Ore Geology Reviews 74 (2016) 15–25

Contents lists available at ScienceDirect

Ore Geology Reviews

journal homepage: www.elsevier.com/locate/oregeorev

Regional mineral resources assessment based on rasterized geochemical data: A case study of porphyry copper deposits in Manzhouli, China

Jiang Chen *, Renyi Chen, Zhaoxia Mao, Hongzhi Yang, Chunpeng Zhang, Renping Han

Shenyang Institute of Geology and Mineral Resources CGS, No. 280, Huanghebei St, Shenyang, Liaoning 110034, China

A R T I C L E I N F O

Article history:
Received 13 August 2015
Received in revised form 6 November 2015
Accepted 7 November 2015
Available online 10 November 2015

Keywords:
Geochemical atlas
Ore-bearing hydrothermal alteration coefficient
Denudation coefficient
Mineralization intensity coefficient
Prospective target area
Porphyry copper deposits

A B S T R A C T

This study used regional geochemical survey data (1:200,000 scale) from the Manzouli area of China to assess mineral resources. Geochemical survey data was rasterized and a geochemical atlas was generated, with the image pixel size determined according to geochemical exploration sample point spacing. The Wunugetushan, Babayi, and Badaguan porphyry copper deposits were selected as model areas for the assessment of copper mineral resources. Three parameters were considered for the calculation of the mineral resources. An ore-bearing hydrothermal alteration coefficient was determined based on geological characteristics and geochemical characteristics of the model area, in order to determine alteration intensity; a denudation coefficient was calculated to determine denudation extent; and a mineralization intensity coefficient was calculated to determine the intensity of mineralization within each pixel. Resource estimation was conducted through regression analysis of model deposit resources and coefficients. The results can be used to determine prospecting target areas based on frequency classification and can be used to estimate the number of ore deposits. Results show that resource estimation using rasterized geochemical data provides high prediction precision and accurate positioning.

1. Introduction

Mineral prospectivity analysis is used for regional exploration targeting. While mineral prospectivity analysis is intended to identify where undiscovered deposits are most likely to be located, quantitative resource estimation is key for estimation of how much metal is likely to be contained in these undiscovered deposits. Porwal and Kreuzer (2010) provided an overview of the history, status, and future of mineral prospectivity analysis and quantitative resource estimation.

Mineral resources assessment, the qualitative and quantitative assessment of mineral resources based on different scales of geochemical survey data, includes geochemical quantitative estimation. As early as the last century, American scholars noted a linear relationship between the abundance of 26 crustal elements and recoverable reserves of tonnage in the US (McKelvey, 1960); other scholars then pursued related research, with many notable achievements (Garrett, 1978; Mookherjee and Panigrahi, 1994; Nishiyama and Adachi, 1995).

Solovov (1957) studied the calculation of metal resources in dispersion haloes, the estimation of displacement, and the evaluation of ore-bearing properties. He also founded a method for estimating surface metal resources. European and American scholars established abundance relationship models applicable to rock type units or to regional or geological provinces (Celenk et al., 1978); Zhao (1991) proposed a residual metal resources method and designed a formula to assess mineralization intensity based on the results of stream sediment survey data. Xie et al. (2004) proposed the concept and methodology of large geochemical blocks that are the net results of Earth's original heterogeneity and of the distribution and redistribution of metals during its evolution. This method includes calculation formulae for determining metal endowments, geochemical block mineralization coefficients, and resources/potential resources, with this approach adopted in different parts of China and for different minerals (Liu and Xie, 2005).

In summary, different methods for estimating mineral resources in terms of geochemical data have been established in the past, but these have some deficiencies. Key points are as follows:

1) Minimum targeting area: in the past, there was no specific requirement for the classification of minimum targeting areas, especially in terms of area size and interpolation parameters for spatial data, which need to be determined multiple times (Gong et al., 2013). The minimum targeting area is not only different from geometrical morphology, but in practice also needs to combine the geological background, ore-forming mechanisms, and the coexistence of many elements.
2) Denudation parameter: There are many methods for resource estimation based on the principle of analogy. In calculating an endowment, the depth of the ore body is often considered, and the majority of depths of predicted ore bodies are estimated by referring to known model deposits of the same mineralization type. However, in the case of large deposits, there is a need to fully account for the

* Corresponding author.
E-mail address: chen07761@itc.nl (J. Chen).

http://dx.doi.org/10.1016/j.oregeorev.2015.11.009

extent of denudation of the ore deposit. According to the theory of primary halo zoning (Liu and Ma, 2007), due to differences in element activity and in precipitation temperature, a front halo is often formed around the ore body at low temperature, a near-ore halo is formed at medium temperature, and a tail halo is formed under high temperature conditions. If multiple phase superposition is not considered, the higher the intensity of the tail halo elements, the deeper the extent of denudation; in turn, the higher the intensity of front halo elements, the shallower the denudation. Using a combination of stream sediment elements, it is possible to distinguish the degree of denudation of the deposit (Zheng et al., 2014).

3) Deposit positioning in prospective areas: mineral deposit density and target counting are two common methods used for estimating the numbers of deposits in the past (Cox, 1993; Mamuse et al., 2010; Singer, 1993). However, previous research seldom positioned deposits within a small area and seldom calculated endowments within a specific predicted deposit.

Based on existing research and on these limitations, we propose using regional geochemical data to estimate resources within a specific type of deposit. This paper discusses calculation methods, proposing important parameters for computation of resources and deducing corresponding equations for their calculation.

