

# 3D Metallogenic Prediction Research based on GFH Analysis Method

Song Huang, Yuling Xie, Huaming An

**Abstract**—In this paper, we systematically developed a three-dimensional quantitative metallogenic prognosis system for concealed ore bodies based on spatial data mining. We collected detailed geology information and constructed a multiple-source geology database. Based on the geology database, major ore-controlling factors were defined using correlation analysis between current mineralized ore bodies and all related geology information, which included strata, faults, mineralization, mineral density, geophysics, geochemistry, etc. The new Grey-Fuzzy-Hierarchy (GFH) analysis method, a typical combined method including Grey relational, Fuzzy comprehensive evaluation and Hierarchy analytic process theories, was applied for the determination of the corresponding weights for all major ore-controlling factors. Finally, mineralization advantage degree (MAD) values were obtained and the three potential mineralization target areas were determined. Related high MAD value blocks were visually displayed and reported as the guide of future exploration strategy. The research achievements can also be used as a reference for further research on 3D metallogenic prediction fields.

**Index Terms**—Metallogenic prediction, Ore-controlling factor, Correlation analysis, Grey rational analysis, Fuzzy theory, Hierarchy analysis

## I. INTRODUCTION

At present, the deep extraction and comprehensive analysis of the information related to the formation of mineral deposits, such as basic geological information, geophysical information, geochemical information, and remote sensing, are important for the three-dimensional prediction of mineral resources. Using massive geological multi-source databases has become an urgent task to process and analyze the data in a timely manner to serve the prediction work of mineral resources. Spatial data mining technology has naturally drawn more attention from geologists and scholars. By using the spatial data mining techniques we can automatically and efficiently discover the hidden rules and patterns in the basic geological information, and the method of quantifying information can also enhance the data analysis ability and reduce the randomness. The application of spatial data mining technologies in the field of geoscience has gained more attention and motivate more scholars and experts to develop various research methods [1].

Three-dimensional visualization metallogenic prediction

technology which based on spatial data mining is a combination product of geology, mineral exploration, geographic information systems, database technology, spatial data mining technology, machine learning, pattern recognition, and visualization technology. It combines traditional metallogenic prediction processes and spatial data mining processes with visualization technology, using the multi-source geological spatial database as the data source, analyzing the relationship between various data sources, extracting favorable indexes for mineralization, selecting the appropriate spatial data mining methods, excavating the hidden mineral distribution information, and can be displayed visually [2], [3].

With the development of computer and GIS technology, the prediction method of mineral resources has gradually evolved from traditional qualitative analysis to semi-quantitative and quantitative predictions. The quantitative prediction of mineral resources is the application of computer and mathematical knowledge to geological problems, making the prediction of mineral resources more efficient, objective and accurate. There are many theories and methods for the quantitative prediction of mineral resources, such as multivariate statistical methods, fuzzy mathematical methods, analytic hierarchy processes, Grey theory, artificial neural networks, fractal theory, evidence weight methods, information quantity methods, etc. In this study, we mainly used the fuzzy comprehensive evaluation model, the analytic hierarchy process model, and the Grey rational systematical theory to set up a completely new method of GFH analysis to study the selected related projects.

## II. ANALYSIS FLOWCHART

The original data for GFH analysis include basic geological database, basic geological 3D model database, and basic 3D metallogenic factors database. In the process of selecting three-dimensional ore controlling factors, all the potential ore controlling factors should be extracted from the source geological database, and the acceptability is judged and confirmed by the correlation analysis with the actually exposed ore bodies. In the process of three-dimensional metallogenic prognoses, a key problem is the determination of the weights set, which determines the reliability of the result of GFH analysis to a certain extent. Since there are no widely accepted methods to generate weights, it's subjective to choose each independent method. In view of the above problems, a combination weighting method based on the combination of subjective and objective weights was proposed to assign values for the three-dimensional quantitative metallogenic prediction indexes. The grey relational method was used to analyze the influence degree of

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the ore controlling factors on the mineralization, and then the hierarchical analysis model was used to quantify the importance of the ore controlling factors in the prediction of the concealed ore bodies, which could better solve the problem that the prediction indexes are difficult to be quantified and count accurately, so that the prediction results are more accurate. The overall technical research flowchart adopted in this study is shown in Fig 1 as below:

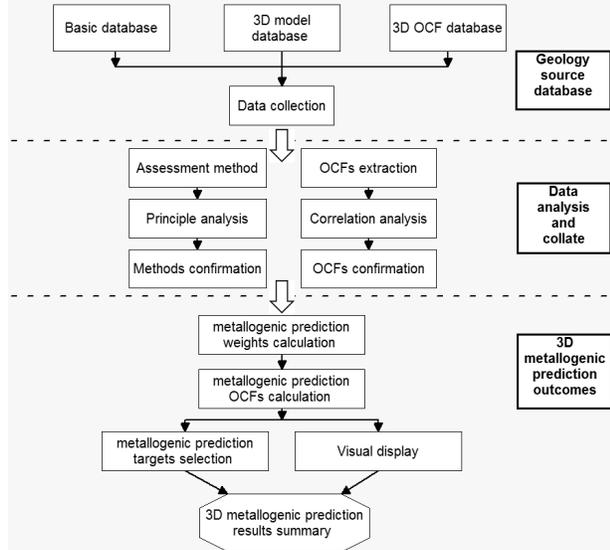


Fig. 1. Overall flowchart of 3D metallogenic prediction research

### III. ORE-CONTROLLING FACTORS ANALYSIS

It is necessary for us to fully understand the quantitative relationship between the mineralized distribution and the ore-controlling geological conditions or the ore prospecting criteria (defined as the ore controlling factors, “OCF”) for the prediction of the concealed ore body in the deep and marginal areas of the study area. On the basis of the analysis of ore body metallogenic regularity and original exploration data of the deposit within the study area, geological block models were used primarily, the quantitative and qualitative indexes of geological mineralization controlling functions were extracted, and the mineralized distribution model associated with the index variables of geological control, mineralization type, and the grade distribution index was established. Based on the model, the mineralized distribution of undetected areas such as deep and marginal areas was estimated and predicted. Based on the three-dimensional entity model and block model, the spatial database was used as the original data source. The statistical analysis technique was used to analyze the relationship between the ore-controlling geological factors and the mineralization distribution, and the quantitative analysis results were integrated into the current mine geological spatial database and the index prediction database.

The ore-controlling factors are the ore-controlling geological variable or the ore-finding symbol variable which varies with time and space. It is a quantitative symbol of geological characteristics or geological phenomena. Its extraction and valuation will directly affect the accuracy of the resource prediction results. There are two main types of ore-controlling factors:

1) Quantitative ore-controlling factors: Some survey

results of geological phenomena are directly reflected as continuous variables, such as ore grade and resources, distance, geophysical results such as resistivity and polarization rate and geochemical results, etc. Some geological characteristics are reflected as discrete variables, such as the number of faults within a block and the maximum number of samples searched in a certain radius sphere. The concept of quantity reflected by these two variables is the most important category of ore-controlling factors.

2) Qualitative ore-controlling factors: These mainly define parameters without certain values. These parameters do not have the concept of quantity, and only different geological codes can be used to distinguish them, such as strata, mineralization belt, alteration zone, etc., These parameters are generally labeled in the geological model as "yes" and "no" or "0" and "1" and cannot be further described in detail in the same type of geologic parameter code. On one hand, we can use these parameters as direct constraint conditions to calibrate the mineralization degree of a potential area; on the other hand, we can combine the relevant quantitative data to define new complex geological ore-controlling factors to guide the analysis of ore-forming prediction.

Through the detailed analysis and summary of the geological background and metallogenic regularity of this research area, the summary table of all potential ore-controlling factors for the prediction model of concealed deposit in the Shambesai Gold Deposit is as below in Table I.

TABLE I  
ORE-CONTROLLING FACTORS SUMMARY

ORE-CONTROLLING factors category	ORE-CONTROLLING factors	Main content
Tectonic position	tectonic domain	South Tianshan orogenic Belt - Turkestan-Alai segment
	Division of metallogenic belts	Shambesai main mineralization belt, secondary mineralization belt
Ore-forming Strata	Stratum	Quaternary sediments, Middle Carboniferous Tolubay Formation, Middle Carboniferous Pyrkaf Formation, early Silurian sediments
	Ore-bearing rock formation	Fine-grained sediments mainly composed of siltstone and carbonate rocks
	Ore-containing rocks	Pyrkaf Limestone formation
Ore-controlling structure	Enrichment positioning conditions	magmatic metamorphism, tectonic reverse thrusting action
	Tectonic geological body	Multi-stage formation of complex fault structures
	Magmatic Rock activity	Two magmatic events in the western Tianshan Mountain Zone
Mineralization characteristics	Metallogenic Age	Early Permian (290 - 280 Ma)
	Ore Minerals	Chalcopyrite, barite, cinnabar, antimonite, arsenopyrite, realgar, gamboge, Galena, malachite, chalcopyrite, limonite, hematite, goethite
	Gangue Minerals	Calcite, quartz, fluorite, pyrite, gypsum, sulfur, green curtain stone, chlorite, Sericite, kaolinite, Graphite,
	Ore structure	Veinlets, veins, reticular, disseminated, etc.
	Orebody morphology	stratiform, stratiform-like, veins
Orebody characteristics	ore body orientation	Main ore body striking NE 90°, Dipping South 30°-50°, plunging 10°-20°
	Orebody size	The main orebody's west-east extension is 1000 m, and north-south extension is 500 m.
Alteration of the surrounding rock		The types of alteration that can be observed in the research area are silicification, carbonization, argillization, kaolinization, sericitization, chloritization, etc.
Surface oxidation Zone		Oxidation zone, oxidation sulfidation transition zone, sulfidation zone
Geophysical characteristics		Anomaly zone of apparent resistivity and polarization of local deposit range
Geochemical characteristics		Anomaly areas of various elements

## IV. ORE-CONTROLLING FACTORS SELECTION

According to ore-controlling factors summary Table I and the actual data collected from the deposit area, the main considered potential three-dimensional prediction indexes of concealed ore body in the deposit are determined which include index of strata lithology ore-controlling factors, the index of faults ore-controlling factors, the index of geophysical and chemical ore-controlling factors, the index of typical minerals distribution ore-controlling factors and the index of geological statistics of ore body. In order to analyze the ore-controlling factors and carry out quantitative and qualitative analysis, the spatial distance and distribution density analysis method was used on the basis of three-dimensional solid models and geological parameter estimation block models of geological deposits. Most of the major factors are illustrated in Fig 2.

