Journal of Geoscience and Environment Protection, 2023, 11, 27-40
https://www.scirp.org/journal/gep
ISSN Online: 2327-4344
ISSN Print: 2327-4336

Delineation of Prospecting Prospect Area Based on Maximum Entropy Model

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How to cite this paper: Chen, Z., & Shi, L. W. (2023). Delineation of Prospecting Prospect Area Based on Maximum Entropy Model. *Journal of Geoscience and Environment Protection, 11,* 27-40.
https://doi.org/10.4236/gep.2023.1111002

Received: October 17, 2023
Accepted: November 12, 2023
Published: November 15, 2023

Abstract

Taking the Dapingzhang copper-polymetallic deposit in Yunnan Province, China as the research object, the maximum entropy model was used to extract the mining information, and the mineral resource prediction model was established by using the exploration data of the deposit and related regions in this area, so as to determine the prospecting prospect area in the study area. In this paper, the Jacknife analysis module of maximum entropy model is used to quantitatively rank the importance of 39 geochemical element variables, and finally obtain the prospecting prospect map of the study area. The research results show that the Dapingzhang mining area has the potential to find hidden ore in the deep and surrounding areas, and the northern and southern ends and western sides of the rock ore control structural belt in the eastern region of the mining area have good prospecting prospects. The research results provide an important basis for the deployment of follow-up exploration work in the study area, and the maximum entropy model has a good application effect in mineral resources exploration.

Keywords

Target Area Demarcation, Peripheral and Deep Exploration, Maximum Entropy, Exploration and Prediction, Geological Big Data

1. Introduction

Metallogenic prediction should apply geological theories and scientific methods, synthesize geological, geophysical, geochemical and other basic data to obtain metallogenic information, summarize metallogenic conditions and rules, establish deposit models, and delineate ore-forming exploration areas of different levels (Xiao, Zhang, & Chen, 1999).

The era of big data (Mayer-Schonberger & Cukier, 2013) has opened up possibilities for mineral prediction and deep ore exploration theories and methods. The significance of mineral prediction based on big data lies not only in mastering massive data information, but also in the professional processing of these geological data in various geological disciplines or even across disciplines, so as to make it more targeted (Wang, Liu, & Liu, 2015). (Zhou, Zhang, Zhang, & Wang, 2018) published a monograph entitled Earth Science and Machine Learning Big Data Mining. (Luo, Zhang, Song, Wang, Yang, Zhao, & Liu, 2017) studied the correlation between 41 geophysical and geochemical variables and Pb-Zn-Fe deposits in Beishan area of Gansu Province based on big data thinking, delimit the prospecting target area for gold polymetallic deposits, and achieved good results. At present, the mineral prediction based on big data has achieved better prospecting results, and will have great potential and application value in prospecting prediction.

The prospecting prediction map is generated by identifying and deducing various geological representative evidence variables, so it is necessary to fully understand the geological conditions of the relevant metallogenic system. The ore exploration prediction map illustrates the spatial correlation between each evidential variable and deposit occurrence, as well as a new understanding of the metallogenic system (Porwal & Carranza, 2015). Techniques widely used in this field include fractal and multifractal analysis (Cheng, 1999; Cheng, 2007; Agterberg, 2007), principal component analysis, and factor analysis (Carranza, 2010; Wang, Zhao, Cheng, & Carranza, 2015), all of which can deepen our understanding of spatial correlations between various geological evidence variables.

There are usually two approaches to exploration prediction mapping, namely data-driven and knowledge-driven. Data-driven features are extracted from training data sets and weights are assigned to the features of evidence variables, while knowledge-driven research and judgment of the features of each geological evidence variable are based on expert experience (Bonham-Carter, 1994). Both data-driven and knowledge-driven approaches have their own advantages and disadvantages. In contrast, knowledge-driven approaches are subjective and require a deep understanding of the mineralization process and the relationship between mineral sites and various geological evidence variables. The data-driven method is to study the prospecting rule according to the characteristics of mathematical statistics. Despite their respective shortcomings in assigning weights to evidence variables (Yousefi & Nykanen, 2017), data and knowledge-driven approaches are still widely used. In recent years, many machine learning and deep learning methods have been developed for data-driven modeling (Lewkowski, Porwal, & Gonza'lez-A'lvarez, 2010). Decision tree (Breiman, 2017; Elith, Leathwick, & Hastie, 2008), artificial neural network (ANN) (Brown, Gedeon, Groves, & Barnes, 2000; Porwal, Carranza, & Hale, 2003), support vector machine (SVM) (Zuo & Carranza, 2011; Abedi, Norouzi, & Bahroudi, 2012), random forest (RF) (Breiman, 2001; Rodriguez-Galiano, Chica-Olmo, & Chica-Rivas, 2014), etc., are widely used in these methods.