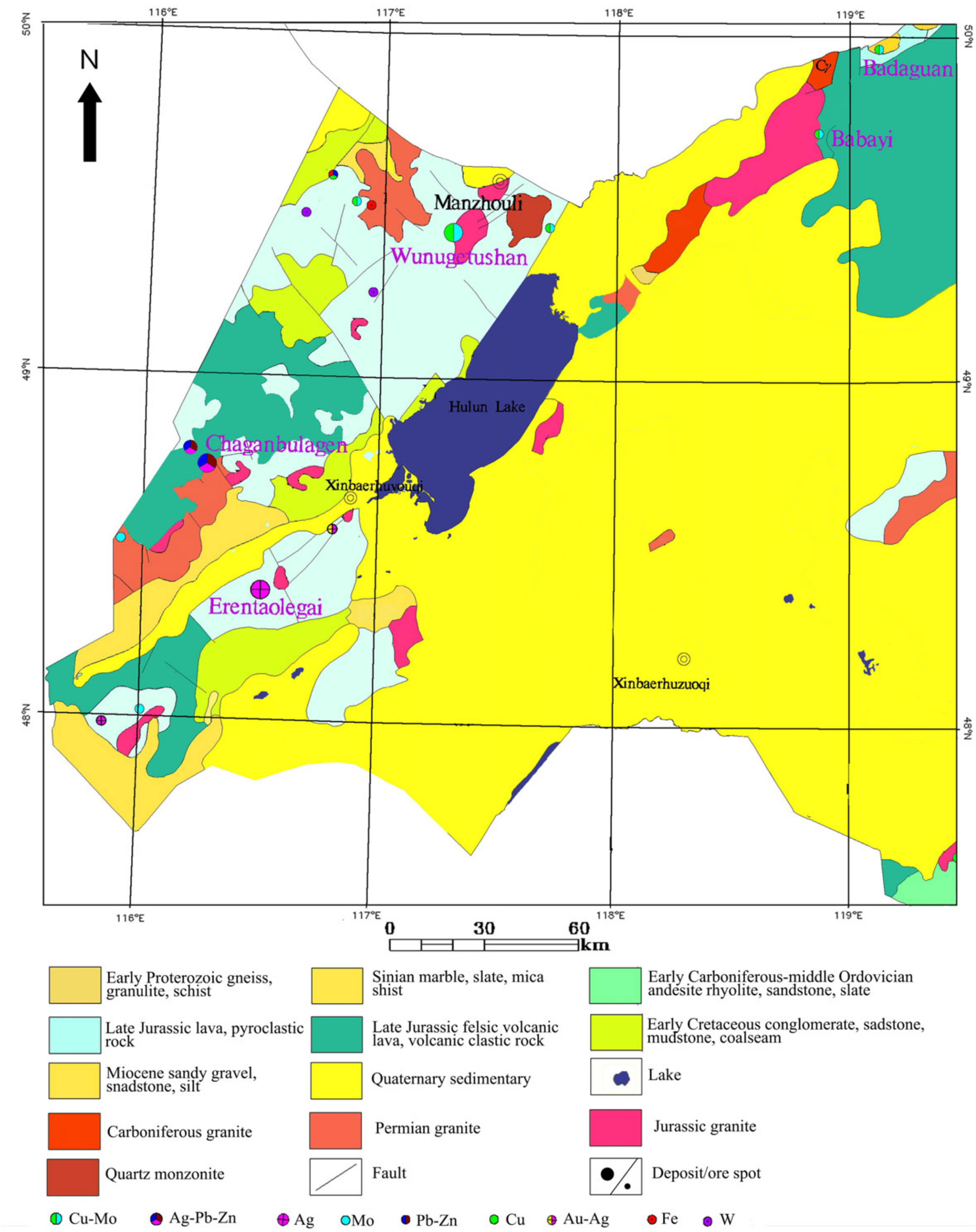

Fig. 1. Regional geological map of the Manzhouli area, Inner Mongolia.

2. Method for estimating metal endowment

2.1. Minimum unit cell

As noted above, the earliest method used for resource estimation in China was based on the geochemical block (Xie et al., 2004). The geochemical block is ≥1000 km^2. In subsequent studies of other proposed anomalous blocks, the geochemical block was reduced to small blocks of local geochemical anomalies, with areas of several km to tens of km.

This study uses rasterized geochemical images to create geochemical image sets, with the size of image pixel values being the area of the minimum unit cell. Because image pixels are fixed, the per unit area of the minimum unit cell is also fixed. The regional geochemical survey sampling interval is 1 point/4 km^2 and the use of geochemical image pixels of 1 km is determined to fit the required mapping precision. The minimum unit cell area used in the study is thus 1 km^2.

2.2. Geochemical features of model deposits

The existence of an ore deposit arises from a combination of ore-controlling factors. New mineral deposits can be predicted through studying the ore-controlling factors of a known model deposit. In this study, geochemical analysis was carried out at a model deposit, in order to enable understanding of the characteristics of alteration and mineralization in minimum unit cells at pixel scale.

2.3. Parameters

We comprehensively analysed previously established resource estimation equations, combining these with the characteristics of regional geochemical data, and proposing the following important parameters for resource computation.

2.3.1. Ore-bearing hydrothermal alteration coefficient

This parameter is based on the metallogenic regularity of typical ore deposits. It has been found that alteration and mineralization are closely related to hydrothermal activity, with some ore-forming elements enriched in specific ore body parts, and other elements depleted. The following procedure is used to determine an element's enrichment or depletion according to its normalized value. If the normalized geochemical element value in a region is between 0 and 1, then elements with a value of 0.9–1 are enriched, while elements with values between 0.7–0.9 may be enriched, with this determined subjectively based on previous studies or personal experience. Similarly, normalized values ranging 0–0.1 represent depleted elements, while values of 0.1–0.3 could subjectively represent depleted elements, based on the situation. The ore-bearing hydrothermal alteration coefficient reflects the change in content of various elements. It includes two parts, the degree of enrichment (namely, the total sum of enriched elements in the model deposit position minus the average value over the whole study area) and the degree of depletion (total sum of regional average minus actual depletion elements in the typical ore deposit). The sum of the degrees of dilution and enrichment elements divided by the sum of involved

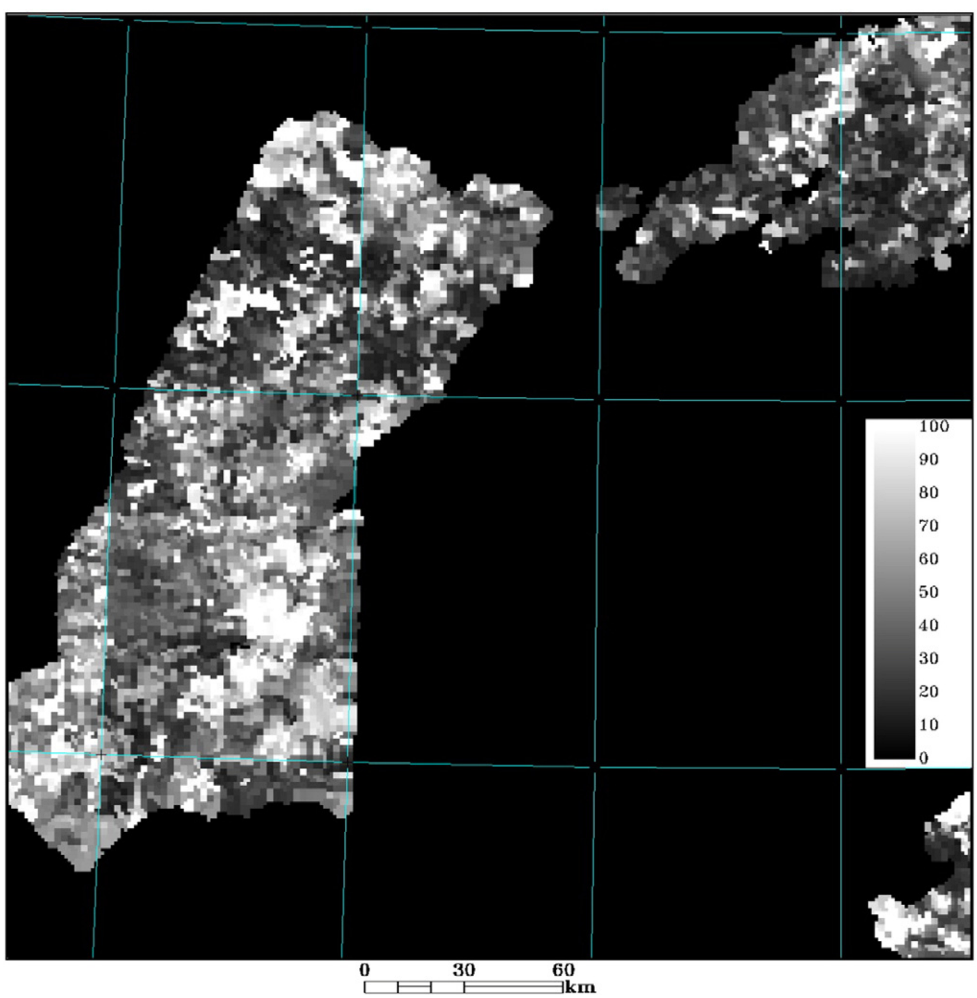

Fig. 2. Greyscale map of rasterized Cu element concentration in the Manzhouli area.

Table 1
Results of geochemical element analysis of the Wunugetushan copper molybdenum deposit (centre and adjacent pixels). The unit for oxide content unit is %, that for Au, Ag, and Hg is ppb, and that for other elements is ppm.

