

Comparison between ordinary kriging (OK) and inverse distance weighted (IDW) based on estimation error. Case study: Dardevey iron ore deposit, NE Iran

Shahab Shahbeik · Peyman Afzal · Parviz Moarefvand · Mania Qumarsy

Received: 11 March 2013 / Accepted: 17 May 2013 / Published online: 28 June 2013
© Saudi Society for Geosciences 2013

Abstract Estimation of mineral resources and reserves with low values of error is essential in mineral exploration. The aim of this study is to compare inverse distance weighted (IDW) and ordinary kriging (OK) methods based on error estimation in the Dardevey iron ore deposit, NE Iran. Anisotropic ellipsoid and variograms were calculated and generated for estimation of Fe distribution by both methods. Density, continuity of ore and waste, the number of points involved, and the discretization factor in the estimation of ore and waste boundaries were determined and the resource estimated by IDW and OK methods. Estimation errors were classified based on JORC standard, and both methods were compared due to distribution of error estimation. Results obtained by the study indicate that error estimation of OK method is less than IDW method and that the results of OK method are reliable.

Keywords IDW · OK · Error estimation · Block modeling · JORC classification

Sh. Shahbeik (✉) · P. Afzal
Department of Mining Engineering, South Tehran Branch,
Islamic Azad University, Tehran, Iran
e-mail: shahab.shahbeik@gmail.com

P. Afzal
Camborne School of Mines, University of Exeter, Penryn, UK
e-mail: P_Afzal@azad.ac.ir

P. Moarefvand
Mining and Metallurgy Faculty, Amirkabir University of
Technology, Tehran, Iran
e-mail: parvizz@aut.ac.ir

M. Qumarsy
Madan Ara Falat Aria Consulting Engineer Company (MAFA),
Tehran, Iran
e-mail: m.qumarsy@gmail.com

Introduction

Geostatistical estimation of ore grade is necessary in mine planning and designing (Asghari and Madani Esfahani 2013; Monjezi et al. 2013). An important problem in mineral exploration is the estimation of two- or three-dimensional regional variables in a studied area, especially ore grade distribution. According to this problem, which is known as spatial interpolation, several methods were proposed which consist of linear and non-linear kriging methods, inverse distance weighted (IDW), interpolating polynomials, splines, and power and Fourier series fitting (Franke 1982; Lam 1983; Cressie 1993; Zimmerman et al. 1999). In many cases, kriging procedure was found to be the best estimator, while IDW or splines were considered as proper methods in other cases (Matheron 1967; Marechal and Serra 1971; Rouhani 1986; Laslett and McBratney 1990; Weber and Englund 1994; Laslett 1994; Phillips et al. 1997; Abed et al. 2013; Arfaoui and HédiInoubli 2012; Laslett et al. 1987; Weber and Englund 1992; Gallichand and Marcotte 1993; Brus et al. 1996; Declercq 1996; Yasrebi et al. 2009; Zimmerman et al. 1999). Using real data rather than synthetic data has several advantages: for example, it precludes one method from having an unfair advantage merely because the data used for the comparison are generated under the same model on which the method is based. On the other hand, only with synthetic data can the effect of certain data characteristics on interpolation accuracy be systematically evaluated (Weber and Englund 1992 and 1994; Englund et al. 1992; Zimmerman et al. 1999). Evaluation of ore element distribution is an important parameter for mine planning and design (Hustrulid and Kochta 2006). Determination of estimation method is essential for decreasing the error estimation and increasing the accuracy of resource and reserve evaluation (Dimitrakopoulos et al. 2007; Parhizkar et al. 2011; Asghari and Madani Esfahani 2013).

The purpose of this paper is to evaluate Fe distribution and compare the estimation error of two interpolation methods

based on an analysis of subsurface lithogeochemical data resulting from drill cores in Dardevey iron ore deposit, NE Iran. The interpolation methods OK and IDW were used in this study. The IDW method used in this paper has been developed by utilizing variography and anisotropic ellipsoid.

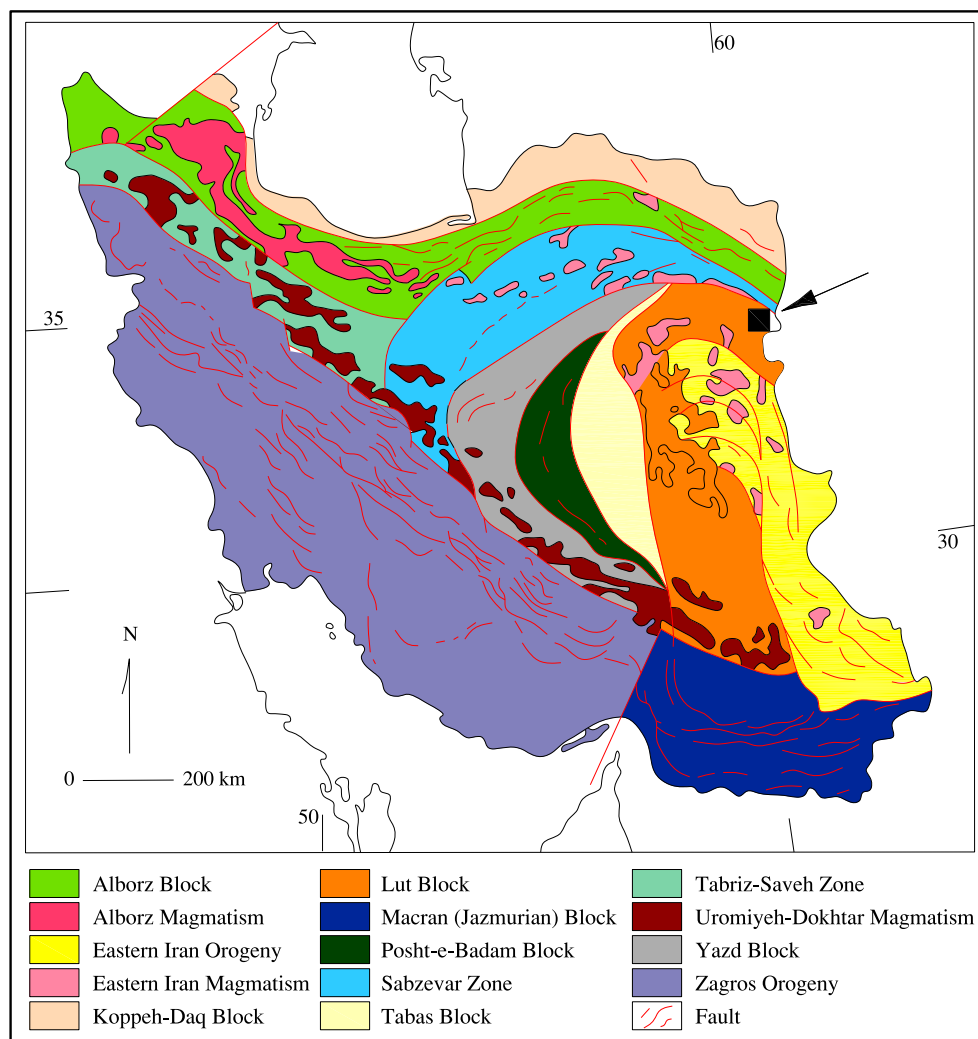
Geological setting of Dardevey deposit

The Sangan iron ore complex is located approximately 300 km SE of Mashhad, NE Iran, which is one of the great Iranian iron ore resources. The Sangan complex consists of several ore bodies such as Dardevey, Baghak, A, A', B, C, and C North. The Dardevey deposit is situated at about 18 km NE of Sangan, as shown in Fig. 1. This area is located in Lut structural zone, which is one of the subdivisions of the Iranian central structural zone at the northern part of Darouneh fault, as depicted in Fig. 1. Dardevey iron ore includes Fe skarn system, and its metallic minerals are magnetite, hematite, goethite, pyrite, and martite (Hasanipack et al. 2009).