The innovation of this paper lies in the improvement of the entropy model, which takes the maximum entropy and achieves an equilibrium state, reflecting the essence of things. The equilibrium state has the highest entropy because it is a measure of irreversible events, and entropy only decreases and does not increase. Equilibrium state means that events do not change and are in the same state, so entropy does not decrease to the maximum! Once an event changes, entropy decreases, and the event cannot be reversed.

The Dapingzhang polymetallic deposit in Puer City, Yunnan Province is a massive sulfide deposit (VHMS) located in the "Sanjiang" area. The discovery of the deposit provides evidence for searching for VHMS in the volcanic belt of Lancang River. The deposit contains medium level of metal resources. Through the study of "ore-forming geologic body, ore-forming structure, ore-forming structural plane and ore-forming trinity", this paper adopts maximum entropy model to study the prospecting prospect of the study area, analyzes the ore-forming process and the relationship between the deposit and various geological evidence variables, draws the prospecting prediction map of the mining area, and finally makes a comprehensive evaluation of the mining area.

2. Geological Background

2.1. Geological Overview

The Dapingzhang copper polymetallic deposit in Puer City, Yunnan Province is a volcanic massive sulfide (VHMS) deposit found in the "Sanjiang" area. The discovery of this deposit provides a basis for searching for the same type of deposit in the Lancangjiang volcanic belt. In this paper, the ore-forming geological body, ore-forming structure, ore-forming structural plane and ore-forming characteristics of the trinity "are studied, and the prospecting prospect of the study area is studied by weight of evidence method.

There are Proterozoic, Devonian, Carboniferous, Permian, Triassic, Jurassic, Cretaceous, Tertiary and Quaternary strata in the Dapingzhu copper mine in Puer City, Yunnan Province. The Lower Paleozoic is mainly missing. The total thickness of the strata is about 20,000 meters. The Damenglong Group of Palaeoproterozoic distributed in the east of Menghai-Lincang granite base, is a set of migmatite and regional metamorphic rock association. The Upper Devonian-Lower Carboniferous Dawazi Formation (DCd), covering an area of about 55 square kilometers, is distributed in the Dpingzhang mining area and the Yinshan area. The Carboniferous Permian system is composed of carbonate rocks, clastic rocks and argillaceous rocks, and locally contains basic and medium acid volcanic rocks and pyroclastic rocks. Regional metamorphism has occurred in the western Daxinshan Formation.

The mining area is located in the Paleozoic island arc volcanic belt on the west margin of Lanping-Simao microplate and adjacent to Lancang River junction zone in the west. From the analysis of regional tectonic environment, the deposit is located in the area of interaction between the South Lancang River oceanic crust and Lanping-Simao microplate, and is the product of volcano-jet deposit mineralization in the backarc rift zone during the eastward subduction of the oceanic crust. The metallogenic belt belongs to the W, Cu polymetallic belt of Yunxian Jinghong volcanic Arc in the middle and south section of Lanping-Puer Block Cu-Pb-Zn-Ag-Fe-Hg-SB-As-Au gypsum-siderite-salt metallogenic belt in the Sanjiang Orogenic Belt of the Tethyan metallogenic domain. The study area is a marginal active zone between the Yangtze landmass and the Indian plate. From late Paleozoic to Early Tertiary, it has experienced many tectonic changes, intersected faults and joined each other, accompanied by magmatic intrusion and volcanic eruption activities, making this area show complex tectonic features. The main structural lines are mainly north-south, and the main faults include Lancang River fault and Jiufang fault.

Magmatic rocks are developed in the area, accounting for one third of the whole area, and the magmatic activity period is from Varissian to Alpine. The intrusive rocks are mainly distributed in the west of Jiufang fault, and the rock types are mainly medium-acid rocks, with a small amount of ultrabasic and basic rocks. The Varissian intrusive rock is the Lincang-Menghai granite base, and the lithology is the medium coarse-grained biotite monzonitic granite and porphyritic monzonitic granite. The Indosinian intermediate acid and neutral intrusive rocks are represented by Jiujie (quartz) diorite and Mengxiang granodiorite. The Yanshanian intrusive rocks are represented by Banpo ultrabasic and basic rock complex. The alpine intrusive rocks are mainly distributed in the Yakou area, including granite porphyry, quartz porphyry, monzonite granite porphyry, granodiorite porphyry, plagioclase granite porphyry, felsite porphyry, etc., which is a favorable area for searching porphyry deposits. Volcanic rocks are distributed between Lancang River fault zone and Jiufang fault, and only a small amount of volcanic rocks are exposed to the east of Jiufang fault. The volcanic-bearing beds include Devonian, Carboniferous, Permian and Triassic. It is mainly medium-acid rocks with less basic properties, including volcanic rocks and pyroclastic rocks. Dawazi Formation (DCd) and its related subvolcanic rocks are the production horizon of the Daping palm-type volcanic copper-polymetallic deposit. The geological map of the study area is shown in **Figure 1**.

