Mineral potential targeting and resource assessment based on 3D geological modeling in Luanchuan region, China

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A B S T R A C T
In this paper, we used 3D modeling and nonlinear methods (fractal, multifractal, and probabilistic neural networks (PNN)) for regional mineral potential mapping and quantitative assessment for porphyry and skarn-type Mo deposits and hydrothermal vein-type Pb–Zn–Ag deposits in the Luanchuan region, China. A 3D geological model was constructed from various geographical maps, cross sections, boreholes, and gravity and magnetic data. Geological features associated with mineralization were extracted using the 3D geological model and metasomatic models of porphyry and skarn-type Mo and Pb–Zn–Ag deposits. The multifractal method, principal component analysis, and power spectrum–area method were used to separate regional variability from local variability in the geochemical data. A 2.5D forward modeling of gravity and magnetic data was carried out to define the geometry, depth, and physical properties of geological bodies at depth. 3D visualization of the results assisted in understanding the spatial relations between the deposits and the other geological bodies (e.g., igneous intrusions). The PNN method was applied to represent and integrate multiple anomalies for mineral potential modeling. The concentration–area fractal method was used to classify the PNN mineral potential model. Three levels (ground surface and two subsurface horizontal planes) of mineral potential models were evaluated for undiscovered Mo and Pb–Zn–Ag deposits. Validation of the results shows that 3D modeling was useful for not only accurately extracting geological features but also for predicting potential mineral targets and evaluating mineral resources. The mineral potential targets identified consist of eight Mo potential targets and 15 Pb–Zn–Ag potential targets. Based on grade–tonnage data from the known Mo and Pb–Zn–Ag deposits and the results of 3D modeling, estimated potential resources of each of these types of deposits are 10.8 and 153.1 Mt (Pb+Zn is 152.9 Mt and Ag is 0.92 Mt), respectively.

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1. Introduction

Mineral potential mapping and mineral resource assessment aim to delineate target zones and to estimate the probable size of undiscovered mineral deposits and the total mineral resource of certain types of mineral deposits (Singer, 1993, 2008; Bonham-Carter, 1994; Cheng, 2008; Carranza et al., 2009; Carranza and Sadeghi, 2010; Carranza, 2011). In general, two-dimensional (2D) geographical information systems (GIS) are particularly valuable in mineral potential mapping for extracting spatial information from exploration datasets, and more so in recent years given that statistical and expert-system modeling tools are increasingly being embedded in GIS, such as Arc-WoE, ArcGIS SDM, and GeoDAS systems (Agerberg et al., 1990; Cheng, 2000; Bonham-Carter and de Kemp, 2003; Sawatzky et al., 2008). In 2D GIS, geological bodies are represented as map objects in two spatial dimensions and, therefore, are inappropriate for many three-dimensional (3D) geological applications since they cannot represent 3D spatial geological relationships and properties with 3D spatial variations (Apel, 2006).

To represent exploration targets for undiscovered mineral deposits accurately, the key parameters needed must consist of 3D locations, the number of deposits, and the volume of potential minerals. Modeling in 3D is an important technology enabling 3D information about mineralization to be leveraged for the computation or extraction of the key parameters. 3D GIS or modeling software packages (e.g., Micromine, GOCAD, and Surpac) have proven to be excellent means of data presentation and interpretation (Smirnoff et al., 2008). The development of sophisticated 3D visualization software has made it possible to integrate geological, geochemical, and geophysical data fully into a 3D model of the geological environment.
The present study area in Luanchuan (China) provides a challenge in 3D mineral resource assessment because it has a complex geological setting, with skarn-type Mo deposits or occurrences, various metallogenic models, many geological factors, and a range of data sources on multiple scales and in various formats. In order to accurately identify Mo and Pb–Zn–Ag potential targets in 3D, and to estimate their mineral resources for further exploration, we applied a methodology of mineral resource assessment involving 3D modeling and nonlinear methods such as probabilistic neural networks (PNN) and fractal/multifractal analysis (Sawatzky et al., 2008; Cheng and Li, 2002; Cheng, 2008).

2. Methodology

The methodology for quantitative mineral resource assessment described in this paper involved four aspects: (1) 3D geological modeling; (2) anomaly information extraction; (3) anomaly information integration; and (4) 3D mineral potential modeling and resource assessment. 3D modeling and nonlinear methods have been adapted to enable 3D mineral potential modeling by analysis and integration of geochemical, geological, and geophysical datasets. The PNN method was used to integrate anomaly information in predicting mineral potential targets via training from known mineral deposits or occurrences. The fractal method was used (a) to extract geochemical anomalies by analysis of their scale-invariant spatial properties and (b) to define thresholds for classification of 2D mineral potential models in three different levels.

2.1. Geological modeling in 3D

The usefulness of 3D geometric models to understand surface and subsurface geology better is now well established (Houlding, 1994; Mallet, 2002; Wu et al., 2005; Lemon and Jones, 2003; Calcagno et al., 2008; Caumont et al., 2009). A 3D geological modeling software environment provides a single platform that adopts a common 3D coordinate system for representation and integration of geoscientific (i.e., geological, geophysical, and geochemical) datasets in terms of 3D spatial geological relationships and other properties with 3D spatial variations (Fallara et al., 2006; Apel, 2006; Kaufman and Martin, 2008; Wang et al., 2009b). In the present study, 3D geological modeling provides for effective extraction of spatial information from exploration data-sets in 3D (e.g., mineral stratum and Jurassic granite porphyry, and mineral anomalies from geochemical and geophysical data) to identify the optimum buffer distance around mineralized faults by combining interpretative mineralized strata and granite porphyry models to cross-validate the exploration targets through querying and visualizing various kinds of spatial information from metallogenic models of known mineral deposits in the study area.