The Dardevey deposit is located in the southern margin of the Upper Eocene Sar-Nowsar granite (biotite–amphibole granite) and occurs in an east–west trending sequence of Upper Mesozoic sedimentary rocks. Magnetite skarn is formed in black limestone and dolomite (Jurassic–Lower Cretaceous). They are massive and, in some localities, they are about 200 m in thickness. Mineral paragenesis are magnetite±hematite±pyrite and some chalcopyrite±garnet (andradite)±actinolite±chlorite±phlogopite calcite±dolomite. This deposit is Mg-skarn, the Mg content of magnetite of which is about 1.22–1.26 %. Four stages of skarn formation and ore deposition have been recognized at the area (stage I, II, III, and IV a, b). Based on the multi-spectral images and field observation, the Dardevey deposit was displaced by strike slip fault more than 1 km from Baghak deposit (Ghavi and Karimpour 2010).

Exploration drill cores and surface magnetic surveys in the study area illustrated that the dips of mineralization zones are declining towards the south (80–85°). In addition, the main structural features are two-fault systems trending NW–SE and E–W, as depicted in Fig. 2 (Ghavi and Karimpour 2010).

Fig. 1 Location of studied area in structural map of Iran (black square; Stocklin 1977)



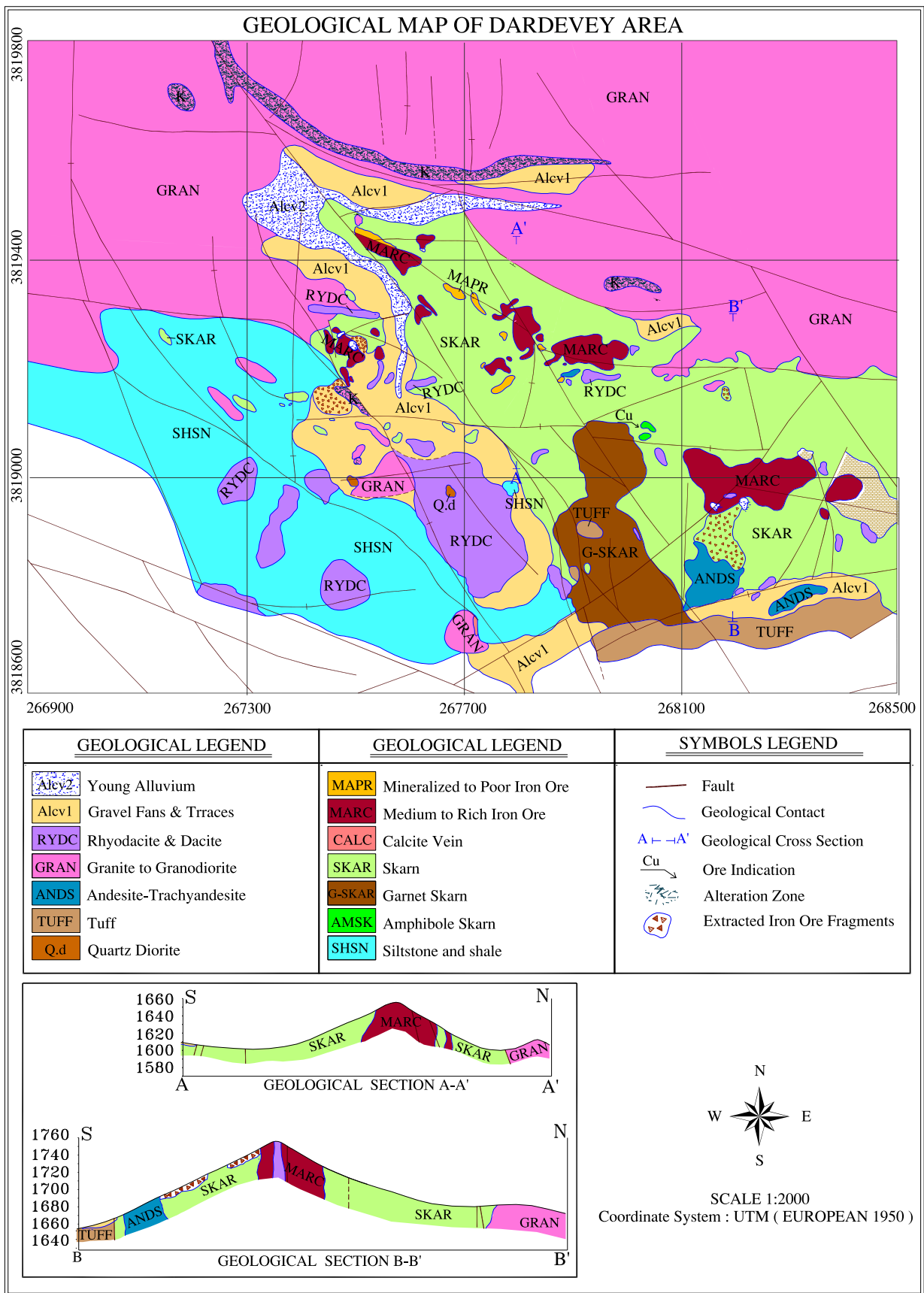


Fig. 2 Geological and structural map of studied area (Hasanipack et al. 2009)