The predicted area is located in the western part of Lanping-Simao biaxial backarc-continental basin. The ore-bearing strata are volcano-sedimentary rocks and related subvolcanic rocks of the Upper Devonian-Lower Carboniferous Dawazi Formation (DCd), and the tectonic environment for mineralization is the Late Devonian-Early Carboniferous Marine eruption-sedimentary basin and volcanic eruption center. The orebodies occur in specific submarine volcanic eruption-sedimentary cycles and related subvolcanic rocks, belonging to a more typical micropyritic and keratophyre formation. The ore-forming age is 306 -

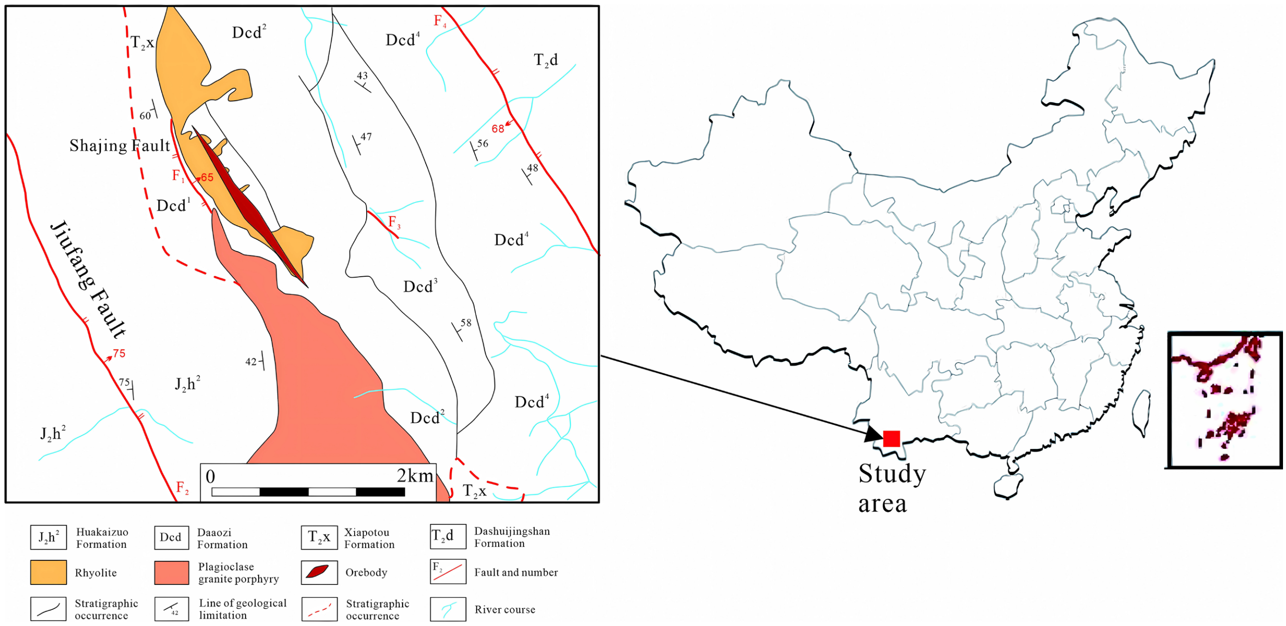

Figure 1. Geological map of Dapingzhang mining area in Yunnan Province.

358 Ma. The submarine volcanic eruption-sedimentary cycle and related subvolcanic rocks controlled the formation and production of volcanic copper polymetallic deposits, including the famous large copper polymetallic deposit in Puer, Yunnan.

At present, only two copper polymetallic deposit areas have been found in the area, except the Dpingzhang large copper polymetallic deposit in Puer City, and only one copper polymetallic deposit in Yindenshan, which has low geological exploration and research work, and its metallogenic geological background, prospecting conditions and mineralization characteristics. It is basically the same as Dpingzhang mining area and has strong comparability, so the study area has certain copper polymetal prospecting prospect and resource potential.

The deposit in this area was controlled to form in the stage of acid-basic volcanic effusion-deposition, and the genesis of the deposit is directly related to volcanic activity. In the Late Devonian to Early Carboniferous (D3-C1) Lanping-Simao biaxial backarc-continental basin, a volcanic basin was formed by the eruption of acid-basic volcanic rocks due to crustal stretching, and four eruption-sedimentary cycles developed from bottom to bottom in the basin. Cu, Pb, Zn, Ag, Au, S, P, CO_2, etc. brought by volcanic activities enter the sea basin in the form of air and hot springs, forming dense massive copper polymetallic ore (black ore) in favorable locations. In the late period of volcanic activity, the secondary volcanic rocks were filled in the volcanic mechanism (channel), and the hidden waterfall on the top of it formed the late fine vein disseminated copper ore (yellow ore).

