A Predictive GIS Model for Potential Mapping of Copper, Lead, and Zinc in Langping Area, China

Tarik. B. Benomar  HU Guangdao  BIAN Fuling

Abstract  Mineral resource potential mapping is a complex analytical process, which requires the consideration and the integration of a number of spatial evidences like geological, geomorphological, and wall rock alteration. The aim of this paper is to establish mineral exploration model for copper, lead, and zinc in Lanping basin area using the capability of analytical tools of Geographic Information System (GIS) and remote sensing data to generate maps showing favorable mineralized area. The geo-exploration dataset used for the research includes copper, lead, and zinc deposits, geological maps, topographic maps, structural maps, and ETM+ imagery. Geological features indicative of potential copper, lead, and zinc were extracted from the datasets input in the predictive model. The method of weights of evidence modeling is a probability-based technique for generating mineral potential maps using the spatial distribution of indicative features with respect to the known mineral occurrences. The method of weights of evidence probabilistic modeling provides a quantitative method for delineating areas with potential of copper, lead, and zinc mineral deposits in the Lanping Basin area. weights (W+, W−) and contrast (C=(W+)(W−)) calculations guide the data-driven modeling. The four most important spatial features for exploration guide for copper, lead, and zinc mineralization hosted in the Lanping Basin area are alteration zones, faults, host rocks, and lineaments. The host rocks and deep faults have the strongest spatial association with the known copper, lead, and zinc deposits. The hydrothermal alteration zones have the moderate spatial association with the copper, lead, and zinc deposits. The predicted high-favorability zones do not show the strong affinity with lineaments. The distribution of 22 (copper, lead, and zinc) occurrences in the Lanping Basin was examined in terms of spatial association with various geological phenomena. The analysis of these relationships using GIS and weights of evidence modeling has predicted areas of high and moderate mineral potential, where a little or no mining activities exist.

Keywords  remote sensing; geographic information system; weights of evidence; Lanping Basin (China)

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Introduction

The mineral exploration procedures always need to integrate data in order to consider a vast range of combination and to make different hypotheses. The analysis of spatial located data is one of the basic concerns of exploration geologists and can be more efficiently executed by means of Geographical Information Systems (GIS). GIS is a computer-based information system used to digitally represent and analyze the geographic features present on the Earth’
surface and the events (nonspatial attributes linked to the geography under study) taking place on it. One of the major applications of GIS is the ability to integrate and combine the multiple layers of lithology, structure, geophysical, and geochemical characteristics to delineate the mineral prospective maps. GIS integrates spatial and other kinds of information within a consolidated system. GIS makes connections between activities based on geographic proximity, looking at data geographically can often suggest the new insights and explanations. These connections are often unrecognized without GIS but are vital to understand and manage activities and resources. A Geographical Information System is a “computer-based system that integrates the data input, data storage and management, data manipulation and analysis, and data output for both spatial and attribute data to support the decision-making activities”. The mineral resource potential mapping is a very complex analytical procedure that requires the simultaneous consideration of a number of spatial evidences—geological, geomorphological, structural, geochemical, geophysical, etc. The capability of Geographic Information System to manipulate the classified spatial information through amalgamated layers makes it a unique tool for delineating potential locales. The flexibility of experimenting with spatial data followed by visualization gives GIS a cutting edge over other contemporary techniques for modeling mineral deposits. The predictive GIS model is based on weights of evidence analysis of lithological, structural, geochemical, and geophysical datasets employing knowledge-driven GIS approach. In this study, a GIS-based spatial analysis was applied to build maps showing areas favorable for copper, lead, and zinc deposits in the Lanping Basin.

1 Study area

Yunnan Province is located in the southwest of China between latitudes 21°05′–29°10′N and longitudes 97°30′–106°10′E. It is more than 380 thousand square kilometers in area. The study area, Lanping Basin is situated in the northwest part of Yunnan Province between latitude (26°28′ and 28°22′ N) and longitude (98°26′ and 99°89′ E). Fig.1 shows the study area location. The study area is accessible to Kunming city by highway and lies in the region of high mountains.