By using spatial data mining methods such as spatial correlation analysis and statistical analysis, the relationships between ore-controlling factors such as strata information, faults information, geophysical information, geochemical information and mineral distribution density in three-dimensional geological space were analyzed and judged quantitatively, and then the main evaluation and utilization indexes for the three-dimensional metallogenic prediction of concealed ore body in the deep level of the mine were determined.

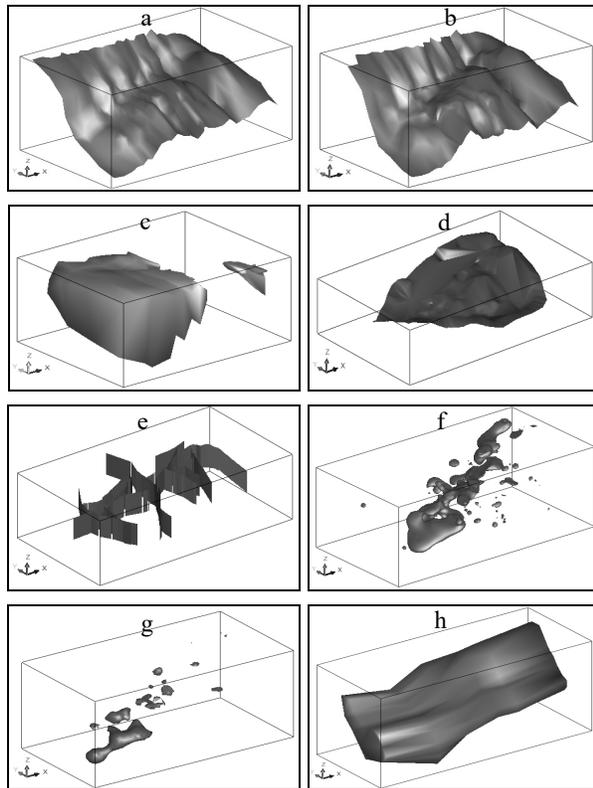


Fig. 2. Main ore controlling factors models (a: Pyrkaif bottom; b: Tolubay bottom; c: Silurian model; d: Quaternary surface; e: Faults; f: Geochemical Arsenic anomaly; g: Mercury anomaly; h: Geophysical model)

Although the types of data sources are different in the fields of lithology, fault, geophysics, geochemistry, and minerals distribution density, similar analytical methods were applied. For example, the relationship between the stratigraphic distance field and the distribution of mineralized block in Pyrkaif strata model is analyzed below which

provides a detailed description of the process of identifying the ore-controlling indexes.

The correlation analysis and T-test methods were used to extract the ore investigation information of ore-controlling factors and the relationship with the distribution of mineralization, the main factor set of the three-dimensional metallogenic prognosis evaluation of the Shambesai deposit are finally determined, as shown in the below Table II.

TABLE II  
FINAL SELECTED ORE-CONTROLLING FACTOR

No.	Variable	Description	Type	Data Source
1	Dis_py	Strata Pyrkaif distance field	real	Pyrkaif strata model (3dm_pyrkaif.dtm)
2	Dis_to	Strata Tolubai distance field	real	Tolubai strata model (3dm_tolubai.dtm)
3	Dis_si	Strata Silurian distance field	real	Silurian (si.dtm)
4	Dis_fault	Faults distance field	real	Faults model (faults.dtm)
5	Dis_geop	Geophysical distance field	real	Geophysical anomaly model (geo_model.dtm)
6	Dis_geoc_as	Geochemical distance field	real	Geochemical anomaly model (geoc_model.dtm)

## V. 3D METALLOGENIC PREDICTION ANALYSIS METHODS

Grey relational analysis is an important part of the grey system theory founded by Professor Deng J.L in the 1980s and is based on the prediction of the Grey Dynamic Model (GM) [4]. In recent years, the grey systematical theory has aroused wide attention of many scholars globally and has been successfully applied in many fields, such as social science, economic management, meteorology, environment, system engineering and so on [5]-[8]. Since the introduction of geological field, it has been considered as an effective way to solve the large scale quantitative metallogenic prognosis with the advantages of fewer requirements, simple calculation and high prediction precision [9]. It has been applied in the deposits' deep area metallogenic prospect prediction of some mining areas and satisfactory outcomes have been achieved. The comprehensive evaluation of the research object is mostly referring to the sequencing of multiple objects, that is to say, the optimal order is selected among the objects. The basic idea of grey relational analysis is to judge the correlation based on the similarity of the geometric shape of the sequence curves. The closer the curve is, the greater the correlation degree between the sequences will be, and on the contrary, the correlation degree will be less. According to the degree of correlation, we can make an advantage analysis between the sequences, so as to know the influence extent of many different influence factors [10], [11]. The grey relational degree is mainly based on (1):

$$R = EW \quad (1)$$

In the above formula,  $R = [r_1, r_2, \dots, r_n]^T$  is n comprehensive evaluation results vector;  $W = (w_1, w_2, \dots, w_m)$  is weight assignment vector of evaluation indexes, and,  $\sum w_j = 1$  is assignment matrix of all indexes, the matrix format is as (2):

$$E = \begin{bmatrix} e_1(1) & e_1(2) & \dots & e_1(m) \\ e_2(1) & e_2(2) & \dots & e_2(m) \\ \dots & \dots & \dots & \dots \\ e_n(1) & e_n(2) & \dots & e_n(m) \end{bmatrix} \quad (2)$$

The main procedure of calculation is:

1) Determine the evaluation index system and collect the evaluation data according to the purpose of the evaluation.

