Geologically-Constrained Fuzzy Mapping of Gold Mineralization Potential, Baguio District, Philippines[1]

Emmanuel John M. Carranza[2]
Mines and Geosciences Bureau (MGB)
Regional Office No. 5, Philippines

Martin Hale
International Institute for Aerospace Surveys and Earth Sciences (ITC)
Hengelostraat 99, P.O. Box 6, 7500 AA Enschede, The Netherlands

ABSTRACT

An application of the theory of fuzzy sets to the mapping of gold mineralization potential in the Baguio gold mining district of the Philippines is described. Proximity to geological features is translated into fuzzy membership functions based upon qualitative and quantitative knowledge of spatial associations between known gold occurrences and geological features in the area. Fuzzy sets of favorable distances to geological features and favorable lithologic formations are combined using fuzzy logic as the inference engine. The data capture, map operations and spatial data analyses are carried out using a geographic information system. The fuzzy predictive maps delineate at least 68% of the known gold occurrences that are used to generate the model. The fuzzy predictive maps delineate at least 76% of the "unknown" gold occurrences that are not used to generate the model. The results are highly comparable with the results of previous stream sediment geochemical survey in the area. The results demonstrate the usefulness of a geologically-constrained fuzzy set approach to map mineral potential and to re-direct surficial exploration work in the search for yet undiscovered gold mineralization in the mining district. The method described is applicable to other mining districts elsewhere.

Key words: mineral potential mapping, fuzzy sets, fuzzy logic, spatial association, Baguio gold district (Philippines)

INTRODUCTION

The geology of any given area is probably the single most important indicator of its mineral potential. Qualitative knowledge of spatial associations between known mineral occurrences and geological features in well-explored areas is the basis for most, if not all, explorations programs in less-explored areas. However, because the spatial association of mineral occurrences with geological features varies from place to place, a qualitative knowledge alone is inadequate for finding new deposits. In addition, the degrees of spatial association between mineral occurrences and different geological features are variable because these features play a unique role in the localization of mineral deposits. A quantitative knowledge of the spatial

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[2] Corresponding author. Present address: ITC, Hengelosestraat 99, 7514 AE Enschede, The Netherlands. E-mail: carranza@itc.nl

association between known mineral occurrences and the different geological features present is therefore equally or more important.

The spatial association we are dealing with here is the distance or range of distances at which mineral occurrences are favorably located with respect to the geological features. This spatial association thus represents the favorableness of zones in and around geological features for the occurrence of a mineral deposit. In an earlier work, Carranza and Hale (2000, 2001) quantified the spatial association of the gold occurrences with the different geological features in the Baguio district. The quantified spatial associations between the gold occurrences and the different geological features are used to convert multi-class maps of proximity to geological features into binary predictor patterns. The binary predictor patterns are then assigned weights based on the optimum spatial association to calculate a gold potential map (Carranza and Hale, 2000).

Using binary predictor patterns for mapping mineral potential assumes a crisp boundary between favorable and unfavorable ground (e.g., Bonham-Carter *et al*., 1989; Carranza and Hale, 2000). In reality and in most cases, however, the boundary between grounds that are favorable and unfavorable for the occurrence of mineralization is imprecise and thus fuzzy. Classifying mineral potential, therefore, requires a method capable of using imprecise concepts where a precise boundary membership or non-membership in a class may be impossible or impractical. Gettings and Bultman (1993) applied the possibility theory from fuzzy logic to the quantification of favorableness of quartz-carbonate vein deposits in southeast Arizona. They defined conditions necessary for the formation of the deposits and represented each condition as a fuzzy set enumerated in a grid over the area. The intersection of the fuzzy sets measures the degree of simultaneous occurrence of the necessary conditions and provides a measure of the possibility of deposit occurrence. Cheng and Agterberg (1999) developed an approach of weights of evidence method based on fuzzy sets and fuzzy probabilities for mineral potential mapping. Instead of separating spatial evidences of mineralization into binary or ternary form, they created fuzzy sets that contain genetic elements. They then defined fuzzy probabilities to construct a model for calculating posterior probability of a unit area to contain mineralization based on the fuzzy evidence for a unit area. Knox-Robinson (2000) developed a new technique called vectorial fuzzy logic, based on fuzzy logic principles, for the integration of spatial data for enhanced mineral prospectivity mapping. The technique, based on vector mathematics, differs from existing methods of spatial data integration (e.g., Boolean logic, index-overlay, weights of evidence) in that it displays prospectivity as a continuous surface and allows a measure of confidence to be incorporated.

The methods described above, based on fuzzy logic principles, demonstrate the efficacy of representing spatial data into fuzzy sets for GIS-based predictive mapping of mineral potential. In this paper, we report the results of mapping gold potential in the Baguio district by employing the theory of fuzzy sets (Zadeh, 1965). Due to the general lack of mineral exploration data other than geological data for most of the Philippines, we demonstrate the applicability of geologically-constrained mineral potential mapping. Results of previous geochemical exploration work in the district are shown initially with which we later compare our results. We use the quantified spatial associations between the known gold occurrences and geological features in the district (Carranza and Hale, 2001) to evaluate individual classes of proximity maps regarding their fuzzy membership. The input maps of geological fuzzy sets are combined using a geographic information system (GIS).

FUZZY SETS

In classical set theory, the membership of a set is defined as true (=1) or false (=0). In fuzzy set theory, a fuzzy set is defined as a subset from a large set whose membership in the subset may not be complete. Fuzzy sets are represented by means of membership functions. A membership function, $\mu_A(x)$, is a mapping of the fuzzy membership of x from the universe of discourse X into the unit interval [0,1], thus:

$$\mu_A(x) : X \rightarrow [0,1] \qquad \text{Eq. (1)}$$

The grade of membership is large (traditionally 1) for objects which fully belong to the fuzzy set; it is small (traditionally 0) for objects which do not belong to the fuzzy set. For a particular object or class, the more certainly it belongs to the fuzzy set, the closer its membership grade is to 1. Thus, individual classes of maps can be evaluated regarding their membership in a fuzzy set, based on a subjective judgment. Grade of membership is usually represented by a membership function which need not be linear or even continuous; indeed, many interesting fuzzy sets have extremely nonlinear membership functions (Zimmerman, 1985). The membership always relates to a certain proposition. In our case, the proposition is "favorable location for gold mineralization".