2.2. Geophysical Characteristics

In the aeromagnetic ΔT contour plan, the positive anomaly is dominant, while the negative anomaly appears in the northwest corner, which is north-northwest, with high intensity and steep slope. The positive anomalies are divided into three high-value zones with a strength of 20 nT traps, and the extreme value is above 90 nT. The anomalies are generally caused by alkaline volcanic rocks, in which iron ore may appear locally, and are located in the eastern part of the deep fault of the Lancang River. In the north-northwest direction of the aeromagnetic anomaly zone, the intensity is 30γ, the gradient is very low and gentle, almost symmetrical. According to regional survey data, rhyolite and Triassic clastic rock outcrops, they are caused by volcanic rocks. The eastern region is located on a low relaxation elliptic anomaly with an intensity of less than 20γ. The surface is non-magnetic Permian limestone and clastic rocks, and the anomaly is caused by volcanic rocks. The Dapingzhang mining area is located in the low and slow area of normal aeromagnetic anomaly. The geophysical analysis diagram is shown in Figure 2.

2.3. Geochemical Characteristics

In the 1:200,000 drainage sediment survey mining area of the study area, there were abnormal combinations of Cu, Zn, Ag, Au, Mo and Hg, and the abnormal concentration center was obvious, with three-level concentration zoning. The 1:50,000 drainage sediment survey has formed Cu, Pb, Zn, Ag, Au, Sb and other element combination anomalies in the mining area, with high intensity, large range and strong correspondence with the ore body. When the depth of the ore body is large, the anomaly weakens.

As and Sb are highly enriched elements in this study area with enrichment coefficients greater than 2.5, which may be related to the thick red layer in this

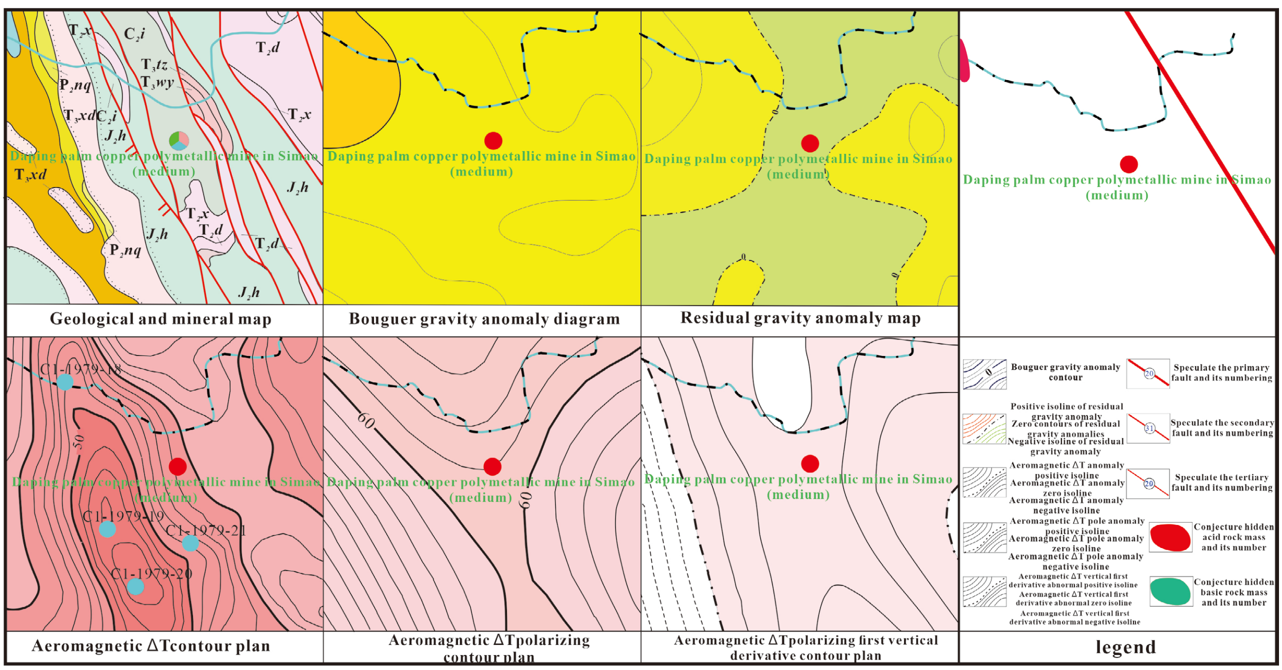

Figure 2. Schematic diagram of geology, mineral resources and geophysical exploration.

area. Pb, Ag and Zn are moderately or relatively enriched elements with enrichment coefficients of 1.61, 1.04 and 1.02, respectively. The relatively depleted elements are Cu, Hg, Mo and Au with enrichment coefficients of 0.85, 0.59, 0.53 and 0.43, respectively, suggesting that the main ore-forming elements Cu and Au may come from deeper sources. The statistical table of geochemical characteristics is shown in Table 1.

