary and volcanic rock hosted mineral potential maps showed high spatial correlation with expert-delineated mineral permissive tracts. In blind tests, the sedimentary and volcanic rock-hosted mineral potential maps predicted 10 out of 12 and 5 out of 5 occurrences, respectively. The key mineral predictor factors, in order of importance, were determined to be: geology (including lithology, structure, and lithotectonic terrane), geochemistry (indication of alteration), and geophysics.

II. INTRODUCTION:

The Great Basin is a “classic” modern extensional tectonic regime located in the central Cordilleran interior of the southwestern United States. It has a long and complex geologic history of crustal rifting, shortening, and accretion that can be traced back to the Archean. The Great Basin is host to a large number and a variety of base- and precious-metal deposits. In recent years, it has emerged as one of the more important gold-producing areas in the world, especially since the start-up of the Carlin open-pit mine in 1965 and the rise in gold price to more than $200US per ounce in 1978 (Mohide, 1981; Coope, 1991). The greater and richest part of the Great Basin lies within the State of Nevada, and it is here that the well-known precious-metal deposits occur.

A high level of economic interest has stimulated much research into the genesis of precious metal mineralization in Nevada. As a result, a comprehensive collection of geological, geophysical, and geochemical spatial data has been generated. Since the early 1990’s, computer-based *Geographical Information Systems* (GIS) applications have become an integral part of many mineral resource exploration programs. A GIS is an integrated system of hardware, software, and methodologies for the management of spatial (geo-referenced) data. It facilitates data compilation and synthesis, and permits exploratory data analysis and modeling. Evaluation of geoscience data with GIS can provide support for various geological investigations and aid decision making processes, such as determining successful and cost-effective exploration or management strategies.

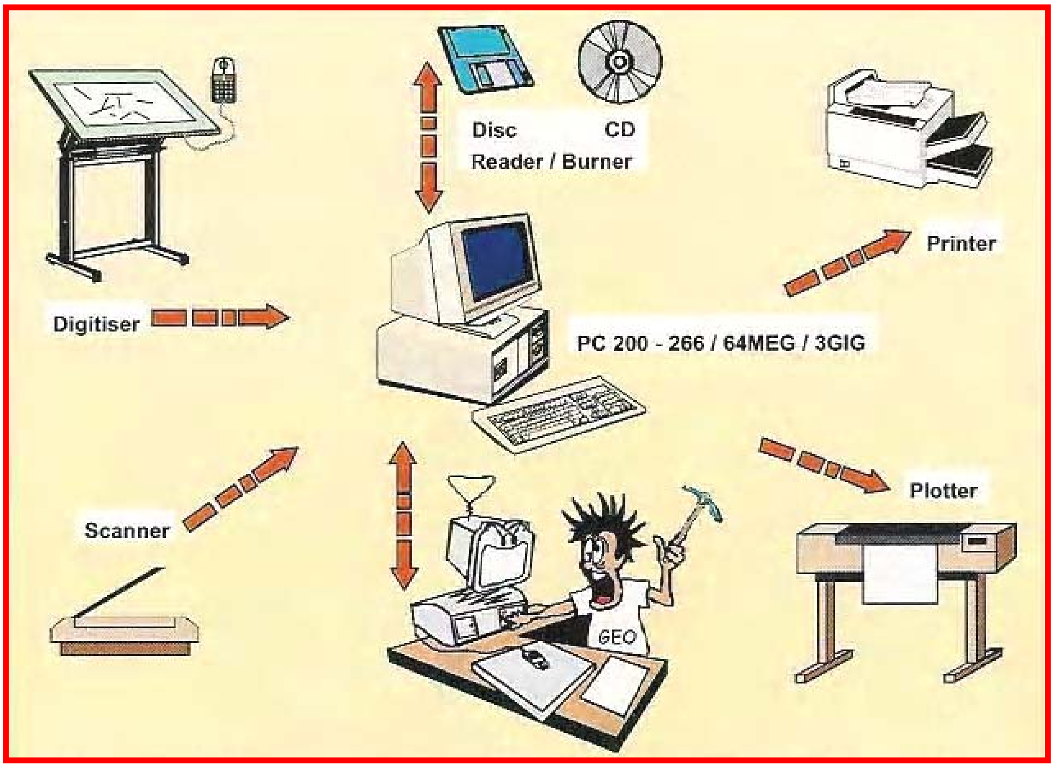
In this study, quantitative mineral potential modeling with a GIS has been used to investigate the regional-scale distribution of precious-metal mineralization in the Nevada Great Basin. *Weights of evidence*, a recently developed mineral potential modeling method, has been applied to this task. Weights of evidence is a data-driven, discrete multivariate statistical method that uses conditional probabilities to determine the relative importance of mineralization “evidence” and Bayesian principles for integrating multiple “layers of evidence”. The purpose of this study was to produce maps of mineral potential that predict the distribution of sedimentary and volcanic rock-hosted gold-silver-bearing occurrences across Nevada. The objectives were to:

- Determine and evaluate the spatial associations between the gold-silver-bearing occurrences and a variety of regional-scale geoscientific data.
- Produce predictive maps of mineral potential (favorability) for sedimentary and volcanic rock-hosted occurrences, which include analyses of error and uncertainty associated with the mineral potential maps.
- Delineate promising regional-scale exploration targets for sedimentary and volcanic rock-hosted occurrences, and determine the important mineral potential evidence in these areas.
- Determine the first-order geologic factors controlling the regional-scale spatial distribution of the sedimentary and volcanic rock-hosted occurrences.

III. WEIGHTS OF EVIDENCE:

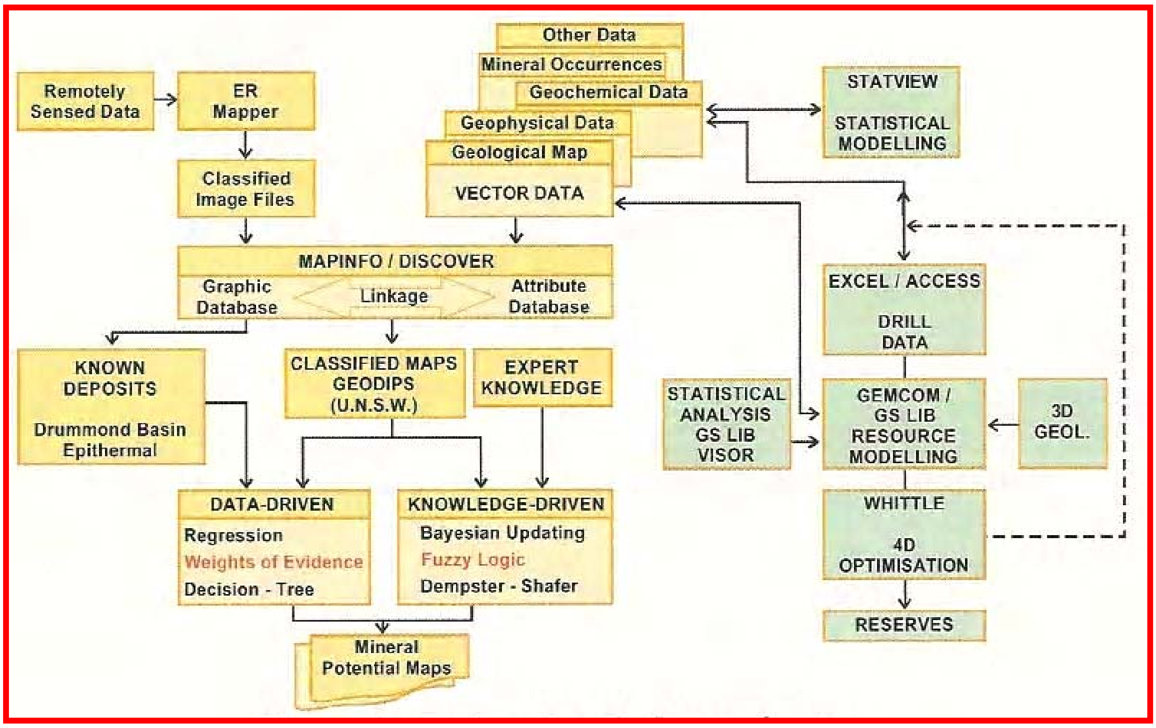
a) Introduction:

It is important that risks of developing mineral resources are known as accurately as possible. This process starts at the pre-discovery exploration stage and should continue through feasibility to the development stage. The task of the Exploration Group is to take diverse spatial data-sets at a variety of scales to produce accurate economic estimates of the mineral potential of areas chosen for exploration. Until recently this type of analysis has been carried out manually and on an unplanned basis (Greg Partington 2000), leading to spontaneous judgments being made that have no statistical basis (figure# 1).