To construct accurate regional 3D geological models from geological data (e.g., geological maps at different scales, cross sections, and boreholes), it was necessary to develop a methodology that took into account also gravity and magnetic data. Geological maps synthesize geological information but they do not give a complete representation of the subsurface geology. Geological cross sections and borehole logs add the third dimension and give a more detailed interpretation of subsurface geology. However, modeling of gravity and magnetic data allows better interpretation of the geometry of geological features at depth and geometrical relationships of those features, which provide 3D geological modeling with essential information about locations, orientations, and relationships of geological features at depth. For example, geophysical information about the younging direction is essential in 3D geological modeling of a sedimentary series (Calcagno et al., 2008). The methodology that we propose for 3D geological modeling involved the following steps:

1. **Geoscience data handling**: this involved compilation of geological, geophysical, topographical, and geochemical information, and standardization of lithological units relating to the same 3D coordinate system.

2. **3D geological modeling**: this involved interpretation, construction, and integration of regional geological cross sections used for the homogenization and simplification of regional geological contacts. Geological surfaces were built from contact curves and dip vectors derived from the surface geological maps, cross sections, and digital elevation models (DEMs). Orientation data from the surface geological maps and cross sections provide information for interpretation and modeling of geometry and geometrical relationships of 3D unit vectors according to the geological characteristic in the study area. For example, the dips of strata in the Meiyaogou Formation are multiple, but average dip can be used as the basis for the orientation of individual stratum. However, geophysical data-sets were used for constraining depths, dips, and boundaries of geological bodies (orebodies, strata, faults, folds, and granite (porphyry)) in the subsurface.

3. **Interpretation and validation**: borehole data were used for control and validation of geological, geophysical, and geochemical sections and 3D geological models at depth.

2.2. Extraction of anomalies

Geological, geochemical, and geophysical features associated with mineral deposits are referred to as anomalies and have usually been extracted in 2D datasets (Agterberg et al., 1990; Cheng, 2000; Zhao, 2002; Bonham-Carter and de Kemp, 2003; Sawatzky et al., 2008; Carranza and Sadeghi, 2010). In this paper, geological features related to mineralization were extracted by directly querying vector/raster objects in 3D geological models based on metallogenic features of porphyry- and skarn-type Mo deposits (i.e., metallogenic strata, porphyry bodies, and structures). Multifractality analysis, principal component (PC) analysis, and power spectrum–area (S–A) analysis were used to define filters in the frequency domain to distinguish regional variability from local variability in the geochemical data (Cheng, 2000). Combined 2.5D forward modeling and upward continuation of gravity and magnetic potential fields allowed us to extract anomaly information about geometry, depth, and physical properties of geological bodies associated with mineralization.

2.3. Integration of anomalies

2.3.1. **PNN method of modeling mineral potential**

The PNN method has been applied in various studies to analyze and identify predictor variables, integrate various geoscience information, and classify mineral deposits (e.g., Singer, 2006; Sawatzky et al., 2008; Leite and Filho, 2009). In this study, the PNN algorithm of the ArcGIS Spatial Data Modeler (ArcSDM) software was used to integrate multiple layers of thematic (i.e., geological, geochemical) anomalies to model potential for occurrence of Mo and Pb–Zn–Ag deposits in the subsurface. The PNN algorithm, which is a Bayes–Parzen classifier, was first introduced by Specht (1990). It has gained popularity in geoscientific studies because it is easy to implement and it offers a way to interpret the network’s structure in the form of a probabilistic density function (PDF) as follows:

\[
 f_k(x) = \frac{1}{(2\pi)^{D/2}\times\sigma^D} \sum_{i=1}^{m} \exp \left( -\frac{(X-X_{ki})^T(X-X_{ki})}{2\sigma^2} \right) 
\]
Here $X$ is a test vector to be classified, $f_k(X)$ is a value of the PDF of anomaly theme $k$ at point $X$, $m$ is number of training vectors in anomaly theme $k$, $p$ is dimensionality of the Gaussian functions evaluated at each training vector, $X_{ij}$ is $p$-dimensional $j$th training vector of anomaly theme $k$, $T$ indicates a transposed matrix or vector, and $\sigma$ is a smoothing parameter.

The PNN consists of four layers: input, pattern, summation, and output. The input layer passes the data to the next layer. The input data are processed by neurons in the pattern layer through an activation function, which is usually an exponential function as in Eq. (1):

$$\exp\left(-\frac{(x_i-w_{ij})^2}{2\sigma^2}\right).$$

Here $x_i$ is the $i$th variable of the test pattern to be classified, $w_{ij}$ is the $i$th variable of the $j$th training pattern, and $T$ is the transpose of a vector. The values of the activation function indicate degrees of similarities between the test and the training patterns; the smaller the values, the stronger the similarities between the test and the training patterns. Values in the pattern layer range between 0 and 1. The summation layer accumulates the output of the pattern layer. The output layer classifies a test pattern to one of the classes based on the summation layer output. More details regarding the PNN method adopted in this paper can be found in Kim et al. (2005).