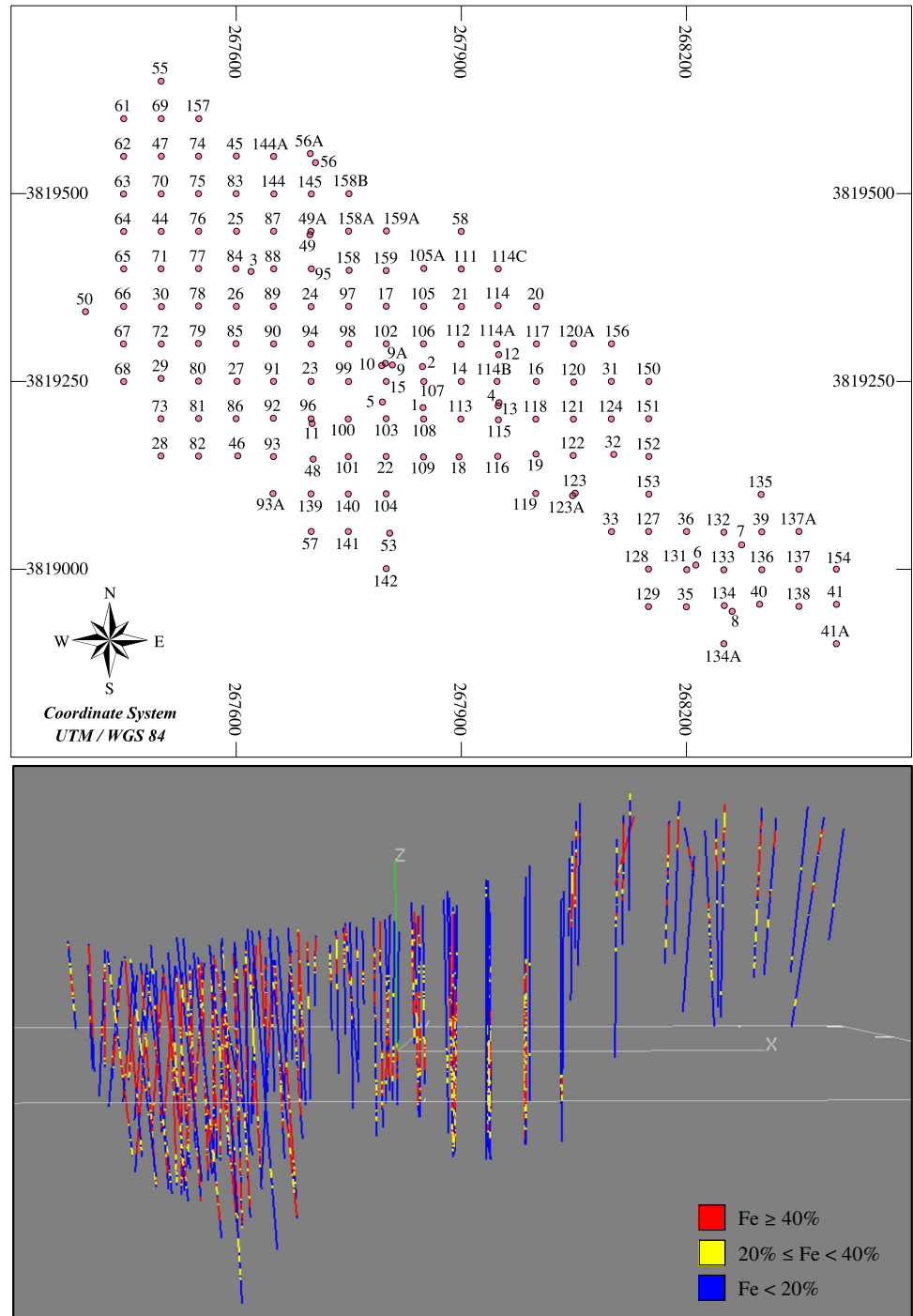
Discussion

The success in a mining operation depends on the accuracy of the reserves evaluation as well as the distribution of ore grades. Geostatistics techniques such as OK and IDW are widely used for ore grade estimation (Tahmasebi and Hezarkhani 2010).

Kriging is a group of geostatistical methods for interpolation of the different regional variables' values (e.g., ore element in this paper) at an unobserved location from observations of

its value at nearby locations, which consist of OK, universal kriging, indicator kriging, co-kriging, and others (Bayraktar and Turalioglu 2005; Emery 2005; Hormozi et al. 2012). The selection of a proper method depends on the particulars of the data and type of spatial model desired. The most commonly used method is OK, which is selected for this study (Lefohn and Knudsen 2011). OK plays a special role because it is compatible with a stationary model, only involves the variogram, and is in fact the form of kriging that is most often

Fig. 3 2D and 3D grid drilling in Dardevey deposit



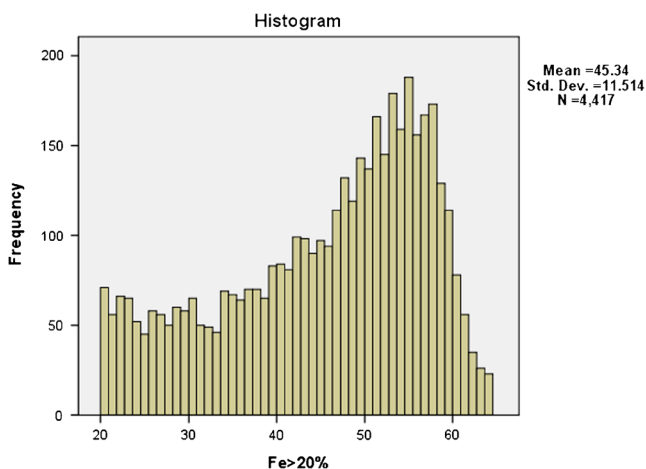


Fig. 4 Histogram of raw data with Fe grades above 20 %

used (Chile's and Delfiner 1999; Afzal et al. 2011). OK estimates based on the moving average of the variable of interest satisfying various dispersion forms of data, e.g., sparse sampling points (Goovaerts 1997; Afzal et al. 2011). OK works under the assumption of a stationary condition. Moreover, it is a linear model based on local neighborhood structure (Tahmasebi and Hezarkhani 2010).

IDW is one of the most common techniques for interpolation of scatter points. IDW has a fundamental assumption that the interpolating surface should be influenced most by the nearby points and less by the more distant points. The interpolating surface is a weighted average of the scatter points, and the weight assigned to each scatter point diminishes as the distance from the interpolation point to the scatter point increases. The values to unknown points are calculated with a weighted average of the values available at the known points (Homayoon et al. 2010; Yasrebi et al. 2009; Zimmerman et al. 1999).

The OK method requires the preliminary modeling step of a variance distance relationship, but IDW does not involve such step and is very simple and quick (Yasrebi et al. 2009; Zimmerman et al. 1999). Estimated values at unsampled locations are based on the measurements at surrounding locations with certain assigned weights for each measurements in both of them (Yasrebi et al. 2009).

Table 1 Statistical parameters for raw data with grades above 20 %

Raw Data (Fe≥20 %)	
Sample number	4,417
Mean	45.34
Median	48.08
Std. deviation	11.51
Variance	132.57
Skewness	-0.58
Kurtosis	-0.75
Minimum	20.00
Maximum	64.00

Table 2 Result of non-directional and directional variograms

Variables	Range	C-value	Sill	Nugget effect	Variogram model
Non-direction	412.8	45.3	147.2	101.9	Spherical
Axis 1	244.8	64.1	148	83.9	Spherical
Axis 2	113.4	40.2	131.1	90.9	Spherical
Axis 3	45.7	56.7	111.2	54.5	Spherical

However, the IDW method was developed by using results derived via variography and anisotropic ellipsoid. In this study, 5,500 lithogeochemical samples have been collected at 2-m intervals from 156 drill cores in the Dardevey deposit. Grid drilling was 50×50 m, although the network has a number of boreholes drilled for additional information, as shown in Fig. 3.

After chemical analysis of the collected samples by ICP-MS method, statistical studies were performed on the raw data, the results of which are shown in Fig. 4 and Table 1 for Fe values more than 20 %. Since the Gaussian kriging method was not used in this study, the data were therefore not normalized and raw data can be utilized. The parameters of estimation were calculated for both estimation techniques. Fe grade, tonnage, and estimation error were determined for both methods, and the IDW and OK techniques were compared based on the estimation error in the Dardevey iron ore deposit.