According to the distribution of main metallogenic elements and associated elements, the general anomaly trend is consistent with the stratigraphic trend in the predicted working area. The abnormal internal fault structure is developed and overlaps with the known Dapingzhang copper-polymetallic deposit. They have obvious concentration centers and tertiary concentration zones, and the concentration centers are well coordinated with each other. The geochemical association anomaly diagram is shown in Figure 3.

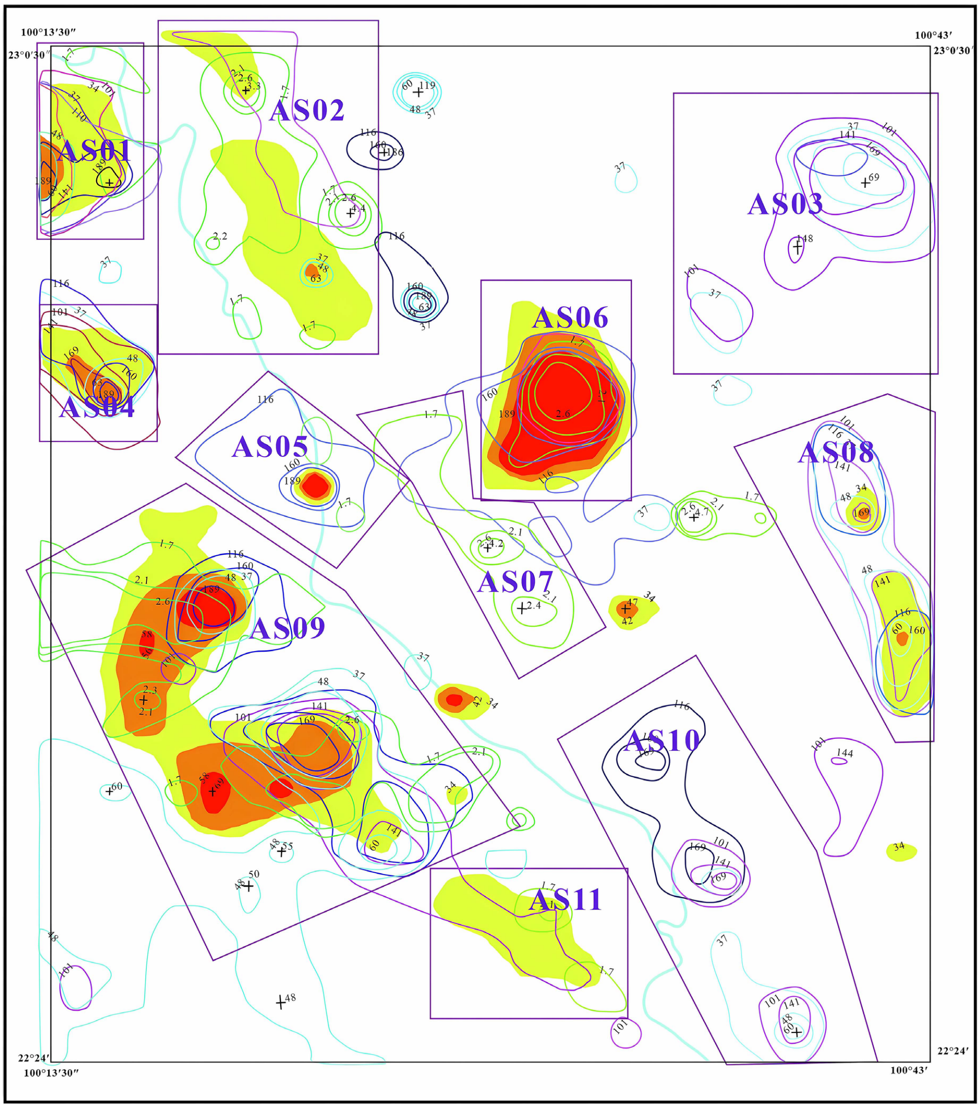

Figure 3. Anomaly map of Cu, Pb, Zinc-AG and Au geochemical combination in the prediction area of the Great Plain palm of Pu'er City.

Table 1. Drainage sediment geochemical characteristics in Daping Palm prediction area, Yunnan Province.

element	Record number	Elimination number	Maximum value	Minimum value	median	Background value	Lower limit of anomaly	Continental crust element content	Enrichment coefficient
Ag	945	78	1300.0	20.0	80.00	73.12	120.00	70.00	1.04
As	945	150	329.7	1.6	10.80	9.18	27.80	1.70	5.40
Au	945	24	33.0	0.3	1.18	1.09	1.80	2.50	0.43
Cu	945	59	574.9	4.8	21.90	21.31	34.90	25.00	0.85
Hg	945	145	482.0	2.0	26.00	23.64	64.00	40.00	0.59
Mo	945	123	16.1	0.1	0.60	0.58	1.30	1.10	0.53
Pb	945	54	278.7	5.4	24.80	23.76	39.10	14.80	1.61
Sb	936	20	30.0	0.1	0.90	0.83	1.80	0.30	2.78
Zn	945	90	656.7	19.7	70.10	65.98	104.10	65.00	1.02

Note: Au, Ag, Hg units are 10^{-9}, others are 10^{-6}; the content values of continental crust elements are cited from K. H. Wedepohl, 1995. The background value is the statistical average after removing the 2 times logarithmic standard deviation. The lower limit of the anomaly is the value corresponding to 85% of the repeated frequency.