### 2.3.2. Threshold analysis of mineral potential model via C–A fractal method

The concentration–area (C–A) fractal method was used to determine threshold values for classifying the results of PNN modeling in order to define the spatial and geometrical properties of mineral potential information. Fractals and multifractals are concepts dealing with the geometry or fields of scale-invariant properties that are characterized by self-similarity or self-affinity (Mandelbrot, 1983; Cheng, 2000; Cheng and Li, 2002). Fractal/multifractal modeling involves power–law relationships between a measure $M(\hat{z})$ and the measuring units $\hat{z}$, $M(\hat{z}) \propto \hat{z}^{-\alpha}$, where $\alpha$ stands for “proportion to,” a single value of $\alpha$ represents a monofractal, whereas multiple values of $\alpha$ represent multifractals. The power–law function has a unique scale-invariant property such that changing the measuring unit $\hat{z}$ does not change the function type, or $M(\hat{z}) \propto \hat{z}^{-\alpha}$. This function not only provides a mathematical relationship between a measure $M(\hat{z})$ and the measuring unit $\hat{z}$ but also implies self-similarity or self-affinity of the objects or measures considered. This is a useful property of physical processes that create similar types (point, polylines, and polygons) of features on the ground, such as earthquake epicenters as point features and lakes as polygon features. These features can be distinguished according to their fractal dimension.

The relationship between area ($A$) occupied by pixels with values equal to and greater than a threshold ($s$) and pixel value can be approximated by the power–law relationship $A(\geq s) \propto s^{-\beta}$ (Cheng et al., 1994). For values equal to or greater than $s$, the power–law function is determined by a value of $\beta$ representing a self-similar relationship between $A(\geq s)$ and $s$. For example, a $\beta$ of $<2$ indicates that locations of mineral deposits are clustered more strongly than randomly distributed point features whereas a $\beta$ of $>2$ implies that locations of mineral deposits are not densely distributed compared to regularly and randomly distributed point features. Segmentation of $A$ can also be automated, using a predefined number of classes. During each classification, the original map is reclassified automatically using cutoff values determined by the straight-line fitting, and the straight-line fitting can be viewed in a table containing threshold or cutoff values, slopes and intercepts of straight-line segments, and the standard errors associated with the best fit of each straight-line segment (Cheng, 2000; Cheng and Li, 2002). More details regarding the C–A method adopted in this paper can be found in Cheng (2000).

### 2.4. Mineral resource assessment

Methods for estimation of undiscovered deposits and total mineral resources, each representing some form of analogy based on mathematical modeling and geological knowledge, include applying the frequency distribution of deposits derived from well-explored regions (Bliss, 1992; Bliss and Menzie, 1993), counting and assigning probabilities to anomalies and occurrences (Cox, 1993), applying process constraints and relative frequencies of related types of deposit (Drew and Menzie, 1993), applying mineral deposit densities (Singer et al., 2005; Singer, 2008), applying power–law models and grade–tonnage models (Cheng, 2008), and “one-level” prediction (McCannon and Kork, 1992; McCammon et al., 1994; Carranza et al., 2009; Carranza and Sadeghi, 2010; Carranza, 2011). In this paper, the methodology we propose for 3D estimation of mineral resources in the study area involved the following steps:

1. Combining PNN models of mineral potential at three different levels (surface (> 850 m), 850–500, and 500–100 m) using grade and tonnage parameters of the known mineral deposits, and additional 3D geological modeling to construct a 3D mineral potential model.
2. Deriving 3D mineral potential targets from the 3D mineral potential model, and further classification using 3D spatial query into Mo and Pb–Zn–Ag deposits or occurrences and their metallogenic setting.
3. Estimating volumes of Mo and Pb–Zn–Ag in potential targets by query and statistical analysis in 3D, and calculating potential Mo and Pb–Zn–Ag resource using the grade and tonnage parameters of the known deposits.

### 3. Application to the study area

#### 3.1. Geological setting

Luanchuan, the case study area located in southwestern Henan province, China, is an important Mo and Pb–Zn–Ag region covering 212.4 km$^2$ (Fig. 1). In this area, the main exposed strata are the Middle Proterozoic Guandaokou Group and the Upper Proterozoic Luanchuan and Taowan Groups (Yan and Liu, 2004). The Guandaokou Group (ca. 2100 m thick) comprises fluvial–neritic facies clastic-carbonate rocks, or carbonate rocks containing stromatolites. The Luanchuan Group consists of shallow marine carbonate-clastic rocks with total thickness of ca. 3100 m and ca. 2050 m, which comprises the Meiyaoogou, Sanchuan, and Nannihu Formations, which are associated with mineralization. The Luanchuan Group lies conformably on or is locally parallel unconformable with the Guandaokou Group and it is in fault or unconformable contact with the overlying Taowan Group (ca. 2100 m thick). The Taowan Group consists of clastic sedimentary carbonate rocks, the southern boundary of which is controlled by the Luanchuan Fault and its northern boundaries are unconformable with the Luanchuan and Guandaokou Groups.

Late Proterozoic syenite, metamorphic gabbro, and Jurassic granite porphyry are associated with mineral resources in the study area. The latter consists of strong and extensive granite bedrock and granite porphyry, and the granite porphyry is related to 6 Mo deposits, 4 Mo, and 51 Pb–Zn–Ag occurrences in the study area. The Nannihu, Shangfang, and Sandaizhuang Mo deposits are well

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known in China for their large ore reserves, including ca. 2.6 Mt of Mo (Table 1).