Figure# 1: Exploration Office Hardware Configuration, after Greg Patington (2000)

With GIS and resource estimation software now available on personal computers this task can be automated and consequently these estimations have become considerably more sophisticated (Bonham- Carter 1997; Singer 1995), allowing probabilistic models to be generated (figure# 2).



Figure# 2: Exploration Software System, after Greg Patington (2000)

Weights-of-evidence methodology combines spatial data from diverse sources to describe and analyze interactions, provide support for decision makers, and make predictive models. The method was originally developed for a non spatial application in medical diagnosis. In this application, the evidence consisted of a set of symptoms, and the hypothesis was “this patient has disease X.” for each symptom, a pair of weights was calculated, one for presence of the symptom and one for the absence of the symptom. The magnitude of the weights depended on the measured association between the symptom and the occurrence of disease in a large group of patients. The weights could then be used to estimate the probability that a new patient would get the disease, based on the presence or absence of symptoms.

The weights-of-evidence methodology was adapted for mineral potential mapping with GIS. The process used in weights-of-evidence modeling essentially is a quantitative version of the inspection method of overlaying several different map themes to identify areas where mineralization may be present (figure# 3). In the inspection method, the larger the number and magnitude of appropriate overlapping anomalies in data maps such as geochemistry, geology, or others, the greater the qualitative indication that mineralization may be present. In weights-of evidence modeling, the importance of theme layers in delineating areas with potential for deposits is determined mathematically by how it compares with the areal distribution of the training set. When several themes are combined, the areas with the greatest coincidence of weights produce the greatest probability of occurrence of undiscovered mineralization.

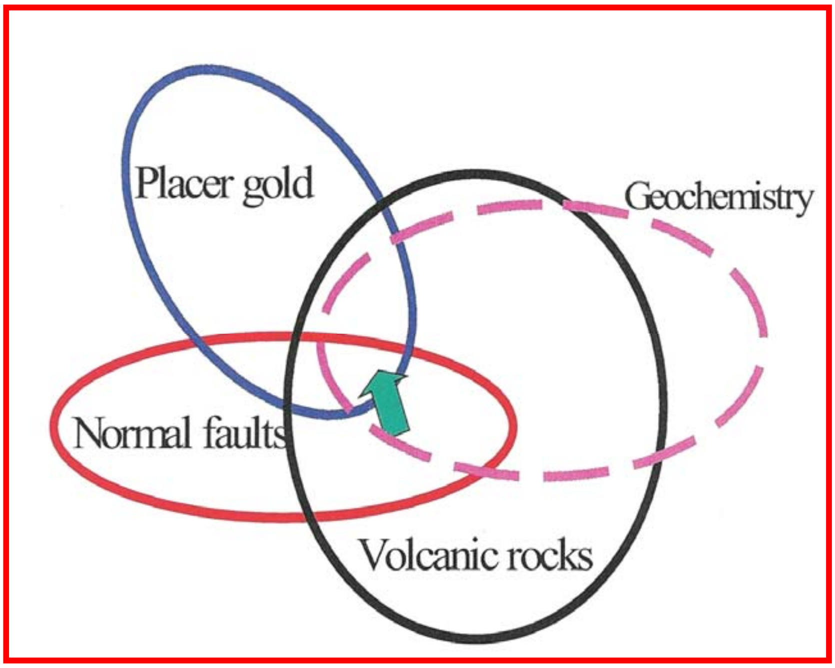


Figure 3: Venn diagram showing overlay of geologic and geochemical themes used in weights-of-evidence analysis. The probability that a deposit exists increase where the predictor themes areally overlap (green arrow), after USGS (2002)

The weights-of-evidence method is based on the application of loglinear formulation of Bayes' Rule of Probability theorem, with an assumption of conditional independence, to combine the map patterns to predict the distribution of the point or polygon objects. As applied to mineral potential modeling, the point objects represent known mineral deposits. The multi-class map patterns are typically maps of particular geologic phenomena, such as geology, geochemistry, geophysics, etc., which are likely to be useful mineral deposit predictors. These maps are referred to as *"evidence maps"*, representing geo-spatial evidence for the occurrence of mineralization. In order to facilitate combination, the evidence maps are usually reduced to deposit-indicator or mineral *"predictor maps"* of a few discrete states (typically binary) where the spatial association between mineralization-favorable evidence and the occurrences is optimized. The mineral predictor maps collectively constitute the *"layers of evidence"* for the mineral potential model.

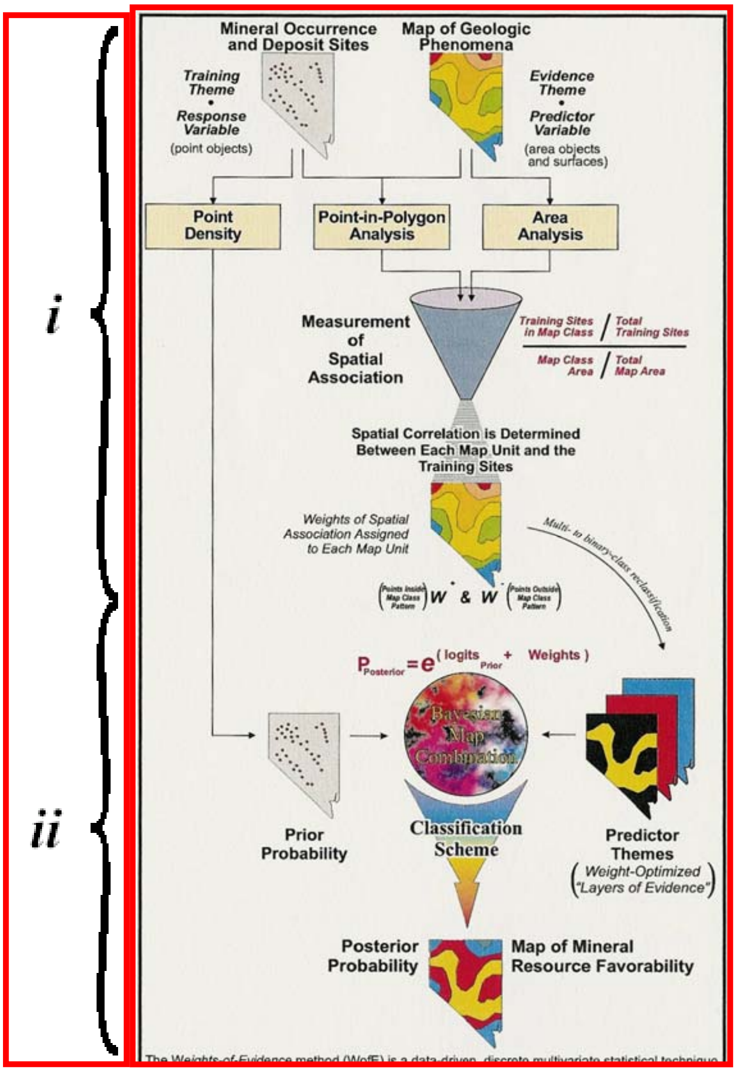
b) Theoretical Framework:

Weight of evidence (WOE) is a *data-driven* method, requiring data about the distribution of known mineral deposits to estimate weights of spatial association for the mineralization evidence layers. It is a discrete, multivariate statistical method based on a technique originally developed in a non-spatial context for medical diagnosis and has been to deal with spatial prediction - "diagnosing" mineral deposits using the "symptoms" of various geologic phenomena (Bonham-Carter, 1994b). WOE evaluates the spatial distribution of known mineral deposits (the *response variable*) relative to multi- or binary - class map patterns (the *predictor variables*), calculates weights of spatial association (W+ and W‾) for each pattern, and produces a multi-map signature for mineralization (Bonham-Carter et al., 1989). The evidence layers are combined using a loglinear formulation of Bayes' Rule in a multi-map overlay operation where the *prior probability* of an occurrence - the probability of an occurrence given no information (random), equal to the average density of known occurrences in the study area, and held constant over the whole area - is updated by the addition of predictor variables and their weights to produce a single *posterior probability* map of occurrence (Bonham-Carter et al., 1989; Bonham-Carter, 1991). In this case, the posterior probability map is a map of mineral potential, which reflects the distribution of known occurrences and predicts the distribution of yet unidentified occurrences (Bonham-Carter et al., 1988). The whole process is similar to that of an exploration geologist manually integrating information and combining maps in order to delineate favorable areas of mineralization (Agterberg et al., 1990).

Weights of evidence mineral potential modeling can be subdivided into two main procedures, as illustrated in (figure 4):

i. Conditional probabilities that involve area proportions are used to calculate two weights of spatial association between the occurrences and each individual evidence map class: W+ for a particular map class present, W– for not present (the occurrence points are not themselves classified or weighted, and each point is treated as equally important). Weights are relative, dimensionless values, which depend on the ratio of occurrences that fall on a particular map class to the total number of occurrences, against, the ratio of the particular map class area to the total map area. A positive correlation between occurrences and a map class is represented by W+ > 0 and W– < 0 (there are more occurrences in a particular map class than would be expected due to chance); a negative correlation by W+ < 0 and W– > 0. Where no spatial association exists (i.e. - the two ratios are equal), the weights are both zero. Where data are unknown or missing (incomplete evidence map coverage), the weights are assigned the value zero (Bonham-Carter, 1991). The weights can be combined into a single coefficient called the *contrast* (C = W+ – W–), which provides a useful measure of the strength of the spatial association between the occurrences and a particular map class. The weights and C provide a guide for reducing the multi-class evidence map to a binary-class deposit-indicator (or predictor) map pattern. For each evidence map, an individual map class that is highly correlated (spatially) with the mineral occurrences may be selected as a deposit-indicator pattern, or multiple map classes may be grouped in such a way as to maximize the spatial association between the occurrences and the map.

ii. The binary-class mineral predictor maps (layers of evidence) are combined in a multi-map overlay operation where a loglinear formulation of Bayes' Rule (based on an assumption of conditional independence) is used to sum and update the weights associated with each of the predictor map classes that come into coincidence, producing a posterior probability mineral potential map which closely exhibits the distribution of known deposits and indicates areas where more deposits are expected than are observed.



Figure# 4: Flow chart illustrating the weights of evidence mineral potential modeling method, after Mark Mihalasky (2001)

In summary, the prior probability of an occurrence for a unit area is successively "updated" by the addition of each new layer of evidence (information) to produce a posterior probability. The prior probability is equal to the probability of an occurrence within a unit area given no further information, which for this study is taken to be equal to the density of known occurrences in the study area (total number of occurrences divided by the total area of the study region, assuming a 1 km^2 unit area of measure and where an occurrence point is represented by one unit area). Bayes' Rule effectively revises the prior probability by incorporating the new evidence into the model (Mark Mihalasky, 2001). The posterior probability reflects both the prior and the new evidence, and with each subsequent addition of new evidence, the posterior is treated as the prior, thus providing a more efficient model for prediction (Bonham-Carter, 1994a). The posterior probability calculated after the addition of new evidence may be larger or smaller than the prior probability, depending on the overlap combination of predictor maps and their weights (i.e. - if evidence of factors favorable to mineralization are added, the posterior probability rises, and vice versa) (Bonham-Carter et al, 1989). The mineral potential map is generated by grouping into intervals the calculated posterior probabilities according to a user-defined classification scheme ("density slicing"; often based on quintiles, an area-based percentiles classification where the posterior probability interval break-points are determined in such a way that each interval is roughly equal in area).

The "initial conditions" of the mineral potential model are established using the mineral predictor maps, as indicated above in procedure ***"i"***. A model may be further calibrated using other factors such as mineral deposit size, where different schemes for weighting the layers of evidence are calculated for each deposit size subset (Wright and Bonham-Carter, 1996). The selection of evidence maps is largely guided by an accepted or proven deposit or exploration conceptual model (this is the standard mode of implementation)

The choice of evidence should reflect current understanding on the genesis of the particular deposit type being modeled as well as the geologic features believed to control its spatial distribution. An evidence map should ideally provide either universal coverage or coverage over the majority of the study area (Bonham-Carter et al., 1989).

c) Conditional Independence:

An important assumption made in WOE modeling is that the mineralization evidence layers included in a model be *conditionally independent* (CI) of one another with respect to the mineral deposits (see Bonham-Carter, 1994a, pp. 312-317). The mineral potential map is adversely affected if, at the locations of the known mineral occurrences, the presence of a mineralization favorable map pattern in one layer of evidence is dependent on the presence of a mineralization favorable map pattern in another layer of evidence. Violation of CI results in either the overestimation or under-estimation of posterior probabilities during the combination of predictor maps, and the expected mineral deposit frequencies either notably exceed or fall short of the observed deposit frequencies in the most and least favorable areas of the mineral potential map (Agterberg et al., 1990). In practice, CI is probably always violated to some degree, and the possibility of the occurrence of CI generally increases with an increase in the number of evidence layers included in a model (Bonham-Carter, 1994a). Because of the CI assumption, calculations of the spatial weights of association are carried out independently between the mineral deposits and each evidence layer, and as a result, WOE has the opportunity to examine bivariate relationships in some depth (Bonham-Carter, 1994b). The assumption of CI leads to a model that, like most models, does not fit the data perfectly, but provides a simplification that is useful for prediction when applied carefully, and gives insight into the relative contributions of the separate sources of evidence (Bonham-Carter, 1994a).

It is important to understand how serious the CI violation is so that the appropriate action can be taken to minimize the problem and so that proper judgments can be made when evaluating areas of high mineral potential. Conditional independence can be checked visually or tested for using *pairwise* and *overall* goodness-of-fit methods. If a predictor map is found to be in serious violation of the assumption of CI, it can then be: (see Agterberg et al., 1990; Bonham-Carter, 1994a).

(1) Rejected from the model,
(2) Combined with another map in order to minimize the dependency,
(3) Modified in some way to reduce the problem

d) Posterior Probability Uncertainty:

An important aspect to interpreting a mineral potential map is recognizing and quantifying the uncertainty inherent to the posterior probabilities. The two primary sources of uncertainty are (Bonham-Carter et al., 1989):

(1) The uncertainty due to variances in weight estimates (W_+ and W_-)
(2) The uncertainty due to one or more of the binary-class predictor maps having incomplete coverage (i.e. - missing data)

The uncertainties due to weights and due to missing data may be examined separately, or combined to produce a *total* uncertainty for a given unique overlap combination of binary-class predictor maps, which is calculated as the variance due to weights, plus, the sum of variances due to missing data (Bonham-Carter et al., 1989). The uncertainty due to the weights, which includes the uncertainty of the prior probability, is in general correlated to the posterior probability, and therefore maps of variance of weights have the same trends as the posterior probability maps.