The reference data column is selected and the reference data column should be an ideal comparison standard. The reference data can be sourced from the optimal values (or the worst values) of each index, and the other reference values can also be selected according to the purpose of the evaluation.

2) Dimensionless data series are created and the original data is as (3).

$$(x_1, x_2, \dots, x_n) = \begin{bmatrix} x_0(1), & x_1(1), & \dots & x_n(1), \\ x_0(2), & x_1(2), & \dots & x_n(2), \\ \dots & \dots & \dots & \dots \\ x_0(m), & \dots & \dots & x_n(m) \end{bmatrix} \quad (3)$$

The commonly used dimensionless methods include averaging, initialization, and transformation.

$$x_i(k) = (x'_i(k)) / (\frac{1}{m} \sum_{k=1}^m x'_i(k)) \quad (4)$$

$$x_i(k) = x'_i(k) / x'_i(l) \quad (5)$$

In the above (4) and (5),  $i = 0, 1, \dots, n; k = 0, 1, \dots, m$

The absolute difference values of each sequence of each target assessment index (comparison sequence) and the corresponding values of the reference sequence are calculated one by one, then  $\min_{i=1}^n \min_{k=1}^m (x_0(k) - x_i(k))$  and  $\max_{i=1}^n \max_{k=1}^m (x_0(k) - x_i(k))$  are determined.

The correlation coefficients of each comparison sequence and the corresponding values of the reference sequence are calculated respectively as (6).

$$e_i(k) = \frac{\min_{i=1}^n \min_{k=1}^m (x_0(k) - x_i(k)) + \rho \max_{i=1}^n \max_{k=1}^m (x_0(k) - x_i(k))}{(x_0(k) - x_i(k)) + \rho \max_{i=1}^n \max_{k=1}^m (x_0(k) - x_i(k))} \quad (6)$$

In the above equation,  $\rho$  is the identification coefficient, with values between (0, 1) commonly  $\rho$  value of 0.5 is selected. Each evaluation object (comparison sequence) is used to calculate the mean value of the correlation coefficient between the index and the reference sequence to reflect the relationship between the evaluation object and the reference sequence, and it is called the correlation degree, and recorded as (7):

$$r_i = \frac{1}{m} \sum_{k=1}^m e_i(k) \quad (7)$$

Analytic Hierarchy Process (AHP) is a kind of method that can make a decision on some more complex and fuzzy problems [12]-[14]. It is especially suitable for the problem which is difficult to carry out a complete quantitative analysis. It is a simple, flexible and practical multi-criteria decision-making method put forward by T. L. Saaty, an American operational research professor in the early 1970s [15]-[17].

There are four main steps in AHP modeling: 1) to establish a hierarchical structure model; 2) to construct all levels judgment matrixes; 3) single ranking and consistency check; 4) total ranking and consistency check.

A fuzzy analytic hierarchy process is used for the research. This fuzzy analytic hierarchy process adopts the fuzzy consistent judgment matrix to replace the original 2 by 2 comparison judgment matrix, thus the consistency problem of the judgment matrix can be solved. This method is easier to be mastered and it meets the accuracy requirement. The specific process is as follows:

1) The target set is divided into different sets of factors  $U_1, U_2, \dots, U_m$  and there is no intersection between the sub-sets.

2) Calculate the weight vector of an index, including the

weight of each subset's relationship and the weight of the internal influence factors of each sub-set.

The conversion process is mainly based on (8) and (9):

$$q = \sum_{j=1}^m f_{ij} (i = 1, 2, \dots, n) \quad (8)$$

$$q_{ij} = \frac{q_i - q_j}{2m} + 0.5 \quad (9)$$

The weight vector is obtained by using row normalization method, the calculation formula is as (10):

$$w_i = (\sum_{j=1}^m q_{ij} - 0.5) / (\sum_{i=1}^n (\sum_{j=1}^m q_{ij} - 0.5)) \quad (10)$$

Or using the method of column summation normalization and row summation normalization, the weight vector value can also be obtained, and finally, the weight vector result can be obtained as below:  $w = (w_1, w_2, \dots, w_m)^T$ .

The fuzzy theory was established by American automation control expert Professor L. A. Zadeh in 1965 [18], [19]. The fuzzy comprehensive evaluation is a comprehensive evaluation of many fuzzy factors, which are closely related to the research objects, and make a comprehensive evaluation in order to get satisfactory results. Evaluation refers to the different evaluation results in accordance with the given conditions; comprehensive, refers to a number of factors contained in the evaluation conditions, and the overall comparison of these factors is necessary. According to fuzzy mathematics theory, fuzzy comprehensive evaluation can be described by the equation  $AR = B$ . In the formula,  $A$  is the weighting set of the evaluation factor, which is a matrix ( $n$  is the total number of evaluation factors);  $R$  is a fuzzy converter, that is, the fuzzy relation matrix ( $n$  as the evaluation level number) is formed by the single factor evaluation row matrix, and  $B$  is a comprehensive evaluation result and is a matrix. Thus, the fuzzy comprehensive evaluation must meet with three conditions:

- (1) The evaluation factors set  $U = \{u_1, u_2, \dots, u_n\}$ ,
- (2) The evaluation decision set  $V = \{v_1, v_2, \dots, v_n\}$ ,
- (3) factor weight set  $A = \{a_1, a_2, \dots, a_n\}$ .