For the application studied here, one large set is the set of distances from all the geological features. The subset is the distances, X, from each of the geological features being studied in the district. Hence, employing the theory of fuzzy sets introduced by Zadeh (1965), the class "favorable distance", *d,* translates into a series of measures (x) such that:

$$d = \{(x, \mu_d(x)) \mid x \in X\} \qquad \text{Eq. (2)}$$

where $\mu_d(x)$ defines a grade of membership of distance x in the class "favorable distance". Another large set used in this study is the set of all lithologic formations. The subset is the lithologic formations, Y, in the study area. Similarly, the class "favorable lithologic formation", l, translates into a series of measures (y) such that:

$$l = \{(y, \mu_l(y)) \mid y \in Y\} \qquad \text{Eq. (3)}$$

where $\mu_l(x)$ defines a grade of membership of lithologic formation y in the class "favorable lithologic formation".

As in classical set theory, set-theoretic operations can be defined or performed on fuzzy sets, including equality, containment, union and intersection, all of which have meanings analogous to their crisp set equivalents. Zimmerman (1991) discusses a variety of fuzzy operations. An *et al*. (1991) discuss five operators that are found to be useful for combining exploration datasets, namely the fuzzy AND, fuzzy OR, fuzzy algebraic product, fuzzy algebraic sum and fuzzy γ-operator.

The fuzzy AND operation is equivalent to a Boolean AND (logical intersection) operation on classical set values of 1 and 0. It is defined as:

$$\mu_{combination} = MIN(\mu_A,\ \mu_B,\ \mu_C, .\ ,\ ), \qquad \text{Eq. (4)}$$

where μ_A is the fuzzy membership value for map A at a particular location, μ_B is the fuzzy membership value for map B, and so on. The effect of this operation is to make the output map be controlled by the smallest (minimum) fuzzy membership value occurring at each location. The fuzzy AND operation is appropriate where two or more pieces of evidence for a hypothesis must be present together for the hypothesis to be true.

The fuzzy OR is like the Boolean OR (logical union) whereby the output fuzzy membership values are controlled by the maximum values of any of the input maps, for any particular location. The fuzzy OR is defined as:

$$\mu_{combination} = MAX(\mu_A,\ \mu_B,\ \mu_C, .\ ,\ ). \qquad \text{Eq. (5)}$$

This operator can be, in some circumstances, reasonable for mineral potential mapping where favorable evidences for the occurrence of mineralization are rare and the presence of any evidence may be sufficient to suggest favorability.

The fuzzy algebraic product is defined as:

$$\mu_{combination} = \prod_{i=1}^{n} \mu_i\ , \qquad \text{Eq. (6)}$$

where μ_i is the fuzzy membership values for the i-th (i=1,2,…,n) maps that are to be combined. The combined fuzzy membership values tend to be very small with this operator, due to the effect of multiplying several numbers less than 1. The output is always smaller than, or equal to, the smallest contributing fuzzy membership value, and is thus 'decreasive'.

The fuzzy algebraic sum operator is complementary to the fuzzy algebraic product, and is defined as:

$$\mu_{combination} = 1 - \prod_{i=1}^{n} (1 - \mu_i). \qquad \text{Eq. (7)}$$

The result of this operation is always larger than, or equal to, the largest contributing fuzzy membership value. The effect is thus 'increasive'. Two or more pieces of evidence that both favor a hypothesis reinforce one another and the combined evidence is more supportive than either piece of evidence taken individually.

The fuzzy "γ-operator" (Zimmerman and Zysno, 1980) is defined as:

$$\mu_{combination} = (\prod_{i=1}^{n} \mu_i)^{1-\gamma} (1 - \prod_{i=1}^{n} (1 - \mu_i))^{\gamma} \qquad \text{Eq. (8)}$$

This "γ-operator" is obviously a combination of the fuzzy algebraic product (Eq. 6) and the fuzzy algebraic sum (Eq. 7), where γ is a parameter between the range 0 to 1. When γ is 1, the combination is the same as the fuzzy algebraic sum; when γ is 0, the combination equals the fuzzy algebraic product. The parameter indicates where the actual operator is located between the logical "and" and "or".

Two or more fuzzy sets combined by any one of the fuzzy operators yield a fuzzy set. For our case, we combine fuzzy sets of favorable distances to geological features and a fuzzy set of favorable lithologic formations to produce a fuzzy set (or map) of favorable zones for gold mineralization.

APPLICATION TO BAGUIO DISTRICT

Geological Background

The Baguio district (Fig. 1) is underlain mainly by five major lithologic units. The Pugo Formation of Cretaceous to Eocene age, is a sequence of metavolcanic and metasedimentary rocks. The Zigzag Formation unconformably overlies the Pugo Formation. It consists largely of marine sedimentary rocks of Early to Middle Miocene age (Balce *et al*., 1980). However, it is intruded by andesite porphyry dated 15.0 ±1.6 Ma (Wolfe, 1981) or pre-Middle Miocene. Mitchell and Leach (1991) consider the Zigzag Formation to be largely Late Eocene, but it may include rocks of Early Miocene age. The Kennon Formation of Middle Miocene age conformably overlies the Zigzag Formation (Balce *et al*., 1980). It is composed of limestones that occur in a discontinuous north-trending belt west of the district. The Klondyke Formation of Late Miocene age unconformably overlies all formations (Balce *et al*., 1980; Wolfe, 1988; Mitchell and Leach, 1991). It consists mainly clastic rocks that are very largely or entirely andesitic in composition. The other major lithologic unit is the Agno Batholith. Its bulk is composed mainly of hornblende quartz diorite. Radiometric dating indicates that the different rocks in the batholith were intruded in several phases. Wolfe (1981) cited an average age of 27 Ma for the earlier phases and a range of 12-15 Ma for the later phases. More recent workers contend that the Agno Batholith intruded mainly into the Pugo Formation (Balce *et al*., 1980) but earlier workers believed that it also intruded the Zigzag Formation (Peña, 1970; Sawkins *et al*., 1979). The Zigzag and Pugo formations have also been intruded by young dioritic, andesitic and dacitic porphyries that vary in age from Late Miocene to Pleistocene (Mitchell and Leach, 1991; Cooke *et al*., 1996).