Variography and anisotropic ellipsoid

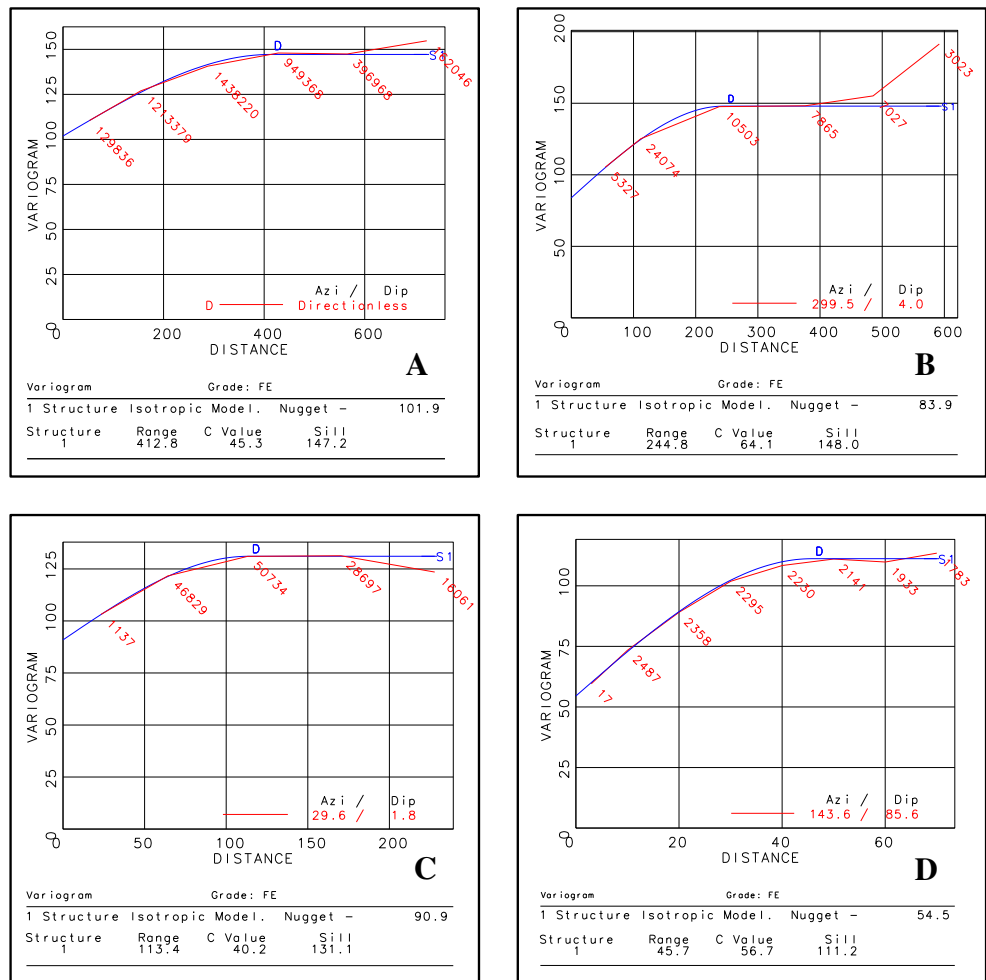
Variogram models and anisotropic ellipsoid are widely used tools for spatial interpolation, which are the fundamental parameters for geostatistical modeling (VerHoef and Cressie 1993; Calder and Cressie 2009). In this study, the non-directional and directional variograms were generated by Datamine Studio software in the Dardevey deposit, as shown in Table 2 and Fig. 5. C-value parameter has a range between 40 and 64 based on the variography (Table 2). In addition, anisotropic ellipsoid is provided (Fig. 6), and the axis characteristics are indicated in Table 3.

Determination of evaluation parameters

Four evaluation parameters were calculated as follows:

- (a) Determination of density
- (b) Continuity of ore and waste
- (c) Optimizing the number of points involved in the estimation of ore and waste boundaries
- (d) Optimizing the discretization factor in the estimation of ore and waste boundaries
 - a) Determination of density. For calculation of density, 1,100 samples were collected from drill cores, and their Fe values and densities are measured.

Fig. 5 Non-directional and directional variograms: **a** non-directional, **b** axis 1, **c** axis 2, and **d** axis 3



The trend line equation obtained by Fe and density values of each voxel is calculated (Li and Heap 2008), as shown in Fig. 7.

- b) Continuity of ore and waste. Thickness continuity of ore and waste in reserve estimation plays a necessary role, which is a function of ore grade continuity. Degree of continuity of grade in the mineralization

is a function of the mineralization type. For example, in a sedimentary mineralization with layer geometry, continuity in directions *X* and *Y* (length and width of the deposit) to *Z* (the thickness of the deposit) has a higher degree (Babak et al. 2011).

Fe grade with 20 % was used for determination of the extent of waste and ore. According to this criterion, the Fe values measured in each drill cores have become to waste and ore (0 and 1), and continuous thickness of ore and waste is measured. The value of continuity was calculated in the composites at 1, 2.5, 5, 10, 15, and 20 m (Fig. 8).

Based on these estimates and assessments, voxels should not be more than 5 m in height (*Z*) because the stripping (waste/ore) ratio is increased. Consequently, a composite 5 m in length was selected and used in

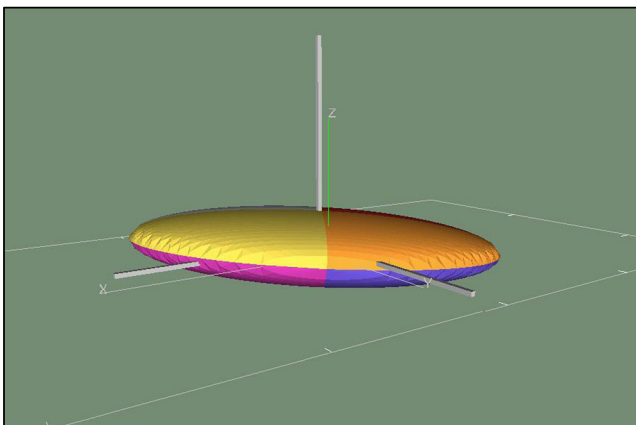


Fig. 6 Anisotropic ellipsoid in the Dardevey deposit

Table 3 Anisotropic ellipsoid particulars in the deposit

Variables	Azimuth	Dip
Axis 1	119.49	-4.00
Axis 2	209.62	-1.78
Axis 3	323.56	-85.62

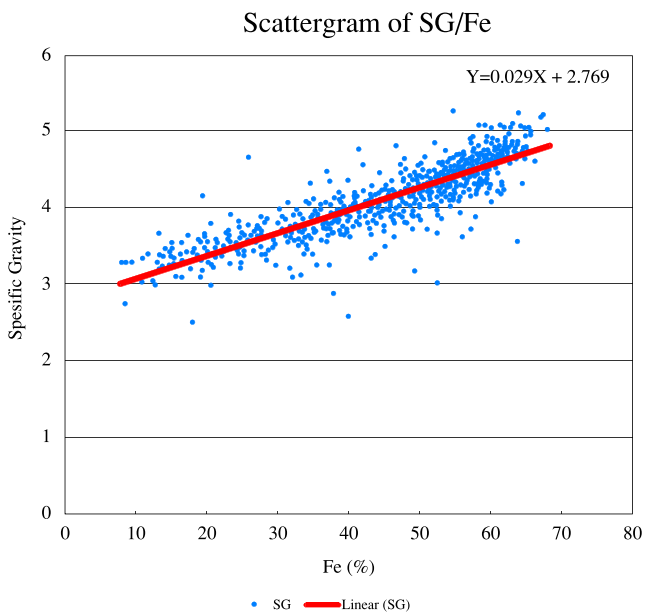


Fig. 7 Correlation diagram between Fe and density values

the estimation operation because it is necessary to use the dataset, which has an equal support, and community samples indicate a homogeneous and an equal probability environment in terms of volume samples.