In addition to the uncertainties due to weights variances and missing data, a *relative certainty* (variance) of the posterior probability can be determined by dividing the posterior probability by its standard deviation (i.e. - a "studentized" posterior probability), which, in effect, applies a student t-test (based on a normal distribution) to determine whether the posterior probability is greater than zero for a given level of statistical significance (i.e. - compared to a tabled t-value) (Bonham-Carter et al., 1989;).

The larger the t-value over the critical tabled t-value cut-off, 1.645 for a significance of 95% for example, the greater the certainty of the posterior probability. The relative certainty is often more useful than the weights variances or missing data uncertainties because it indicates the degree of confidence to which the posterior probabilities are "real", as opposed to being an artifact of "chance" effects (or due to chance). As compared to the uncertainty due to the weights variances or missing data, relative certainty is generally not as highly correlated to the posterior probability.

Ideally, the four uncertainty factors (weight variances, missing data, total, and relative) may be used to create classified uncertainty maps for comparison to the posterior probability mineral potential map, or the uncertainty factors may be combined in various ways and reclassified to a binary-class map which can be used to "mask-out" areas of the mineral potential map that are deemed to be too uncertain (Bonham-Carter, 1994a).

e) Practical Implementation of the Modeling Procedures:

Weights-of-evidence modeling was implemented in a geographical information system (GIS) environment. SPANS GIS (Mark J. Mihalasky, 2001) was used to compile, prepare, and manage the spatial datasets, as well as perform most of the spatial data analysis and modeling procedures. Preliminary procedures, such as visual appraisal and pattern recognition, distance calculation, map reclassification and overlay operations, summary statistical analysis (histograms), and spatial and topological modeling (point and line buffering, point-in-polygon, area, and other coincidence analysis, and surface contouring and interpolation) were carried out using tools commonly available in a GIS. The calculation of W_+, W_-, weights variances, and posterior probabilities for weights of evidence modeling was performed external to the GIS using custom-made command-line FORTRAN utilities. The output of these utilities was imported into the GIS as reclassification templates and used to generate posterior probability mineral potential maps, as well as various maps of posterior probability uncertainty (error maps).

f) Error, Data Accuracy and Limitations:

Uncertainties of various types are inherent to spatial data, as well as its accompanying attribute data. Error associated with spatial data may be subdivided into two broad categories: **(1)** cartographic or positional error, and; **(2)** thematic or attribute error Aronoff (1989) cited six common sources of error encountered in using a GIS:

1. *Data collection* - errors in field data collection, in existing maps used as source data, and in the analysis of remotely sensed data.

2. *Data input* - inaccuracies in digitizing, and fuzziness inherent in the edges of geographic features.

3. *Data storage* - insufficient numerical precision and spatial precision.

4. *Data manipulation* - inappropriate class intervals, boundary errors, error propagation as multiple overlays are combined, and slivers due to polygon edge-matching problems.

5. *Data output* - scaling inaccuracies, error caused by inaccuracy of the output device and caused in medium instability.

6. *Use of results* - the information may be incorrectly understood or inappropriately used.

Thematic, or attribute data are complementary to positional data, and describe something about the spatial object or characterize some phenomena occurring at that location (i.e. - an anomaly in the geomagnetic field).

These data may be discrete or continuous in nature (Aronoff, 1989). Error associated with attribute data can include:

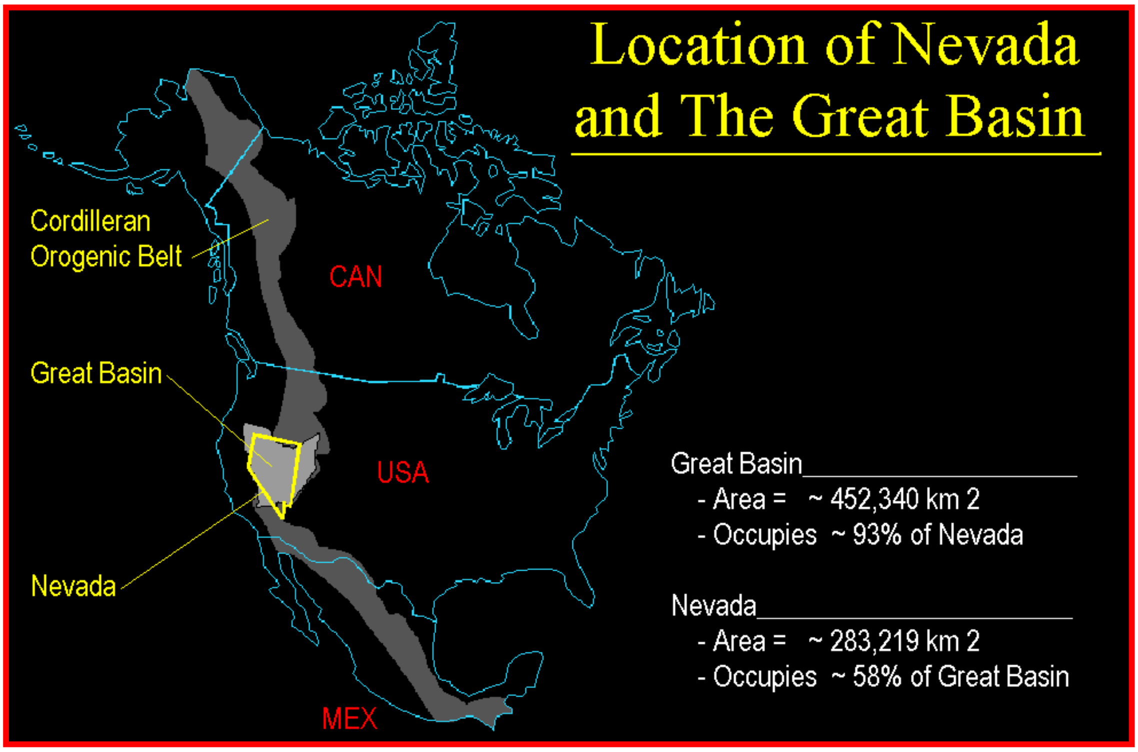
(1) The misclassification of nominal data such as a geological unit,
(2) Incorrectly ranked ordinal data such as metamorphic grade,
(3) Incorrectly determined ratio data such as the length of a fault,
(4) The misrepresentation of continuous data by imposing a classification scheme having too many intervals, thereby giving the impression that the data are more numerous, well distributed, or robust than they might be.

Many errors of this type may result from logical inconsistencies, such as in the misclassification of a geological unit by a field mapper, or from interpolation and estimation processes.

IV. MINERAL POTENTIAL MODELING OF GOLD AND SILVER MINERALIZATION IN THE NEVADA GREAT BASIN:

a) Introduction:

The area of interest in the Great Basin is confined to the State of Nevada (figure# 5).



Figure# 5: Location map of the Great Basin, after Mark Mihalasky (2001)

Nevada, situated near the geographic center of the Great Basin, contains most of the basin's area and precious-metal mineral occurrences. A sound geology base map is essential to a study of this type, and at the time, Nevada was the only region within the confines of the Great Basin for which digital geology of suitable resolution and accuracy was publicly available. Basin-range structure is wide-spread and highly-developed across the region, and consists of roughly north–south-trending, evenly spaced parallel mountain ranges with intervening broad, flat, alluviated desert basins. On a regional-scale, the Great Basin is characterized by (see Mark J. Mihalasky, 2001):

1) ***Uplift and extension*** - mean elevation of ~ 1.5 km and with an average extension of 100%, in excess of 300-400% in some areas

2) ***Thinned crust*** - less than 30 km over much of the region, in comparison to 40-50 km for surrounding regions.

