

## Research paper

## GeoCube: A 3D mineral resources quantitative prediction and assessment system

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## ABSTRACT

This paper introduces a software system (GeoCube) for three dimensional (3D) extraction and integration of exploration criteria from spatial data. The software system contains four key modules: (1) Import and Export, supporting many formats from commercial 3D geological modeling software and offering various export options; (2) pre-process, containing basic statistics and fractal/multi-fractal methods (concentration–volume (C–V) fractal method) for extraction of exploration criteria from spatial data (i.e., separation of geological, geochemical and geophysical anomalies from background values in 3D space); (3) assessment, supporting five data-driven integration methods (viz., information entropy, logistic regression, ordinary weights of evidence, weighted weights of evidence, boost weights of evidence) for integration of exploration criteria; and (4) post-process, for classifying integration outcomes into several levels based on mineralization potentiality. The Nanihu Mo (W) camp (5.0 km × 4.0 km × 2.7 km) of the Luanchuan region was used as a case study. The results show that GeoCube can enhance the use of 3D geological modeling to store, retrieve, process, display, analyze and integrate exploration criteria. Furthermore, it was found that the ordinary weights of evidence, boost weights of evidence and logistic regression methods showed superior performance as integration tools for exploration targeting in this case study.

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## 1. Introduction

Mineral prospectivity mapping (MPM) is one of the most crucial steps in mineral resources exploration and assessment. It aims to delineate prospective areas within a region of interest through analysis and integration of several layers of geoscience information from diverse datasets including geological data, geophysical data, geochemical data and remote sensing data (Zuo and Carranza, 2011; Abedi et al., 2013). Many approaches to MPM that have been proposed and introduced can be categorized as either knowledge-driven or data-driven methods according to the type of inference mechanism used (Bonham-Carter, 1994; Pan and Harris, 2000; Carranza, 2008). Data-driven methods include weights of evidence (WofE) (Bonham-Carter et al., 1990; Agterberg and Bonham-Carter, 1990; Carranza, 2004), logistic regression (Agterberg and Bonham-Carter, 1999; Carranza and Hale, 2001; Mejía-Herrera et al., 2015), neural networks (Singer and Kouda, 1996; Oh and Lee, 2010), evidential belief modeling (Carranza and Hale, 2003; Carranza et al., 2005; Carranza, 2014), and Random

Forest (Carranza and Laborte, 2015a, 2015b, 2015c). Knowledge-driven methods include fuzzy logic (An et al., 1991; Chung and Moon, 1991; Carranza and Hale, 2001), evidential belief functions (An et al., 1992, 1994a, b), and wildcat mapping (Carranza and Hale, 2002; Carranza et al., 2008).

Fractal geometry was developed by Mandelbrot (1983) for describing complex scaling attributes of objects and phenomena in nature. In the geosciences, the concentration–area (C–A) fractal method has been used to describe the morphology and distribution of geological objects and to separate geochemical anomalies from background values (Cheng et al., 1994). The C–A and concentration–volume (C–V) methods (Afzal et al., 2011; Wang et al., 2013) also have been applied to MPM and quantifying mineralization.

3D geological modeling has been regarded as an essential method to interpret and visualize the subsurface geology (Houlding, 1994; Mallet, 2002; Sprague et al., 2006; Smirnov et al., 2008; Caumon et al., 2009). Several software systems have been developed for 3D geological modeling, including GOCAD (Mallet, 1992), Micromine (Micromine, 2015) and Surpac (Geovia, 2015). Presently, 3D predictive modeling of exploration targets is desirable because of its particular advantages over traditional 2D methods for extracting ore-forming information from geoscience data (Carranza, 2011). In contrast with 2D models, a 3D geological

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model provides a more realistic way to delineate zones of high potential at depth (Fallara et al., 2006; Hamedani et al., 2012; Mejía-Herrera et al., 2015). Analysis and modeling of 3D geological objects by integrating geophysics, geochemistry and geology generally provides further insights into the realm of exploration targeting, although it does not totally eliminate uncertainty for mineral exploration (Lindsay et al., 2012).

GeoCube, as a 3D exploration criteria decision-making software system, provides many important functions in four main modules: (1) Import and Export, for compatibility with commercial 3D geological modeling software formats (e.g., GOCAD, Micromine and Surpac); (2) Pre-process, for extracting anomaly information (e.g., Boolean operations, threshold segmentation based on C–V fractal method and 3D buffer analysis); (3) Assessment, for integration of 3D exploration criteria using five data-driven methods; and (4) Post-process, for classifying integration outcomes into several levels according to mineralization potentiality.

## 2. Software system description

GeoCube is written in Visual C# and developed using Visual Studio, which is an integrated development environment (IDE) from Microsoft. The program is based on .Net Framework 4.0, and has a standalone graphical user interface (GUI) developed using the Direct3D software development kit (SDK). GeoCube applies many Windows application programming interfaces (APIs) as well (Fig. 1).

The complete list of menu options is as follows:

- (1) *Import and Export*: Data import and export; data conversion, etc. (Figs. 1 and 3).
- (2) *Edit*: Modification of exploration criteria properties (Fig. 1).
- (3) *View*: Operations for 3D models; rendering and style options (Fig. 1).
- (4) *Pre-process*: 3D-grid cells; Boolean operations; exploration criteria statistics; “Rarefy”; “Discrete” (Fig. 4).
- (5) *Assessment*: Information Entropy, Logistic Regression, Ordinary WofE, Weighted WofE and BoostWofE (Fig. 5).
- (6) *Post-process*: Cluster analysis; C–A fractal; C–V fractal (Fig. 6).
- (7) *Window*: Display mode of the software (Fig. 1).
- (8) *Help*: Help for using the software (Fig. 1).

Main work flow for 3D quantitative modeling in the GeoCube software system is as shown in Fig. 2, and the descriptions of each module are as follows:

### 2.1. Data import and export module

This module can be applied to import or convert data from some commercial 3D geological modeling software to GeoCube, and the processed data can be exported to these commercial 3D geological software as well.

GeoCube is an application based on 3D-grid cell datasets. Similar to the pixel in 2D cell datasets, the basic 3D-grid cell can be observed as a block with  $x, y, z$  coordinates and a series of property values in 3D space. Because most 3D geological modeling software supports the function of transforming a wireframe model into a 3D grid cell block model, the data exported from these software packages can be imported into GeoCube. For the convenience of computation, GeoCube provides a series of interfaces to convert data from other formats (e.g., \*.csv, \*.xls, \*.mdb, etc.) to its custom formats, namely, the GeoCube Header File (\*.ghf) and GeoCube Data File (\*.gdf) (Fig. 3). In this way, data from different software can be processed in a unified way. Coordinate and property information is saved in the GeoCube Data File, which is a type of text

file in ASCII<sup>1</sup> format. For improving the efficiency of reading and writing, spatial data indices for each point are introduced. GeoCube can also export the results to many common formats supported by other geomodeling software systems (e.g., GOCAD, FLAC3D, Micromine, and Surpac).

### 2.2. Pre-process module

GeoCube provides some preprocessing functions such as “Rarefy” and “Discrete.” “Rarefy” consists of a series of randomization methods and is usually used to divide deposit-type locations into two parts: training data and verification data. Other potential uses of “Rarefy” include declustering data and reducing data redundancy and relevance. Because many MPM methods require either binary or ternary input data, a threshold must be set to binarize or ternarize continuous data. “Discrete” provides C–V fractal modeling to classify data according to its spatial distribution characteristics. GeoCube supports custom settings to apply these functions.

GeoCube also offers a function for obtaining the optimum buffer distance around faults, folds, and intrusive rocks based on the ordinary WofE Model. The method that GeoCube uses for buffer distances is based on a research study by Wang et al. (2015). 3D buffer analysis of exploration geochemistry also can be accomplished using GOCAD software (Sprague et al., 2006; Fallara et al., 2006).