- c) Optimizing the number of points involved in the estimation of ore and waste boundaries. The minimum and maximum numbers of points involved in the estimation of each voxel are the important parameters (Sakata and Ashida 2004; Brus and Heuvelink 2007).

For selection of the optimum number of points, minimum points of 2, 4, 6, and 8 and maximum points of 10, 12, 14, 16, 18, and 20 were used in each case of estimation. Based on the estimations, the minimum

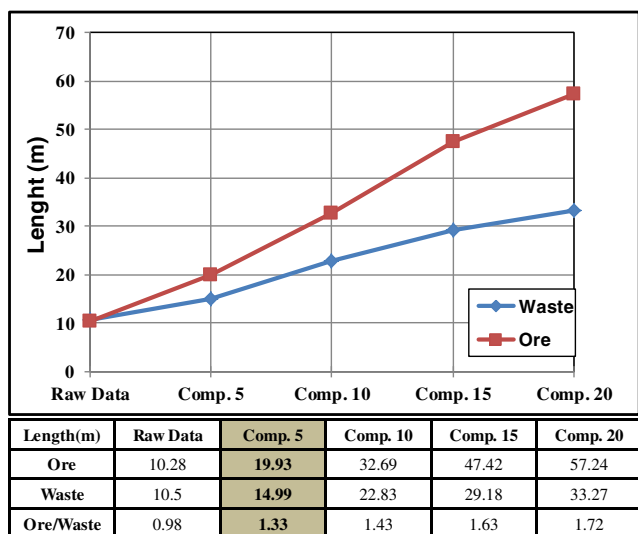


Fig. 8 Continuity of ore and waste in different composites

Table 4 Different models to select the number of points involved in the estimation of ore and waste boundaries

Row	Minimum point no.	Maximum point no.	Accuracy (%)
1	2	10	81.53
2	2	12	81.47
3	2	14	81.41
4	2	16	81.34
5	2	18	81.29
6	2	20	81.30
7	4	10	81.50
8	4	12	81.46
9	4	14	81.40
10	4	16	81.32
11	4	18	81.28
12	4	20	81.29
13	6	10	81.50
14	6	12	81.46
15	6	14	81.40
16	6	16	81.33
17	6	18	81.28
18	6	20	81.29
19	8	10	81.50
20	8	12	81.46
21	8	14	81.40
22	8	16	81.33
23	8	18	81.28
24	8	20	81.29

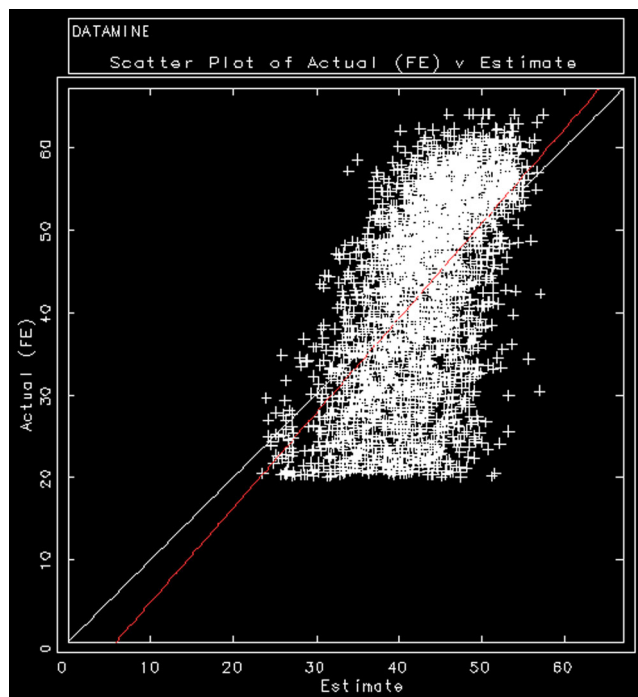


Fig. 9 Validation of the number of point's optimum for the estimation of ore and waste boundaries

Table 5 Result of optimization of discretization factor with the average variance of the estimations

Discretization factor	Average of variance
3×3×3	57.59
4×4×4	57.36
5×5×5	57.21

and maximum number of 2 and 10 points were selected, respectively, with accuracy of 81.53 % as the number of optimal points for estimation of ore and waste boundaries. Based on the results, the accuracy of the estimation decreases with increasing of the minimum and maximum points (Table 4). Additionally, the results of the validation are shown in Fig. 9.

- d) Optimizing the discretization factor in the estimation of ore and waste boundaries. Discretization factor in the estimation of 3D block model is an essential parameter. Therefore, it is necessary to select the optimal because most geostatistical softwares, e.g. Datamine, are estimated based on point, and by applying these parameters, the results are partly closer to the results of the estimation block (Journal 1993; Verly 1984).

In this study, the Fe values were estimated with different discretization factors and based on the precious optimal parameters and the results in three steps (Table 5). The average estimated variance in the discretization factor 5×5×5 m is less than that from other states, and therefore this factor was chosen as the optimal factor (Table 5).

Block modeling

Determination of different dimensions in the 3D block model is important for reserve estimation and mine planning. David (David 1970a, b) proposed a general method for the

operation due to the geometrical particulars of the studied deposit and grid drilling. Based on the method, block dimensions were calculated as follows:

- The length of each voxel is 25 m, which is equal to half of the distance between the drill cores, which is along the least variability (longitudinal direction) deposit.
- The width of each voxel is 12.5 m, which is a quarter of the distance between the drill cores, accords to along the highest variability (longitudinal direction) deposit.
- The height of each block is 5 m, due to the continuity of ore and tailing thickness and selection of 5-m composite (see the subsection “Continuity of ore and waste”).

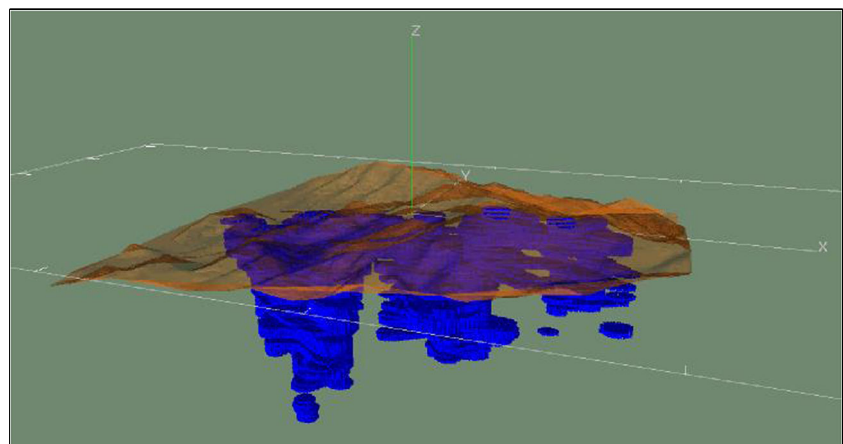
After identification of the optimal size for each voxel, a 3D block model of the deposit was generated. Then, block modeling is limited by 3D surface topography on the top, the deepest borehole in the depth, and estimated space around, as illustrated in Fig. 10.

Evaluation by OK and IDW

According to variography, determination of evaluation parameters, and providing block modeling, Fe values in the deposit were estimated by two methods, including OK and IDW (Fig. 11). High-grade mineralized zones existed in the NW part of the area based on results obtained by both estimation methods (Fig. 11). One of the main problems of estimation is overestimation and underestimation when there is not enough data, and especially, there is the evaluation of mineral resources based on information obtained from boreholes, such as this study, since the density of sampling points along the boreholes is very high and along the distance between the holes is very limited (Boniol and Toth 1999).