2 Geology

The Lanping Basin is the northern part of the Mesozoic-Cenozoic Lanping-Simao Basin, which is tectonically situated in the Qamdo-Simao microplate between the Lancangjiang and Jinshajiang-Ailaoshan tectonic belts. To the east, it is linked with the Yangtze Plate, and to the west, the Tibet-Yunnan Plate. The basin is a small land mass in the Paleotethys during the Proterozoic through the Early Paleozoic. The ocean disappeared at the end of the Caledonian, and a stable land mass developed. The land mass rifted along the Lancangjiang and Jinshajiang belts during the Late Paleozoic; the Lanping Basin was a microplate between the Yangtze and Tibet-Yunnan plates. The Paleotethys closed in the Late Permian or Early Triassic, and the basin became a part of Laurasia. On the Paleotethys basement, the Mesozoic Cenozoic Lanping Basin developed with marine and terrestrial carbonates, volcanic rocks, and clastic rocks. Fig.2 illustrates the geological map of study area, and there are several terrestrial gypsum-salt sequences and sedimentary gaps in the basin stratigraphic column. The tectonic evolution of the Lanping Basin shows the stages as Indosinian rift basin, Yanshanian depression basin, and Himalayan pull-apart basin[6], such as Jinshanjiang-Ailaoshan Fault, Lancangjiang Fault, and Lanping-Simao Fault, cut deeply into the lower crust and upper mantle[7]. The Lanping-Simao syn-sedimentary fault controlled
Tertiary basins and acted as the strongest in the Cenozoic. Some blind E-W trending structures are also recognized by remote sensing, gravity, and aeromagnetic survey. According to the remote sensing interpretation, some annular structures occurred at the cross of NNW- and E-W trending structures, and this may suggest some thermal bodies or intrusive rocks in the depth.

### 3 Method

The methodology involves conceptual modeling, database building, intermediate-layer generation, data integration, and metallogenic interpretation. In this paper, the application of method integrating exploration datasets of weights of evidence is discussed.

The weights-of-evidence (WofE) is a quantitative method that uses a long-linear formulation of the Bayes' Rule of Probability with an assumption of conditional independence to combine the map patterns. WofE has been used by geologists to identify the areas favorable for geologic phenomena, such as mineralization and seismicity. The weights-of-evidence method allows the user to explore the spatial relationship between known mineral deposits and exploration datasets from a variety of sources. In evidence maps (evidential themes) derived from geochemical mineral exploration applications, a series of geophysical and geological evidential themes assessed with respect to the locations of datasets are combined to produce a mineral prospective (or potential) map. The spatial association of known deposits is used as training points. A pair of weights, $W^+$ and $W^-$, determined from the degree of overlap between the known deposits and the binary evidence map (e.g., geochemical anomaly map) is calculated for each map to be used as evidence. If there is no spatial association between the training points and the binary evidence map, then $W^+=W^-=0$. A positive $W^+$
value indicates a positive association between training points and the evidence map. In this case, the more known deposits occur on the map class than what would be expected if the number of deposits occurring could be explained as due to chance. Conversely, a negative association implies the occurrence of fewer known deposits on that map class than what would be expected due to chance. The contrast value $C$, where $C = (W^+) - (W^-)$, is a summary value that reflects the degree of spatial association between the evidence map and the mineral prospects. The larger the $C$ value, the greater the spatial association. A study of weights and contrast values can facilitate the process of identifying breaks between background and anomalous values in geochemical data or in identifying critical distances for buffering linear features, etc.). The effects of various sources of uncertainty on the final result can be modeled, such as the variances of weights and variance due to missing data (incomplete surveys). A recent development allows the effect of kriging variance on the weights to be modeled\cite{3}.

Although the degree of violation depends on the choice and number of maps used as predictors. There are various tests for conditional dependence\cite{4}, but ultimately, the safest way to check the effect of conditional dependence on the results is to carry out a logistic regression analysis on the same input datasets. The response and predictive variables are the same weights of evidence, except that multistate categorical maps must be recoded to binary form. The coefficients are somewhat similar to the “contrast” in weights of evidence, except that they are solved simultaneously and allow the predictors to be intercorrelated. The patterns of the posterior probability maps between the two methods can be compared. In general, apart from minor differences, the rank order of probability values between the two methods is generally similar, except that the scaling can differ\cite{5}.