3) ***Anomalous upper mantle*** - regional Bouguer gravity low, low seismic mantle velocities, high heat flow (*"reduced"* HFU values 50 to 100% and up to 300% greater than in stable regions).

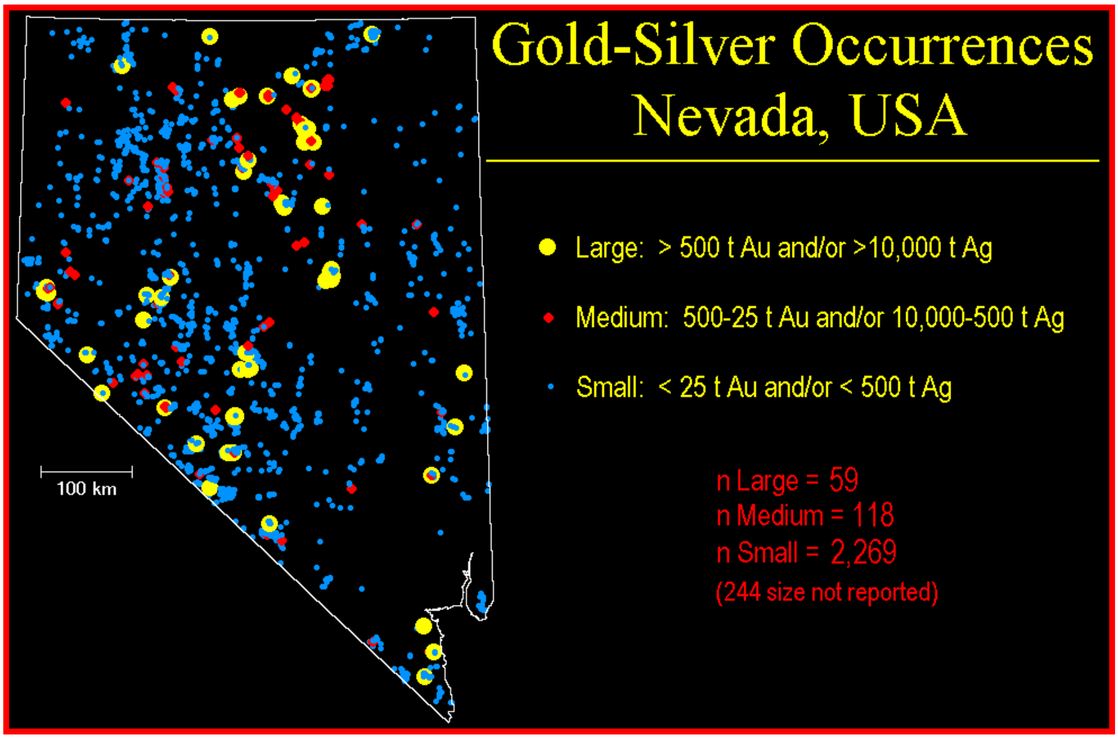
4) ***Modern seismic activity*** - seismicity is concentrated around the margins of the region .

The Great Basin region has a long and complex geologic history, involving major episodes of crustal accretion, sedimentation, igneous activity, compressional deformation, and continental rifting. This includes at least three orogenies in the Precambrian, two compressional orogenies in the Paleozoic, three compressional orogenic phases in the Mesozoic (to earliest Cenozoic), two extensional events in the middle and late Cenozoic, and the present day continued basin-range development (see Mark J. Mihalasky, 2001;). The longevity, diversity, and intensity of tectonomagmatic activity in this region have resulted in the formation of a distinctly unique and rich geologic-metallogenic province.

The *Mineral Resource Data System* mineral occurrence database (MRDS; U.S. Geological Survey, 1993) was used to model the distribution of precious-metal mineralization in Nevada. From a population of 5572 metallic and semi-metal mineral occurrences listed in MRDS, 2690 gold-silver-bearing occurrences (figure# 6) (containing gold and/or silver as the primary commodity listed in MRDS) were selected and subdivided into samples as indicated in Table# 1:

Population	*Metallic and Non-Metallic Mineral Occurrences*											
Occurrence-Type Sample	*Primary-Product Gold-Silver-Bearing Occurrences (all types) (2690)*				*Sedimentary Rock-Hosted Gold-Silver-Bearing Occurrences (98)*				*Volcanic Rock-Hosted Gold-Silver-Bearing Occurrences (415)*			
Size Sub-sample	*Lrg. (59)*	*Med. (118)*	*Sml. (2269)*	*Unkn. (244)*	*Lrg. (8)*	*Med. (30)*	*Sml. (57)*	*Unkn. (3)*	*Lrg. (33)*	*Med. (43)*	*Sml. (317)*	*Unkn. (22)*

Table# 1: The gold-silver-bearing occurrences examined in this study, after Mark Mihalasky (2001)



Figure# 6: Gold & Sliver occurrences in Nevada, USA, after Mark Mihalasky (2001)

The mineral occurrences in MRDS are classified according to the scheme of Cox and Singer (1986). Occurrence size designation is based on precious-metal content (production plus reserves), and is derived from the *Metallogenic Map of North America*. Modeling was carried out using the three principal occurrence-type samples (training datasets). In some instances, analysis and modeling was also performed using the large, medium, and/or small size sub-samples.

b) Spatial Datasets:

The initial steps in developing any GIS database involve data collection and input. This phase typically accounts for 70% to 80% of the time spent on a project. The data used for this study are diverse, and characterize the nature of the lithosphere in the Nevada Great Basin from the earth's surface to the upper mantle. The data are subdivided according to regional geology, physical geography, geophysics, seismology, geochemistry, remote sensing imagery, economic geology, hydrology, and human features. They are listed in Table# 2:

DATA SET	DATA TYPE	OBJECT-TYPE	SOURCE DATA	NUMBER OF ENTITIES	SIZE (bytes)	COVERAGE	DATASET SOURCE(S)
REGIONAL GEOLOGY							
Bedrock and Surficial Geology	Nominal	Line, Area	ARC INFO, Vectors	84,955	36,778,743	Nevada	Turner and Bawiec (1991)
Metamorphic Rocks	Nominal	Line, Area	SPANS, Digitized Lines	158	108,228	Nevada	Ernst (1992)
Metamorphic Core Complex Locations	Binary	Point	SPANS, Digitized Points	25	2,145	Great Basin	Axen et al. (1993)
Corridor of Metamorphic Core Complex Distribution	Binary	Line, Area	SPANS, Digitized Lines	1	490	Great Basin	Axen et al. (1993)
Volcanic Centers	Nominal	Line, Area	SPANS, Digitized Lines	77	46,629	Nevada	Stewart (1980)
Cinder Cones	Binary	Point	SPANS, Digitized Points	19	757	Nevada	Horton (1964)
Mesozoic Plutons Distribution Percentage	Ordinal	Line, Area	SPANS, Digitized Lines	3	3,456	Nevada	Barton (1990)

Table# 2: The geoscience datasets composing the Nevada and Great Basin GIS database, after Mark Mihalasky (2001)

The data are grouped by discipline and characterized by:

Dataset - the data composing a dataset;

Data Type - the scale of measurement in which the data are expressed;

Object-Type - the spatial object-type of the dataset as it exists after processing with SPANS GIS;

Source Data - the file format, and/or spatial data model (raster or vector), and/or spatial object-type of the dataset as it was obtained, before pre-processing and integration into the database;

Number Of Entities - the number of sample points or arcs making up the dataset;

Size - the approximate size in bytes of the source data file; **COVERAGE** - the areal extent of the dataset and distribution of points where appropriate; **DATASET**

Source(S) - the origin of the source dataset and/or source of the data composing the dataset.

The geoscientific spatial data compiled for this study include:

Mineral deposits - various metallic mineral occurrence datasets, and mineral belts and trends.