This problem is obvious in cumulative distribution function of the estimated Fe. For solving this problem, the cumulative distribution function of the estimated and the original values of each variable (composite) got a transfer function that due to the calculation will be estimated (Fig. 12).

Fig. 10 3D block model of the Dardevey deposit



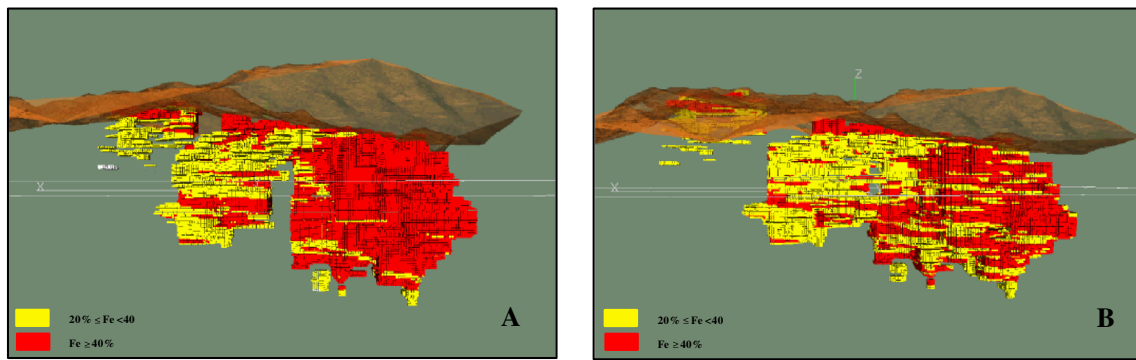


Fig. 11 Evaluation of ore deposit: a OK method and b IDW method

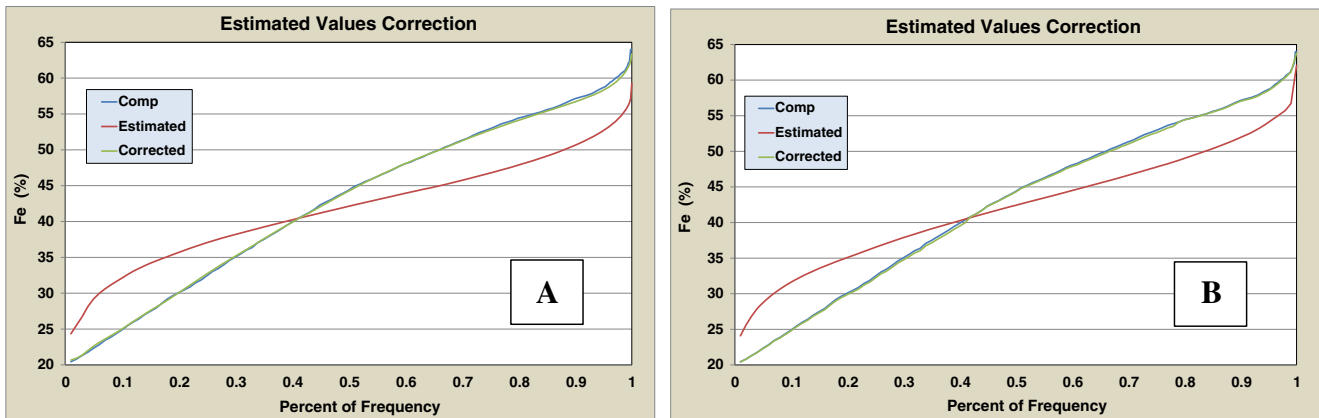


Fig. 12 Correction of estimated values of Fe variable; a) OK method, b) IDW method

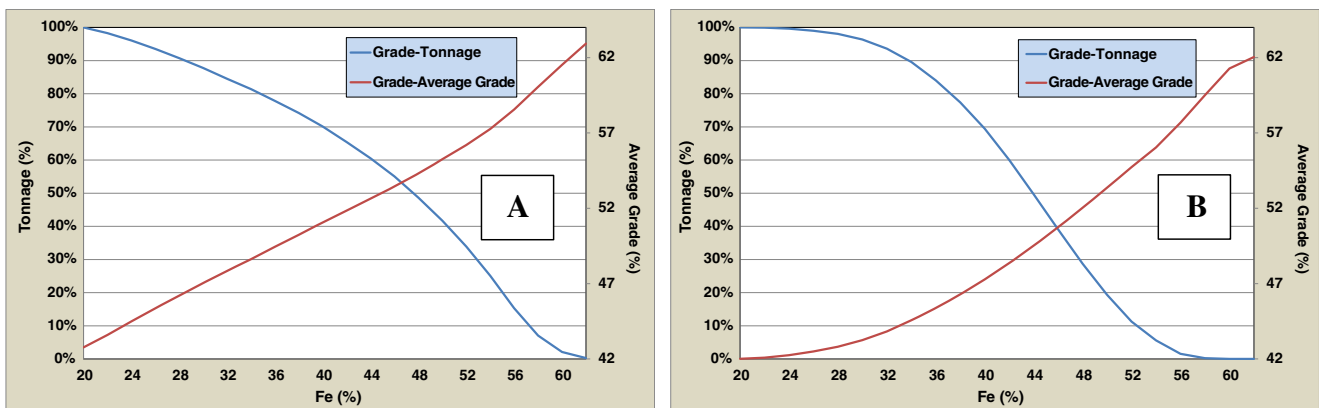


Fig. 13 Curve of grade tonnage: a OK method and b IDW method

Table 6 Reserves classification based on JORC standard

Error	Average grade (%)	Tonnage (%)	Classification
OK method			
0–20 %	42.69	99.78	A
20–40 %	21.51	0.12	B
40–60 %	20.27	0.10	C
>60 %	–	–	Possible
Total	42.54	100	
IDW method			
0–20 %	42.33	81.22	A
20–40 %	40.97	18.77	B
40–60 %	31.79	0.01	C
>60 %	–	–	Possible
Total	42.00	100	

Table 7 Statistical parameters for result of OK and IDW methods with grades above 20 %

	OK method	IDW method
Sample number	182,210	177,909
Mean	42.54	42.00
Median	44.27	42.42
Std. deviation	11.67	7.682
Variance	135.18	59.04
Skewness	–0.29	–0.22
Kurtosis	–1.13	–0.52
Minimum	20.01	20.77
Maximum	63.37	62.07

The function will correct the points of overestimation and underestimation based on the initial amount in the OK

method. This equation showing that Fe_c is the corrected values and Fe_e is the estimated values is as follows:

$$Fe_c = -1937014.3 + 2535647.8 Fe_e^{0.5} - 1418173.4 Fe_e + 435411.46 Fe_e^{1.5} - 77044.283 Fe_e^2 + 6973.4109 Fe_e^{2.5} - 31.637299 Fe_e^3 - 62.705574 Fe_e^{3.5} + 6.5279055 Fe_e^4 - 0.2834302 Fe_e^{4.5} + 0.0045392155 Fe_e^5$$

After correcting the Fe values for both methods, the curve of grade tonnage was generated for different assays, as illustrated in Fig. 13. However, in the cutoff grade of high values, the tonnage of reserve was reduced and the Fe values of reserves are increased.