### 2.3. Assessment module

The Assessment module in GeoCube contains five data-driven MPM methods: ordinary WofE, weighted WofE, boost WofE, logistic regression, and information entropy. The assessment module can be used to integrate spatial data representing exploration criteria by combining their weights and probability in each 3D grid cell of the study area, and the integration results can be divided into specific categories using C–V fractal modeling for delineating prospecting exploration targets.

#### 2.3.1. Ordinary WofE model

The ordinary WofE model is a bivariate statistical model based on Bayes’ rule and probabilistic uncertainty theory, and it is usually applied in areas where a number of mineral occurrences are known (Agterberg, 1992). The ordinary WofE model aims at acquiring the posterior probability ( $P_{posterior}$ ) of each unit within the study area. Before that, the prior probability ( $P_{prior}$ ) must be obtained, which is the probability of occurrence of a mineral deposit without consideration of any known evidence. For the data of the  $i$ -th binary exploration criterion,  $W_i^+$  represents the weight for the presence of the exploration criterion, and  $W_i^-$  represents the weight for the absence of the exploration criterion.  $W_i^+$  and  $W_i^-$  can be estimated respectively as:

$$W_i^+ = \ln \frac{P(B_i | D)}{P(B_i | \bar{D})} \quad (1)$$

$$W_i^- = \ln \frac{P(\bar{B}_i | D)}{P(\bar{B}_i | \bar{D})} \quad (2)$$

In Eqs. (1) and (2),  $P$  is the probability,  $B_i$  is the presence of the  $i$ -th exploration criterion,  $\bar{B}_i$  is the absence of the  $i$ -th exploration criterion,  $D$  is the presence of mineral deposit and  $\bar{D}$  is the absence of mineral deposit. The strength of correlation between an exploration criterion and mineral deposits can be estimated by computing the contrast  $C_i = W_i^+ - W_i^-$ , which can be tested for

<sup>1</sup> ASCII: American Standard Code for Information Interchange.

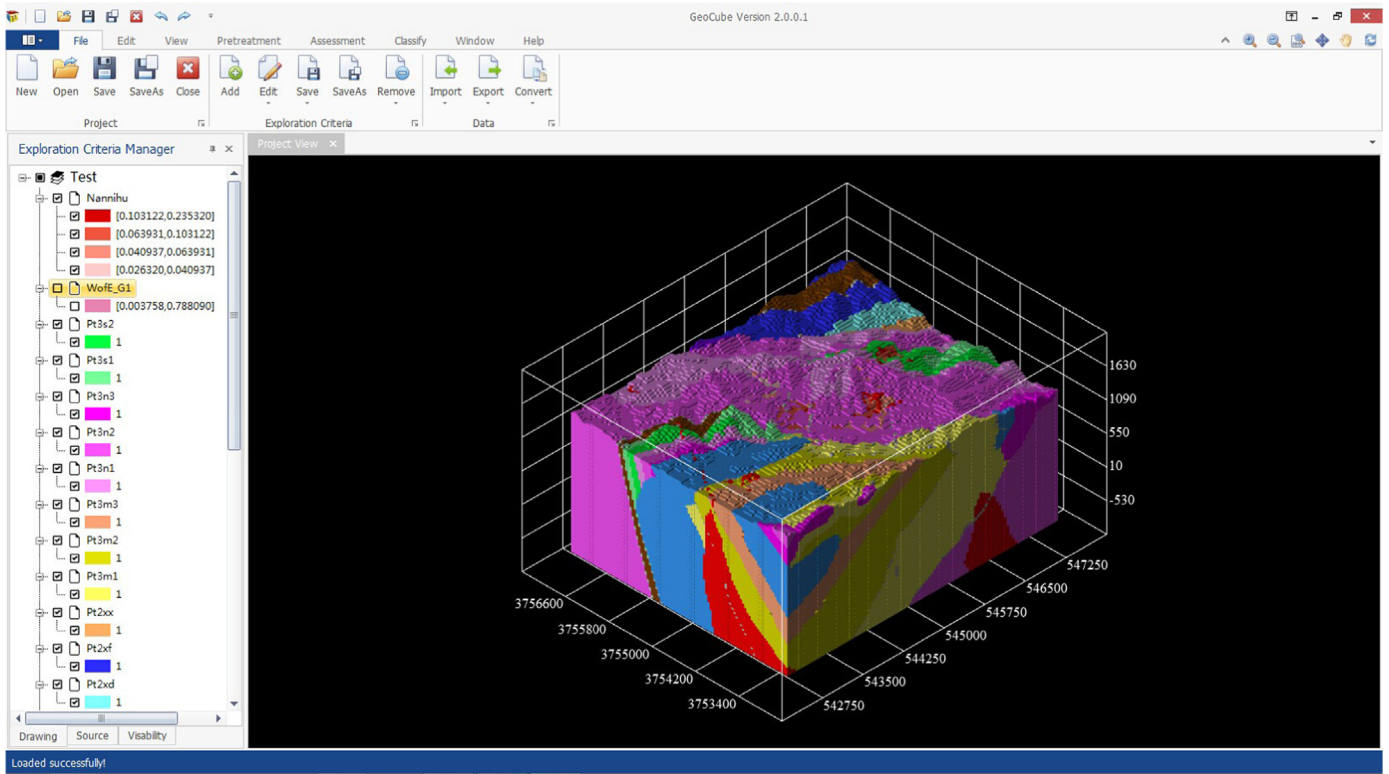


Fig. 1. Main graphical user interface of the GeoCube software system.

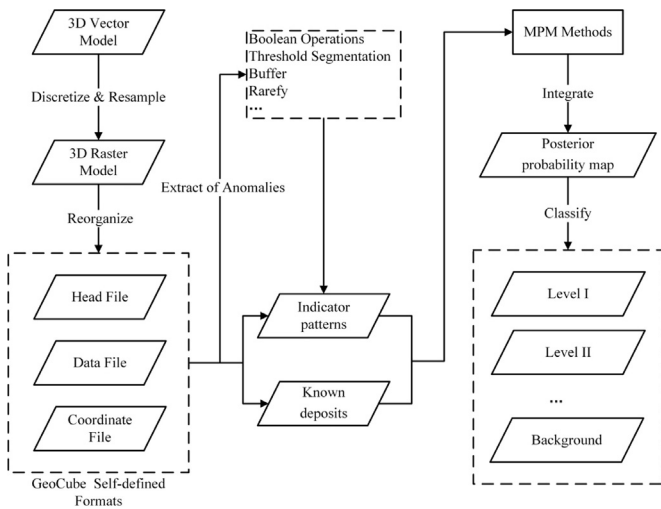


Fig. 2. Main processing steps for 3D quantitative modeling in the GeoCube software system.

statistical significance. Probability can be expressed in terms of odds,  $O_{prior}$  can be estimated as  $P_{prior}/(1-P_{prior})$ , and if the exploration criteria are independent with each other, then  $O_{posterior}$  can be estimated as:

$$O_{posterior} = O_{prior} * e^{\sum_{i=1}^N W_i^k} \quad (i=1, 2, \dots, N) \quad (3)$$

In Eq. (3),  $\sum_{i=1}^N W_i^k$  ( $i=1, 2, \dots, N$ ) represents the accumulated weights for the  $N$  exploration criteria in a unit within the study area. It is linked to the  $W_i^+$  when the  $i$ -th exploration criterion exists in the unit, otherwise it is linked to the  $W_i^-$ . The natural logarithm of Eq. (3) is as follows:

$$\ln O_{posterior}(D | B_1^k B_2^k \dots B_N^k) = \ln O_{prior} + \sum_{i=1}^N W_i^k \quad (i=1, 2, \dots, N) \quad (4)$$

Finally, the posterior probability of each unit can be obtained from Eq. (4).

$$P_{posterior} = \frac{O_{prior}}{1-O_{posterior}} \quad (5)$$

### 2.3.2. Weighted WofE based on the logistic regression model

Agterberg (2011) combined ordinary WofE with weighted logistic regression (WLR), and proposed a modified weights of evidence method. This approach achieves unbiased estimates of the posterior probabilities while keeping the form of WofE. An additional advantage of this approach is that it can cope with missing data on some exploration criteria by setting the weights of unit cells with missing data equal to zero in WofE applications.