Element	Li	Na_2O	K_2O	Be	MgO	CaO	Sr	Ba	Y	La	Th	U	Zr	V	Nb	Cr	Mo	W	Mn
Pixel1	17.84	2.44	3.47	3	0.66	4.17	209.8	719.16	18.08	49.68	9.21	1.95	107.29	40.68	10.17	24.46	4.06	3.33	356.35
Pixel2	18.8	2.35	2.93	2.9	1.1	4.02	296	632	20	65	14	1.66	182	56	14	35	1	1.77	387
Pixel3	17.8	2.44	3.49	3	0.64	4.18	206	723	18	49	9	1.96	104	40	10	24	4.2	3.4	355
Pixel4	21.16	1.38	3.99	2.8	1.04	4.58	215.34	671.03	20.97	49.35	15.95	1.82	159.21	48.5	12.05	29.82	76.11	3.73	287.74
Pixel5	16.54	0.77	4.75	2.8	0.71	2.29	170.08	743.69	23.85	50.38	18.82	1.99	127.95	49.17	15.89	20.54	79.99	8.25	139.21
Pixel6	16.46	0.76	4.76	2.8	0.7	2.25	169.45	744.92	23.89	50.4	18.87	1.99	127.49	49.19	15.95	20.4	29.88	8.32	136.83
Pixel7	16.61	0.75	4.78	2.8	0.7	2.3	167.72	744.65	23.87	49.96	18.87	1.99	127.26	48.96	15.83	20.38	65.7	8.3	136.5
Pixel8	21.3	1.36	4.02	2.8	1.03	4.63	207	668	21	49	16	1.83	156	48	12	29	60.7	3.8	285
Pixel9	16.4	0.72	4.81	2.8	0.69	2.2	166	748	24	50	19	2	126	49	16	20	45.16	8.5	130

elements gives the ore-bearing hydrothermal alteration coefficient, as per Eq. (1):

$$Ka = \frac{\sum_{m=1}^{i}(Cm - Cm\_avg) + \sum_{n=1}^{j}(Cn\_avg - Cn)}{(i + j)} \tag{1}$$

where *Ka* is the ore-bearing hydrothermal alteration intensity index, *i* is the enriched element number, *j* is the dilution element number, *m* represents an enriched element, *n* is the dilution element, *Cm* is the normalized content value of element *m*, *Cn* is the normalized content value of element *n*, *Cm_avg* is the mean value of normalized content of element *m* in the total area, and *Cn_avg* is the mean value of normalized content of element *n* over the total area. The normalized method used for geochemical images is described in Section 4.3.

Calculation of normalized *Ka* gives the final ore-bearing hydrothermal alteration coefficient, as follows:

$$fa = \left(\frac{Ka - Ka\_min}{Ka\_max - Ka\_min}\right) \tag{2}$$

where *Ka* is the ore-bearing hydrothermal alteration intensity index for each pixel, *Ka_min* is the minimum *Ka*, and *Ka_max* is the maximum *Ka*. The final value of the hydrothermal alteration coefficient is between 0 and 1.

2.3.2. Denudation coefficient

The denudation index is determined as follows in this study:

$$Kden = \frac{(V + Co + Ni)}{(Nb + Zr + Sr)}. \tag{3}$$

The choice of numerator and denominator elements is discussed in Section 4.4.2. Normalization of the denudation index then gives the final denudation coefficient:

$$fden = \frac{(Kden - Kden\_min)}{(Kden\_max - Kden\_min)} \tag{4}$$

where *Kden_min* and *Kden_max* are the minimum and maximum values of *Kden*, respectively.

2.3.3. Surface mineralization intensity coefficient

This coefficient is obtained through a simple calculation derived through normalizing the main ore-forming elements; its value is between 0 and 1. It is calculated as follows:

$$f\ mineralization = \frac{(C - C\_min)}{(C\_max - C\_min)} \tag{5}$$

where *C* is the content of ore-forming elements in pixels, while *C_min* and *C_max* stand for minimum and maximum content values, respectively.

The above parameters are calculated separately for each pixel (representing a certain area — for example, a pixel size of 1000 m corresponds to a representative area of 1 km^2), thus with a value of each coefficient for each pixel.

2.4. Resource estimation

Resource estimation is conducted on the basis of the model area (typical ore deposit). The boundary of a deposit is determined according to the following conditions. If the labelled position of the deposit is at the centre of the actual mining area and occupies one pixel in the image, the neighbouring continuous pixels with high concentrations of main metallogenic elements are considered as the deposit area. The ore-bearing index is based on exploration data for the model area and is calculated as follows:

$$K\_ore = \frac{Wpixel}{Vpixel} \tag{6}$$

where *K_ore* is the ore-bearing index, *Wpixel* is the metal endowment in the minimum unit cell in the model area, and *Vpixel* is the volume of the ore body. *Wpixel* is calculated as per Eq. (7) below:

$$Wpixel = K\_ore * Vpixel. \tag{7}$$

The metal endowment is strongly related to the alteration degree of hydrothermal alteration, i.e., *K_ore* is related to the ore-bearing hydrothermal alteration coefficient. Because the pixel size is constant, *Vpixel* is closely related to the denudation coefficient.

If we can obtain the metal endowment of a discovered ore deposit, this can be allocated to the pixels in the ore deposit position and the endowment of the minimum unit cell can thus be obtained. Because the hydrothermal alteration and denudation coefficients are calculated for each unit cell, regression analysis of endowment can be carried out using these two coefficients. The regression equation of resource estimation is as follows:

$$Wpixel = a * fa + b * fden + c \tag{8}$$

where *Wpixel* is the endowment of the minimum unit cell, *fa* is the hydrothermal alteration coefficient, *fden* is the denudation coefficient, and *a*, *b*, and *c* are constants.

The endowment equation for the model area can be applied to every pixel in the study area, so that the sum total of resources can be calculated.

The amount of resources obtained through Eq. (8) is related to the scale of ore-bearing hydrothermal alteration and to the degree of

Fe_2O_3	Co	Ni	Cu	Ag	Au	Zn	Cd	Hg	B	Al_2O_3	SiO_2	Sn	Pb	P	As	Sb	Bi	F
2.32	6.97	15.77	83.02	396.26	0.93	64.96	175.35	24.92	16.65	12.09	65.15	1.86	54.27	318.07	9.95	0.8	1	722.53
3.24	8.5	15.1	29	130	0.97	64	70	23.1	20	12.3	64.78	2.05	15	433	8.75	0.84	0.44	780
2.28	6.9	15.8	85.4	408	0.93	65	180	25	16.5	12.08	65.17	1.85	56	313	10	0.8	1.02	720
2.59	8.51	14.4	70.7	1133.95	1.38	57.24	118.41	112.76	25.81	13.72	63.72	2.77	117.64	373.84	49.65	9.67	0.52	853.63
2.26	4.19	8	124.51	1598.3	1.92	28.44	42.03	194	25.36	15.72	66.66	4.5	155.53	463.57	113.11	5.69	0.98	1164.46
2.26	4.12	7.9	125.37	1605.74	1.92	27.98	40.8	195.3	25.35	15.76	66.71	4.53	156.15	465.12	114.13	5.63	0.99	1169.38
2.24	4.18	7.97	125.66	1625.71	1.93	28.26	43.35	196.44	25.52	15.76	66.63	4.52	158.32	461.77	114.22	5.93	0.98	1166.58
2.55	8.4	14.2	72.1	1162	1.4	57	120	115	26	13.72	63.7	2.8	120	365	50.8	9.92	0.53	860
2.23	4	7.7	128	1646	1.95	27	40	200	25.5	15.85	66.76	4.6	160	466	117	5.76	1	1180

denudation; the results do not take into account mineralization enrichment. In nature, the formation of ore bodies requires highly enriched elements and endowment calculation should thus factor in mineralization intensity. On this basis, the endowment calculation formula can be modified to take into consideration mineralization intensity, as follows:

$$W\_ore = f\ mineralization * Wpixel. \tag{9}$$

Combining Eqs. (8) and (9):

$$W\_ore = fmineralization * (a * fa + b * fden + c) \tag{10}$$

where *W_ore* is the final calculated metal endowment.