Large-scale Mo and Pb–Zn–Ag mineralization occurred about 140 Ma, according to Re-Os isotopic dating (Ye et al., 2006; Mao et al., 2009). Hydrothermal vein-style Pb–Zn–Ag mineralization occurs in layered skarn or interlayer fracture zones. There are three main types of Pb–Zn–Ag deposits in the study area. First, in the Guandaokou and Taowan Group, Pb–Zn–Ag skarn occurs as layers in carbonate rocks or strata between fracture zones. Second, in the Luanchuan Group, Pb–Zn–Ag skarn occurs as layers along clastic-carbonate lithological change interfaces, or lying in the strata between fractures. Third, in the Jurassic granite (porphyry), porphyry-related Pb–Zn–Ag mineralization exists. The three types of Pb–Zn–Ag deposits or occurrences exhibit close space and time relationships with porphyry Mo deposits, and all these deposits share one ore-formation system (Mao et al., 2009). Within this ore system, the ore-bearing granite has been intruded along intersections of NNE- and NW-trending faults and has been emplaced in shallow locations, resulting in the formation of granite porphyries, Mo and Pb–Zn–Ag mineralizations. Folding in the region pertains mainly to the Huangbelling–Shibaogou anticline, which comprises the Luanchuan and Guandaokou Groups (Fig. 1). Therefore, mineral deposits and/or occurrences in the study area are mainly intrusive-related regardless of source metals or heat controls.
3.2. 3D geological models

3D geological models of the study area were constructed from multiple geological data, including cross sections, a 1:10,000 scale geological map, structural geology maps, geophysical sections, 11 geological exploration cross sections, 256 boreholes, 26,000 geochemical samples, and 4095 geophysical survey points (geometric, magnetic, and topographic). Taking into account the ore-controlling geological conditions and the diversity of the metallogenic models, visualization of the resulting 3D geological models together with the DEM provided insights to possible spatial relations between the deposits and the intrusive granite porphyry.

Several geological models can be constructed from surface data. Therefore, on the basis of the 3D subsurface geological modeling, we used a combination of methods to determine possible extensions of geological bodies at depth taking into account various sets of data (i.e., borehole data, physical properties of the rocks, gravity, and magnetic potential field). Information of geological bodies at depth was derived by 2.5D forward modeling of the gravity and magnetic data (Hildenbrand et al., 2001; Williams et al., 2009; Jaffal et al., 2010). Thus, in this study, the main steps/methods of 3D geological modeling mainly involved two aspects. First, 3D subsurface geological modeling is based on geological data as described in Section 2.1 above. This resulted in the 3D geological model shown in Fig. 1, which was constructed using 1:10,000 scale geological map, 11 geological exploration cross sections, and 256 boreholes. Second, 3D deep geological modeling was based on 2.5D gravity and magnetic modeling. In order to extract exact geological units based on residual gravity anomaly and magnetic data of the study area (Fig. 2), we used a 2.5D forward modeling program called MASK to obtain a quantitative representation of subsurface geological bodies. The MASK, which is based on generalized inverse theory, requires an initial estimate of model parameters (depth, shape, density, and magnetization of suspected source; Luo et al., 2009). It then finds values of selected parameters such that the weighted root-mean-square error between the observed and the calculated gravity fields is minimum.

In this paper, the densities and magnetic susceptibilities for each rock group at the near surface were constrained using 220 and 127 measurements, respectively, from outcrops and from boreholes in the study area (Table 2). Thirty-one deep boreholes, each reaching more than 1050 m depth, in the study area have been used to constrain interpretations of anomalous features in the potential field datasets. The average density and magnetic susceptibility values measured for each geological unit have sufficient contrast between geological units, and thus are useful modeling parameters. Three intersecting boreholes M3, M4, and M13 proved the presence of Mo mineralization and granite porphyry in the subsurface from 428 to 903 m depth, 130 to 938 m depth, and from 924.8 to 1117.6 m depth, respectively. This information was used to interactively validate the 2.5D forward processing of gravity and magnetic data along the BB profile (Fig. 2). Details of the gravity and magnetic data processing (e.g., 2.5D forward modeling) performed in this study were adopted from Wang et al. (2011).

3.3. Metallogenic information extraction

The specific objectives of 3D modeling to extract metallogenic information in the study area (i.e., anomalies at different subsurface levels) were: (1) to model geochemical anomalies associated with undiscovered mineral deposits using the PNN method; (2) to increase understanding of the mineral system in terms of geochemical dispersion phenomena; (3) to improve vectoring towards mineral deposits by integrating surface and subsurface data; and (4) to locate bedrock sources of geochemical anomalies in 3D overburden data.

3.3.1. Geological information of mineralization

Based on the analysis of metallogenic factors of mineral deposits, including strata, structures, and magma, geological information on mineralization can be queried and extracted from the 3D geological models of the study area. Possible controlling geological structures, including faults, folds, and unconformity surfaces can be analyzed by distance buffering in 3D (e.g., the zone of influence around a controlling fault can be modeled by directly combining surface surveys of faults with deep borehole data based on inference of space–time relationships of geological formations). To integrate three subsurface levels of mineralization data in the PNN modeling, each of these levels in the 3D geological model was constructed separately before integration (Fig. 1A). This allows better extraction of geological anomaly information by way of 3D query on a per level basis, which especially avoids geological anomaly information intermixed in the vertical direction. In fact, this was beneficial for distinguishing between Mo potential targets and Pb–Zn–Ag potential targets. For example, Mo deposit is generally located in the granite (porphyry) zone in the study area; therefore, the 3D model of Mo potential targets can be validated by distance to the nearest granite (porphyry) zone in three levels, which can be extracted by upward continuation of gravity and magnetic potential field.