3. Research Methods

3.1. Maximum Entropy

Information entropy is used to represent the uncertainty of information. According to the maximum entropy principle, the probability distribution with the maximum information entropy is the most objective when the origin moment constraint is satisfied (Wang, Sun, & Xie, 2015). Under the improved multi-point estimation framework, the maximum entropy can be expressed as:

$$\begin{cases} \max\left\{-\int \omega(y)\ln\omega(y)\,\mathrm{d}y\right\} \\ s.t.\quad \int y^c\omega(y)\,\mathrm{d}y = \alpha_c \quad c = 0,1,\cdots,C \\ \alpha_c = \sum_{i=1}^{m}\sum_{k=1}^{n} p_{i,k}\left(y(i,k)\right)^c \end{cases} \tag{1}$$

In the above formula: represents the probability density function of the random variable y, and C is the order that should satisfy the origin moment constraint. By introducing the Lagrange multiplier method, the following analytical solutions can be obtained.

$$\omega(y) = \exp\left(-\sum_{c=0}^{c}\lambda_c y^c\right) \tag{2}$$

In the above formula: is the Lagrange multiplier corresponding to the origin moment of order C (when C is 0, the origin moment is 1). The unknown parameters are obtained by Newton-Raphson method, and the probability distribution which best conforms to the objective reality is obtained. Compared with the traditional method of fitting the probability density function with finite term series expansion, the maximum entropy probability fitting makes use of the limited information, makes the least assumptions about the unknown information, and obtains the most objective probability distribution based on the limited information. The method also ensures that the value of the probability density function to be solved based on the negative exponential form is not less than 0.

If you want to apply the maximum model, you need to build a series of features based on the information of the current prediction point (a, b), and then train the parameters of the model with the information provided by the training sample.

The main purpose of the learning algorithm is to obtain the parameters of the maximum entropy model. However, different from other machine learning models, the optimization goal of the maximum entropy model is to maximize the entropy. Therefore, the formula used for training of the algorithm is as follows:

$$\lambda_i^{(n+1)} = \lambda_i^{\ n} + \frac{1}{c}\ln\left(\frac{E_{\hat{p}(f_i)}}{E_p n\left(f_i\right)}\right) \tag{3}$$

This paper uses the software "maxent.jar" to obtain the maximum entropy model, and automatically tries the best parameters to achieve the maximum entropy model.

The maximum entropy model is based on probability statistics and can be effectively predicted by simple training data. The mathematical form of the maximum entropy model is very flexible and can be adapted to various application scenarios. The maximum entropy model can provide interpretable decision rules, making it one of the most interpretable machine learning algorithms in many fields.

3.2. Jacknife Method

The Jackknife method, also known as the jackknife method or the large jackknife method, is a non-parametric estimation method in statistics. This method is a new method proposed by mathematician M.H. Quenouille from the point of view of reducing deviation. It is a kind of statistical method which can be applied to the estimation of complex statistics in the sample survey of mathematical statistics. Jacknife method is a data-based re-sampling method in statistical inference (Shi & Zhang, 2016). It is an improvement on the traditional return method. Similar to bootstrap method, both of them are misjudgment probability estimation methods independent of data distribution characteristics.

4. Results and Discussion

4.1. Results

The formation of mineral deposits is formed by the interaction of various geological processes in space, that is, the effective coupling of various geological variables in space can form mineral deposits. The entropy model is a black box, and its predictive effect is related to the internal structure of the method. The key to using maximum entropy method for mineral prediction lies in how to effectively identify these coupling factors and how to use data to express these coupling factors. In addition, the formation of the deposit occurs in a specific region, which is obviously controlled by regional metallogenic conditions and laws.