3. Geological background of mineralization in the study area

The study area is located in China, at the junction with Russia, and Mongolia (Fig. 1). In terms of regional tectonics, the area is located on the south-eastern margin of the Siberian craton and has characteristics of an accreted continental margin (She et al., 2009). The NE–SW trending fault zone controls Mesozoic magmatic rocks and distribution of metal ore deposits. Moving from northeast to southwest, one finds in turn the Badaguan, Babayi, and Wunugetushan Cu–Mo deposits, the Jiawula and Chaganbulagen Pb–Zn–Ag deposits, and the Erentaolegai Ag deposit.

Many copper lead–zinc deposits of volcanic hydrothermal genesis are distributed in mafic and mafic-medium volcanic rocks of the Tamulangou Formation. Near-ore volcanic rocks have evident discolouration alteration. The average copper, silver, and lead contents in the Tamulangou Formation, determined by semi-quantitative analysis, are higher than those of regional strata. Copper polymetallic ore deposits are closely related to intermediate acid intrusive rocks and subvolcanic rocks from late Jurassic. Analysis of altered biotite granite reveals that the average content of copper, silver, zinc, and molybdenum in the vicinity of deposits is higher than in regional magmatic rocks.

There are three porphyry deposits: Wunugetushan, Badaguan, and Babayi Cu–Mo deposits; all of these have alteration characteristics of porphyry deposits. The Wunugetushan deposit is a large porphyry Cu–Mo ore deposit with alteration zoning. From the centre to the outside of the ore body, it can be divided into three alteration belts: a quartz-feldspathization belt, a quartz–sericite–hydromuscovite belt, and an illite–hydromuscovite belt (Jin and Sun, 1990).

According to the prospecting data obtained, the copper ore bodies of the Wunugetushan deposits are 200 m in thickness and 260–600 m in depth, with the average grade of copper being 0.247%. Molybdenum ore bodies with thicknesses of 70–190 m extend for more than 600 m and their average grade is 0.0547%. There are 2,232,000 tonnes of copper resources and 412,000 tonnes of separate molybdenum resources. The resources of the Badaguan deposit total 140,000 tonnes of copper and 20,000 tonnes of molybdenum, while those of the Babayi deposit total 61,000 tonnes of copper 61,000 and 4000 tonnes of molybdenum.

4. Spatial mapping method

Most of the processes described below were carried out using ENVI software, except for the calculation of the regression equation.

4.1. Geochemical data and rasterized geochemical atlas

A geochemical survey at a scale of 1: 200,000 was completed within the study area, using stream sediment. The average sampling density was 1 point per 4 km^2. In total, 39 kinds of geochemical elements/oxides were analysed in the laboratory; analytical methods, detection limits and the precision and accuracy of elements were based on the same Chinese standard (Xie et al., 2009). The rasterization process for each element/oxide used linear interpolation, through an embedded program in ENVI software; after interpolation, the value changed slightly compared to the original value. The spatial resolution of the created geochemical image was 1000 m. The copper element content image is shown in Fig. 2. The geochemical atlas follows the following order : Li, Na_2O, K_2O, Be, MgO, CaO, Sr, Ba, Y, La, Th, U, Ti, Zr, V, Nb, Cr, Mo, W, Mn, Fe, Co, Ni, Cu, Ag, Au, Zn, Cd, Hg, B, Al_2O_3, SiO_2, Sn, Pb, P, As, Sb, Bi, and F. Elements were sorted according to their order in the periodic table, with the purpose of arranging elements with similar properties in adjacent positions.

4.2. Geochemical information extraction for typical ore deposit locations

Using geochemical element content images and the region of interest (ROI) method, we selected pixels where ore deposits are located and surrounding adjacent ones, and exported geochemical data for each pixel for statistical analysis. Porphyry copper deposits were treated as model deposits, and we therefore selected the ROI of the Wunugetushan, Babayi, and Badaguan deposits, respectively. In the case of the Wunugetushan and Badaguan deposits, we chose a centre pixel and its adjacent eight pixels, while in the case of the Babayi deposits, we only selected a pixel in the centre of the deposit. Geochemical data for each pixel of the Wunugetushan deposit were extracted, as shown in Table 1. Of the 38 elements (oxides) listed in the table, only TiO_2 data were not analysed statistically because of failure to qualify in some areas.

4.3. Normalization of geochemical data

This study converted geochemical data to a dimensionless value for contrast purposes. For the normalization of rasterized data, in addition to using calculation equations, we also used a more convenient method, that is, stretching the data, giving minimum and maximum values,

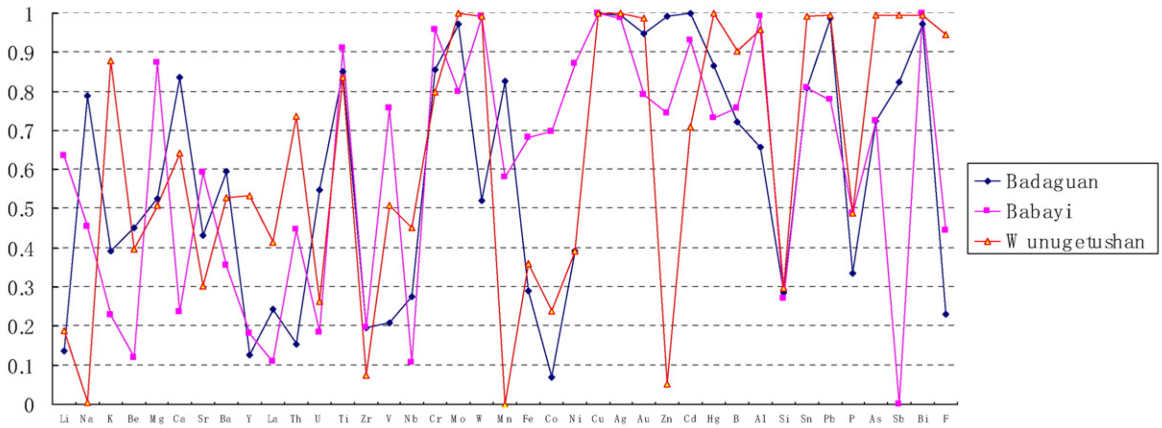

Fig. 3. Normalized geochemical value line chart of three porphyry deposits.

selecting the appropriate type of stretching, and providing output data in the range (0, 1). The normalized method used in this study was thus linear stretching. Fig. 3 is the line chart of the average normalized value of Wunugetushan, Badaguan, and Babayi copper molybdenum deposits, with the ROI method used to select pixels.

4.4. Generation of alteration, denudation, and mineralization intensity coefficient maps

Because the Wunugetushan copper molybdenum deposit in the study area is the largest deposit, it was selected as a model deposit,