### Table 1: Estimates of Mo and Pb–Zn–Ag potential resources based on 3D potential targets in the study area.

<table>
<thead>
<tr>
<th>Resources</th>
<th>Total potential volume (m³)</th>
<th>Non-ore ratio (%)</th>
<th>Average grade of deposits (%)</th>
<th>Cutoff grade (%)</th>
<th>Average grade of potential targets (%)</th>
<th>Mo ore specific gravity (kg/m³)</th>
<th>Reserve of deposits (Mt)</th>
<th>Potential resource (Mt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mo targets including three Mo deposits</td>
<td>6,094,375,000</td>
<td>46.8</td>
<td>0.09</td>
<td>0.03</td>
<td>0.05</td>
<td>2680</td>
<td>2.6</td>
<td>4.3</td>
</tr>
<tr>
<td>Mo parameter in Mo potential targets</td>
<td>23,988,250,000</td>
<td>46.8</td>
<td>0.03</td>
<td>0.036</td>
<td>0.036</td>
<td>2680</td>
<td>10.8</td>
<td>26.8</td>
</tr>
<tr>
<td>Pb–Zn targets including Lengshui deposit</td>
<td>1,092,000,000</td>
<td>64.8</td>
<td>2.50</td>
<td>0.5</td>
<td>2.0</td>
<td>3480</td>
<td>3.36</td>
<td>26.8</td>
</tr>
<tr>
<td>Ag targets including Lengshui deposit</td>
<td>1,092,000,000</td>
<td>64.8</td>
<td>0.012</td>
<td>0.004</td>
<td>0.012</td>
<td>3480</td>
<td>0.02</td>
<td>0.16</td>
</tr>
<tr>
<td>Pb–Zn in Pb–Zn–Ag potential targets</td>
<td>6,480,000,000</td>
<td>64.8</td>
<td>0.50</td>
<td>2.0</td>
<td>3.0</td>
<td>3480</td>
<td>152.9</td>
<td>152.9</td>
</tr>
<tr>
<td>Ag in Pb–Zn–Ag potential targets</td>
<td>6,480,000,000</td>
<td>64.8</td>
<td>0.004</td>
<td>0.012</td>
<td>0.012</td>
<td>3480</td>
<td>0.92</td>
<td>0.92</td>
</tr>
</tbody>
</table>

The underlined values are used for the potential targets on basis of the known similar mineral deposit parameters and their values in study area.
3.3.2. Geochemical information of mineralization

A selection of 26,000 geochemical samples was used to construct 3D models of geochemical anomalies associated with the Mo and Pb–Zn–Ag mineralizations in the study area. The models were classified in each of the three levels of the 3D geological model. Surface to shallow samples and most of the subsurface samples were collected from drill cores; although some surface to shallow samples were obtained from outcrops and some subsurface samples were obtained from virtual boreholes. The latter were constructed from the 3D geological models based on existing knowledge about regional or local mineralization so that virtual borehole samples have the same function as actual borehole samples when used in spatial interpolation (Zhu et al., 2009; Koelling et al., 2009; Wang et al., 2009a).

From mineral deposit studies in the study area (Ye et al., 2006; Yan and Liu, 2004), most Mo deposits occur at depths greater than 1000 m, whereas some Pb–Zn–Ag deposits occur at depths greater than 500 m. Therefore, the metallogenic anomaly information extracted from the subsurface to 500 m depth mainly pertains to Pb–Zn–Ag mineralization, whereas the metallogenic anomaly information extracted from the 500 to 2000 m depth generally pertains to Mo mineralization.

Lithogeochemical data of seven elements (Mo, Cu, Pb, Zn, Ag, Au, and W) were used to extract geochemical anomalies for predicting zones where undiscovered Mo and Pb–Zn–Ag mineral deposits likely occur. The results of the PC analysis show that the PC1 is associated with most of the elements, the dominant elements being Pb, Zn, and Ag. Based on the power spectrum S–A analysis (Cheng, 2008), zones

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**Fig. 2.** Results of 2.5D magnetic and gravity forward modeling: (A) along profile AA; (B) along profile BB. Locations of these profiles are shown in Fig. 1A.

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with positive PC1 scores correspond to regional mineralization anomalies and zones favorable for Mo and Pb–Zn–Ag mineralization. The PC2 shows that zones with high-temperature elements Mo and W can be distinguished from zones with low-temperature elements Au, Pb, Zn, and Ag.

Fig. 3A shows the relationships between $s$ and $A(\geq s)$, fitted with three straight-line segments using the least-squares method to yield two cutoff values, $s_0 = 218.98$ and $s_1 = 2560.29$. The straight lines have slopes of $-1.05$, $-1.17$, and $-1.51$ and intercepts of 16.60, 17.47, and 20.19, with standard errors of, respectively, 0.000025, 0.0000127, and 0.000821, respectively. After some experimentation, the second cutoff value 2560.29 was chosen as the optimum threshold for creating two filters, $s > 2560.29$ and $s \leq 2560.29$. Applying each of these filters allowed the PC1 score map to be decomposed into Mo and Pb–Zn–Ag anomalies. The results for filter $s > 2560.29$ are shown in Fig. 4 (surface to 850 m). The patterns in Fig. 3A mainly correspond to the dominant patterns of PC1 scores with the influence of high frequency signals reduced. The anomalies outline zones surrounding the granite porphyry and contain most of the known mineral deposits in the area.

Similar spatial analyses were applied to the geochemical anomalies at levels 500 and 100 m. Filters $s > 2331.12$ and $s > 2311.68$ correspond to S–A parameters shown in Fig. 3B and C, respectively. Surface geochemical anomalies (PC1) coincide with porphyry–skarn Mo deposits, and hydrothermal vein-type Pb–Zn–Ag occurrences are mainly distributed around the Mo anomalies. Geochemical anomalies in the 500 m level have similar spatial distribution as those on the surface. Anomalies of Mo are concentrated in the 100 m level and show good spatial associated with the main deposits (e.g., Nannihu, Sanbaozhuang, and Shangfang Mo deposits; Fig. 4).