Most of the gold in the district comes from epithermal systems that are confined to a north-trending zone about 7 km wide east of Baguio City (Fernandez and Damasco, 1979). The epithermal veins are commonly fracture-controlled. The most productive veins trend northeasterly to easterly although there are some productive northwesterly trending veins (Mitchell and Leach, 1991). The auriferous veins are hosted mostly by the Zigzag and Pugo formations and the Agno Batholith. Almost all known productive veins are found at the western fringe of the contact zone between the Agno Batholith and the intruded rocks. Wolfe (1988) suggested that the Agno plutons are an important source of the gold. More recent workers, however, claim that the epithermal gold mineralization is related to the young intrusive complexes (Mitchell and Leach, 1991; Cooke *et al*., 1996).

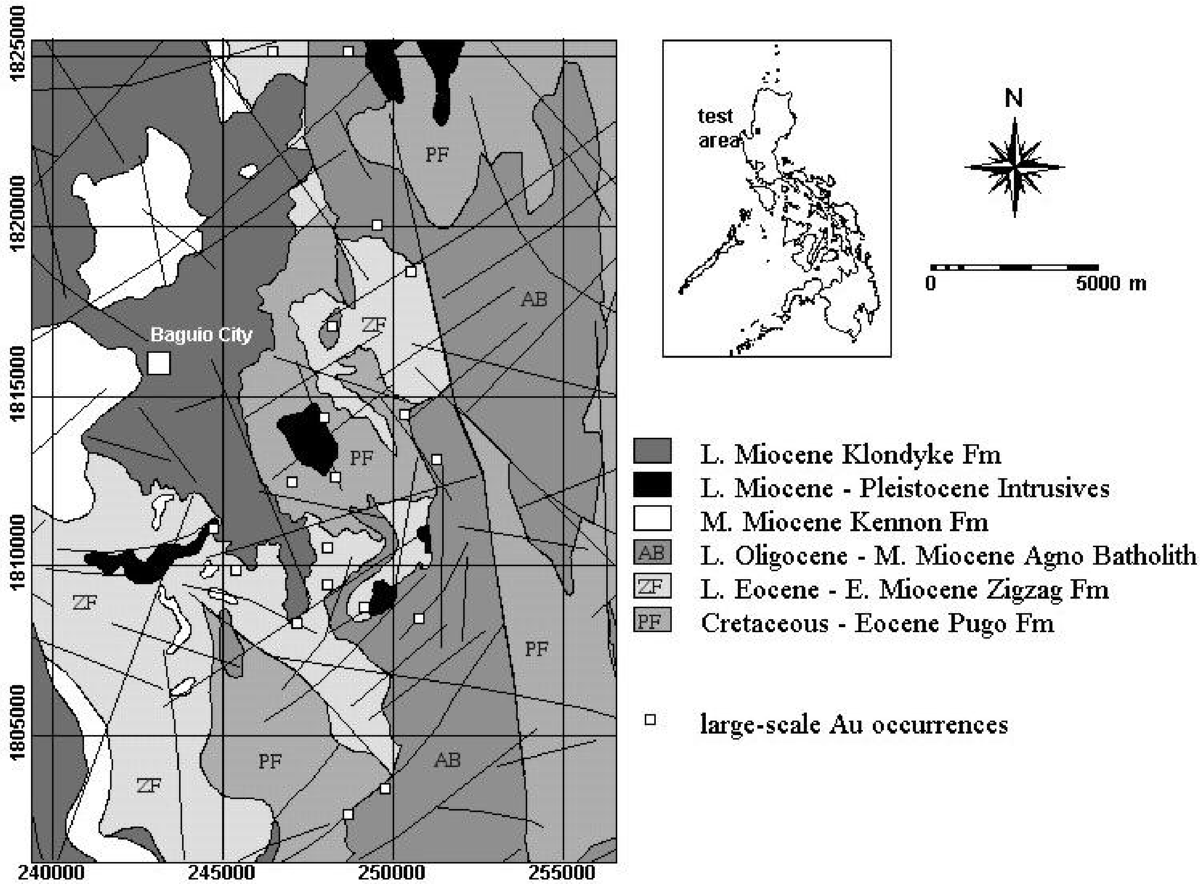

Fig. 1. Simplified geologic map of Baguio district (modified after MMAJ-JICA, 1977; Balce *et al*., 1980). Curvi-linear features are faults/fractures. Map coordinates are in meters (UTM, zone 51). Inset represents map of Philippines.

Geochemical Anomalies

As part of a training program to improve the capability of the Mines and Geosciences Bureau (MGB) of the Philippines to identify areas of potential gold mineralization, geochemical exploration work was carried out in the district (UNDP, 1987). Results of the survey indicated that the gold deposits in the district are characterized by a group of stream sediment geochemical anomalies typical of epithermal gold mineralization. Figure 2 shows the spatial association of the major geochemical anomalies with the gold occurrences. The gold anomalous zones (Fig. 2a) are defined by stream sediment concentrations of ≥ 0.1 ppm Au, the silver anomalous zones (Fig. 2b) by ≥ 0.5 ppm Ag, the arsenic anomalous zones (Fig. 2c) by ≥ 5 ppm As, and the antimony anomalous zones (Fig. 2d) by ≥ 0.3 ppm Sb. These major geochemical anomalies cover an average of about 24% of the total area. The geochemical anomalies accurately reflect the location of about 68% of the known large-scale gold occurrences. We use this geoinformation for comparing and validating the results of our present work.