4 Results and discussion

4.1 Calculating the weights of structure evidence

The spatial association of faults with the mineral occurrences is also quantified by the weights of the evidence method. The faults map was split into two subsets depending on the general trend (NE-SW, NW-SE); both faults were buffered up to 2 000 m at 100m intervals. The results of the first analysis to obtain the optimum proximity distance with the 22 mineral occurrences are presented in the Table 1. The optimum buffer that resulted the maximum studentized $C$ for the NE-SW was defined at 500m within, wherein four deposit points are presenting favorable patterns, as shown in Fig. 3(a). For the other fault trend NW-SE, the significant studentized $C$ is at a distance of 900m within which 11 deposit points are present, as shown in Fig. 3(b). The resulting binary map of the optimum spatial association to the fault of both direction is shown in (Fig. 4) with $W^+ (1.275 4)$ and $W^- (-0.069 6)$ as the weight values for the two domains and value of contrast (1.345 0).
Table 1  Weights of evidence for cumulative distance from structure fault

| Class | Area(Sq.km) | Area(Units) | #Points | W+  | s(W+) | W−  | s(W−) | Contrast | S(C) | Stud(C) |
|-------|-------------|-------------|---------|-----|-------|-----|-------|----------|------|---------|
| 100   | 550.000 0   | 550.000 0   | 2       | 0.622 5 | 0.708 4 | −0.045 3 | 0.223 8 | 0.667 8 | 0.742 9 | 0.898 9 |
| 200   | 318.700 0   | 318.700 0   | 1       | 0.474 5 | 1.001 6 | −0.017 8 | 0.218 4 | 0.492 3 | 1.025 1 | 0.480 3 |
| 300   | 364.710 0   | 364.710 0   | 1       | 0.339 2 | 1.001 4 | −0.013 6 | 0.218 4 | 0.352 9 | 1.024 9 | 0.344 3 |
| 400   | 306.630 0   | 306.630 0   | 2       | 1.209 7 | 0.709 4 | −0.067 8 | 0.223 8 | 1.277 5 | 0.743 9 | 1.717 3 |
| 500   | 384.240 0   | 384.240 0   | 2       | 0.982 7 | 0.709 0 | −0.060 7 | 0.223 8 | 1.043 4 | 0.743 4 | 1.403 5 |
| 600   | 287.250 0   | 287.250 0   | 2       | 1.275 4 | 0.709 6 | −0.069 6 | 0.223 8 | 1.345 0 | 0.744 0 | 1.807 7 |
| 700   | 276.800 0   | 276.800 0   | 1       | 0.615 9 | 1.001 8 | −0.021 7 | 0.218 4 | 0.637 6 | 1.025 3 | 0.621 8 |
| 800   | 310.770 0   | 310.770 0   | 1       | 0.499 8 | 1.001 6 | −0.018 6 | 0.218 4 | 0.518 3 | 1.025 2 | 0.505 6 |
| 900   | 302.570 0   | 302.570 0   | 1       | 0.526 6 | 1.001 7 | −0.019 3 | 0.218 4 | 0.545 9 | 1.025 2 | 0.532 5 |
| 1900  | 193.820 0   | 193.820 0   | 1       | 0.973 8 | 1.002 6 | −0.029 2 | 0.218 4 | 1.003 0 | 1.026 1 | 0.977 5 |
| 2000  | 191.930 0   | 191.930 0   | 0       |         |       |       |       |         |       |         |
| 2001  | 5 709.730 0 | 5 709.730 0 | 8       | −0.333 5 | 0.353 8 | 0.256 4 | 0.267 6 | −0.589 9 | 0.443 6 | −1.329 8 |

Fig. 4  Binary predictor pattern map of structural fault

4.2  Calculating the weights of lineament evidence

In order to create the evidence map of lineaments interpreted from remote sensing data, a lineament is a mappable, simple, or composite linear feature of a surface whose parts are aligned in a rectilinear or slightly curvilinear relationship, which differs distinctly from the pattern of adjacent features and presumably represents a surface phenomenon\(^5\). The cumulative distance of 100m wide was generated around these lineaments with 20 buffers. The deposit point’s locations were superimposed on the buffer map, and the weights for cumulative distances from the faults were calculated. The results of the first analysis to obtain the optimum proximity distance with the 22 deposit points mineral occurrences are presented in Table 2. The variation of the spatial association (sigC) and C with cumulative distance away from the lineament are the highest 1 300 m where 17 of 22 Cu, Pb, and Zn are shown in Fig.5. The resulting binary map of the optimum spatial association to lineament is in W+(1.368 0) and W−(−0.111 3) as the weight values for the two domains and value of contrast (1.479 3).