following formula for the calculation of the estimation error is used (Noppé 1994):

$$\% \text{ Error} = \left(\frac{Z \cdot S}{X \cdot \sqrt{N}} \right) \times 100$$

The curve of grade tonnage is necessary to error calculation of each voxel and classification of reserves. The

S , X , and V are standard deviation of each voxel, assay of each voxel, and the number of samples that participated in grade

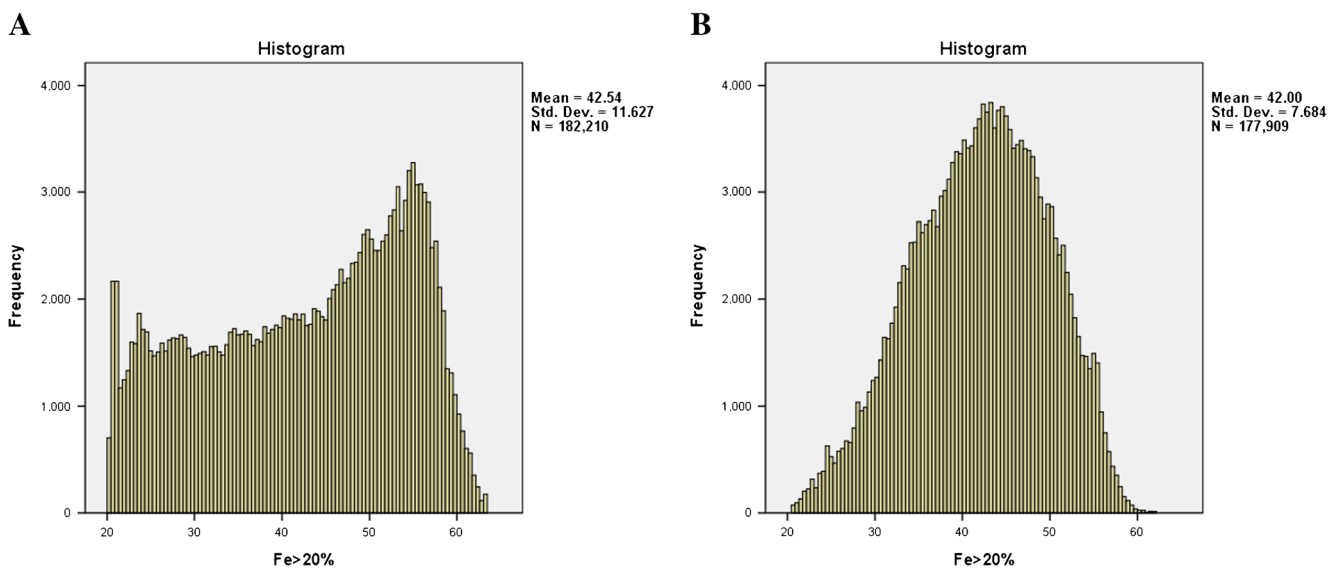


Fig. 14 Histogram of estimated data with Fe grades above 20 % obtained by **a** OK method and **b** IDW method

estimation, respectively, and Z is the integer constant which is 1.96 if the confidence level is 95 % or 1.64 if the confidence level is 90 %. In this study, the confidence level is 90 % and $Z=1.64$.

The reserve was classified based on calculated estimation errors by JORC code. Several methods are utilized for classification of reserves and resources; we used JORC (2012) method, as shown in Table 6. The classification framework based on the prepared code by the Joint Ore Reserves Committee of The Australasian Institute of Mining and Metallurgy, Australian Institute of Geoscientists and Minerals Council of Australia (JORC code), which is one of the international standards for mineral resource and ore reserve reporting, provides a template system that conforms to international society requirements (Li et al. 2008; Asghari and Madani Esfahani 2013).

Most estimated voxels by OK method have low values of errors, which are lower than 20 %, while several evaluated voxels by IDW method (about 19 %) have error estimations between 20 and 40 %. Most parts of the estimated block model derived via OK method (higher than 99 %) is classified in A category based on JORC standard. However, about 19 % of the evaluated tonnages by IDW method were categorized in B class (Table 6).

Moreover, results obtained by the two methods were validated by statistical methods (Fig. 14; Table 7). The histogram obtained by estimated data, which was derived via OK method, is similar to the Fe histogram obtained by raw data (Fig. 4). In addition, standard deviation and variance of estimation of each voxel by OK method are close to the raw data (Table 1).

Conclusion

Choosing the proper method for estimation of reserve with a minimum error is very important in geostatistical operations in mining engineering. In this study, ore reserves were evaluated by OK and IDW methods in an iron ore deposit. The reserves as calculated by both methods and classified based on the JORC standard show that the error of OK method is less than that of IDW technique in A category. High-grade reserves including 99.78 % of reserve have errors less than 20 % based on estimation by OK technique. Based on results obtained by IDW method, parts of the high-grade reserves that include 18.77 % of reserve have an error between 20 to 40 %. A comparison between statistical processing on results obtained by both methods and the raw data illustrates that the results of the OK method are very similar to the raw data due to histogram, variance, standard deviation, mean and median. Based on the comparison between statistical parameters of estimated and raw data, results obtained by OK estimation technique have better correlation with raw data. Therefore, OK method has higher accuracy than the results derived via IDW technique for reserve estimation in the Dardevey iron ore deposit.

Acknowledgments The authors would like to thank Mr. Ravanbakhsh Amiri as executive manager of Iran East Iron Ore Company for authorizing the use of Dardevey exploration dataset. The authors would like to acknowledge Mr. Farzan Rafia, Mr. Alireza Shivaie, Mr. Ali Hooman Arabshahi, Mr. Mohammad Seydi and Mrs. Mona Zandi, managers, and colleagues of Kavoshgaran Consulting Engineers Company, Iran, for consultation and guidance.

References

- Abed AM, Saffarini GA, Sadaqah RM (2013) Spatial distribution of uranium and vanadium in the upper phosphorite member in Eshidiyya basin, southern Jordan. Arab J Geosci. doi:10.1007/s12517-013-0837-1
- Afzal P, Fadakar Alghalandis Y, Khakzad A, Moarefvand P, RashidnejadOmran N (2011) Delineation of mineralization zones in porphyry Cu deposits by fractal concentration–volume modeling. J Geochem Explor 108:220–232
- Arfaoui M, HédiInoubli M (2012) Advantages of using the kriging interpolator to estimate the gravity surface, comparison and spatial variability of gravity data in the El Kef-Ouargha region (northern Tunisia). Arab J Geosci. doi:10.1007/s12517-012-0549-y
- Asghari O, Madani Esfahani N (2013) A new approach for the geological risk evaluation of coal resources through a geostatistical simulation. Case study: Parvadeh III coal deposit. Arab J Geosci 6:957–970
- Babak O, Insalaco E, Henriquel P (2011) On relationship between spatial continuity and the average grade in ore post ore-waste discrimination. Recovery, CSPG CSEG CWLS Convention
- Bayraktar H, Turalioglu FS (2005) Kriging-based approaches for locating a sampling site—in the assessment of air quality. SERRA 19:301–305
- Boniol D, Toth D (1999) Geostatistical analysis: water quality monitoring network for the Upper Floridan aquifer in East-Central Florida. Technical Publication SJ99-1, St. Johns River Water Management District Palatka, Florida.
- Brus D, Heuvelink GBM (2007) Optimization of sample patterns for universal kriging of environmental variables. Geoderma 138:86–95
- Brus DJ, de Gruijter JJ, Marsman BA, Visschers R, Bregt AK, Breeuwisma A (1996) The performance of spatial interpolation methods and choropleth maps to estimate properties at points: a soil survey case study. Environmetrics 7:1–16
- Calder CA, Cressie N (2009) Kriging and variogram models. Elsevier, Oxford, pp 49–55
- Chile's JP, Delfiner P (1999) Geostatistics: modeling spatial uncertainty. Wiley, New York, p 695
- Cressie N (1993) Statistics for spatial data. Wiley, New York, 900 p
- David M (1970) Geostatistical estimation of porphyry-type deposits and scale factor problem. Proceedings, Pribram Mining Symposium. Pribram.
- David M (1970) Geostatistical ore reserve calculation, a step by step case study, IXth International Symposium for Decision-Making in the Mineral Industry. C.I.M.M. Special Vol., no. 12, Montreal.
- Declercq FAN (1996) Interpolation methods for scattered sample data: accuracy, spatial patterns, processing time. Cartogr Geogr Inf Syst 23:128–144
- Dimitrakopoulos R, Martinez L, Ramazan S (2007) A maximum upside/minimum downside approach to the traditional optimization of open pit mine design. J Min Sci 43:73–82
- Emery X (2005) Simple and ordinary kriging multigaussian kriging for estimating recoverable reserves. Math Geol 37:295–319