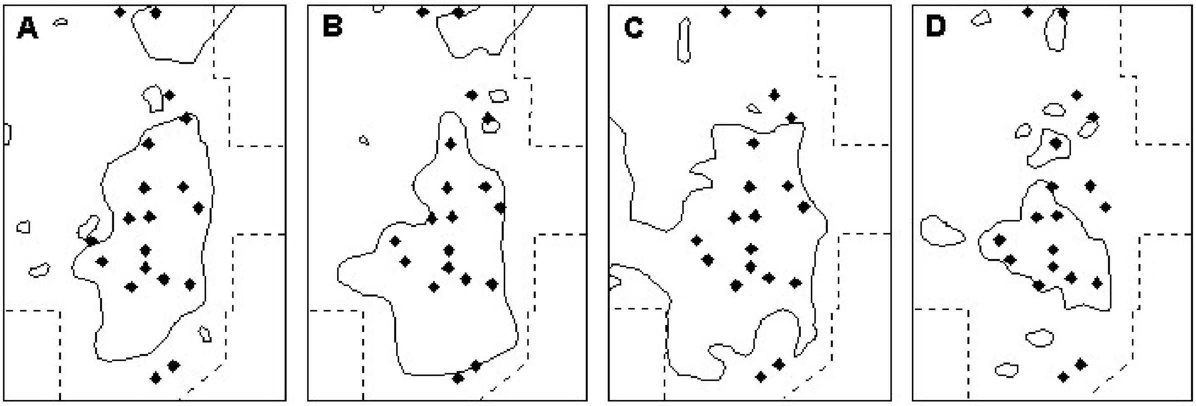

Fig. 2. Geochemically-anomalous zones for (a) Au, (b) Ag, (c) As and (d) Sb stream sediment element concentrations (UNDP, 1987). Solid line = outline of geochemical anaomly. Dashed line = boundary of geochemical survey area. Filled diamonds = locations of large-scale gold occurrences.

Data Input and GIS Operations

The data used are a map of lithologic formations, map of faults/fractures, and locations of 19 large-scale gold occurrences, i.e., explored or mined deposits (Fig. 1). These data were derived from published works (e.g., Mitchell and Leach, 1991; MMAJ, 1996; MMAJ-JICA, 1977) and unpublished maps/reports in the MGB. The boundaries of lithologic units, fault/fractures and the locations of 19 large-scale gold occurrences were digitised from paper maps. The data capture and map operations and analyses were carried out using ILWIS (Integrated Land and Water Information Systems), a GIS software package developed by the International Institute for Aerospace Survey and Earth Sciences (ITC) in the Netherlands. In ILWIS, spatial data are analyzed in raster mode.

Generation of Fuzzy Sets

Geological knowledge of gold occurrences in the Baguio district suggest four fuzzy sets of favorable distances to geological features that are likely to be useful evidences for mapping gold potential. These geological features area: (1) Agno Batholith contact; (2) young (i.e., Late Miocene to Pleistocene) intrusives contact; (3) northeasterly trending faults/fractures; and (4) northwesterly trending faults/fractures. Another useful evidence is a fuzzy set of favorable lithologic formations.

To generate the fuzzy sets of favorable distances to geological features, we make use of the results of an earlier work, summarized in Table 1, to quantify spatial association between gold occurrences and geological features in the district (Carranza and Hale, 2001). Based on the quantified spatial associations between the gold occurrences and the geological features we define classes of distances, from each of the geological features, and assign fuzzy membership values to these classes based on subjective judgment. The distance classes for the different geological features and their fuzzy membership values are given in Table 2. The distance class with the narrower spatial association (Table 1) is assigned the highest fuzzy membership value of 0.9. The following distance classes within the wider spatial association (Table 1) are assigned gradually decreasing fuzzy membership values. The outermost distance class to which the farthest distance with the gold occurrences belongs is assigned the lowest fuzzy membership value of 0.1. From the outermost distance class to the distance class of wider spatial association, gradually increasing fuzzy membership values are assigned. An exception is made with the NW-trending fractures because of their restricted spatial association with the gold occurrences (Carranza and Hale, 2000, 2001). It is only within a distance of 300 m that the gold occurrences tend to have spatial association with the NW-trending faults/fractures. Fuzzy membership values of 0 and 1 are not assigned because we can never be completely certain that a given distance is completely unfavorable or favorable for the occurrence of gold mineralization. There may be other conditions that make the ground within such distance classes more or less favorable.

To generate maps of fuzzy membership values of favorable distances to the different geological features, the following steps were carried out: (1) create maps of distances away from the geological features; (2) classify the distance maps according the distance classes in Table 2; and (3) assign the fuzzy membership values as attributes of the different distance classes. The maps of fuzzy membership values are shown in Fig. 3.

Table 1. Quantified spatial association between gold occurrences and geological features in Baguio district (adopted from Carranza and Hale, 2001).

geological feature	spatial association with large-scale gold occurrences (m)		farthest distance between geological feature and gold occurrences (m)
	by distance distribution method (after Bonham-Carter *et al*., 1985)	by weights of evidence modeling (after Bonham-Carter *et al*., 1989)	
NE-trending faults/fractures	350	400	1588
NW-trending faults/fractures	400	300	1800
Agno Batholith contacts	400	1000	2381
Young intrusives contacts	750	2750	5835

Table 2. Distance classes and fuzzy membership scores for different geological features in Baguio district.

NE-trending faults/fractures		NW-trending faults/fractures		Agno Batholith contacts		Young intrusives contacts	
distance class (m)	fuzzy membership	distance class (m)	fuzzy membership	distance class (m)	fuzzy membership	distance class (m)	fuzzy membership
<350	0.9	<300	0.9	<400	0.9	<750	0.9
350-700	0.8	300-600	0.4	400-800	0.8	750-1500	0.8
700-1050	0.4	600-900	0.3	800-1200	0.7	1500-2250	0.7
1050-1400	0.3	900-1200	0.3	1200-1600	0.4	2250-3000	0.6
1400-1750	0.2	1200-1500	0.2	1600-2000	0.3	3000-3750	0.3
>1750	0.1	1500-1800	0.2	2000-2400	0.2	3750-4500	0.3
		>1800	0.1	>2400	0.1	4500-5250	0.2
						5250-6000	0.2
						>6000	0.1

To generate a map of fuzzy membership values of favorable lithologic formations (Fig. 3e), the fuzzy membership values in the Table 3 are used. The Zigzag and Pugo formations are both given the highest fuzzy membership values because they are known to host the gold mineralization in the district. The Agno Batholith and young intrusives are both given lower fuzzy membership values because they are supposed to be the heat sources for the mineralization although it known that these rock units also host gold mineralization. The Klondyke formation is assigned a fuzzy membership value of 0.5 because it could probably host gold mineralization as it is also intruded by the young intrusives but it has not been reported to contain gold mineralization. The Kennon limestones are given the lowest membership value 0.1 because they are intruded by neither the Agno Batholith nor the young intrusives and are not known to host gold mineralization.