Fig.5  Binary predictor pattern map of structural lineament

4.3  Calculating the weights of host rocks evidence

The following cumulative distances of (0, 100, 200, 300, 400, 500, 600, 700, 12 000, and 21 000 m) from the favorable rocks are considered, and the optimum proximity distance to the favorable rocks was calculated. The distance class having the highest spatial association (studentized C) with the mineral occurrences is determined. The results are presented in Table 3 with the optimum distance being 300 m. The variation in the spatial association of cumulative distance to this geologic feature, and the mineral occurrences in the Lanping Basin is shown in Fig.6. From the graph, the optimum distance is 300m where 8 of 22 Cu, Pb, and Zn deposit points. The resulting bi-
nary predictor map of the optimum distance is shown in Fig. 6 with two domains, the presence of the predictor pattern assigned a weight value $W^+$ (2.5104), and the absence of the pattern assigned $W^-$ (−0.0879).

### Table 2  Weights of evidence for cumulative distance from structure lineament

| Class | Area(Sq.km) | Area(Units) | #Points | $W^+$ | $s(W^+)$ | $W^-$ | $s(W^-)$ | Contrast | S(C) | Stud(C) |
|-------|-------------|-------------|---------|-------|----------|-------|----------|----------|------|---------|
| 100   | 936.340     | 936.340     | 2       | 0.0889 | 0.7079   | −0.0085 | 0.2238   | 0.0974   | 0.7424 | 0.1312  |
| 200   | 536.020     | 536.020     | 0       |        |          |        |          |          |       |         |
| 300   | 695.030     | 695.030     | 2       | 0.5418 | 0.7083   | −0.0410 | 0.2238   | 0.5828   | 0.7428 | 0.7846  |
| 400   | 505.530     | 505.530     | 1       | 0.0120 | 1.0010   | −0.0006 | 0.2184   | 0.0125   | 1.0245 | 0.0122  |
| 500   | 610.200     | 610.200     | 3       | 0.9254 | 0.5788   | −0.0910 | 0.2296   | 1.0164   | 0.6227 | 1.6323  |
| 600   | 462.280     | 462.280     | 1       | 0.1016 | 1.0011   | −0.0046 | 0.2184   | 0.1062   | 1.0246 | 0.1036  |
| 700   | 440.330     | 440.330     | 0       |        |          |        |          |          |       |         |
| 800   | 480.930     | 480.930     | 1       | 0.0620 | 1.0010   | −0.0002 | 0.2184   | 0.0648   | 1.0246 | 0.0633  |
| 900   | 461.540     | 461.540     | 0       |        |          |        |          |          |       |         |
| 1000  | 429.190     | 429.190     | 1       | 0.1760 | 1.0012   | −0.0077 | 0.2184   | 0.1837   | 1.0247 | 0.1793  |
| 1100  | 350.140     | 350.140     | 0       |        |          |        |          |          |       |         |
| 1200  | 330.320     | 330.320     | 1       | 0.4386 | 1.0015   | −0.0168 | 0.2184   | 0.4553   | 1.0251 | 0.4442  |
| 1300  | 393.010     | 393.010     | 3       | 1.3680 | 0.5796   | −0.1113 | 0.2296   | 1.4793   | 0.6234 | 2.3730  |
| 1400  | 304.110     | 304.110     | 1       | 0.5215 | 1.0016   | −0.0192 | 0.2184   | 0.5407   | 1.0252 | 0.5274  |
| 1500  | 306.070     | 306.070     | 1       | 0.5151 | 1.0016   | −0.0190 | 0.2184   | 0.5340   | 1.0252 | 0.5209  |
| 1600  | 248.010     | 248.010     | 1       | 0.7262 | 1.0020   | −0.0243 | 0.2184   | 0.7505   | 1.0256 | 0.7318  |
| 2000  | 216.140     | 216.140     | 1       | 0.8643 | 1.0023   | −0.0272 | 0.2184   | 0.8915   | 1.0258 | 0.8690  |
| 2001  | 2,926.220   | 2,926.220   | 3       | −0.6462| 0.5776   | −0.1548 | 0.2297   | −0.8010  | 0.6216 | −1.2886 |