### 2.3.3. Boost WofE model

Cheng (2012) proposed a new form of weights of evidence model, BoostWofE, which can significantly reduce the influence of conditional dependency among exploration criteria on the outcome of information integration. This approach integrates binary exploration criteria in sequence and updates the prior logits with independent weights for the first exploration criterion and the conditional weights for the subsequent exploration criteria. The conditional weights not only depend on the characteristics of each exploration criterion, but they are also related to the order of exploration criteria added. BoostWofE is more generic and it does not rely on other models and later corrections compared with other ways of handling conditional dependency (Cheng, 2015).

### 2.3.4. Logistic regression

As with any other regression methods, logistic regression is generally used for describing the relationship between a response

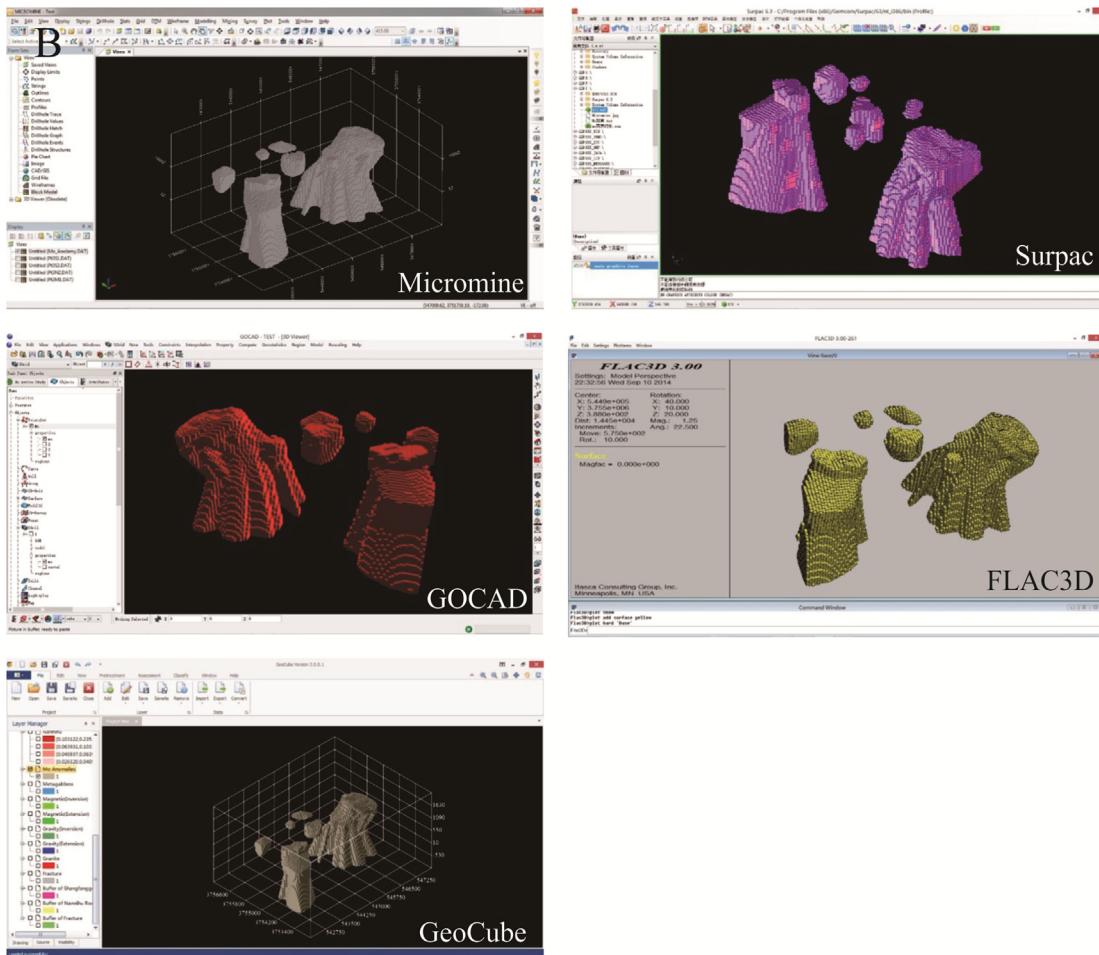
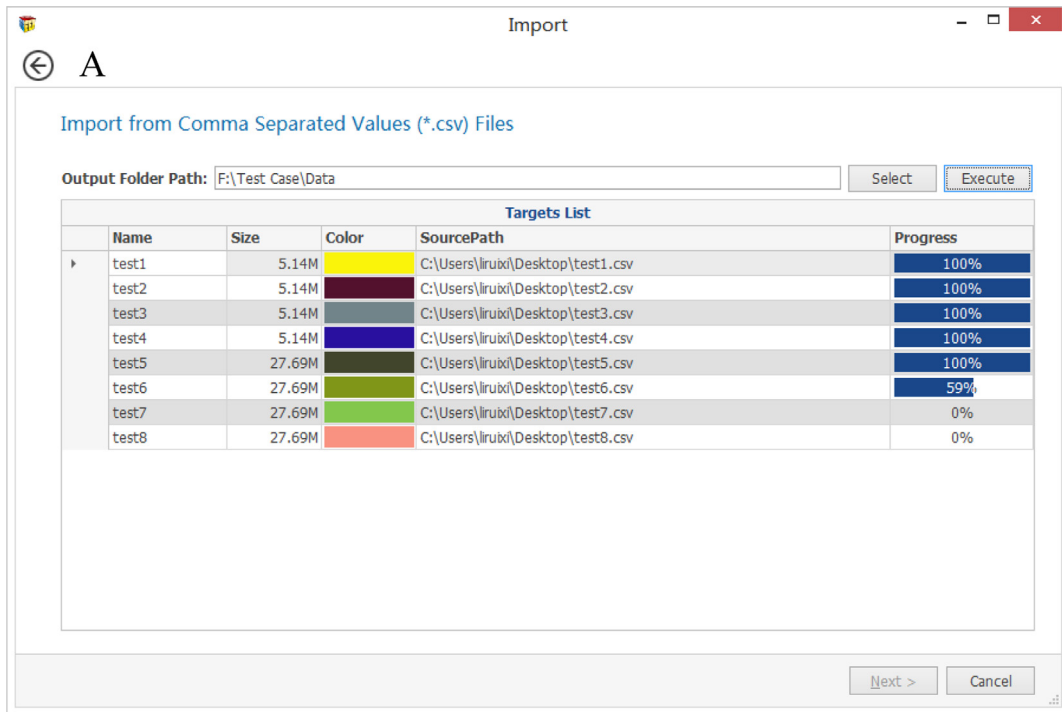


Fig. 3. A: Import and Export modules of GeoCube software system. B: Data conversion workspaces in commercial software and GeoCube software system.

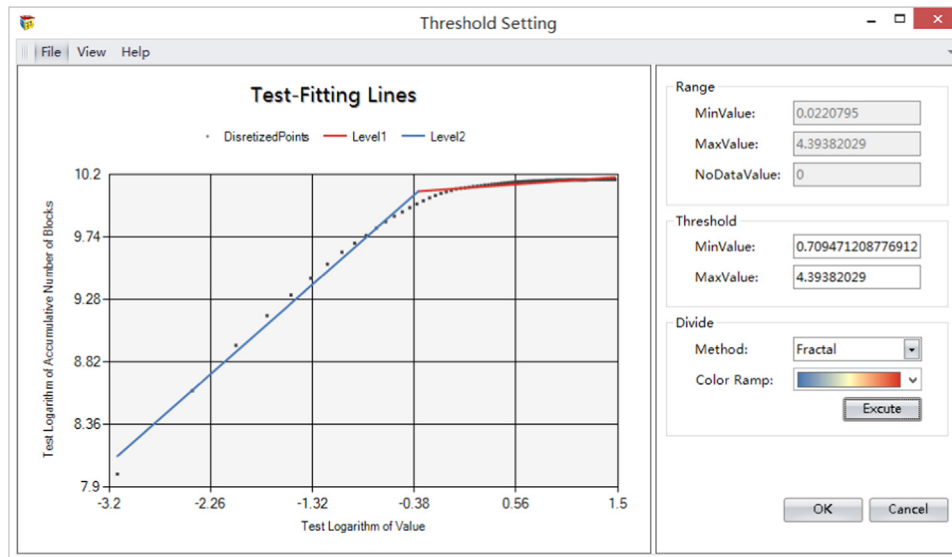


Fig. 4. Application of the “Discrete” function to binarize a data set of exploration criterion.

variable and one or more predictor variables. The response variable in logistic regression must be binary or dichotomous unlike in linear regression models (Hosmer and Lemeshow, 2004). Logistic regression can obtain the true conditional probabilities if the joint distribution of predictors and the response variable is of log-linear form (Schäeben, 2014). Logistic regression need not satisfy the assumption of conditional independence. Maximum likelihood is the most common approach to estimating the regression coefficients and the constant term in multivariate logistic regression (Zhang et al., 2014).