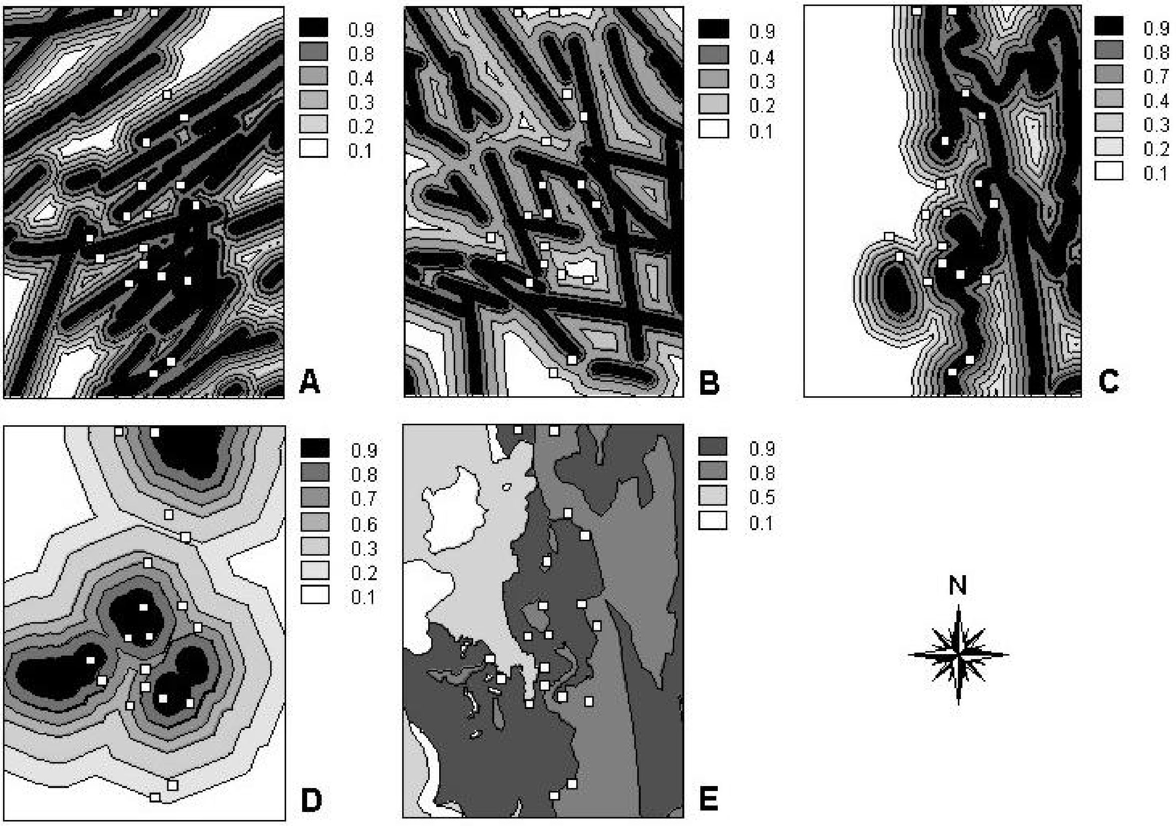

Fig. 3. Maps of fuzzy membership values of (a) favorable distances to NE-trending faults/fractures, (b) favorable distances to NW-trending faults/fractures, (c) favorable distances to Agno Batholith contacts, (d) favorable distances to young intrusives contacts and (e) favorable lithologic formations.

Integration of Fuzzy Sets

Fuzzy sets can be combined altogether using one fuzzy operator or a variety of different fuzzy operators. For example, our five input fuzzy sets (Fig 3.) could be combined using the fuzzy AND (intersection) operator in support of the hypothesis that the evidences should occur jointly. For our case, we combine the fuzzy sets of evidence in a number of steps to represent intermediate hypotheses regarding the significance of the evidence(s) for the occurrence of gold mineralization. We have three intermediate hypotheses. First, the heat sources for the epithermal gold mineralization in the district are the Agno Batholith and/or the young intrusives. Second, the channelways for the mineralizing solutions that brought about gold mineralization in the district are the northeast-trending and/or the northwest-trending faults/fractures. Third, the combined occurrence of heat sources, channelways for mineralizing solutions and favorable host rocks are essential for the deposition of gold mineralization. Fig. 4 shows the schematic inference network for predicting gold mineralization potential in the Baguio district using fuzzy logic as the 'inference engine'. For the first hypothesis, the input maps of fuzzy scores for proximity to northeast-trending and northwest trending faults/fractures (Figs. 3a and 3b) are combined to derive an output map of 'favorable fault/fracture zones'. For the second hypothesis, the input maps of fuzzy scores for proximity to Agno Batholith and younger intrusives (Figs. 3c and 3d) contacts are combined to derive an output map of 'favorable heat flow zones'. For the third hypothesis, the maps of favorable lithologic formation (Fig. 3e), 'favorable fault/fractures zones' and 'favorable heat flow zones' are combined to derive a final output map of 'favorable zones of gold mineralization potential. It is evident from Fig. 4 that there are several possible combinations of fuzzy operations to integrate the fuzzy input maps in order to derive a final fuzzy membership map of 'favorable zones of gold mineralization potential'.