Regional geology - bedrock and surficial geology, metamorphic rocks and core complex locations, volcanic centers and cinder cone locations, Mesozoic pluton distribution, geosyncline facies boundaries, regions of strong upper crustal extension, numerous fault and thrust fronts datasets, deep-seated fracture zones, lithotectonic terranes, and Tertiary rock attitudes.

Physical geography - 30 arc-second and 5 arc-minute gridded elevations, mountain peak heights, generalized and detailed Great Basin physiographic province boundaries.

Geophysical - various gravity anomaly data (observed, isostatic, Bouguer, free air), geomagnetism, geothermal heat flow, geothermal conductivity, geothermal heat production, geothermal well/hot spring temperatures, and paleothermal anomaly.

Seismic - depth to reflection Moho, earthquake depth and magnitude, and crustal stress data.

Geochemical - igneous rock radiometric age dates, base- and precious-metal mineralization radiometric age dates, 87Sr/86Sr initial values and I_{Sr} = 0.706 and 0.708 isopleths, and major and minor element data.

Remote sensing imagery - LANDSAT linear features, AVHRR, and SLAR radar.
Hydrology - drainage divides streams and water bodies.

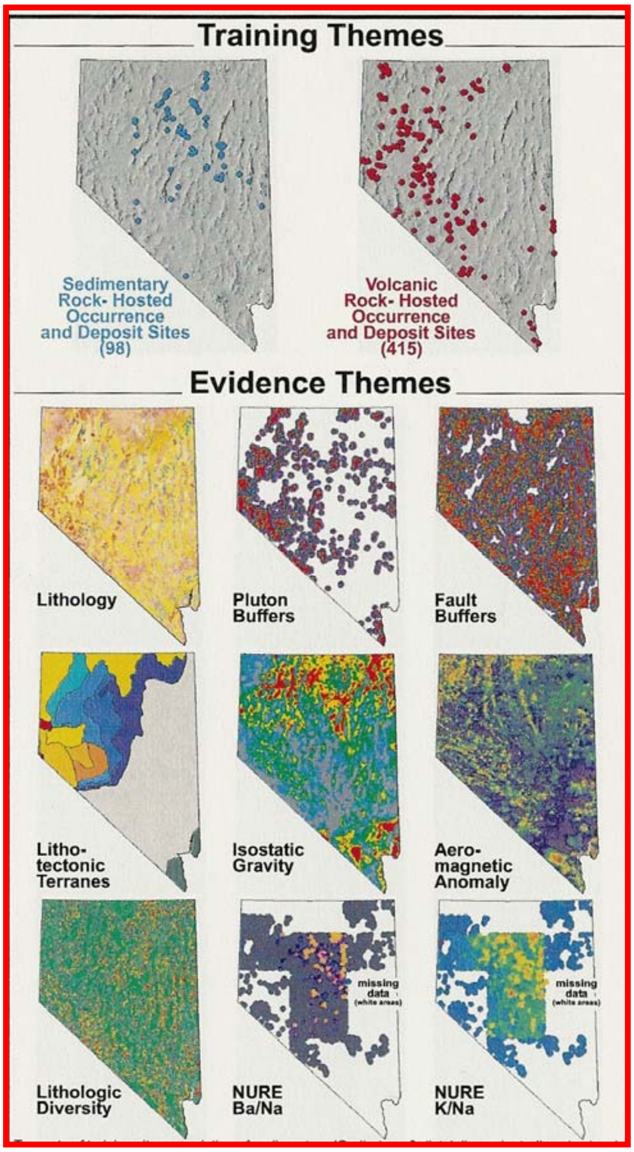
Human/cultural-features - major cities, administrative boundaries, roads, highways, and railways.

A series of mineral potential evidence maps was prepared from these datasets. Some were used for weights of evidence analysis and modeling while others served as supplementary material for interpretation, exemplification, and referencing.

c) Modeling Specification:

Two sets of training sites, consisting of sedimentary (Carlin-type & distal disseminated) and volcanic (epithermal) gold-silver-bearing mineral occurrences and deposits, are used to “calibrate” the models.

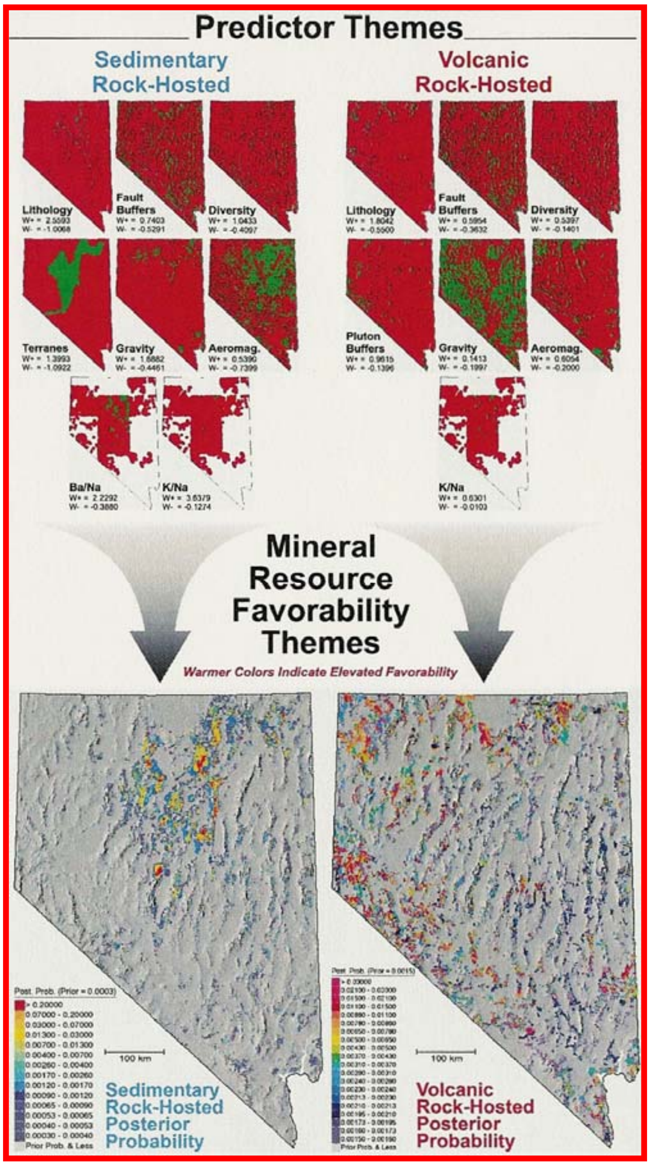
Evidence themes, consisting of multiple multi-class maps of various geologic phenomena, represent evidence for the presence of a training site (figure# 7). Where no spatial association exists between an evidence map class and the training sites (random), $W+ = W^{-} = 0$. Where training sites are more frequent than chance, the map class is assigned a positive weight; less frequent than chance, a negative weight. Areas of missing data are set to 0 (neither up-nor down-weighting a particular piece of evidence)



Figure# 7: Model Specification, after Mark J. Mihalasky (2001)

d) Model Estimation:

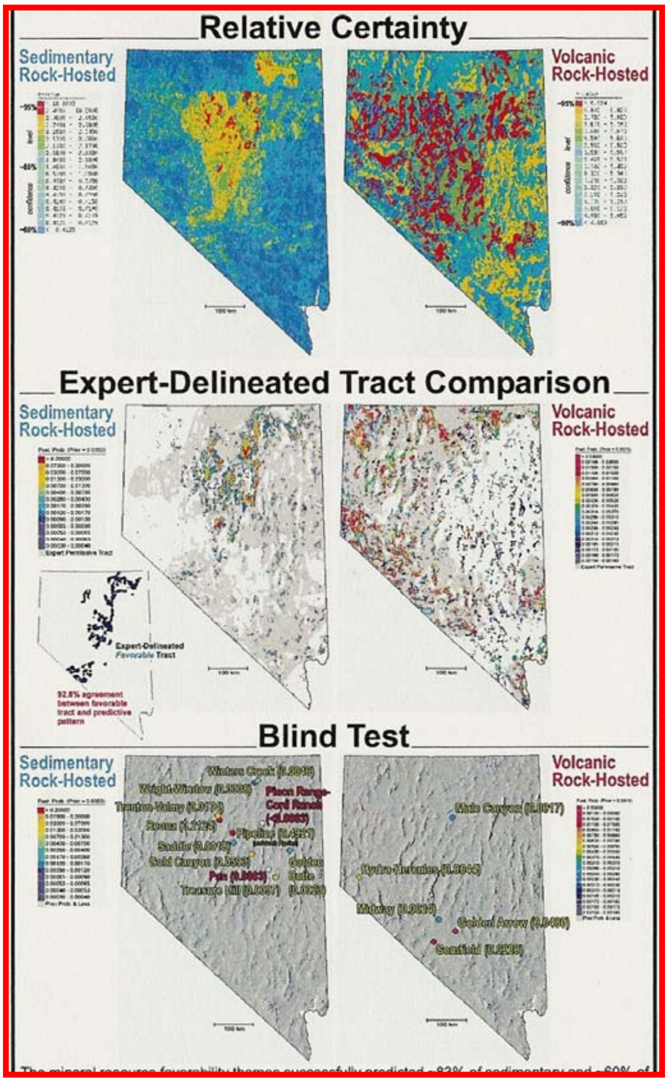
To facilitate map combination and interpretation of the model output, the multi-state evidence themes are usually reduced to mineral resource indicator (or "predictor") themes of a few discrete states (typically binary), where the spatial association between the theme and training sites is maximized. In the predictor themes below, green areas are assigned W+ (positive association with training sites), red areas W^{-} (negative association with training sites) (figure# 8). The predictor themes represent "layers of evidence" which collectively make up the mineral resource models. The key resource-indicator factors, in order of importance, are geology, geochemistry (indication of alteration), and geophysics.



Figure# 8: Model Estimation, after Mark J. Mihalasky (2001)

e) Model Validation:

The mineral resource favorability themes successfully predicted ~ 83% of sedimentary and ~ 60% of volcanic rock-hosted training sites. Relative certainty of the posterior probability estimates, the posterior probability divided by its standard deviation, indicates that the mineral resource predictive patterns are real, as opposed to being an artifact of "chance" effects (e.g. areas of elevated t-value are spatially coincident with the predictive patterns). Sedimentary and volcanic rock-hosted mineral resource maps show a high spatial correlation with expert-delineated mineral permissive tracts: ~ 85% of the predictive and ~ 95% of the elevated predictive patterns for sedimentary rocks-hosted mineral resources lie within permissive tracts, with an overall agreement of 92.8% between the predictive pattern and the expert-delineated favorable tract; ~ 73% of the predictive and ~ 91% of the elevated predictive patterns for volcanic rock-hosted mineral resources lie within permissive tracts.



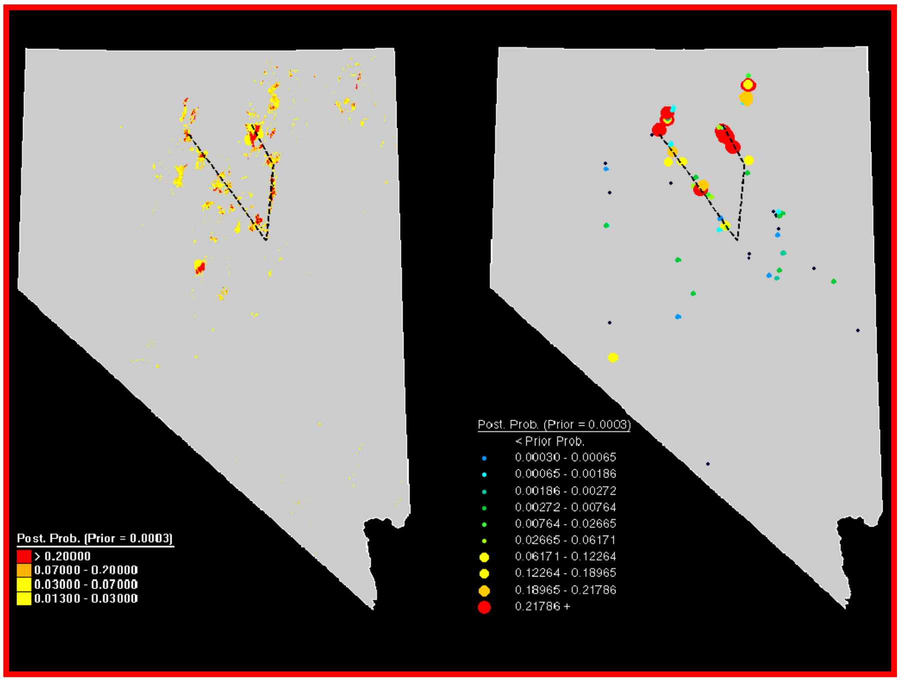
Figure# 9: Model Validation, after Mark J. Mihalasky (2001)

In blind tests, 10 of 12 sedimentary rock-hosted deposits were estimated to have posterior probabilities higher than the prior probability (0.0003), with 4 relatively high predictions; 5 of 5 epithermal deposits were estimated to have posterior probabilities higher than the prior probability (0.0015), with 2 relatively high predictions (figure# 9).

f) Model Interpretation:

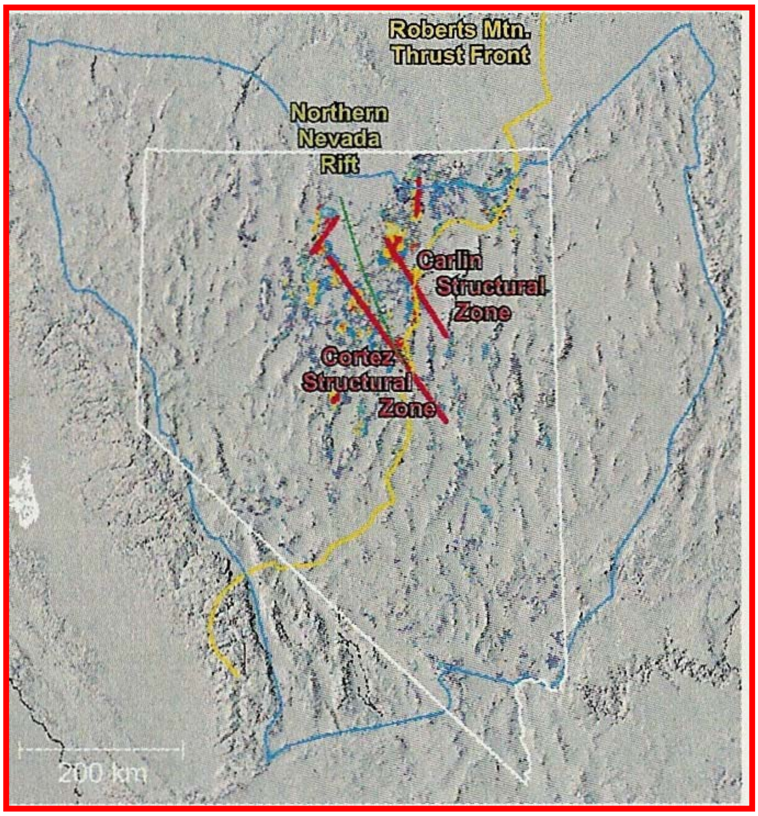
1) Sedimentary Rock-Hosted Mineralization:

Areas of elevated sedimentary rock-hosted mineral resource favorability are generally confined to central, north-central, and north-eastern Nevada. These areas a conspicuous “V” shape pattern (figure# 10) that is coincident with the Battle Mountain-Eureka (Cortez) and Carlin mineral trends and a segment of the Roberts Mountain thrust front, which bridges the trends.