### 2.3.5. Information entropy

Information entropy is a method of statistical analysis introduced by Vysokoostrovskaya and Zelenetsky (1968) into the regional mineral prediction field. The information entropy model can be defined as:

$$H_N = - \sum_{i=1}^N P_i \ln P_i \quad (6)$$

In Eq (6),  $H_N$  is the information entropy of  $N$  exploration criteria, and  $P_i$  represents the exploration criteria  $i$  in  $N$  exploration criteria system. Information entropy modeling is based on geological, geophysical, geochemical and remote sensing data and is guided by the geo-anomaly theory in this paper. The model determines favorable locations for mineralization by calculating the geological factors and prospecting indicators.

### 2.4. Post-process module

A study area generally needs to be classified into several levels according to mineralization potentiality for clarity. GeoCube provides the C–V fractal method (Afzal et al., 2011; Wang et al., 2013) for classification. The specific approach is to map posterior probabilities computed by an MPM method on a log–log plot, apply fitting methods (e.g., Least Square Fitting) and obtain the cutoff values of adjacent segments, and finally to classify the data based on the cutoff values.

## 3. Application to the study area

### 3.1. Geological setting

The case study area is the Nannihu camp in the Luanchuan region, China. It mainly consists of Nannihu porphyry-type Mo (W) deposits, Sandaozhuang skarn-type Mo (W) deposits, and Shangfanggou porphyry-type Mo (Fe) deposits. The surface of the study area is 4.0 km × 5.0 km and the depth is less than 2.7 km.

The study area is tectonically located in the east of the Nannihu Mo polymetallic metallogenic belt along the southern margin of the North China Craton (Wang et al., 2011, 2012b). The main strata hosting mineralization in the study area are the Middle Proterozoic Guandaokou Group and the Upper Proterozoic Luanchuan Group. The Guandaokou Group (~100 m thick) is composed of fluvial-neritic facies clastic-carbonate rocks, or carbonate rocks containing stromatolites. The Luanchuan Group (~3100 m thick) consists of shallow marine carbonate-clastic rocks, of which ~2050 m (i.e., the Meiyaogou, Sanchuan and Nannihu Formations) is associated with mineralization (Wang et al., 2011, 2012c). Regional faults and folds are well-developed in the study area. There are small intrusive rocks formed at the intersections of NW–W-trending and NNE-trending faults, which control the formation of Mo deposits. Late Proterozoic syenite, metamorphic gabbro, and Jurassic granite porphyry are associated with mineral resources in the study area. Porphyry-skarn Mo (W) deposits and skarn-type polymetallic sulfide deposits are mainly distributed in the center belt of the geochemical anomaly. According to Re–Os isotopic dating, large-scale Mo mineralization occurred ~140 Ma ago (Mao et al., 2009).

### 3.2. Exploration criteria extraction and integration

Binary exploration criteria of the 3D Mo orebody model of Nannihu (i.e., stratum, rock, buffer of fracture, Mo anomaly, gravity continuation, gravity inversion, magnetism continuation, magnetism inversion) are applied to calculate the weights of each exploration criterion and the conditional probability of Mo mineral occurrence in the study area. The calculation was implemented using GeoCube.

Table 1 reports the spatial correlations of the major exploration criteria with the Mo deposits. The contrast  $C$  is a statistic to measure the correlation between exploration criteria and mineral

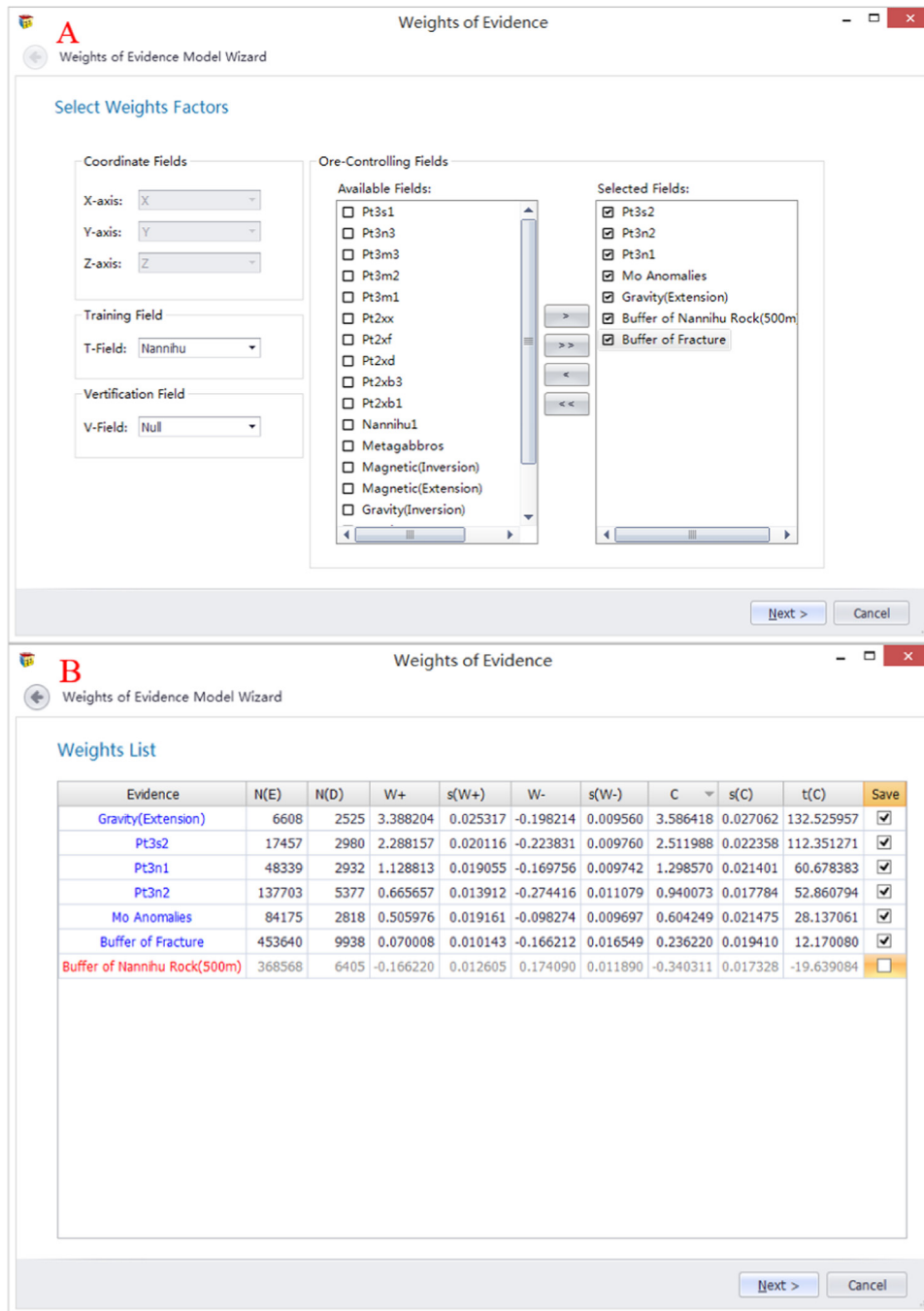


Fig. 5. A: Exploration criteria filter in WofE modeling. B: Exploration criteria list for calculation, including 3D-grid cells number, weights, and other common parameters of WofE modeling.