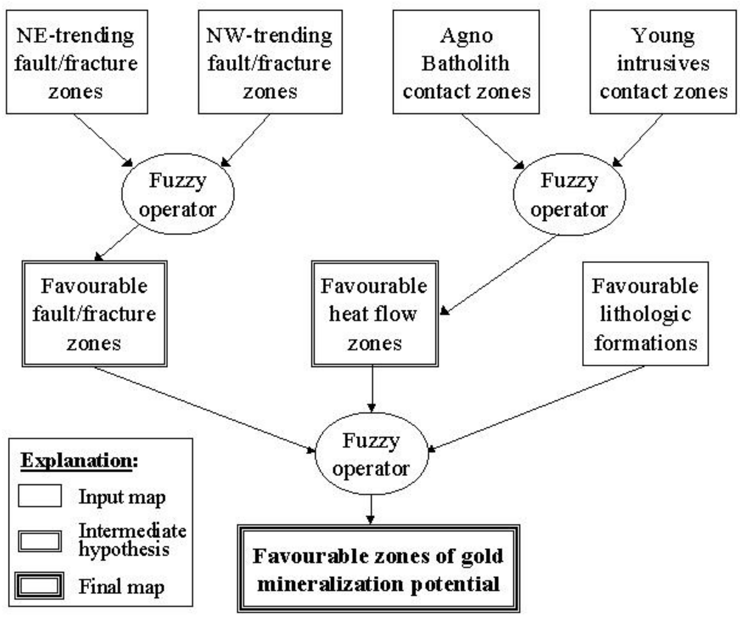

Fig. 4. Schematic inference network for predicting gold mineralization potential in Baguio district.

RESULTS

We experimented with various combinations of fuzzy operations to produce a final fuzzy membership map that best predicts zones favorable for gold mineralization. To select the map that best predicts zones favorable for gold mineralization, the following criteria were implemented: (1) the favorable zones are characterized by a fuzzy score of ≥ 0.7; (2) the favorable zones occupy at most 24% of study area; and

(3) the favorable zones contain at least 68% of the known gold occurrences. The first criterion is based upon the fuzzy membership scores subjectively assigned to the different distance classes (Table 2). We select a subjectively high fuzzy score of 0.7 to discriminate between zones that are unfavorable for gold mineralization potential and zones that are favorable. The last two criteria are based on the geoinformation derived from stream sediment geochemical anomalies (see above; UNDP, 1987).

Of the various combinations of fuzzy operations we experimented on to produce a final map, only one was considered optimal for predicting zones that are favorable for gold mineralization potential. This predictive map is shown in Fig. 5a; it is the result of the inference network shown in Fig. 6a. It delineates about 21% of the study area as favorable for gold mineralization and predicts at least 68% of the known large-scale gold occurrences (Table 3). In this predictive map, the unpredicted known gold occurrences are on average less than 710 m from the delineated favorable zones. The three 'next best' predictive maps are shown in Figs. 5b, 5c and 5d; these maps are, respectively, the results of the inference networks shown in Figs. 6b, 6c and 6d. These 'next best' predictive maps predict equal percentages of the known gold occurrences (Table 3). In these predictive maps, the unpredicted known gold occurrences are on average less than 700 m from the delineated favorable zones.

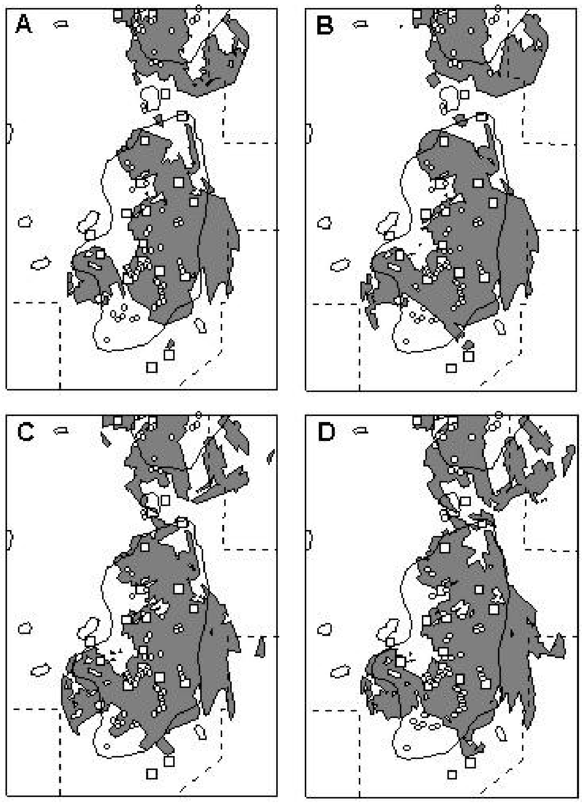

Fig. 5. Fuzzy predictive maps of gold potential (a) based on Fig. 6A, (b) based on Fig. 6B, (c) based on Fig. 6C and (d) based on Fig. 6D. Gray shaded areas = favorable zones; unshaded area = unfavorable zones; unfilled squares = known large-scale gold occurrences; unfilled small scircles = “unknown” smalls-scale gold occurrences; solid line = stream sediment geochemical anomaly for Au contents; dashed line = boundary of geochemical survey (UNDP, 1987).

Summarized in Table 4 are the percentages of the geochemically-anomalous zones delineated by the predictive maps. The predictive maps coincide with (or predict) about 50 to 66% of the areas that are anomalous for Au, Ag and Sb. The maps predict about 40 to 50% of the larger As anomaly. The maps predict between 78 and 86% of the known gold occurrences delimited by the geochemical anomalies.

Summarized in Table 5 are the percentages of geochemically non-anomalous zones delineated by the predictive maps. The predictive maps delineate as favorable ground between 9 and 23% of the geochemically non-anomalous zones, depending on which element is considered. Between 20 and 50% of the known gold occurrences in geochemically non-anomalous zones fall within 'geologically' favorable zones.

Table 3. Percentages of study area outlined as favorable and percentages of known and “unknown” gold occurrences predicted by gold potential maps.