### 3.3.3. Geophysical information of mineralization

The greatest advantage of gravity and magnetic information is their deep penetration. The analysis and interpretation of gravity and magnetic anomalies can be used to infer concealed geological features. The upward continuation method is generally useful for approximate separation of regional and residual gravity values (Robinson and Coruh, 1988; Chen and Zhao, 2009; Jaffal et al., 2010). On basis of 2.5D forward modeling of gravity data (Fig. 2), we applied upward continuation to the gravity data, followed by determination of horizontal gradient maxima, to evaluate strikes of contacts and dips of linear structures at the 100, 500, and 850 m (surface) levels. In addition, separate models of gravity anomalies were defined by applying preferential continuation (Jacobsen, 1987; Zeng et al., 2008; Meng et al., 2009). The resulting regional and local anomalies are clearly distinct (Fig. 5A). Likewise, based on the 2.5D forward modeling of magnetic data (Fig. 2), we extracted and compiled magnetic anomalies in the same way we did to extract/compile gravity anomalies. The resulting regional and local anomalies are well separated (Fig. 5B). The gravity and magnetic anomaly models show that mineral deposits or occurrences in the study area are characterized by relatively low density and high magnetic contrasts, which is consistent with the presence of low-density rocks surrounded by higher density materials.

### 3.4. 3D mineral potential modeling

#### 3.4.1. Mineral potential modeling with PNN and C-A methods

The evidential data layers used in the PNN method must be integer rasters because the neural nets are limited to about 20,000,000 unique conditions and PNN calculation of randomly generated neurons requires a computer memory buffer. In the process of converting vector or grid layers into integer rasters, individual layers tend to form rasters with the same cell size. Based on research of optimum grid cell for mineral potential mapping (Carranza, 2008, 2009) and on the scales of the various geoscience datasets used in this study, grids for all layers were resampled to a nominal resolution of 50 m. Thus, 8,496,000 rasters (3540 × 2400) were required to optimize all 50 × 50 m² cell information in the study area (Fig. 6A).

The PNN method was applied based on the geological, geophysical, and geochemical anomaly information using six different evidential variables (strata, structure, granite porphyry, PC1 scores for Mo and PC2 scores for Pb–Zn–Ag, gravity, and magnetism). These variables were input vectors for the pattern layers (Figs. 1, 5, and 6). The 6 Mo deposits, 4 Mo, and 51 Pb–Zn–Ag occurrences were used as training points; each deposit is restricted to mineralization type, scale, size, and depth in PNN processing. Each of the training deposits is contained in only one cell. Five nondeposit training points, each contained also in only one cell, are Fe and Au deposits that exist in the study area (Fig. 6A and B). These five nondeposit training cells are in addition to all the other cells not containing any known mineral deposit in the study area. For the training deposit cells (i.e., 6 Mo deposits, 4 Mo, and 51 Pb–Zn–Ag occurrences), we obtained a mean-squared error (MSE) of 0.0309 and a summed-squared error (SSE) of 0.2658, which are very low and acceptable because of the small number of training points compared to the total number of 50 × 50 m² cells. For all cells to be classified in terms of likelihood for Mo/Pb–Zn–Ag mineralization, the MSE was 0.0318 and the SSE was 27.3638. The larger SSE for the overall classification compared to the SSE for the training is due to the larger

<table>
<thead>
<tr>
<th>Geological body</th>
<th>Number of measurements</th>
<th>Measured density (kg/m³)</th>
<th>Measured magnetic susceptibility (SI)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>Qiumugou Formation</td>
<td>20 (10 boreholes)</td>
<td>2710</td>
<td>0.06</td>
</tr>
<tr>
<td>Fengmimiaojie Formation</td>
<td>20 (10 boreholes)</td>
<td>2690</td>
<td>0.05</td>
</tr>
<tr>
<td>Sanchakou Formation</td>
<td>20 (10 boreholes)</td>
<td>2750</td>
<td>0.06</td>
</tr>
<tr>
<td>Sanchuan Formation</td>
<td>20 (10 boreholes)</td>
<td>2670</td>
<td>0.05</td>
</tr>
<tr>
<td>Yu Ku Formation</td>
<td>20 (10 boreholes)</td>
<td>2800</td>
<td>0.09</td>
</tr>
<tr>
<td>Dahongkou Formation</td>
<td>20 (10 boreholes)</td>
<td>2780</td>
<td>0.08</td>
</tr>
<tr>
<td>Menyaogou Formation</td>
<td>20 (10 boreholes)</td>
<td>2780</td>
<td>0.08</td>
</tr>
<tr>
<td>Nannihu Formation</td>
<td>20 (10 boreholes)</td>
<td>2650</td>
<td>0.05</td>
</tr>
<tr>
<td>Baishangou Formation</td>
<td>20 (10 boreholes)</td>
<td>2680</td>
<td>0.06</td>
</tr>
<tr>
<td>Duguan Formation</td>
<td>20 (10 boreholes)</td>
<td>2490</td>
<td>0.03</td>
</tr>
<tr>
<td>Syenite porphyry</td>
<td>20 (10 boreholes)</td>
<td>2590</td>
<td>0.03</td>
</tr>
<tr>
<td>Metamorphic gabbro</td>
<td>20 (10 boreholes)</td>
<td>3030</td>
<td>0.12</td>
</tr>
<tr>
<td>Granite (porphyry)</td>
<td>60 (30 boreholes)</td>
<td>2580</td>
<td>0.03</td>
</tr>
</tbody>
</table>
Fig. 3. Plots showing results of S–A filtering method: (A) Pb/Zn anomaly classification in the first level (surface elevation is 850–1600 m); (B) Pb/Zn anomaly in the second level (elevation 500 m); (C) Mo anomaly based on Mo deposits in the third level (elevation 100 m).