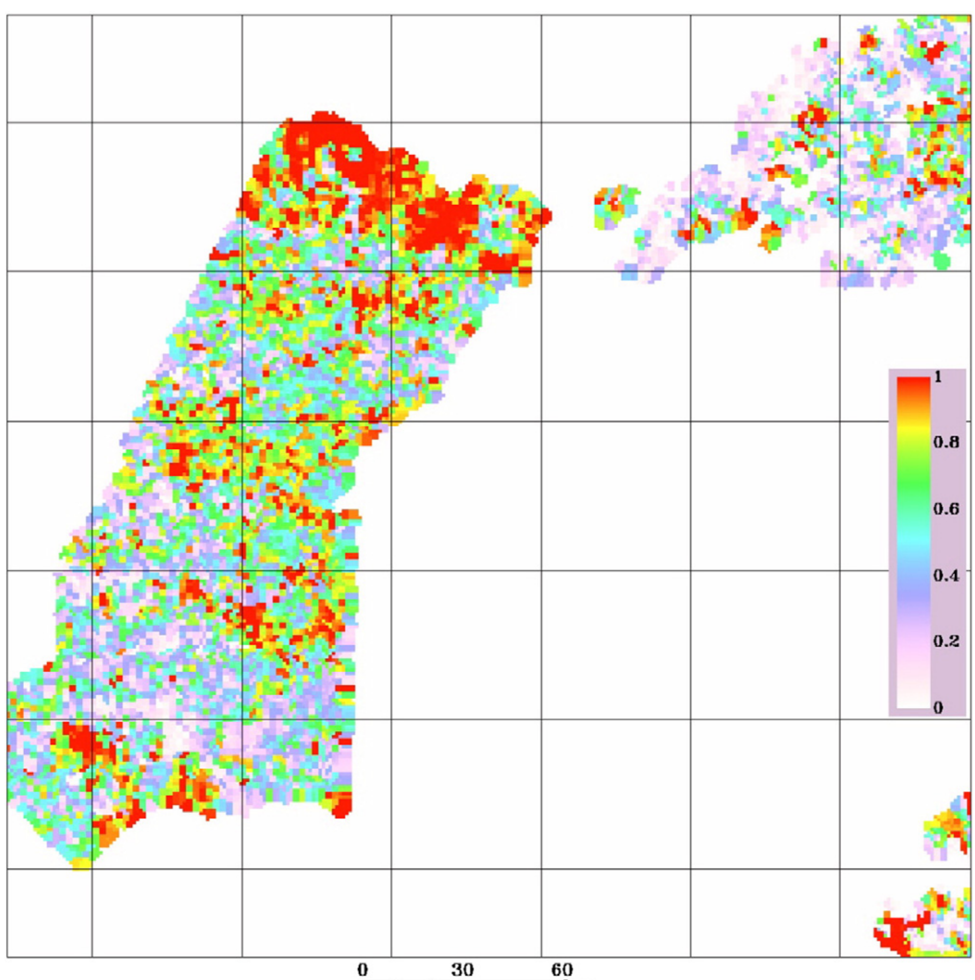

Fig. 4. Pseudo-colour map of ore-bearing hydrothermal alteration coefficient, calculated as per Eq. (1). Red colour indicates intense alteration.

with geochemical data used to calculate hydrothermal alteration, denudation, and mineralization intensity coefficients.

4.4.1. Ore-bearing thermal alteration coefficient map

It can be seen from Fig. 3 that Na, Zr, Mn, U, Li, and Si are dilution elements, while Cr, Cd, Pb, F, B, Sn, Sb, As, Au, Hg, W, Mo, Bi, Ag, and Cu are enrichment elements. Applying Eq. (1) to each geochemical image, it was possible to derive the ore-bearing hydrothermal alteration coefficient diagram shown in Fig. 4.

4.4.2. Denudation coefficient map

When calculating the denudation coefficient, there will be interference from sedimentary rocks; only after having removed the sedimentary area can the denudation coefficient of magmatic and volcanic rocks be correctly calculated and mapped.

Sedimentary and magmatic/volcanic rocks differ mainly in the amount of alkaline elements present, with the alkali content of magmatic and volcanic rocks usually higher than that of sedimentary rocks. The total sum content of Li, Na, K, Be, Ca, Mg, Sr, and Ba can thus enable a distinction to be made. Sedimentary rock can be divided by cumulative frequency percentages from normalized alkaline elements. The denudation coefficient of classified sedimentary rocks is assigned a value of 1, indicating that the area may conceal magmatic rocks and that there is therefore the possibility of finding porphyry deposits.

The denudation coefficient was for the remaining area of magmatic and volcanic rocks using Eq. (4). The final denudation coefficient map is shown in Fig. 5.

4.4.3. Surface mineralization intensity coefficient map

The surface mineralization intensity coefficient map was derived using Eq. (5). Because the model deposit is a porphyry Cu Mo deposit, the surface mineralization intensity coefficient was calculated only for the main ore-forming elements, i.e., copper and molybdenum. The surface mineralization intensities of copper and molybdenum were calculated separately, with the intensity coefficient map then created as the product of the two maps. The calculated surface mineralization intensity map is shown in Fig. 6.

5. Resource estimation and deposit prediction

5.1. Resource estimation

After the various coefficients were calculated, they could be compared to the deposits in the Manchuria area. The copper resources of the Wunugetushan copper molybdenum deposit total 2,232,000 tonnes, those of the Badaguan deposit 140,000 tonnes, and those of the Babayi deposit 61,000 tonnes. These resources are not generated within a single pixel; it is therefore necessary to consider which pixels are able to provide these resources. The search for these pixels is conducted by comparing the original copper content image.

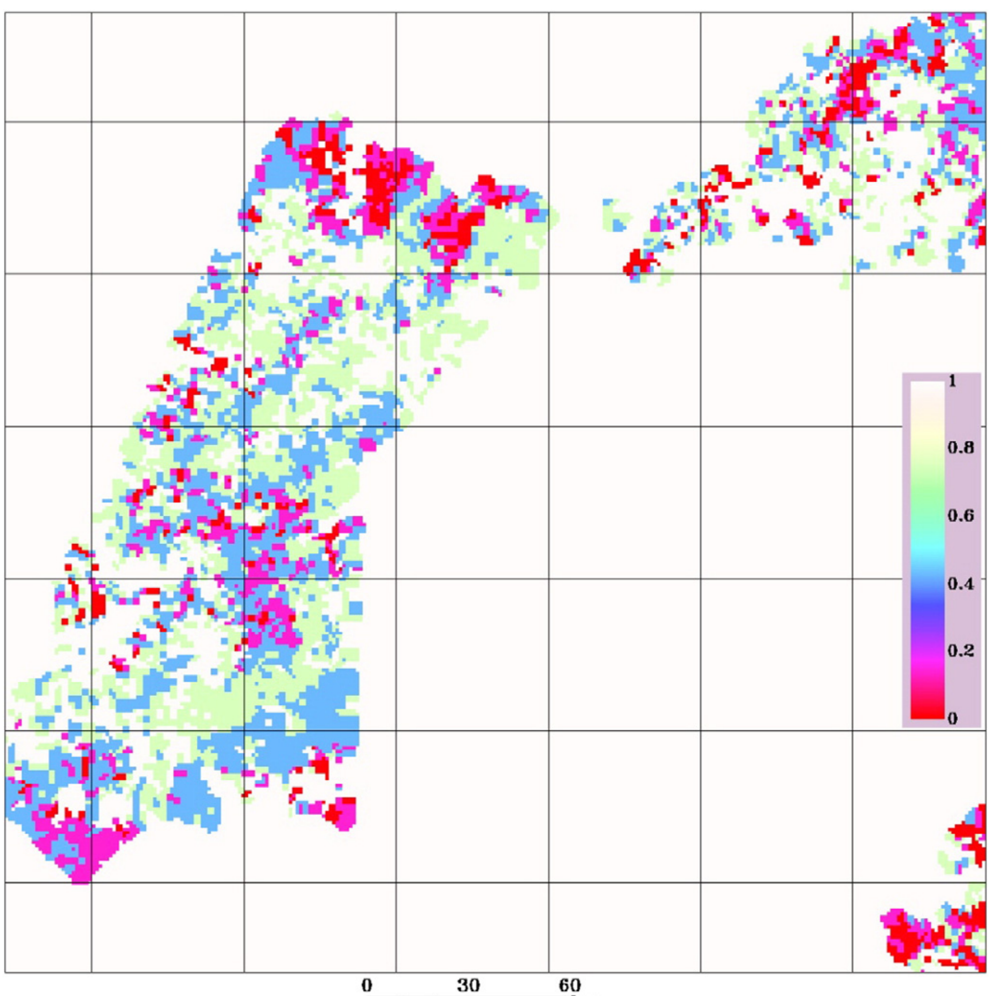

Fig. 5. Pseudo-colour map of denudation coefficient, calculated as per Eq. (4). Light-coloured areas have experienced less denudation, while areas in red have experienced more extensive denudation.