Gold potential map	% favorable zones	% predicted known gold occurrences	% predicted “unknown” gold occurrences	mean distances of unpredicted occurrences to favorable zones (m)	
				known occurrences	“unknown” occurrences
Fig. 5A	21.28	68.42	76.19	709.9	882.8
Fig. 5B	24.29	68.42	77.78	690.5	720.4
Fig. 5C	25.12	68.42	82.54	603.4	447.0
Fig. 5D	26.05	68.42	76.19	574.3	609.2

Table 4. Cross-table to compare between predicted zones of favorable gold potential and stream sediment geochemical anomalies.

Gold potential map	Au Geochemical Anomaly (Fig. 2A)			Ag Geochemical Anomaly (Fig. 2B)			As Geochemical Anomaly (Fig. 2C)			Sb Geochemical Anomaly (Fig. 2D)		
	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]
Fig. 5A	55.5	85.7	77.2	50.6	78.6	75.7	39.8	84.6	78.7	54.4	81.8	89.2
Fig. 5B	61.9	85.7	78.9	55.8	78.6	77.6	45.5	84.6	80.8	57.3	81.8	91.9
Fig. 5C	65.6	85.7	77.2	59.1	78.6	82.8	48.5	84.6	89.4	58.3	81.8	89.2
Fig. 5D	64.6	85.7	84.2	57.8	78.6	75.7	45.6	84.6	80.8	57.9	81.8	86.5

[1]anomalous zones predicted; [2]known occurrences predicted; [3]”unknown” occurrences predicted

Table 5. Cross-table to compare between predicted zones of favorable gold potential and geochemically non-anomalous zones.

Gold potential map	Au Geochemical Background (Fig. 2A)			Ag Geochemical Background (Fig. 2B)			As Geochemical Background (Fig. 2C)			Sb Geochemical Background (Fig. 2D)		
	% g.f.z.[1]	% k.o.p.[2]	% u.o.p.[3]	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]	% a.z.p.[1]	% k.o.p.[2]	% u.o.p.[3]
Fig. 5A	9.8	20.0	33.3	10.6	40.0	80.0	12.8	33.3	68.7	16.5	50.0	57.7
Fig. 5B	11.8	20.0	33.3	12.8	40.0	80.0	14.5	33.3	68.7	19.5	50.0	57.7
Fig. 5C	13.1	20.0	33.3	14.0	40.0	80.0	15.7	33.3	62.5	21.4	50.0	73.1
Fig. 5D	11.6	20.0	33.3	13.2	40.0	80.0	15.7	33.3	62.5	22.3	50.0	61.5

[1]'geologically' favorable zones; [2]known occurrences predicted; [3]”unknown” occurrences predicted

DISCUSSION

Selection criteria for best predictive map

To discriminate between zones that are unfavorable for gold mineralization potential and zones that are favorable, a subjectively high fuzzy score of 0.7 was selected. This selection is purely based on visual inspection of the input fuzzy maps shown in Fig. 3 and based on the expectation that the product of fuzzy scores 0.9 and 0.8 is 0.72. The discriminant fuzzy score of 0.7 was also chosen so that fewer areas are classified as favorable for gold potential. Experience in mineral exploration shows that truly favorable ground is quite rare. Consequently, and based on the results of previous geochemical exploration work in the area, two other criteria were implemented to discriminate between zones that are unfavorable for gold mineralization potential and zones that are favorable. First, the area of geologically favorable zones should not be greater than the average area of the geochemical anomalies. Smaller areas mean higher probabilities for locating mineralization. In addition, experience shows that significant geochemical anomalies have wider areal extent than the truly mineralized zones with which they area associated. Second, the geologically favorable zones should predict a higher percentage of the known gold occurrences. If the geologically-constrained mineral potential mapping described here is to be more reliable than grassroots exploration techniques, then its higher prediction or success rate has to be demonstrated.