### Table 3  Weights of evidence for cumulative distance from host rock

| Class | Area(Sq.km) | Area(Units) | #Points | $W^+$ | $s(W^+)$ | $W^-$ | $s(W^-)$ | Contrast | S(C) | Stud(C) |
|-------|-------------|-------------|---------|-------|----------|-------|----------|----------|------|---------|
| 100   | 533.170     | 533.170     | 6       | 1.7226 | 0.4105   | −0.2685 | 0.2502   | 1.9911   | 0.4804 | 4.1420  |
| 200   | 73.150      | 73.150      | 0       |        |          |        |          |          |       |         |
| 300   | 84.960      | 84.960      | 2       | 2.5104 | 0.7156   | −0.0879 | 0.2238   | 2.5937   | 0.7498 | 3.4655  |
| 400   | 75.350      | 75.350      | 0       |        |          |        |          |          |       |         |
| 500   | 96.990      | 96.990      | 1       | 1.6714 | 1.0052   | −0.0379 | 0.2148   | 1.7093   | 1.0287 | 1.6671  |
| 1500  | 80.700      | 80.700      | 1       | 1.8573 | 1.0063   | −0.0374 | 0.2148   | 1.8967   | 1.0297 | 1.8420  |
| 1600  | 69.360      | 69.360      | 1       | 2.0108 | 1.0073   | −0.0404 | 0.2148   | 2.0512   | 1.0307 | 1.9901  |
| 1700  | 80.420      | 80.420      | 1       | 1.8609 | 1.0063   | −0.0394 | 0.2148   | 1.9003   | 1.0297 | 1.8454  |
| 1800  | 72.120      | 72.120      | 0       |        |          |        |          |          |       |         |
| 1900  | 77.740      | 77.740      | 0       |        |          |        |          |          |       |         |
| 2000  | 78.300      | 78.300      | 1       | 1.8879 | 1.0064   | −0.0396 | 0.2148   | 1.9275   | 1.0299 | 1.8716  |
| 2001  | 9180.570    | 9180.570    | 9       | −0.6910| 0.3335   | 1.1692  | 0.2782   | −1.8603  | 0.4343 | −4.2832 |

### 4.4 Calculating the weights of alteration zones evidence

The variation in the quantified spatial association of proximity distances to the alteration zones and the mineral occurrences is shown in Fig. 7. The result of the analysis is presented in Table 4. The optimum proximity distance to the alteration zones, which is 1,600 m for this analysis is determined by the distance class with the highest studentized C value and contrast, where 4 of 22 Cu, Pb, and Zn occurrences
are present in the favorable pattern. The binary predictor map of the optimum distance to alteration zones is then created using the values of $W^+(2.7106)$ and $W^-(−0.089 2)$ and contrast $C (2.799 8)$.