deposits. A  $C > 0$  implies positive correlation between an exploration criterion and the Mo deposit. Conversely, a  $C < 0$  implies negative correlation between the exploration criteria and the Mo deposit. The studentized C, the ratio of C to its standard deviation, is a useful measure of statistical significance of the contrast because of the uncertainties of the weights and missing data, and it becomes useful in determining cutoff levels to convert multiclass or continuous data into binary exploration criterion. A value of the studentized C equal to 1.96, corresponding to a confidence level of 97.5%, was considered in determining threshold or cutoff levels (Bonham-Carter et al., 1988). Accordingly, there are nine exploration criteria with statistically significant positive correlations with the Mo deposit. Considering the conditional dependence, "Fracture" is highly correlated with "Buffer of fracture" and "Gravity

continuation" is highly correlated with "Gravity inversion", and two of these four exploration criteria must be excluded in the data integration because their inclusion would over-estimate the posterior probability. Considering studentized contrast (Table 1), "Fracture" is excluded while "Buffer of fracture" is retained and "Gravity inversion" is excluded while "Gravity continuation" is retained.

The intersections of each of the seven remaining exploration criteria with the mineral deposits are shown in Fig. 7. Based on Table 1 and Fig. 7, the studentized contrast is directly related to the number of spatial units of intersections between exploration criteria and mineral deposits ( $N(D)$ ) and it is inversely related to the number of spatial units of exploration criteria ( $N(E)$ ). The result of integration of exploration is not the entire study area, but the

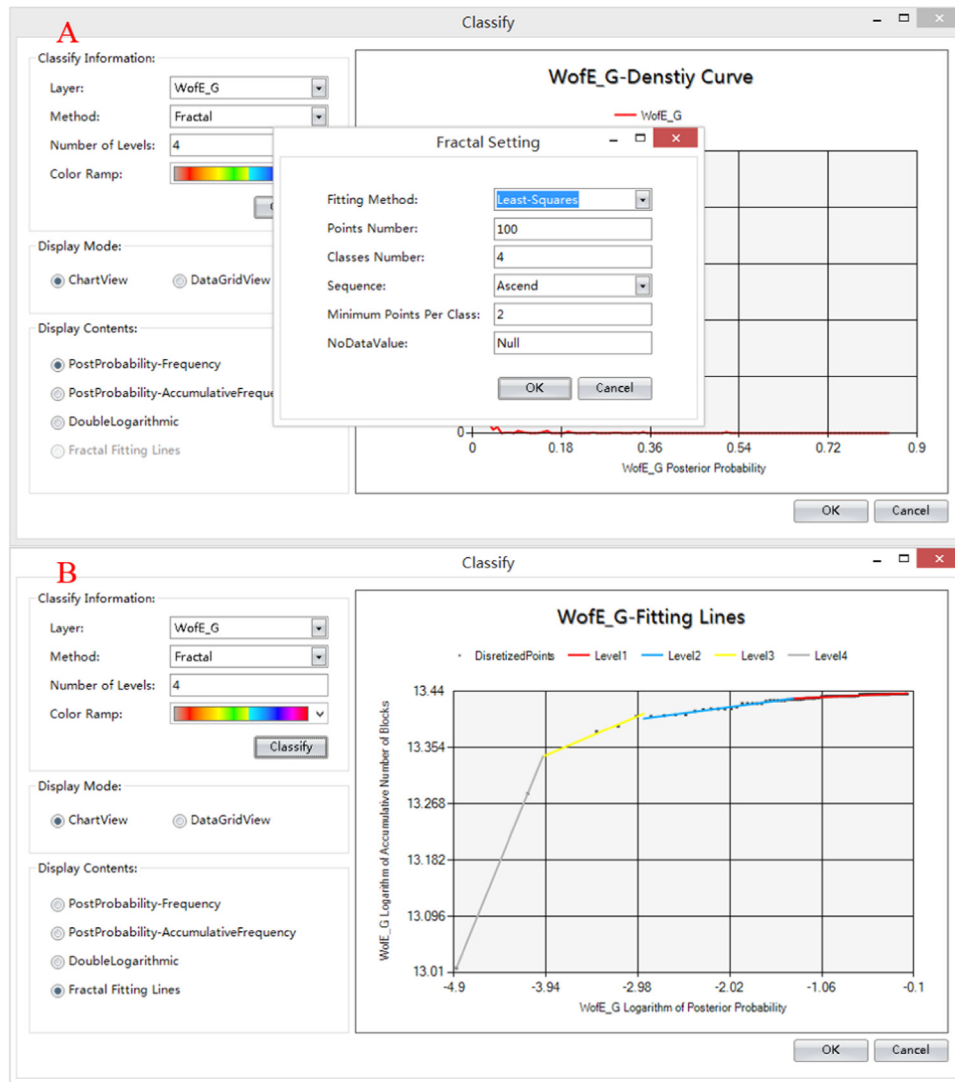


Fig. 6. A: Classification using fractal method; the pop-up window includes some specific parameter settings of fractals. B: Result of the classification.

Table 1

List of parameters for the weights of evidence model.

Exploration criteria	$N(E)$	$N(D)$	$W^+$	$s(W^+)$	$W^-$	$s(W^-)$	$C$	$s(C)$	Studentized(C)
Gravity continuation	6608	2525	3.5889	0.0253	-0.1994	0.0095	3.7883	0.0271	140.0127
Pt3s2	17,457	2980	2.4889	0.0201	-0.2279	0.0097	2.7168	0.0224	121.5484
Pt3n1	48,339	2932	1.3295	0.0191	-0.1832	0.0097	1.5128	0.0214	70.7126
Pt3n2	137,703	5377	0.8664	0.0139	-0.3195	0.0111	1.1859	0.0178	66.7292
Mo Anomalies	84,175	2818	0.7067	0.0192	-0.1238	0.0097	0.8305	0.0215	38.6875
Buffer of fracture (500m)	453,640	9938	0.2707	0.0101	-0.4912	0.0165	0.7620	0.0194	39.3588
Gravity inversion	130,730	3260	0.4034	0.0177	-0.0990	0.0099	0.5024	0.0203	24.7435
Fracture	12,089	251	0.2159	0.0638	-0.0036	0.0087	0.2195	0.0644	3.4103
Buffer of granite (600 m)	368,568	6405	0.0345	0.0126	-0.0295	0.0118	0.0641	0.0173	3.7033
Magnetism continuation	172,766	1790	-0.4898	0.0238	0.1002	0.0093	-0.5900	0.0255	-23.1341
Granite	220,729	1651	-0.8185	0.0247	0.1915	0.0092	-1.0100	0.0264	-38.3046
Pt3s1	42,218	186	-1.3509	0.0735	0.0403	0.0087	-1.3912	0.0740	-18.8008
Magnetism inversion	72,769	184	-1.9080	0.0738	0.0817	0.0087	-1.9897	0.0743	-26.7703
Pt2xb3	85,223	61	-3.1719	0.1281	0.1082	0.0087	-3.2801	0.1284	-25.5510
Gabbro	34,024	2	-5.6721	0.7071	0.0434	0.0086	-5.7154	0.7072	-8.0820

$N(E)$  refers to unit cells number of evidence factor.  $N(D)$  refers to unit cells number of mineral deposits.  $W^+$  and  $W^-$  are positive and negative weights of evidence, respectively.  $s(W^+)$  and  $s(W^-)$  are standard deviations of  $W^+$  and  $W^-$ , respectively.  $C$  is spatial contrast, estimated as  $W^+ - W^-$ .  $s(C)$  is standard deviation of  $C$ , estimated as  $\sqrt{s^2(W^+) + s^2(W^-)}$ , of which  $s^2(W^+)$  is variance of  $W^+$  and  $s^2(W^-)$  is variance of  $W^-$ . Studentized(C) is studentized contrast, estimated as  $C/s(C)$ . Studentized(C) indicates statistical significance of spatial association, and is a useful statistic to determine the most significant cutoff distance in situations with few known information.