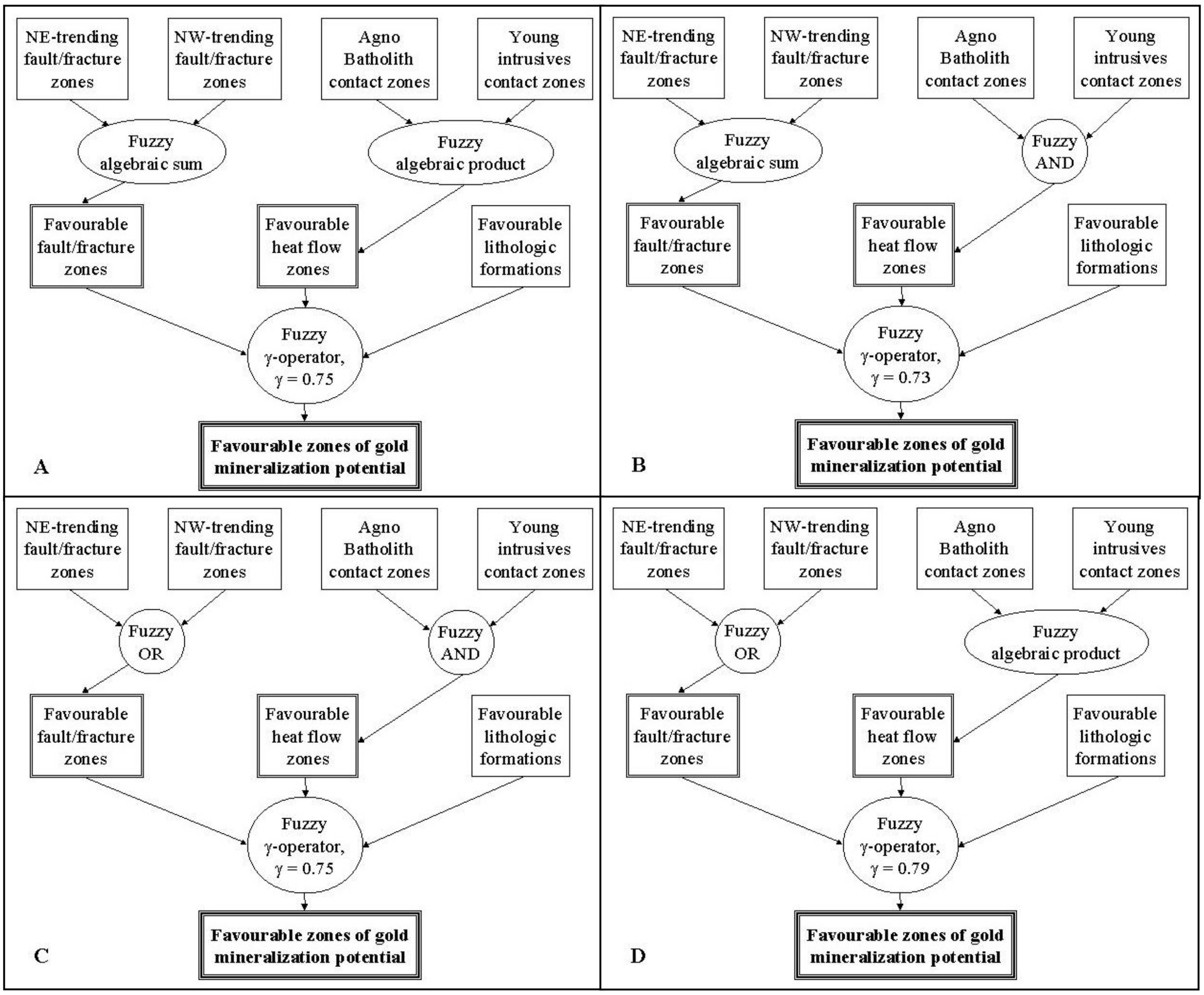

Fig. 6. Inference networks for producing fuzzy predictive map of gold potential shown in (a) Fig. 5A, (b) Fig. 5B, (c) Fig. 5C and (d) Fig. 5D. See Fig. 4 for explanation of box borderlines.

Validation of the results

The results are validated for two reasons. First, to demonstrate that the geologically-constrained mineral potential mapping described here is equally or more reliable than grassroots exploration techniques. Second, to demonstrate that the predictive maps are capable of locating accurately not only the known gold occurrences used to develop the predictive maps but also “unknown” occurrences.

For the first validation objective, the results of the geologically-constrained fuzzy mapping of gold potential are compared with the results of previous geochemical exploration work in the area. The predictive maps show two potential zones favorable for gold mineralization, one at the northern section and the other at the central section of the study area. These two predicted geologically favorable zones coincide spatially with two geochemically-anomalous zones for stream sediment Au (Fig. 5) and Ag contents (see Fig. 2b). There is more than 50% spatial coincidence between the predicted geologically favorable zones and the geochemically-anomalous zones except for the As geochemical anomaly. These pieces of geoinformation suggest that the method described here is capable of mapping zones of mineral exploration interest that are comparable to favorable zones defined by significant stream sediment geochemical anomalies.

For the second validation objective, we determine whether the predictive maps are capable of predicting accurately locations of “unknown” or “undiscovered” gold occurrences. The “unknown” or “undiscovered” gold occurrences we refer to are 63 known gold occurrences worked by the local people through small-scale mining operations. These “unknown” occurrences were not used to develop the predictive maps shown in Fig. 5 and therefore provide a more convincing validation of the results. The predictive maps delineate at least 76% of the “unknown” occurrences (Table 3). In the predictive maps, the unpredicted “unknown” occurrences are on average less than 900 m from the delineated favorable zones. The predictive maps predict between 75 and 92% of the “unknown” occurrences reflected by the geochemical anomalies (Table 4). The predictive maps predict between 30 and 80% of “unknown” occurrences that fall within geochemically non-anomalous zones (Table 5). These pieces of geoinformation show that the predictive maps have prediction rates for the “unknown” occurrences that are similar or even better than the prediction rates for the known occurrences.

Analysis of the fuzzy inference networks

The best fuzzy inference networks (Fig. 6) used to produce the best and the 'next best' predictive maps (Fig. 5) show a number of striking features. First striking feature, the fuzzy sets of intrusive contact zones are best combined only by using either the fuzzy algebraic product or the fuzzy AND operator. These operators are appropriate where two or more pieces of evidence for a hypothesis must be present together for the hypothesis to be true. Indeed, both the Agno Batholith and the younger intrusives are together important for the deposition of economic gold mineralization in the Baguio district (Wolfe, 1988; Fernandez and Damasco, 1979). The second striking feature, the fuzzy sets of fault/fracture zones, are best combined only by using either the fuzzy algebraic sum or the fuzzy OR operator. These operators are appropriate where two or more pieces of evidence complement one another although the presence of any of the evidences may be sufficient to suggest favorability. In the Baguio district, the northeast-trending faults are interpreted as conjugate shears with the northwest-trending left-lateral strike-slip faults (Balce *et al*., 1980). Hence, both sets of faults are complementary although it is not necessary that both sets are present at a particular location for gold deposition to occur. The third striking feature, the fuzzy set of lithologic formations and intermediate fuzzy sets of fault/fracture and heat flow zones, are best combined only by using the fuzzy γ-operator with very similar values of γ that range between 0.7 and 0.8. The values of γ used to produce the best predictive maps (Fig. 5) imply that the evidences used complement one another and that they should not be taken individually. Indeed, all the three evidences or factors used (i.e., heat sources, channelways and host rock) are important for the deposition of economic gold mineralization in the Baguio district (Wolfe, 1988; Fernandez and Damasco, 1979).

CONCLUSIONS

1. The application of the theory of fuzzy sets to mineral potential mapping provides a quantitative yet subjective technique for predicting mineral potential where a number of mineral occurrences are known.

2. A qualitative and quantitative knowledge of the spatial association between known mineral occurrences and geological features in an area is important for mineral potential mapping.

3. The qualitative and quantitative knowledge of spatial association between known mineral occurrences and geological features are together useful in the subjective decision on the appropriate fuzzy membership functions or scores. A qualitative knowledge alone may have proven inadequate to produce a fuzzy predictive map of gold potential for the area.

4. The best predictive maps produced by this study are comparable with the results of previous geochemical work. These maps predict at least 76% of the “unknown” occurrences. These maps can be used to direct exploration work to search for undiscovered occurrences in the area.

5. The design of the fuzzy inference network to combine the evidences for mapping mineral potential must be based upon the knowledge of the genesis or mode of formation of known mineralization in a particular area.

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