The first level fuzzy comprehensive evaluation process is as follows:

1) Set up the factor set:  $U = \{u_1, u_2, \dots, u_n\}$  of the evaluation objects which is the evaluation indexes system which comprehensively reflects the main factors that affect the attribution of the identified samples.

2) Set up evaluation set:  $V = \{v_1, v_2, \dots, v_n\}$ ; that is, the fuzzy scale set (hazard level or importance degree or risk grade) of the evaluation grade;

3) Establish single factor judgment, identify fuzzy relation, and get fuzzy relation matrix as (11) (single factor evaluation matrix):

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \dots & \dots & \dots & \dots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \quad (11)$$

In the above matrix,  $m$  is the total number of sub-set of evaluation factors,  $n$  is the total number of factor set related to all sub-sets. Thus, a comprehensive  $(U, V, R)$  evaluation model is created.

4) Different weights are assigned for all factors in the judge

factor set  $U$ , which is considered as a fuzzy sub-set  $A = \{a_1, a_2, \dots, a_n\}$  in  $U$  and the condition also meets the requirement of the equation  $\sum a_i = 1$ .

5) Comprehensive evaluation with (12):

$$A.R = B \tag{12}$$

$B = \{b_1, b_2, \dots, b_n\}$  is one fuzzy sub-set of  $V$ , and  $b = \sqrt[n]{\bigwedge_{j=1}^n (w \wedge w_j)}$  ( $j = 1, 2, \dots, m$ ).  $\vee$  means taking the max value and  $\wedge$  means taking minimum value, if  $\sum b_i \neq 1$ , we need to normalize it with (13):

$$B' = [1 / \sum_{i=1}^n b_i] \times (b_1, b_2, \dots, b_n) \tag{13}$$

Then  $B'$  is judged according to the principle of maximum membership and the result is obtained.

In this paper, a combined weighting assignment method combining subjective and objective weighting methods is proposed to evaluate the weights of three-dimensional quantitative metallogenic predictions. The detailed GFH analysis method flowchart is as below Fig 3. The grey relational method is used to analyze the influence degree of the ore controlling factors on the mineralization and determine the memberships of all related factors, and the fuzzy analytic hierarchy model is used to quantify the importance of the ore controlling factors in the prediction of the concealed orebody, which can better solve the problem that the prediction index is difficult to be quantified and counted accurately, so that the prediction results are more accurate.

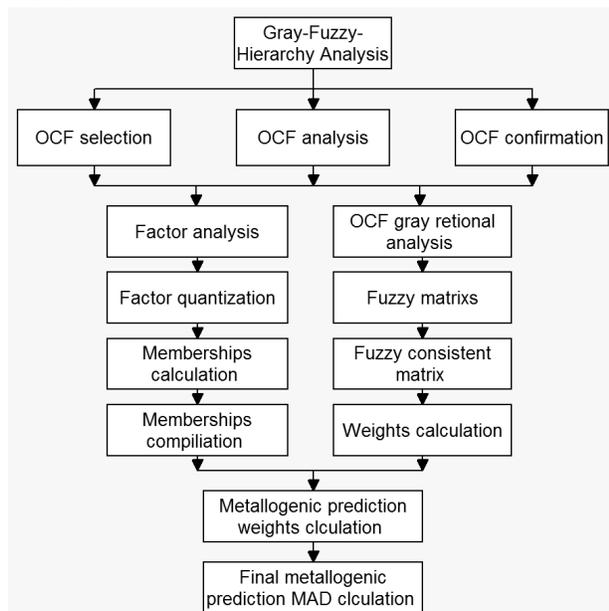


Fig. 3. Flowchart of GFH analysis method

## VI. PREDICTION RESULTS AND ANALYSIS

### A. Results of three-dimensional metallogenic prognosis analysis

The membership function is the first condition for applying the fuzzy comprehensive evaluation method to three-dimensional prediction. How to correctly construct a membership function is very important. Since each prediction index is modeled by three dimensions, the extraction of metallogenic information has been transformed

into quantitative data. Because the units of quantitative data are not uniform, or their numerical coverage is inconsistent, in order to make these data comparable, it needs to be dimensionless and converted to the degree of the membership whose values range in the  $[0,1]$  interval. For the smaller-the better of cost type objects and the larger-the-better of benefit type objects, (14) and (15) were used to transform the relative membership degree matrix  $R = (r_{ij})_{m \times n}$  respectively.

$$r_{ij} = (r_{ij} - r_{i\min}) / (r_{i\max} - r_{i\min}) \tag{14}$$

$$r_{ij} = (r_{i\max} - r_{ij}) / (r_{i\max} - r_{i\min}) \tag{15}$$

In the above formula,  $r_{i\max}$  is selecting maximum value calculation,  $r_{i\min}$  is selecting minimum value calculation.