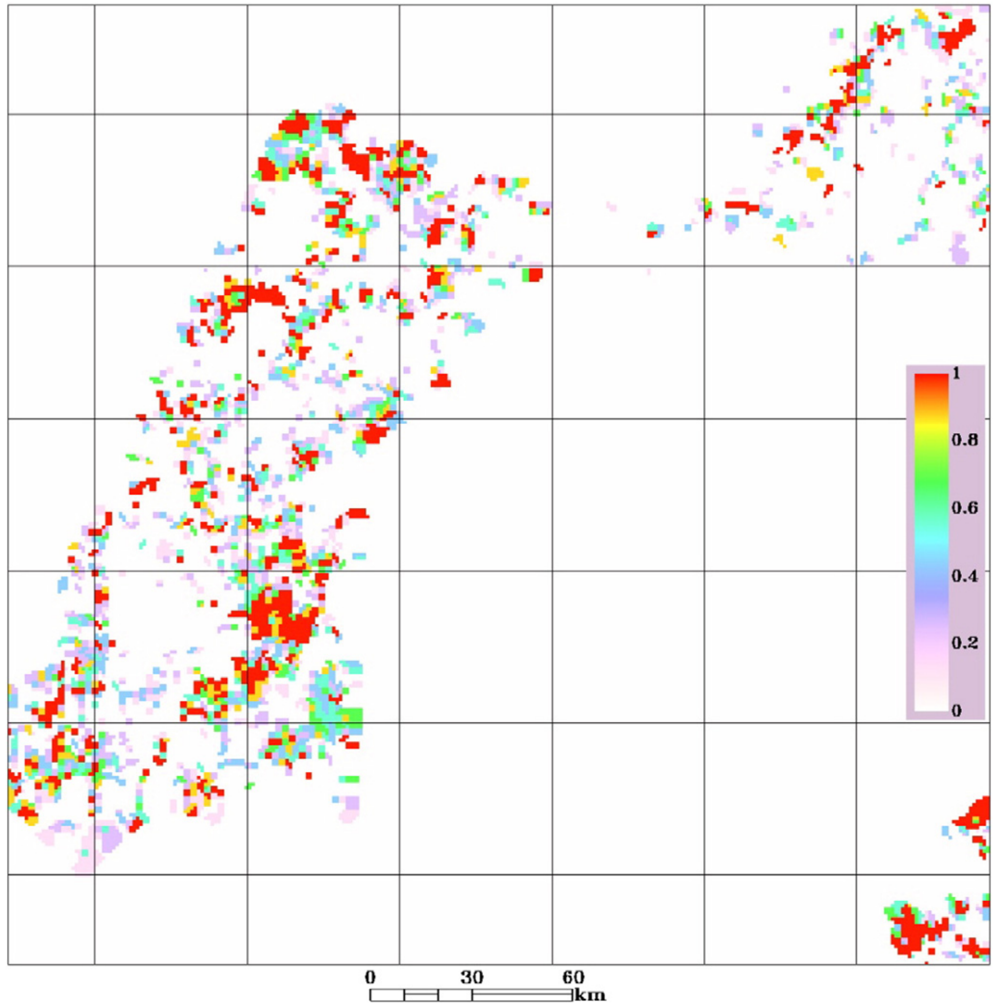

Fig. 6. Pseudo-colour map of surface mineralization intensity, based on Eq. (5).

It was found that there are 32 adjacent pixels in the Wunugetushan deposits that have a high copper content. Each pixel is considered to be able to provide 69,687.5 tonnes of copper endowment. Similarly, the copper endowment of each pixel of the Babayi (5 pixels) and Badaguan (6 pixels) deposits was 12,200 and 23,330 tonnes, respectively. The mean coefficient of a pixel in each deposit was analysed, with statistical values given in Table 2.

In order to summarize the relationship between coefficients and copper endowments, SPSS software was used for multiple regression analysis. After calculation, R square was found to be 1.00 and the regression equation was obtained as follows:

$$Wpixel = 4.224 * fden + 31.763 * fa - 25.822 \tag{11}$$

where *Wpixel* is the pixel endowment, *fden* is the denudation coefficient, and *fa* is the ore-bearing hydrothermal alteration coefficient. Using this equation, the quantity of resources can be calculated, and the endowment image for each pixel is obtained.

After calculating *W_ore* based on Eq. (10), the endowment image is obtained, which is controlled by mineralization intensity. This image can provide information regarding surface mineralization intensity; the higher the value, the larger the endowment in the pixel. Prospective target areas can be predicted based on the classification of pixel endowments (Fig. 7) and the number of deposits can also be obtained.

5.2. Summary of predicted resources

The final copper endowment map covers the whole area. Because mineralization intensity is controlled, if the content of the main ore-forming elements is lower than the regional average, there is no significance. The total amount of resources was found to add up to 11,966,700 tonnes. The total amount of resources for pixels with endowments of 0–1,000,000 tonnes, 1,000,000–2,000,000 tonnes, 2,000,000–5,000,000

Table 2
Comparison of minimum unit cell coefficients and copper endowments for the main deposits in the Manzhouli area.

	Coefficient			
Deposit	Denudation coefficient	Surface mineralization intensity coefficient	Ore-bearing hydrothermal alteration coefficient	Copper endowment (tonnes/km^2)
Wunugetushan	0.245833	0.452083	0.999877	69,687.5
Babayi	0.050196	0.829804	0.844706	12,200
Badaguan	0.797386	0.637255	0.780392	23,333

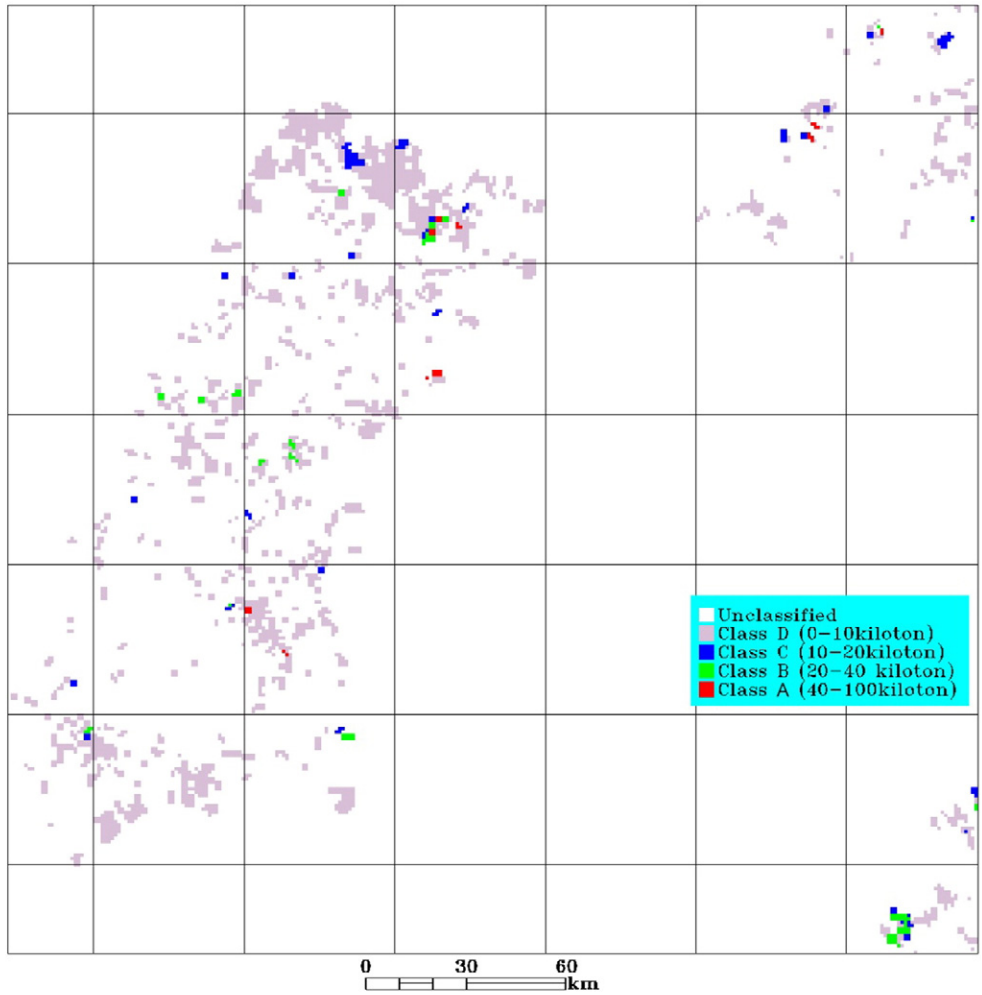

Fig. 7. Classification map of porphyry copper deposit endowments in the Manzhouli area. Classification was conducted by applying the slicing density method to the image generated from Eq. (10).