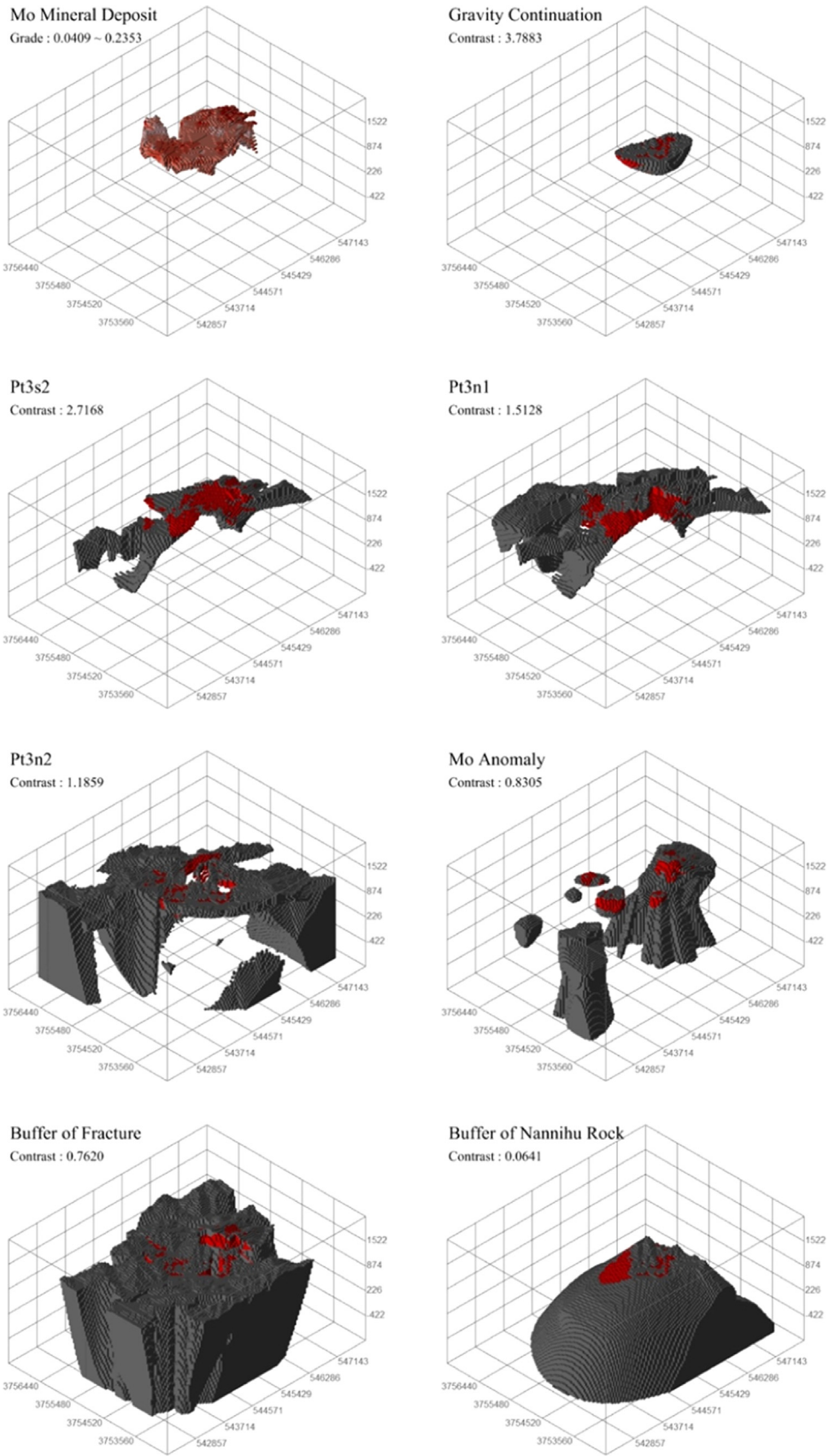


Fig. 7. Intersection of exploration criteria and the 3D orebody model of the Nannihu Mo deposit.



intersections of all of the valid exploration criteria. Considering that all of the exploration criteria are binary, if there are  $N$  number of independent exploration criteria, then the posterior probability is associated with at most  $2^N$  possible distinct intersections (or unique conditions) of exploration criteria. As there are seven exploration criteria integrated in this case, there are at most 45 unique conditions. The prediction result is composed of 3D-grid cells with values between 0 and 1, representing posterior probability. The range of posterior probability is from 0.0038 to 0.7881. To separate the prospect areas from background, we use the C–V fractal approach for classifying the results of WofE.

### 3.3. Classification using fractal modeling

Cheng et al. (1994) proposed a C–A fractal model for separating geochemical background and anomalies, and demonstrated that background always obeys either normal or lognormal distribution, whereas anomalies may correspond to a fractal distribution. The C–A approach was also extended to 3D space by means of replacing area with volume because element distributions in horizontal or vertical directions conform with fractal models. The identification of mineralization zones is based on power-law relationships between Mo concentrations and the volume of unit cells with specified posterior probability. In this case study, Mo concentrations are represented by the posterior probability of Mo mineralization and the volume is represented by the number of unit cells.

The fractal model can be defined as:

$$N(r) = Cr^{-D} \tag{7}$$

In Eq. (7),  $r$  is a characteristic exponent referring to posterior probability in this case,  $N(r)$  is the number of unit cells for which

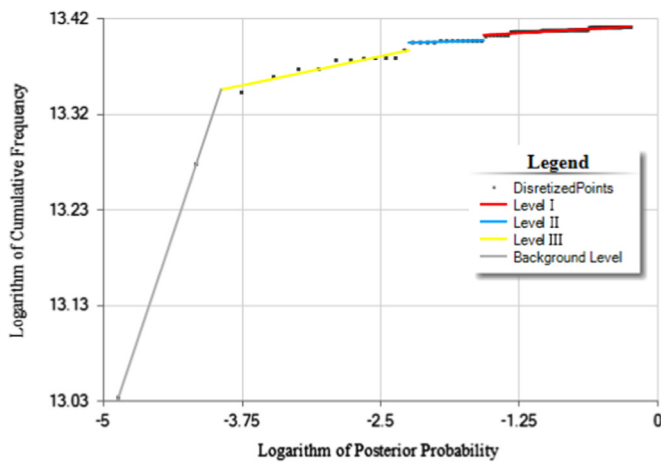


Fig. 8. Log–log C–V plots and line segments fitted using least-squares fitting method.

Table 2  
Coefficients of main exploration criteria depending on method.

Exploration criteria	Information model Information	Logistic regression Coefficient	Ordinary WofE Studentized contrast	Weighted WofE Contrast	Boost WofE Contrast
Gravity continuation	3.1244	4.3091	140.0127	4.3091	3.7788
Pt3s2	2.3187	3.4953	121.5484	3.4953	2.5120
Pt3n1	1.2840	3.4812	70.7126	3.4812	1.7411
Pt3n2	0.8435	1.8993	66.7292	1.8993	1.3984
Mo Anomaly	0.6896	1.0102	38.6875	1.0102	0.4579
Buffer of fracture (500 m)	0.2655	0.6412	39.3588	0.6412	0.1384
Buffer of granite (600 m)	0.0339	0.4915	3.7033	0.4915	–0.8827

posterior probability is equal to or less than  $r$ ,  $C$  is a proportionality coefficient, and  $D$  is the fractal dimension. The logarithm of Eq. (7) is:

$$\ln N(r) = \ln C - D \ln r \tag{8}$$

According to Eq. (8),  $\ln r$  is linearly associated with  $\ln N(r)$ . The least squares method can be applied to the piecewise fitting of straight lines to the log–log plots of  $N(r)$  versus  $r$ . The points demarcating adjacent straight lines are considered cutoff values separating background and prospect areas of different levels of potentiality (i.e., different ranges of posterior probability).