Table 4  Weights of evidence for cumulative distance from alteration zones

| Class | Area(Sq.km) | Area(Units) | #Points | W+  | s(W+)  | W−  | s(W−)  | Contrast | S(C)  | Stud(C) |
|-------|-------------|-------------|---------|-----|--------|-----|--------|----------|-------|---------|
| 900   | 68.570 0    | 68.570 0    | 1       | 2.024 | 1.007 4 | −0.040 5 | 0.218 4 | 2.062 9 | 1.030 8 | 2.001 3 |
| 1000  | 72.380 0    | 72.380 0    | 0       | 1.082 | 0.537 2 | 0     | 0.294 4 | 1.376 6 | 0.734 5 | 1.017 3 |
| 1500  | 81.200 0    | 81.200 0    | 1       | 1.851 | 1.006 2 | −0.039 4 | 0.218 4 | 1.890 4 | 1.029 6 | 1.836 0 |
| 1600  | 69.910 0    | 69.910 0    | 2       | 2.710 6 | 0.717 4 | −0.089 2 | 0.223 8 | 2.799 8 | 0.751 5 | 3.725 4 |
| 1700  | 82.710 0    | 82.710 0    | 1       | 1.832 4 | 1.006 1 | −0.039 2 | 0.218 4 | 1.871 6 | 1.029 5 | 1.817 9 |
| 1800  | 77.790 0    | 77.790 0    | 0       | 1.082 | 0.537 2 | 0     | 0.294 4 | 1.376 6 | 0.734 5 | 1.017 3 |
| 1900  | 83.440 0    | 83.440 0    | 0       | 1.082 | 0.537 2 | 0     | 0.294 4 | 1.376 6 | 0.734 5 | 1.017 3 |
| 2000  | 86.290 0    | 86.290 0    | 0       | 1.082 | 0.537 2 | 0     | 0.294 4 | 1.376 6 | 0.734 5 | 1.017 3 |
| 2001  | 9 775.040 0 | 9 775.040 0 | 17      | −0.117 | 0.242 7 | 0.548 4 | 0.448 0 | −0.665 4 | 0.509 5 | −1.306 0 |

Fig.7  Binary predictor pattern map of alteration zones

4.5 Combining binary evidential maps

In weights of evidence modeling, two or more ($j = 1, 2, n$) binary predictor patterns are combined to generate a map of posterior. The binary predictor patterns generated by weights of evidence equations and considered important for predictive mapping for zones with potential for mineralization of Cu, Pb, and Zn in Lanping Basin area are those of the deep faults, host rocks, and lineaments. This consideration was based on the value of studentized C. The value of studentized C should be positive and statistically significant, which indicates a significant positive spatial association. These binary predictor patterns values are presented in Table 5, based on the magnitude of the value of studentized C, which indicates the strength of their spatial association with the Cu, Pb, and Zn in the Lanping Basin area. Figure 8 shows the classified posterior probability map generated by combining the host rock, lineament structure, alteration zones, and faults binary predictor maps. In general, maps derived from geological features (host rocks) and deep faults were extracted and digitized from available geological and geophysical maps of the area; they have the greatest contrast values, indicating that they are the best predictors of known deposits and indications.

Fig.8  Predictive model map of Lanping Basin region in which high prospective Cu, Pb, and Zn zones

Table 5  Binary predictor pattern based on the value of studentized and contrast C in Lanping

| Evidential theme | Optimal spatial association distance (m) | W+  | W−  | C contrast | sigC |
|-----------------|----------------------------------------|-----|-----|-----------|------|
| Host rocks      | 300                                    | 1.759 3 | −0.387 3 | 2.146 6 | 4.825 3 |
| Alteration zones| 1 600                                  | 0.732 1 | −0.142 1 | 0.874 2 | 1.715 4 |
| Lineaments      | 1 300                                  | 0.161 5 | −0.277 3 | 0.438 8 | 0.957 8 |
| Faults          | 600                                    | 0.818 6 | −0.444 0 | 1.262 6 | 29.571 |

Table 5  Binary predictor pattern based on the value of studentized and contrast C in Lanping
5 Conclusion

This research sought to identify model function(s) that can be effectively used in the framework of weight of evidence models to evaluate the relationship between a set of recognition geological factors and the target mineral deposits for mineral potential mapping.

GIS-based weights of evidence probabilistic modeling provided a quantitative method for delineating areas with potential to copper, lead, and zinc mineral deposits in the Lanping Basin area.

The four most important spatial features or exploration guides to hosted copper, lead, and zinc mineralization in the Lanping Basin area as seen in the genetic model are alteration zones, faults, host rocks and lineaments.

The host rocks and deep faults have the strongest spatial associations with the known Cu, Pb, and Zn deposits.

The four mineral potential maps created using different map sets define the broadly coincident favorable areas, boosting confidence in the predictive maps. The predictive models generated four new target areas without known Cu, Pb, and Zn deposits, especially in the northwest, southwest, southeast, and northeast parts of the study area.

All the generated predictive models can be used to guide further exploration work in the study area.

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