For the decision whether we use the selecting maximum value calculation or selecting minimum value calculation to normalize the data to get the assessment memberships, we referred to the statistical correlation between the ore-controlling factors and the mineralization distribution, and establish the regression equation of the mineralization distribution and the ore-controlling factors. If the regression analysis is significant, it can be considered that the geological variable can be used as a judging factor. The positive and negative correlations between mineralization distribution and geological variables can be judged by using the positive and negative of the coefficient B1 of the regression equation. If  $B1 > 0$ , the positive values indicate a positive correlation between the mineralized distribution and the geological variables, the geological variable should be calculated with a selecting maximum value calculation method. If  $B1 < 0$ , the negative values indicate a negative correlation between the mineralized distribution and the geological variable should be calculated with a selecting minimum value calculation method. All the unknown mineralized blocks are converted to calculate the fuzzy relation matrix of the prediction indexes.

### B. Analysis of membership degree by the grey relational method

We define the mineralized distribution of the exploration area in the 3D metallogenic prediction index database as the parent sequence, and the index set of the hidden ore-controlling factors listed in the table were used as the subsequence to calculate the correlation between the subsequence and the parent sequence. As a measure of the correlation measurement among the factors within the system, the greater the correlation degree, the more closely the relative ore-controlling factors and mineralization are related which means that the greater influence of the ore-controlling factors to the mineralization. According to equation (6), the correlation coefficient between the sequences of each comprehensive evaluation matrix of each block is calculated in all the prediction-index data. In the prediction index database, the total number of block units of the experimental area is 488,225, and the scattered information is not enough to support for comparison. Therefore, it is necessary to concentrate the correlation coefficient of the factor values of each sub-block unit into fixed value. In this study, we used the average value method as a solution for information concentration processing, which is equal to an absolute correlation degree. The general expression is  $r_i = (1/n) \sum_{k=1}^n \mathcal{E}_i(k)$ .

Absolute correlation is an index reflecting the degree of

correlation between different objects, and it can indicate the correlation between factors. Through statistical calculation, the absolute correlation degree between each mineralization factor and Au element distribution is obtained, and the final results are listed in the below Table 3.

The relationship between ore-controlling factors and mineralization is listed in the table above. The greater the correlation is, the more important it is for metallogenic prognosis. From included data, we can see that among all critical ore-controlling factors, stratigraphic data (Pyrkaf formation) and fault data are most important for ore prospecting, followed by stratigraphic data (Tolubay formation) and geophysical data. The Silurian strata and geochemical data have less influence on mineralization.

TABLE III  
AU MINERALIZATION CORRELATION SUMMARY

Ore-controlling factors	Code	Au mineralization correlation degree
Dis_py	C1	0.825
Dis_to	C2	0.783
Dis_si	C4	0.736
Dis_fault	C5	0.807
Dis_geop	C6	0.796
Dis_geoc_as	C3	0.771

C. Fuzzy analytic hierarchy process analysis of index weight values

(1) According to the process of the fuzzy hierarchy evaluation method introduced in previous chapters, the fuzzy complementary matrix is constructed by us for this research project. According to the correlation degree of various ore-controlling factors, six ore-controlling indexes are compared and the fuzzy complementary matrix is constructed as below Table IV.

(2) Then the fuzzy complementary matrix was transformed into a fuzzy consistent matrix as below Table V.

TABLE IV  
ORE-CONTROLLING FACTORS FUZZY COMPLEMENTARY MATRIX

Ore-controlling factors	C1	C2	C3	C4	C5	C6
C1	0.5	0.7	0.9	0.9	0.7	0.7
C2	0.3	0.5	0.7	0.9	0.5	0.5
C3	0.1	0.3	0.5	0.7	0.3	0.3
C4	0.1	0.1	0.3	0.5	0.3	0.3
C5	0.3	0.5	0.7	0.7	0.5	0.5
C6	0.3	0.5	0.7	0.7	0.5	0.5

TABLE V  
ORE-CONTROLLING FACTORS FUZZY CONSISTENT MATRIX

Ore-controlling factors	C1	C2	C3	C4	C5	C6
C1	0.50	0.58	0.68	0.73	0.60	0.60
C2	0.42	0.50	0.60	0.65	0.52	0.52
C3	0.32	0.40	0.50	0.55	0.42	0.42
C4	0.27	0.35	0.45	0.50	0.37	0.37
C5	0.40	0.48	0.58	0.63	0.50	0.50
C6	0.40	0.48	0.58	0.63	0.50	0.50

(3) According to (10), the weight vector of the fuzzy synthetic judgment model was obtained as (16):

$$A = (0.213, 0.180, 0.140, 0.120, 0.173, 0.173)^T \tag{16}$$

According to the equation (10), we constructed the parameter min\_ratio of the block model and used the weighted average calculation method to calculate the membership degree of the forecast area. The (17) was used for the weighting calculation and the results were stored in the geological database:

$$\begin{aligned} \text{min\_ratio} = & 0.213 * \text{nor\_py} + 0.18 * \text{nor\_to} + 0.14 * \text{nor\_si} + \\ & 0.12 * \text{nor\_fault} + 0.173 * \text{nor\_geop} + 0.173 * \text{nor\_geoc\_as} \end{aligned} \tag{17}$$

We can make a conclusion from Table VI that the advantage degrees of mineralization of Au is more than 0.5 for about 80% of the total blocks, and more than 0.8 for 30% of the total blocks.