The Jackknife analysis of the results of the maximum entropy model reveals

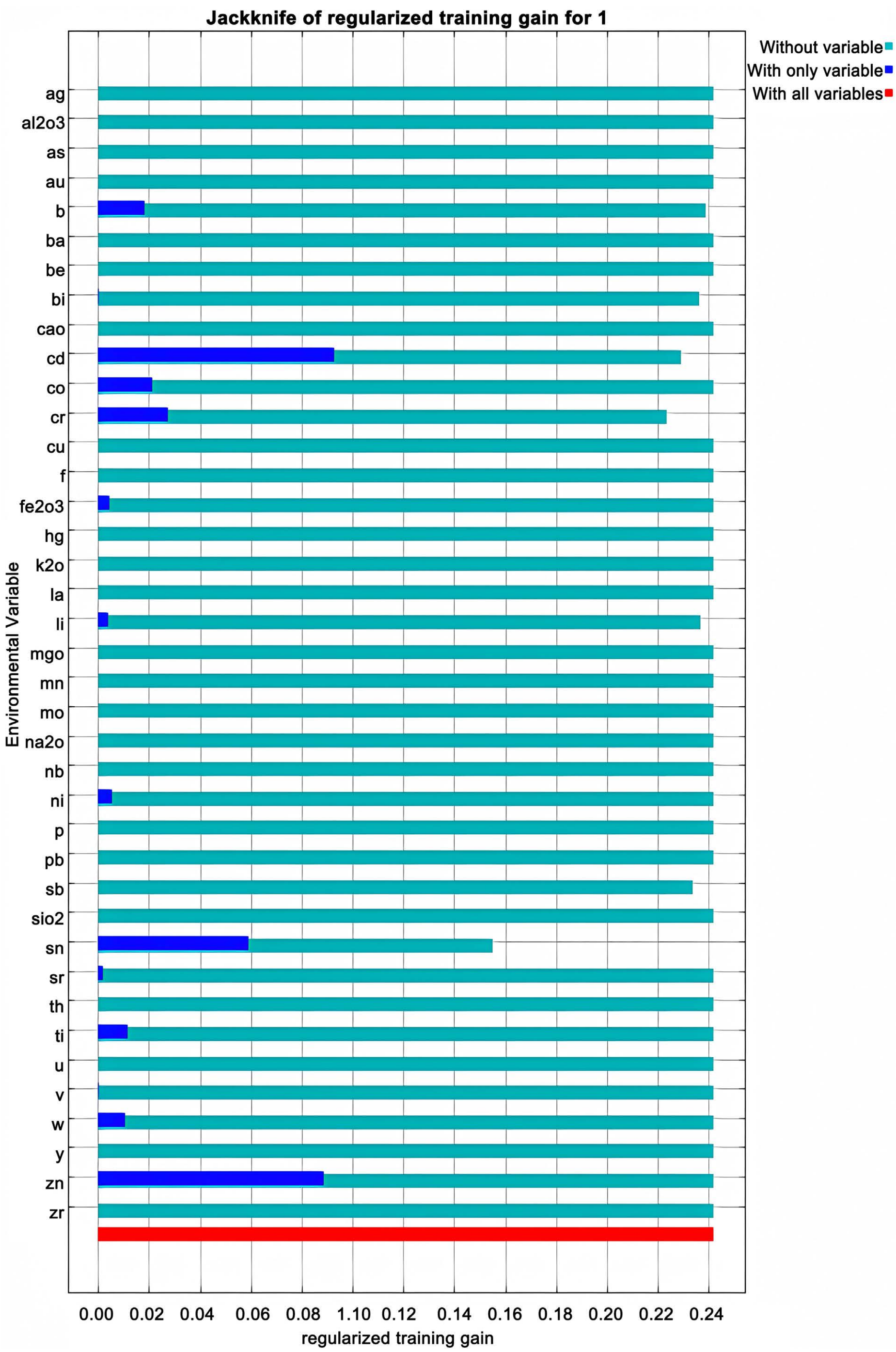

Figure 4. Schematic diagram of Jackknife analysis results.

the relative importance of each evidence variable in the model, which has guiding significance for the exploration work in the study area. Jackknife analysis in turn excludes evidence mapping from the analysis and then traverses the maximum entropy model using other evidence variables to determine the relative importance of each layer of evidence variable based on the final probability determined by the model.

The Jackknife analysis results of MaxEnt (maximum entropy) model reveal the relative importance of each variable in the model, which has guiding significance for the exploration of Cu, Zn, Sn and Cr in the study area. First, through Jackknife analysis, we screened the evidence variables in turn. Second, we rerun the MaxEnt model with other evidence variables. Running a separate model that contains only the excluded evidence variables allows us to determine the relative importance of each evidence variable relative to the prospecting probability determined by the model (**Figure 4**).

By studying the evidence variables related to the type of deposit, and using principal component analysis and other methods to comprehensively analyze the mining area, the information for exploration modeling is obtained. Finally, the results of the maximum entropy model are used to generate a prospecting prospect map (**Figure 5**).

Figure 6 shows the receiver operating characteristic (ROC) curve of the training data. ROC curve refers to a line drawn under specific stimulus conditions with the probability P (y/N) obtained by the subject under different judgment criteria as the horizontal coordinate and the hit probability P (y/SN) as the vertical coordinate. The AUC area of the training data is 0.83 (**Figure 6**), which proves that the maximum entropy model has high accuracy in prospecting prediction.