Figure# 10: Areas of elevated sedimentary rock-hosted mineral potential.
These areas form a conspicuous "V"-shape pattern t after Mark J. Mihalasky (2001)

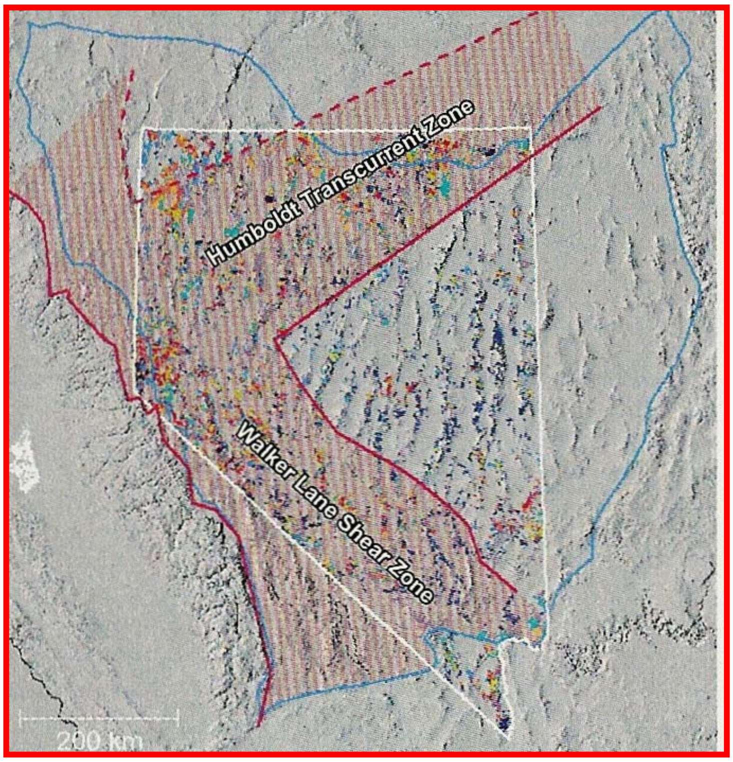
This pattern appears to delineate two well defined, sub parallel, northwest-southeast trending crustal-scale structural zones. These features, here termed the “Carlin” and “Cortez” structural zones (figure# 11), are believed to control the regional-scale distribution of the sedimentary rock-hosted deposits. Mineralizing processes were focoused along these structural zones and significant ore deposits exsit where they intersect other tectonic zones, favorable host rock-type, and (or) where appropriate physio-chemical conditions were present. The origin and age of the Carlin and Cortez structural zones are not constrained, however, they are considered to be transcurrent features representing a long-lived deep crustal or mantle rooted zone of weakness.



Figure# 11: Sedimentary Rock-Hosted Mineralization, after Mark J. Mihalasky (2001)

2) Volcanic Rock-Hosted Mineralization:

Areas of elevated volcanic rock-hosted mineral favorability are principally distributed along two broad and diffuse belts that trend (figure# 12) (1) northwest-southeast across southwestern Nevada, parallel to the sierra Nevada, and (2) northeast-southwest across northern Nevada, extending diagonally from the Sierra Nevada to southern Idaho. The first belt corresponds to the Walker Lane shear zone, a wide region of complex strike slip faulting. The second, here termed the “Humboldt transcurrent zone”, may represent a structural zone of strike-slip movement. Together, the Walker Lane shear and Humboldt transcurrent zones are believed to control the regional scale distribution of volcanic rock-hosted deposits. Volcanic rock-hosted mineralization was closely tied to the southward and westward migration of Tertiary magmatism across the region. Both magmatisim and mineralizing processes were localized and concentrated along these structural zones. The Humboldt transcurrent zone likely has origins relating to the mid-Proterozoic assembly of the Laurentain protocraton and (or) late Proterozoic rifting.



Figure# 12: Volcanic Rock-Hosted Mineralization, after Mark J. Mihalasky (2001)

g) Summary of Findings:

Preliminary findings suggest; 1) statistically significant differences in host lithology type and spatial distribution between the "small occurrences" and that of the "medium and large occurrences", 2) an increase in the number and in the spatial association between an occurrence of any size and a map area of greater lithologic diversity; and 3) a strong association in the space-time migration patterns between gold-silver occurrences and igneous activity.

Most deposits occur in the western half of the state. The most common gold-silver occurrence host lithologies are marine and/or shelf carbonates of late Precambrian to late Paleozoic age. Approximately 35 % of all occurrences, and ~27 % of the medium and large size occurrences, fall within these units. However, the greatest numbers of the medium and large occurrences (~36 %) are hosted by felsic to intermediate extrusive and intrusive igneous rocks of late Cenozoic age. In comparison to the medium and large occurrences, the small occurrences generally are hosted by a wider variety of lithologies, which include more sedimentary rock types. In addition to these strong associations, statistically significant host rocks for occurrences of any size include silicious igneous and sedimentary units, felsic to intermediate extrusive units, granitic plutons, and ultramafic rocks. The statistical measure of association (W+) for the ultramafic rocks is especially high.

Posterior probability maps of mineral potential, based on the spatial association of gold-sliver occurrences to lithology, predict that both medium and large occurrences (as a group) should form in similar host lithologies, and that these lithologies are substantially different from those predicted to host smaller occurrences. Lithologies hosting medium occurrences are weakly gradational between lithologies hosting small occurrences and those hosting large occurrences. Lithologies having a high (=/> 80th percentile) posterior probability of hosting medium and large occurrences are preferentially located in the Walker Lane shear belt, north-central Nevada, and in the central part of the northeastern quarter of Nevada. Rocks of high posterior probability for medium and large occurrences highlight regions of known mineralization in the Carlin and Battle Mountain-Eureka trends, and in the Independence group area.

V. CONCLUSIONS:

The distribution of 2,690 gold and silver occurrences in the Nevada Great Basin was examined in terms of spatial association with geological, geochemical, and geophysical phenomena. Analysis of these relationships, using GIS (SPANS) and weights of evidence modeling techniques, has predicted areas of high mineral potential where little or no mining activity exists. Mineral potential maps for sedimentary ("disseminated") and volcanic ("epithermal") rock-hosted gold-silver mineralization revealed two distinct patterns that highlight two sets of crustal-scale geologic features that likely control the distribution of these deposit types.

The weights-of-evidence method is a probability-based technique for mapping mineral potential using the spatial distribution of known mineral occurrences. Mineral potential maps predicting the distribution of gold-silver-bearing occurrences were generated from structural, geochemical, geomagnetic, gravimetric, lithologic, and lithotectonic-related deposit-indicator factors. The maps successfully predicted nearly 70% of the total number of known occurrences, including ~83% of sedimentary and ~60% of volcanic rock-hosted types. Sedimentary and volcanic rock-hosted mineral potential maps showed high spatial correlation (an area cross-tabulation agreement of 85% and 73%, respectively) with expert-delineated mineral permissive tracts. In blind tests, the sedimentary and volcanic rock-hosted mineral potential maps predicted 10 out of 12 and 5 out of 5 occurrences, respectively. The key mineral predictor factors, in order of importance, were determined to be: geology (including lithology, structure, and lithotectonic terrane), geochemistry (indication of alteration), and geophysics.

The application of GIS to the earth sciences facilitates data compilation and synthesis, permits exploratory data analysis and modeling, and may reveal insights not readily obtained by more traditional means of data analysis and display. GIS is quickly becoming an integral part of many mineral resource management and exploration programs. Such programs typically evaluate a wide variety of data in order to determine the optimum approach to managing and exploring for mineral resources. The Great Basin has an impressive collection of geoscience data and provides an ideal opportunity to evaluate the potential benefits of statistical modeling in a GIS to minerals exploration.

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