TABLE VI  
STATISTICAL RESULTS OF MINERALIZATION ADVANTAGE DEGREE FOR MINERALIZATION UNITS

Analyze items	Au mineralization degree	
Minimum	0.12	
Maximum	0.97	
	10%	0.46
	20%	0.56
	30%	0.63
	40%	0.69
Accumulative percentage	50%	0.74
	60%	0.78
	70%	0.82
	80%	0.85
	90%	0.9

There is a certain relationship between the mineralizing indexes and the ore controlling factor set, which can be expressed by the mathematical model of mapping (such as linear regression model). We tried to establish the multivariate linear regression equation with the mineralized grade as the dependent variable and applied it to the auxiliary verification process of the potential target location of the three-dimensional metallogenic prognoses.

SPSS software was used to conduct multiple regression analyses of ore controlling factors. In this paper, the ore block is selected as the research object, and the relationship between 6 normalized ore-controlling factors and ore body evaluation grades were researched. The parameters of the multivariate linear regression model obtained were listed in below Table VII:

TABLE VII  
LINEAR REGRESSION COEFFICIENT SUMMARY

Regression coefficient	Standard Deviation	Sig.	
B1	-21.544	3.896	0.000
nor_py	-1.592	0.384	0.000
nor_to	9.615	0.771	0.000
nor_si	-5.496	1.985	0.006
nor_fault	3.909	0.375	0.000
nor_geop	-2.187	0.298	0.000
nor_geoc_as	19.938	3.075	0.000

Based on the above regression coefficients summary data, we can get 6 variables regression formula is as (18) which can only need be referred for the determination of potential target areas.

$$\begin{aligned} u = & -21.544 - 1.592 * \text{nor\_py} + 9.615 * \text{nor\_to} - 5.496 * \text{nor\_si} + \\ & 3.909 * \text{nor\_fault} - 2.187 * \text{nor\_geop} + 19.938 * \text{nor\_geoc\_as} \end{aligned} \tag{18}$$

VII. PREDICTION RESULTS 2D AND 3D VISUALIZATION

In the previous sections of the paper, we only used a special distance field and samples special distribution density data as judgment tools. All ore-controlling factors were considered for all blocks inside the created block model. Some extra constraints need be taken into account for the definition of actual potential mineralized blocks. These constraints include:

- 1) The highest priority constraint which we used is just the

mineralization advantage degree we calculated in previous sections. This is the main indicator parameter for differentiating the low and high potential mineralization areas. According to the accumulative percentage statistics results, 0.9 of MAD is considered to be used as the constraint with which the 10% highest MAD values of all un-detected blocks were retained and will be mainly used for the final definition of exploration target areas. (Min\_ratio  $\geq$  0.9)

2) All blocks above topography DTM has been assigned as code = air and should be excluded from consideration scope. (Type  $\neq$  air)

3) All un-mineralized or low-grade samples were not included in the consideration. All these samples with grades lower than geological cut-off grade should be assigned proper negative weight in the mineralization advantage degree calculation. We chose another alternative approach to involve the influence of these outside samples with which we excluded all sub-blocks whose distances to closed samples are less than 50m. (Dis\_hole  $>$  50)

4) For the overall distribution of the potential targets, the geological cut-off grade 1g/t is still necessary to be applied for constraining the displayed target areas. (Au\_prospect  $\geq$  1)

5) For those sporadically distributed blocks whose scales are not enough to support any economic mining activities, we excluded them from the potential target areas list as it's meaningless to define these tiny high mineralization advantage degree spots which will never be potentially economically extractable. A specific boundary string was created to cover the main three clustered areas. (Block inside string target\_area.str)

Based on the above five constraints, all the blocks which meet with the requirements are displayed as an inclined map as below Fig 4,

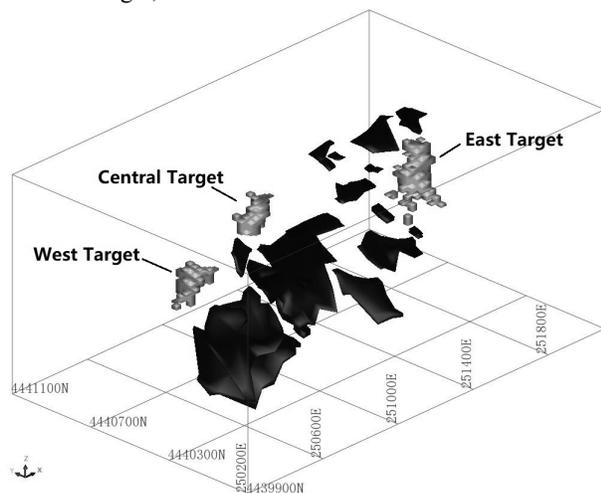


Fig. 4 - Potential targets location inclined map

According to the displayed results of the high mineralization advantage degree target areas, there are mainly three high mineralization advantage degree value areas defined based on the created 3D metallogenic prediction block model which include the west target area, central target area, and east target area. The total volume of the three target areas takes approximately 10% of the total volume of all un-detected areas and the overall mineralization advantage degrees are more than 90%. As we

analyzed in ore-controlling factor sections, the high mineralization advantage degrees indicated the high weighted average values combined with all the selected valuable ore-controlling factors including strata Tolubay, Pyrkaf, and Silurian, faults, geophysical anomaly area and geochemical As anomaly area.