tonnes, and 5,000,000–10,000,000 tonnes, was 5,595,800 tonnes, 2,153,100 tonnes, 2,976,200 tonnes, and, 1,241,750 tonnes, respectively (Table 3).

5.3. Estimation of deposit numbers

Fig. 8 shows the amount of resources at each level, reflecting the quantity of resources within a pixel. If the pixel level is classified as B, it means there is a 20,000–40,000 ton copper endowment in the range of 1 km^2. In practice, the distribution of deposits tends to occur over more than 1 km^2, so in the prediction of deposit numbers, the classification level of surrounding pixels needs to be considered; if surrounding pixels are at higher levels, they can be classified together. Deposit numbers were predicted by merging adjacent pixels of A and B classes, with the location of deposits shown in Fig. 8.

The resources of predicted ore deposits were calculated, and the positions of predicted deposits were contrasted with the distribution of known ore deposits in the study area (Table 4). It can be seen that the predicted deposit is a known deposit or near to the periphery of a known copper point. A few predicted deposits are on the periphery of the known large lead–zinc ores and silver ores; this is explained by the metallogenic series theory, which states that there may be different types of ore deposits within a mining area and its periphery.

The resources accumulated in predicted deposits were counted (Table 4), and mineralization in the pixel or in neighbouring pixels was compared with that of deposits discovered in the past (Table 4). It can be seen that predicted deposits are within identified deposits, or on the close periphery of known copper points. Another few predicted deposits are located on the peripheries of large lead–zinc and silver deposits; this can be explained by the metallogenic series theory described above.

5.4. Discussion

Quantitative resource estimation is closely associated with the minimum unit cell, and the latter is determined based on geochemical

Table 3
Histogram statistics for copper endowments exceeding 50,000 tonnes per pixel.

Value	Numbers of pixels	Cumulative pixels	Percentage	Cumulative percentage	Endowment (tonnes)
5.011454	1	82,340	0.0012	99.9757	50,114.54
5.038111	1	82,341	0.0012	99.9769	50,381.11
5.171394	1	82,342	0.0012	99.9781	51,713.94
5.224707	1	82,343	0.0012	99.9794	52,247.07
5.304677	1	82,344	0.0012	99.9806	53,046.77
5.331334	2	82,346	0.0024	99.983	106,626.7
5.464617	2	82,348	0.0024	99.9854	109,292.3
6.077721	3	82,351	0.0036	99.9891	182,331.6
6.264318	2	82,353	0.0024	99.9915	125,286.4
6.424258	2	82,355	0.0024	99.9939	128,485.2
6.477571	1	82,356	0.0012	99.9951	64,775.71
6.557541	1	82,357	0.0012	99.9964	65,575.41
6.664168	1	82,358	0.0012	99.9976	66,641.68
6.717481	1	82,359	0.0012	99.9988	67,174.81
6.797451	1	82,360	0.0012	100	67,974.51

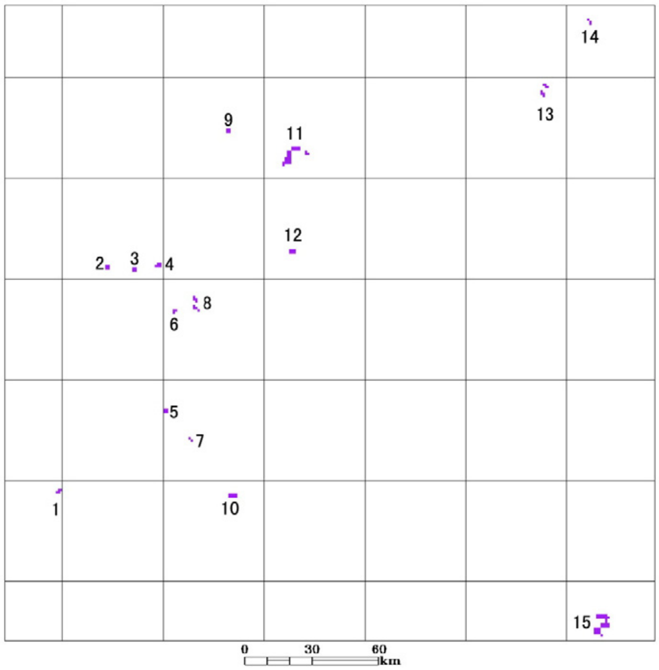

Fig. 8. Prediction of ore deposit locations, based on the classification map of copper endowment.

sample spacing. The smaller the sample spacing, the smaller the minimum unit area. In the Manzhouli area, the sampling density is 1 point per 4 km^2 and thus establishing a 1000 m pixel is more reasonable. The objective of mineral prospectivity analysis is to determine the range of ore deposits; in the case of large and medium-sized ore deposits, it is very normal that the mining area is 1–10 km^2. This 1 km^2 minimum unit cell provides much better predictions than previous methods; for example, the geochemical block method provides predictions at thousands of km^2 (Zhu et al., 2004). Setting the minimum prediction unit to 1 km^2 provides advantages in terms of accuracy and targeting locations.

Previous resource estimation often needed to use parameters such as depth and ore weight of ore bodies. The calculation formulae of resource estimation do not require these parameters but factor in their roles. The function of these parameters lies in the model deposit resources. The metal endowment of a model deposit is derived from the density, grade, and depth of ore bodies. In this study, the regression equation of metal endowment is considered consistent with the parameters of the model deposit.

In estimating resources, ore-bearing hydrothermal alteration and surface mineralization intensity coefficients could be applied in other areas. However, the application of such coefficients is generally more complicated. Some scholars (e.g. Jin and Sun, 1990) have studied the degree of denudation in Wunugetushan deposits, noting that depth differences reflect the Mo/Pb ratio.

Xiong and Lei (1995) put forward the relation of (Nb + Zr + Rb)/(V + Cr + Ni) and denudation degree; in some rock types, if the ratio is high, this indicates shallow denudation. Ni and Co are typical mantle type elements and belong to the first transition with V in the periodic table, having similar geochemical properties. In magmatic rocks, they are inversely correlated with SiO_2 content. Rb, Nb, and Zr are typical lithophile elements, increasing with SiO_2 content and thus positive correlated. It has been proven that with a transition from shallow to deep crust, SiO_2 and lithophile element content gradually decreases, while the content of transition metal elements gradually increases. Ni, Co, V, Nb, Zr, and Rb are stable or relatively stable elements. These properties make them suitable for calculating the denudation coefficient. In this paper, using the inverse value and then normalizing this provides a denudation coefficient range between 0 and 1; this indicates that the higher the denudation coefficient, the greater the extent of denudation. This study adopts this method but since there is no Rb geochemical data, Sr is used instead, taking into account the fact that these elements share similar properties.