- Englund EJ, Weber DD, Leviant N (1992) The effects of sampling design parameters on block selection. *Math Geol* 24:29–343
- Franke R (1982) Scattered data interpolation: tests of some methods. *Math Comput* 38:181–200
- Gallichand J, Marcotte D (1993) Mapping clay content for subsurface drainage in the Nile delta. *Geoderma* 58:165–179
- Ghavi J, Karimpour MH (2010) Geological investigation and mineralization of the Dardway iron deposit, Sangam Ore Field, Northeast Iran. The 1st International Applied Geological Congress, Department of Geology, Islamic Azad University—Mashad Branch, Iran, 2–28 April 2010.
- Goovaerts P (1997) *Geostatistics for Natural Resources Evaluation*. Oxford University Press, New York, 496 pp
- Hasanipack AA, Halaji A, Rajaiean F (2009) Modeling and reserve evaluation of Dardevey deposit. Madankav Co., Persia
- Homayoon SR, Keshavarzi A, Gazni R (2010) JSEA Application of artificial neural network, kriging, and inverse distance weighting models for estimation of scour depth around bridge pier with bed sill. *J Softw Eng Appl* 3:944–964
- Hormozi H, Hormozi E, RahimiNohooji N (2012) The classification of the applicable machine learning methods in robot manipulators. *Int J Mach Learn Comput* 2:560–563
- Hustrulid WA, Kochta M (2006) *Open pit mine planning and design*, 2nd edn. Taylor & Francis, 991 p.
- JORC (2012) *Australasian Code for Reporting of Identified Mineral Resources and Ore Reserves (The JORC Code)*. The Joint Ore Reserves Committee of the Australasian Institute of Mining and Metallurgy, Australian Institute of Geoscientists, and Minerals Council of Australia.
- Journel A (1993) Geostatistics: roadblocks and challenges. In: Soares A (ed) *Geostatistics-Troia*, vol 1. Kluwer, Dordrecht, pp 213–224
- Lam NS (1983) Spatial interpolation methods: a review. *Am Cartogr* 10:129–149
- Laslett GM (1994) Kriging and splines: an empirical comparison of their predictive performance in some applications. *J Am Stat Assoc* 89:391–409
- Laslett GM, McBratney AB (1990) Further comparison of spatial methods for predicting soil pH. *Soil Sci Soc Am J* 54:1553–1558
- Laslett GM, McBratney AB, Pahl PJ, Hutchinson MF (1987) Comparison of several spatial prediction methods for soil pH. *J Soil Sci* 38:325–341
- Lefohn AS, Knudsen HP (2011) Using ordinary kriging to estimate the April–September 24-hour W126 and N100 ozone exposure metrics for 2010 for the United States. http://webcam.srs.fs.fed.us/ozone/spatial/2010/contractor_2010.pdf
- Li J, Heap AD (2008) A review of spatial interpolation methods for environmental scientists. *Geoscience Australia*, Canberra
- Li S, Dimitrakopoulos R, Scott J, Dunn D (2008) Quantification of geological uncertainty and risk using stochastic simulation and applications in the coal mining industry. *Ore Body Model Strateg Miner Plann Spectrum Ser* 14:253–260
- Marechal A, Serra J (1971) Random kriging. In: Merriam DF (ed) *Geostatistics*. Plenum, New York
- Matheron G (1967) Kriging or polynomial interpolation procedures. *CIM Bull* 60:1041–1045
- Monjezi M, Rajabalizadeh Kashani M, Ataei M (2013) A comparative study between sequential Gaussian simulation and kriging method grade modeling in open-pit mining. *Arab J Geosci* 6:123–128
- Noppé MA, (1994) Practical geostatistics for on-site analysis—a coal example. *Mining Geostatistics Conference*, Geostatistical Association of South Africa, Kruger National Park, South Africa, September 1994
- Parhizkar A, Ataei M, Moarefvand P, Rasouli V (2011) Grade uncertainty and its impact on ore grade reconciliation between the resource model and the mine. *Arch Min Sci* 56:119–134
- Phillips DL, Lee EH, Herstrom AA, Hogsett WE, Tingey DT (1997) Use of auxiliary data for spatial interpolation of ozone exposure in southeastern forests. *Environmetrics* 8:43–61
- Rouhani S (1986) Comparative study of ground-water mapping techniques. *Ground Water* 24:207–216
- Sakata S, Ashida F (2004) An efficient algorithm for Kriging approximation and optimization with large-scale sampling data. *Comput Methods Appl Mech Eng* 193:385–404
- Stocklin JO (1977) Structural correlation of the Alpine ranges between Iran and Central Asia. *Memoir Hors Serv Soc Geol France* 8:333–353
- Tahmasebi P, Hezarkhani A (2010) Application of adaptive neuro-fuzzy inference system for grade estimation; case study, Sarcheshmeh porphyry copper deposit, Kerman, Iran. *Australian Journal of Basic and Applied Sciences* 4:408–420, ISSN 1991–8178.
- VerHoef JM, Cressie N (1993) Multivariable spatial prediction. *Math Geol* 25:219–239
- Verly G (1984) Estimation of spatial point and block distributions: the multiGaussian model. Ph.D. thesis, Stanford University, Stanford.
- Weber DD, Englund EJ (1992) Evaluation and comparison of spatial interpolators. *Math Geol* 24:381–391
- Weber DD, Englund EJ (1994) Evaluation and comparison of spatial interpolators, II. *Math Geol* 26:589–603
- Yasrebi J, Saffari M, Fathi H, Karimian N, Moazallahi M, Gazni R (2009) Evaluation and comparison of ordinary kriging and inverse distance weighting methods for prediction of spatial variability of some chemical parameters. *Res J Biol Sci* 4:93–102
- Zimmerman D, Pavlik C, Ruggles A, Armstrong MP (1999) An experimental comparison of ordinary and universal kriging and inverse distance weighting. *Math Geol* 31:375–390