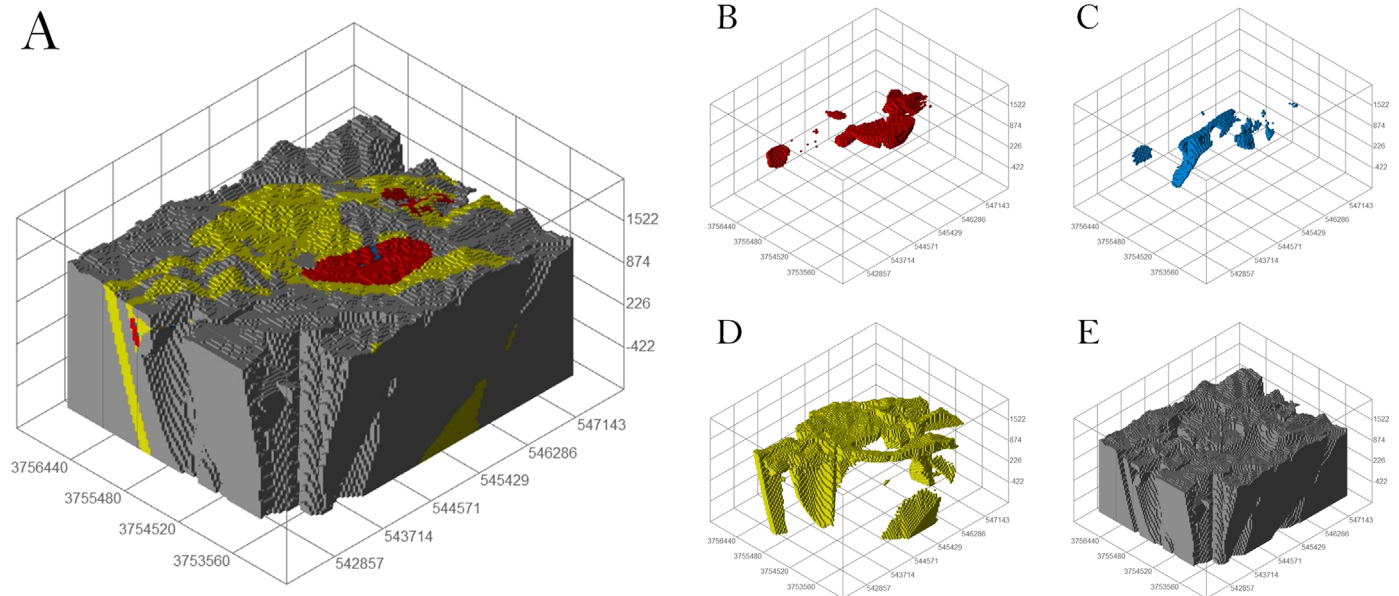
In this case study, the study area was divided into background and three levels of prospect areas. As shown in Fig. 8, the fitted line segment of background and the fitted line segments of prospect areas have significant differences, and the prospect areas can be further subdivided into three parts. The differences among the classes defined in the log–log plots of  $N(r)$  versus  $r$  are reflected by the different fractal dimensions: the spatial distribution of background has a fractal dimension of 0.3383, and the spatial distributions of prospect areas of different levels have fractal dimensions of 0.0066 (first classification), 0.0031 (second classification) and 0.0238 (third classification) (Table 3). As shown in Fig. 9, first level prospect areas are controlled mainly by the Gravity interpretation using 3D probability inversion (Wang et al., 2012a), and by the Pt3s2 and Pt3n1 strata of the Luanchuan Group. Second level prospect areas are controlled mainly by the Pt3s2 and Pt3n1 strata of the Luanchuan Group, whereas third level prospect areas are controlled mainly by the Pt3n2 strata of the Luanchuan Group.

## 4. Discussion

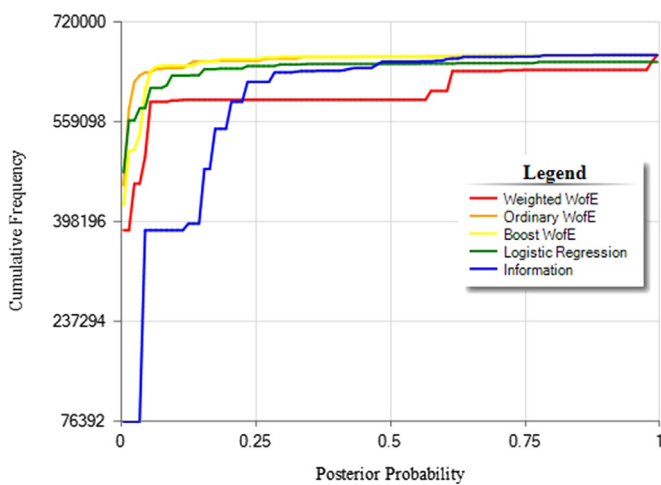
For the case study at the Nanihu Mo (W) camp of the Luanchuan district, the 3D deposit model was constructed using 1:2000 scale geological and topographic maps, 288 boreholes (total core length of 158,700 m), and 32 1:2000 scale cross-sections using Micromine software (Qu, 2013). The 3D-grid cell size is 50 m × 40 m × 27 m, based on borehole distances in the exploration net, and it can delineate clearly boundaries of geological objects and exploration criteria (Fig. 1). A total of 15 exploration criteria were analyzed (Table 1) and finally seven exploration

Table 3  
Details of classification of posterior probabilities obtained using ordinary WofE.

Class	Interval	Fractal dimension	Goodness-Of-Fit
Classification I	[0.2076, 0.7881]	0.0066	0.8877
Classification II	[0.1056, 0.2076]	0.0031	0.6922
Classification III	[0.0194, 0.1056]	0.0238	0.8937
Background	[0.0038, 0.0194]	0.3383	1.0000



**Fig. 9.** A: 3D exploration target model. B: First level exploration targets. C: Second level exploration targets. D: Third level exploration targets. E: Background zones.



**Fig. 10.** Comparison of posterior probability – cumulative frequency plots obtained by the different methods used.

criteria were integrated by information entropy, logistic regression, boost WofE, weighted WofE, and ordinary WofE methods (Table 2), and the results were classified by the C–V fractal method for identification of exploration targets and background (Table 3; Figs. 10 and 11).

According to contrast and studentized contrast (Table 1), nine exploration criteria are suitable for 3D targeting. However, "Fracture" and "Buffer of fracture (500 m)" exploration criteria are strongly correlated (i.e., spatially dependent) and "Gravity continuation" and "Gravity inversion" are also strongly correlated. For each pair of strongly correlated exploration criteria, the one with weaker spatial correlation with the target deposit was excluded for the data to avoid over-estimation of posterior probability. Therefore, only seven exploration criteria (Table 2) were integrated for exploration targeting.