As noted above, the model deposit used in this study is a porphyry copper molybdenum deposit. As commonly known, porphyry copper deposits are large scale and of uniform grade. It is therefore appropriate to use the ore-bearing hydrothermal alteration and denudation coefficients to estimate the amount of resources. However, other types of ore deposits may require determination of other coefficients, based on the characteristics of mineralization type. In addition, resource estimation is carried out on the premise of known ore deposit resources. If the amount of resources is unknown, the regression equation cannot be established and cannot be used to quantitatively predict resources. However, the coefficient product can be used to identify the prospecting target area and to provide other related information.

6. Conclusions

In this study, geochemical data for the Manzhouli area obtained at the 1:200,000 scale were used to identify prospective target areas and to estimate the amount of copper ore resources. Resource estimation was based on a model deposit; i.e., through the study of a typical

Table 4
Relative parameters of predicted deposits and geological interpretation.

Deposit code	Centre coordinate		Area (km^2)	Amount of resources (tonnes)	Geological interpretation
	Map X	Map Y			
1	25	218	4	261,951	Location of Gaojigaoer Mo deposit
2	47	117	4	257,128	7 km north of Jiawula lead–zinc deposit
3	58	119	4	283,111	10 km northeast of Jiawula lead–zinc deposit
4	69	117	5	333,863	15 km northeast of Jiawula lead–zinc deposit
5	73	181	4	30,321	5 km east of Erentaolegai silver deposit
6	76	138	3	192,846	
7	84	195	2	124,827	
8	86	132	8	552,863	
9	101	56	4	395,948	2 km west of porphyry Cu-Mo ore spots
10	102	220	8	607,666	
11	128	69	28	1,964,526	Wunugetushan Cu-Mo deposit
12	129	110	6	478,133	
13	241	40	8	477,053	Babayi Cu-Mo deposit
14	262	8	3	160,630	Badaguan Cu-Mo deposit
15	267	274	31	1,714,235	10 km northeast of two copper ore spots

deposit, we determined the ore-bearing hydrothermal alteration, denudation, and surface mineralization intensity coefficients, also calculating the formation of resources. The following are the key findings:

1. In this study, resource estimation made full use of 1:200,000 regional geochemical survey data. This was done by rasterizing the content of each element to generate geochemical images, with each image pixel predicted as a unit cell. Because the prediction unit area is smaller than in previous work, prediction of deposit position is of higher precision.
2. Three levels of predicted metal endowment (Classes A, B, and C) were identified based on rasterized geochemical data. Copper resources amounted to 11,966,700 tonnes, with great potential for prospecting in the study area. In addition, by merging Class A and B areas of metal endowment, we predicted the location of 15 deposits, and highlighted the direction of prospecting.
3. The concepts and methods used for resource estimation in the Manzhouli area were confirmed to be feasible; however, whether these can be applied equally to other regions or to other types of ore deposits in future will need to be determined through future research.

Conflict of interest statement

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, this manuscript.

Acknowledgements

This research was supported by ‘pilot projects on ore-prospecting and exploration technique method in Daxinganling metallogenic belt’ of the Extensive Land Resources Survey programme (1212010781026). Prof. Keyan Xiao and Prof. Tianzhu Ye provided substantial help in the drafting of this paper. We also benefited from discussions with Jianbo Shao, researcher at the Shenyang Institute of Geology and Mineral Resources.

References

Celenk, O., Clark, A.L., Vletter, D.R.D., Garrett, R.G., Staaldvinen, C.V., 1978. Workshop on abundance estimation. J. Int. Assoc. Math. Geol. 10 (5), 473–480.

Cox, D.P., 1993. Estimation of undiscovered deposits in quantitative mineral resource assessments — examples from Venezuela and Puerto Rico. Nonrenewable Resour. 2 (2), 82–91.

Garrett, R.G., 1978. An abundance model resource appraisal for some Canadian commodities. J. Int. Assoc. Math. Geol. 10 (5), 481–494.

Gong, P., Li, J., Hu, X., Liu, X., Ma, Z., 2013. Regional geochemical quantitative prediction method and technology in the mineral resource potential assessment. Geol. Rev. 58 (6), 1101–1109.

Jin, L., Sun, F., 1990. Correlation between the northern southern ore sections in Wunugetushan porphyry copper deposit, Inner Mongolia, China. J. Changchun Univ. Earth Sci. 20 (1), 61–67.

Liu, C.M., Ma, S.M., 2007. The main achievements of the study on primary halo in the past 50 years in China. Comput. Tech. Geophys. Geochem. Explor. 29 (1), 215–221 (In Chinese with English abstract).

Liu, D.W., Xie, X.J., 2005. Evaluation of China's tin resources potential based on the geochemical block concept. Chin. Geol. 32 (1), 25 (In Chinese with English abstract).

Mamuse, A., Beresford, S., Porwal, A., Kreuzer, O., 2010. Assessment of undiscovered nickel sulphide resources, Kalgoorlie terrane, Western Australia: part 1. Deposit and endowment density models. Ore Geol. Rev. 37, 141–157.

McKelvey, V.E., 1960. Relation of reserves of the elements to their crustal abundance. Am. J. Sci. 258-A, 234–241.

Mookherjee, A., Panigrahi, M.K., 1994. Reserve base in relation to crustal abundance of metals: another look. J. Geochem. Explor. 51 (1), 1–9.

Nishiyama, T., Adachi, T., 1995. Resource depletion calculated by the ratio of the reserve plus cumulative consumption to the crustal abundance for gold. Nat. Resour. Res. 4 (3), 253–261.

Porwal, A.K., Kreuzer, O.P., 2010. Introduction to the special issue: mineral prospectivity analysis and quantitative resource estimation. Ore Geol. Rev. 38 (3), 121–127.

She, H.Q., Li, H.H., Li, J.W., Zhao, S.B., et al., 2009. The metallogenetical characteristics and prospecting direction of the copper–lead–zinc polymetal deposits in the northern-central Daxing'anling Mountain, Inner Mongolia. Acta Geol. Sin. 83 (10), 1456–1472 (In Chinese with English abstract).

Singer, D.A., 1993. Basic concepts in three-part quantitative assessments of undiscovered mineral resources. Nonrenewable Resour. 2 (2), 69–81.

Solovov, A.P., 1957. Theory and practice foundation of metallometric survey. China Industry Press, Beijing, pp. 46–121 (Russian translated into Chinese).

Xie, X., Liu, D., Xiang, Y., Yan, G., Lian, C., 2004. Geochemical blocks for predicting large ore deposits—concept and methodology. J. Geochem. Explor. 84 (2), 77–91.

Xie, X.J., Ren, T.X., Huan, X., X. I., CAGS, & Chengdu., 2009. The implementation of the Regional Geochemistry-National Reconnaissance Program in China in the past thirty years. Acta Geosci. Sin. 30 (6), 700–716.

Xiong, J., Lei, R., 1995. Attempt to decide denudation degree of intrusive masses with (Nb + Zr + Rb)/(V + Co + Ni) ratio. Hubei Geol. Min. Resour. 9 (1), 74–83.

Zhao, Y., 1991. According to the water system sediment survey results to predict the abnormal scale of mineralization area. Geol. Prospect. 2, 46–49 (In Chinese with English abstract).

Zheng, Y., Sun, X., Gao, S., Wang, C., Zhao, Z., Wu, S., et al., 2014. Analysis of stream sediment data for exploring the Zhunuo porphyry Cu deposit, southern Tibet. J. Geochem. Explor. 143 (3), 19–30.

Zhu, X.B., Mao, D.F., Liu, X.B., Liao, S.P., Zhan, T.W., 2004. Study of calculative method for metal reserve in anomalous block. World Geol. 23 (3), 227–244 (In Chinese with English abstract).