Fig. 4. Pb/Zn and Mo anomalies associated with Mo deposits/occurrences and Pb–Zn–Ag occurrences at three levels in the study area in 3D. Thresholds of geochemical anomalies were calculated using S–A method (see Fig. 3).
The output of the PNN method is a continuous field model that requires classification. Various classification techniques available in ArcGIS software (e.g., equal interval, standard deviation, quartile, geometrical interval, and manual) result in several classes, which are not satisfactory in terms of mineral exploration needs.

In contrast, the C–A method provided reasonable results, however, reflecting features that are associated with deposits or occurrences that were not clearly identified using any of the conventional classification techniques noted earlier.

Fig. 6A is a PNN potential grid model of the surface in the study area, showing 187 classifications from 8,496,000 rasters. Based on values for 10 Mo deposits and occurrences in the C–A plot, anomalies on the filtered surface model depict six clear threshold values (Fig. 6B). Anomalies on the filtered surface model show clear patterns with an orientation distribution that is apparently due to the NW-trending ore-controlling faults in the area. Six straight-line segments were optimally fitted by least-squares method to the plots of $A(\geq s)$ versus $s$ (Fig. 6C, D, and E) depicting five cutoff/threshold values. Thus, the C–A plots (Fig. 6C, D, and E) have effective classifications associated with the mineral deposits or occurrences.

All the Mo deposits/occurrences and most of the Pb–Zn–Ag occurrences are delineated in 29.2358–166.0380 areas (29.2358 and 166.0380 are threshold values of the mineral potential targets; Fig. 6B and C), except two Pb–Zn–Ag occurrences of the sedimentary type but not of the hydrothermal vein-type like most Pb–Zn–Ag occurrences. Those two sedimentary type Pb–Zn–Ag occurrences are delineated in 0.9998–29.2358 areas, and the Fe and Au deposits are delineated in either 0.9998–29.2358 or 166.0380–187.1663 areas (Fig. 6B and C). The PNN potential grid models show 197 classes for the 500 m level and 250 classes for the 100 m level (Fig. 6D and E). Based on the above threshold values, mineral potential models were constructed for the three levels (Fig. 6F). The classes for the potential targets in three levels can be further mutually contrasted and synthetically analyzed to delineate Mo and Pb–Zn–Ag potential targets in 3D environment.

3.4.2. 3D mineral potential model

A 3D mineral potential model was constructed from the three levels of mineral potential models, 3D geological models and known mineral deposits or occurrences. For example, it is known that Pb–Zn–Ag deposits and occurrences are mostly hosted in the Meiyaogou and Sanchuan Formations, whereas Mo deposits and occurrences are mostly hosted in the Nannihu Formation. Potential targets falling outside these metallogenic strata are likely false and, thus, were deleted. However, those “false” targets should be further examined because they may be related to other mineral resources (e.g., tungsten deposits), but this is beyond the objective of the present study. Fig. 7 is the 3D mineral potential model of the study area based on three-level mineral potential models (Fig. 6F) and the 3D geological models (Fig. 1). From 50 × 50 m² cells in the three-level mineral potential models, 50 × 50 × 50 m³ voxels were obtained to estimate the volume of the different targets according to mineral deposit type. Eight potential Mo targets and 15 potential Pb–Zn–Ag targets are shown in the 3D model.

3.5. Mineral resource quantitative assessment

Based on 31 exploration boreholes (each reaching the third level; i.e., 500–100 m) in the study area, the known Mo and Pb–Zn–Ag orebodies have been explored by 12 and 9 exploration
boreholes, respectively, and the known nonmineralized zones have been explored by 9 exploration boreholes (Figs. 7 and 8). Each of the 8 t Mo potential targets contains different proportions of the known Mo deposits and each of the 15 Pb–Zn–Ag potential targets contains different proportions of the known Pb–Zn–Ag occurrences (Fig. 6B, Fig. 7). Furthermore, all the 15 Pb–Zn–Ag potential targets are near the Mo potential targets, which is in accordance with the metallogenic models of Mo and Pb–Zn–Ag deposits in the study area. Therefore, the 3D mineral potential targets for Mo or Pb–Zn–Ag deposits have high reliability.

From Fig. 7 and parameters (grade and tonnage) of known mineral deposits, undiscovered resources of Mo deposits in the study area were estimated (Table 1). The most important potential target, which includes three well known Mo deposits, has the greatest potential Mo resource of 48,755 voxels (or 6,094,375,000 m³), potentially yielding at least 4.3 Mt of Mo. In the whole study area, there is a huge potential Mo resource of 191,906 voxels (or 23,988,250,000 m³), which would yield at least 10.8 Mt of Mo. Based on parameters of the Lengshui Pb–Zn–Ag deposit, the resources in the 15 Pb–Zn–Ag potential targets were estimated (Table 1). The estimation program of Pb–Zn–Ag potential targets was similar to that for estimation of Mo potential targets.

Comparing the known reserves of deposits with the estimated potential resources of Mo and Pb–Zn–Ag indicates that the study area has large mineral potential, with the volume of Mo potential targets being larger than that of Pb–Zn–Ag potential targets (Table 1). The 3D Mo potential targets are spatially correlated with the Pb–Zn–Ag potential targets, the latter are usually near and above the former, and most of the Pb–Zn–Ag potential targets are located 500–1000 m from the Jurassic intrusive granite (porphyry; Fig. 7). These characteristics depict the relationship of granite (porphyry) with the mineralizations and the hydrothermal model of Mo and Pb–Zn–Ag deposits. Therefore, it appears that the Mo and the Pb–Zn–Ag deposits/occurrences belong to the same ore-forming system. That is, the main metallogenic material was the Jurassic granite (porphyry), the secondary metallogenic materials were Meiyaoqou, Nannihu, and Sanchuan Formations in the Luanchuan Group, and NNE- and NW-trending faults were key pathways for migration and focusing of metallogenic fluids.