Referring to similar type gold deposits which are located at the same mineralization belts such as Kumtor, Muruntau, Zamitan gold deposits, and an approximate density value of 2.9 was assigned for all potential mineralized blocks for the potential resource quantity reporting. The final tonnage and grade results were reported by target areas as below Table VIII,

TABLE VIII  
POTENTIAL RESOURCE QUANTITY BY TARGET AREAS

Target	Volume (m <sup>3</sup> )	Tones (t)	Au Prospect (g/t)	Metal(t)
West	4,772,500	13,840,250	1.99	27.54
Central	2,122,500	6,155,250	1.87	11.51
East	2,572,500	7,460,250	2.19	16.34
Total	9,467,500	27,455,750	2.02	55.46

According to the resource report, there are potential of 55 t gold metal located at three potential target areas. The numbers for the resource quantity are just highly predicted data and the more detailed resource numbers and extract distribution location still need further exploration works to confirm. All the contents in the table can still be used as the guide of the research of local mineralization distribution and the compilation of the next stage exploration plan.

## VIII. DISCUSSION

The Carlin-type gold deposits are mainly formed in intracontinental rift zones and back-arc basins. The Carlin-type deposits contain gold mineralization in a wide range of ore-bearing rocks, and related lithology is mainly marine sedimentary rocks, impure carbonate rocks, and fine-grained rocks. The strata and structures are the main factors, in local areas, the structural fracture contact zones are the main mineralization controlling structures or containers and mineralized liquid migration passes at the beginning of the formation of the deposit. In the paper, structural faults and strata layers of Tolubay and Pyrkaf were concluded as the main ore-controlling factors, and the distribution locations of contact areas of different strata layers are also consistent with the distribution characteristics of typical mineral distribution density, the geophysical anomaly, and geochemical anomaly. All the selected ore-controlling factors are highly correlated with the group of ore controlling structure. The location relationship of the final targets and main related ore-controlling factors are included in the below figure. All the east, west and central mineralization target areas are located at the contact zone between the Tolubay bottom surface and Pyrkaf bottom surface, or between the south Silurian 3DM and Pyrkaf bottom surface. The high MAD blocks area highly correlated with the distribution of structural faults as well. There are 2 main S-N string faults which are directly crossing the central part of the west and central targets, 2 sub-NW-SE faults are intersected with the east deep target as well. Based on the comparison results of the actual geological information characteristics and final analysis results, we can conclude that the selected ore-controlling factors are proper and can be used for the correct and efficient extraction of useful 3D metallogenic

prediction critical information.

In the fuzzy comprehensive evaluation process, the critical step is the determination of the weights. Most of the time, the subjective method mainly based on researchers' experience and objective method main based on the fixed data. Both determinations of the weights methods should be adjusted to be in accordance with the current research purpose. Thus, after applying the grey relational theory for the calculation of membership values of selected ore-controlling factors, the new developed fuzzy hierarchy analysis method was applied for the calculation of weights based on creating the fuzzy matrix and consistent matrix. The weights were calculated with a reasonable approach in which the subjective and objective influence factors were all considered properly.

For the selection and extraction of ore-controlling factors, on one hand, the relatively low influence factors may need to be considered and involved in the final calculation once any local geological condition changed; one the other hand, besides the distance and density fields were considered as the analysis source, the other type of original data may need be considered such as direction field extracted from the variogram ellipse analysis, and orientation characteristics of different geology solids, etc. For the GFH analysis method, the analysis procedure is still potential to be adjusted and optimized, other new developed analysis methods such as chaos theory, neural network theory could be absorbed into the current analysis system.

#### IX. CONCLUSION

A three-dimensional quantitative metallogenic prognosis system for concealed ore bodies based on spatial data mining is systematically put forward. In this paper, the author used different spatial data mining methods to establish a three-dimensional prediction model based on multiple source geospatial databases. Through the comparison and analysis of the prediction results, the three-dimensional quantitative prediction of the concealed ore body of the Shambesai gold deposit is been researched for the first time, and the prospecting target areas at the deep and edge areas of the mining area has been determined.

The ore body-related ore-controlling factors were analyzed with the correlation relationship analysis method. Six major ore-controlling factors were selected from all defined factors and all these most important ore-controlling factors were directly used for the weighted calculation of mineralization advantage degree for the later 3D metallogenic prediction research.

The grey system theory, fuzzy mathematics theory, and the analytic hierarchy process are applied for the three-dimensional quantitative prediction of the concealed ore body creatively, and a three-dimensional quantitative prediction block model is established for the concealed ore body. This is a new attempt in resource forecasting technology.

A Grey relational method and fuzzy analytic hierarchy process were introduced to construct the weight coefficient of the mineral resources prediction index. In the past, the weight of the mineral resources prediction evaluation index is basically through expert scoring method or artificial determination. Due to the complexity and uncertainty of

geological ore controlling factors, the weight values are often difficult to be accurately determined; and the objective method of weight assignment may be contrary to the actual situation. Based on the above reasons, in the new developed GFH analysis method, the subjective and objective methods of the assignment were all considered as a combined solution to avoid the defects of the objective and assignment method.

Finally, based on proper selected ore-controlling factors, the GFH comprehensive analysis method was used for the determination of all weights for each factor. The final calculated mineralization advantage degree values which were calculated from weights and membership values were used for the determination of the three main potential mineralization target areas.

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