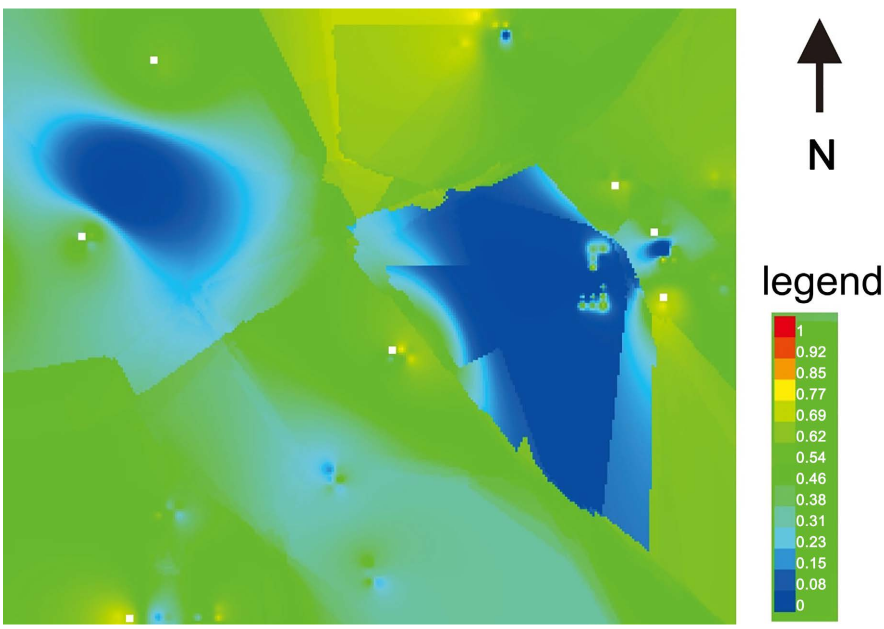

Figure 5. Prospecting prospect.

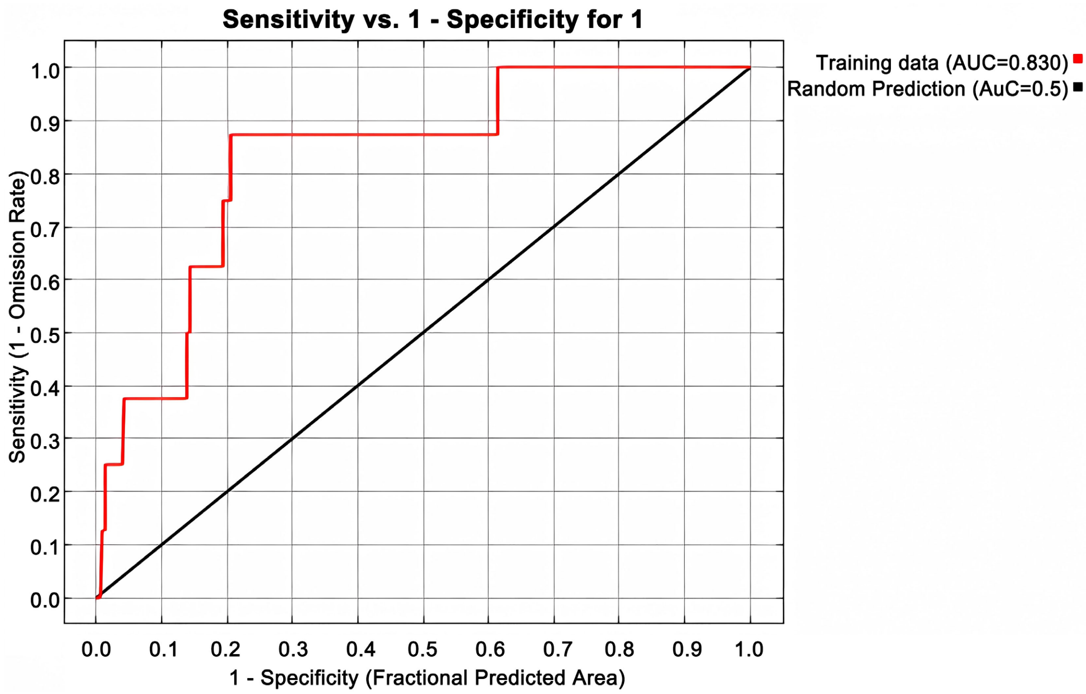

Figure 6. ROC accuracy verification curve of maximum entropy model.

4.2. Discussion

The AUC values of MaxEnt model were 0.83 respectively (**Figure 6**), indicating a high accuracy of prospecting prediction. The results show that MaxEnt model has reasonable probability distribution results. This model is a good prospecting prediction algorithm model, which can analyze the spatial relationship of prospecting prospect area and provide more reliable results for further exploration.

5. Conclusion

In this paper, the application effect of maximum entropy model in prospecting prediction is evaluated, and the metallogenic variables are input into the maximum entropy model to obtain the prospecting prediction model. The results show that this method can effectively identify geochemical element combination and improve the accuracy of prospecting prediction. The maximum entropy model is used to comprehensively evaluate the mineral resource potential of the study area, which can provide technical support for future prospecting work.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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