4. Discussion

Querying in the 3D environment is appropriate if there are known constraints on the distribution of mineralization, such as proximity to a stratigraphic contact, fault, intrusion, or zonation relationship. The analysis of geoscience data through basic 3D
Fig. 7. 3D mineral potential model of the study area viewed from two different directions (red bodies are Mo targets and green bodies are Pb–Zn–Ag targets).

Fig. 8. 3D mineral potential targets and geological bodies associated with mineralization (see Fig. 1A).
space queries is a key step in defining relationships between the various datasets, enabling the conversion of conceptual geological model components into quantitative exploration criteria (Koelling et al., 2009). One of the greatest strengths of this approach is the query capability where various quantitative and spatial queries are applied to multiple objects or subsets based on 3D geological models. A typical targeting query for base-metal exploration may include identifying cells that share the following properties: (1) interpreted as mineral stratum, fault, or rock; (2) within a defined distance from a fault; (3) within a defined distance from a magnetic or gravity anomaly; (4) within close proximity to known mineralization; (5) in previously untested locations, such as those far from boreholes; and (6) virtual boreholes based on existing boreholes and known geological units.

Fig. 8 is a 3D model of mineral potential targets and geological bodies associated with mineralization in the study area. This model depicts key geological factors for resource assessment. The most important Mo potential target includes three known Mo deposits and it is defined by a combination of all variables/layers used in the PNN modeling (Figs. 1, 9, 5, and 6): (1) the Sanchuan, Yuku, and Namihu Formations of the Luanchuan Group; (2) Jurassic granite (porphyry); (3) northeastern fault and pitching fold; (4) low gravity value: class 2 (−7.2 to −3.1 m gal) or class 3 (−3.1 to 1.0 m gal) at three levels (Fig. 5A); (5) high magnetic value, class 5 (350–890 nT) or class 6 (890–1810 nT) at three levels (Fig. 6B); and (6) obvious Mo or PC1 anomaly at three levels (Fig. 6). The other seven Mo potential targets have similar characteristics as the most important Mo potential target, but some of them are defined by fewer than six variables used in the PNN modeling, and they contain fewer Mo deposits or occurrences (Fig. 8). All of the Mo potential targets contain the Luanchuan Group, the Jurassic intrusive granite (porphyry), and the northeastern fault or pitching fold.

3D models of geochemical dispersion from deeply buried mineralization have been proposed, and analytical techniques have been tested in several orientation surveys (Jackson, 2007). Lithgeochemical information about mineralization can be further interpreted in other 3D geological models of the study area, not only showing the location of mineralization but also interpreting or identifying corresponding information at depth, by combining 3D geological models and metallogenic models. The 3D geological models of the study area, known Mo and Pb–Zn–Ag deposits or occurrences, sparse boreholes and virtual boreholes, gravity and magnetic data inversion, and mineralization anomalies extraction all contributed to the effective delineation of potential mineral targets.

In this paper, the 2D mineral potential models at three levels were cross-validated in 3D. The Mo deposits and occurrences at the deepest level were contrasted with the Mo and Pb–Zn–Ag deposits and occurrences at the two upper levels (Fig. 6F). The 3D mineral potential model derived in this study area (Fig. 7) illustrates that the Mo and Pb–Zn–Ag mineralizations plausibly have a single metallogenic source, and this assessment gave a quantitative estimation for the volume and mineral resource of the potential targets. The defined mineral potential targets depended on the details of the PNN integration of the geoscience information inputs and the 3D geological model. In particular, we have shown that datasets from a 3D mineral potential model can constrain exploration targets at depth. Therefore, mineral deposit models from 3D geological models are a powerful way of combining diverse geoscience information for mineral resources assessments and exploration strategies.

The uncertainty of the 3D mineral potential targets has been deduced as follows: (1) the mineral potential targets at different depth based on nonlinear methods were cross-validated; (2) the 3D mineral prediction targets were further validated using 3D geological models and metallogenic models of Mo and Pb–Zn–Ag deposits or occurrences in the study area. The second validation scheme includes metallogenic models such as the vein-type Pb–Zn–Ag deposits or occurrences located in strata close to the Jurassic porphyry, the distribution of which was constrained by depth along with other features, including thickness, scale, and attitude. Therefore, mineral resource estimation based on 3D mineral potential targets could complement and supplement conventional statistical methods for resource assessment with sound subsurface 3D geological information as well as resource estimates for cross-comparison. However, mineral potential targets can be accurately delineated through 3D modeling, and the prediction assessment can be more easily revisited with the level of exploration detail improved and developed, for instance, when a new borehole is sunk.

5. Conclusion

The methodology of mineral resources assessment based on 3D modeling and nonlinear technologies has been applied to identify Mo and Pb–Zn–Ag potential targets and to estimate mineral resources in the Luanchuan region (China). This methodology can be imported, and adapted if necessary, to other regions with similar complex geological and metallogenic settings as well as multiple geoscience data in 3D. Displaying and querying geoscience data using a 3D geological model provide for significant advancement in mineral exploration. The multidisciplinary approach used in 3D geological modeling demonstrates that this method can be used as a regional interactive exploration tool, allowing the use of various criteria to constrain and refine queries, and leading to the definition of meaningful geological information, particularly exploration targets. Probabilistic neural network modeling combined with fractal analysis not only helped to delineate potential targets accurately but also gave reasonable theoretical insights to ore genesis in the study area. Existing 3D technology enables geologists to manipulate, analyze, and interpret 3D geological models analogously as they work with 2D geological maps. Integration of geological, geochemical, and geophysical data in 3D can create new opportunities for mineral exploration and an increased understanding of mineral systems.

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References