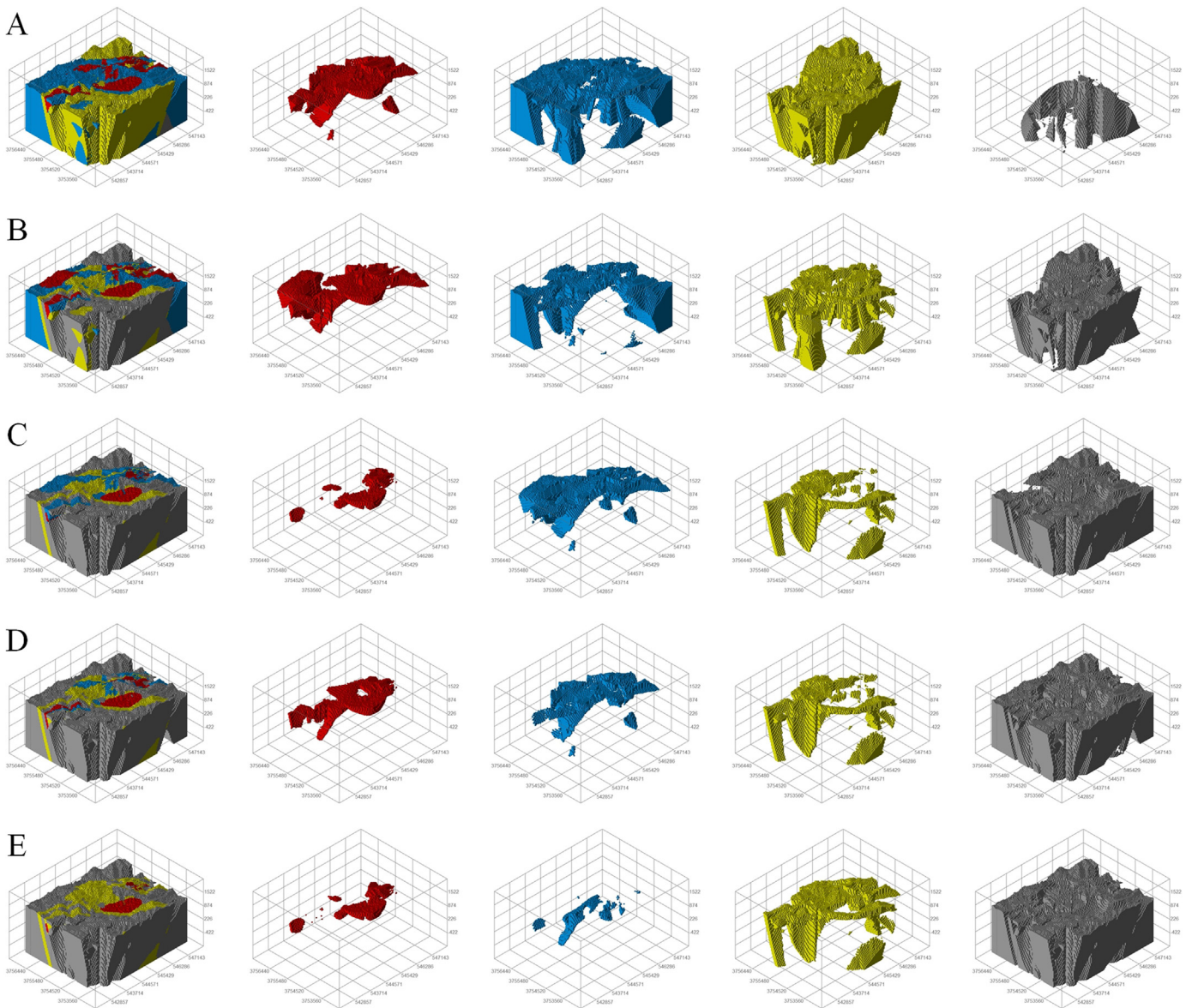
The values of studentized contrast obtained in this case study (Table 1) are far greater than those in the general cases of 2D WofE calculations, due mainly to the spatial scale of 3D modeling, which is much finer than in most cases of 2D regional-scale WofE calculations, such that the number of grid cells of training deposits in

3D WofE is enormous compared with those in most cases of 2D WofE. However, the estimates of studentized contrast are considered only in a relative sense rather than absolute sense in the spatial association analyses. The magnitudes of studentized contrast depict relative importance of each exploration criterion only at a particular spatial scale, but not across a range of spatial scales. Therefore, the magnitudes of studentized contrast in finer scales (e.g., 3D modeling at deposit scale) cannot be compared to the magnitudes of studentized contrast in coarser scales (e.g., 2D modeling at regional scale) for geological controls on mineralization at finer scales are not same as geological controls on the same mineralization at coarser scales.

Fig. 10 shows the contrast of different models in posterior probability–cumulative frequency plots (standardized from 0 to 1): (i) the curves of ordinary WofE, boost WofE and logistic regression methods are smoother than the weighted WofE and information entropy methods in this case study; (ii) the posterior probability values of the weighted WofE and information entropy are discontinuous. These differences indicate the different contributions of exploration criteria as well as the different ways by which exploration criteria values are integrated according to each method. However, the vertical to sub-vertical parts of the different curves commonly represent exploration target values and the horizontal to sub-horizontal parts of the curves commonly represent background values, and the common cutoff value is in the vicinity of 0.04. The BoostWofE is related to the sequence of exploration criteria summed. If exploration criteria are added in different sequences, the weights for these exploration criteria will be different accordingly. In this case study, exploration criteria are applied according to their weights in ordinary WofE with the order from large to small.

Fig. 11 shows the C–V classification results per posterior probability output of each data integration algorithm. The results show that the logistic regression, ordinary WofE, and boost WofE models are better than the information entropy and weighted WofE models for identification of background and exploration targets. The main interpretations of the results are as follows:

(1) There are four C–V classification levels of posterior probabilities of mineral occurrence in the case study area: (i) classification I targets (red blocks of 3D-grid cells) have high posterior probabilities; (ii) classification II targets (blue blocks of 3D-grid cells) have



**Fig. 11.** Five models of exploration targets. A: Information entropy model. B: Weighted WofE model. C: Logistic regression model. D: BoostWofE model. E: Ordinary WofE model.

moderate posterior probabilities; (iii) classification III targets (green blocks of 3D-grid cells) have low posterior probabilities; (iv) the background zones (gray blocks of 3D-grid cells) have non-significant posterior probabilities. The classification targets I and II obtained by the ordinary WofE method are smaller compared to those obtained by the other methods, and the classification targets I and II obtained by ordinary WofE, boost WofE and logistic regression have similar smooth features. These results show that the ordinary WofE model of exploration targets is the best among all models of exploration targets obtained by the five integration methods used in this case study, and the boost WofE and logistic regression models of exploration targets have less uncertainty compared to the weighted WofE and information entropy models of exploration targets. In general, the models of exploration targets obtained by using ordinary WofE, logistic regression, and boost WofE models are regarded as useful guides for further exploration of the study area.

(2) Potential exploration targets should be associated with exploration criteria and metallogenesis in the study area. Potential exploration targets of classifications I–III using weighted WofE and information entropy are strictly constrained by the strata (Pt3n2 and

Pt3n1) exploration criteria. Potential exploration targets of classifications I–III using the other three methods show better multiple exploration criteria constraints and are correlated with skarn spatial features (Fig. 11, Table 3), which are associated with metallogenesis of the study area. Based on the results of logistic regression, ordinary WofE and boost WofE models (Figs. 7–9, and 11; Table 2), 3D spatial correlations of orebody with strata, faults and granite confirm that the skarn-type (hydrothermal) mineralization is controlled by Yanshanian intrusive rocks and the Luanchuan Group in the study area. Skarn is the ore-bearing geological body. The results show that zones to the north, northwest and southeast of the known Nannihu ore body are favorable targets for further exploration.

## 5. Conclusions

In this paper, the standalone GeoCube is used in combination with commercial software Micromine for an exploration criteria analysis of the Nannihu camp in the Luanchuan district. The results are as follows.

- (1) The GeoCube software system facilitates the use of 3D geological models to store, retrieve, process, display, analyze, and integrate exploration criteria.
- (2) The C–V fractal method is useful for classifying posterior probabilities of mineral occurrence into different levels of exploration targets.
- (3) Exploration criteria play important roles in 3D exploration targeting. In this case study, exploration criteria used are derived mainly from geological and geophysical data. Exploration criteria from geochemical data were not considered in this case study because the available geochemical data are sparse and unevenly distributed in 3D space.
- (4) In this case study, the ordinary WofE, boost WofE and logistic regression methods are proved to be superior integration tools for exploration targeting because these methods can present more details of integration result and the distribution of their integration result is more steady and continuous. The ordinary WofE and C–V fractal methods in the GeoCube software system are effective for integrating exploration criteria in the Luanchuan district. (measuring 25 km × 20 km × 2.5 km). Further testing and application of this software to other mineral districts is in order.

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## Appendix A

GeoCube software system is available at <http://www.mediafire.com/download/7dn243zkv7d3oy6/GeoCube.rar>.

The GeoCube.rar file contains all the codes of Information Entropy and Ordinary Weights of Evidence methods, and the \*.txt files from GOCAD/Micromine, test dataset, software system for Information Entropy (effective module).

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