Application of nonlinear geostatistical indicator kriging in lithological categorization of an iron ore deposit

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Nonlinear geostatistics is commonly used in ore grade estimation and seldom used in lithological characterization. Categorization of lithological units is essential in ore grade estimation, and this can be done based on the lithological information obtained from drill-hole data. In general, a conventional classification method was used to delineate different lithological units using geological cross-sections derived from borehole logs. In this study, we suggest an approach based on geostatistical nonlinear indicator kriging (IK) to delineate different lithological units of an iron ore deposit. Iron ore has been broadly grouped into eight litho units based on physical and chemical characteristics of the core samples recovered from drill holes during exploration stage. IK helps in the construction of litho maps for different benches of the mining deposit. Fe grades were estimated using ordinary kriging model and grade maps were prepared for all the benches of the deposit. A comparison was done between the grades of each litho type resulting from the two methods, i.e. IK model and geological cross-sectional model and the relative merits of the IK approach have also briefly discussed.

Keywords: Grade estimation, indicator semi-variograms, indicator kriging, lithological maps, nonlinear geostatistics.

ALTHOUGH geostatistical methods are widely used in mineral resource estimation across the world, in India its application is not very common and if at all used it is restricted to linear geostatistical methods. These geostatistical applications take lesser time in computing the estimates and also give more accurate results when appropriate input parameters are used. The advantage of these methods is that in addition to kriged estimates of a variable, the error of the estimate can also be assessed in the form of kriging variance[1]. This also provides an alternative tool for validation of spatial modelling results. In view of this, we make an attempt in this communication to apply nonlinear geostatistical methods for delineation of different litho units in an iron ore deposit.

In mineral resource estimation, it is important to classify the mineral deposit into different lithological units. Inaccurate categorization of litho types in a block model will have negative impact on resources estimation as bulk density of various lithological units varies. However, the classification cannot be properly done on a point-by-point or block-by-block basis as it ignores the geological continuity[2]. Thus, the modelling of lithological domains is a critical step in mineral reserve evaluation[3]. In any deposit, the lithological information is available only at the exploratory borehole locations and using this information, spatial interpolation of lithological units can be done to get information on litho types of each block.

In the conventional classification method, the lithological type was assigned to blocks using a geological cross-sectional model approach. In this approach, sectional interpretations are constructed, generally orthogonal to the strike of mineralization. Each separate litho intersection on each drill hole is allocated its own volume of influence, which usually extends halfway to the next drill hole up and down dip, and halfway to the next section in each strike direction[4]. Based on these cross-sections, geological models (solid models) are constructed for each lithological unit and blocks of each litho type are obtained. Further, bench plans and grade maps are also prepared using these cross-sections.

The geological cross-sectional method mostly relies on interpretation of the available drill hole data and does not account for the uncertainty in the spatial extent of the lithological units[3]. An alternative model has been suggested by Chatterjee *et al.*[5], in which lithological type is assigned to blocks using a nonlinear geostatistical indicator kriging (IK) method. In this approach, a probabilistic model based on IK is used to map the probabilities of occurrences of the litho units within the deposit, which reflects the spatial extent of the lithological units at unsampled locations.

This concept of probabilistic modelling of lithological domains and its application to resource evaluation of copper deposit was discussed by Emery and Gonzalez[3], in which they applied probabilistic models based on conditional simulation. Pasti *et al.*[6] have also used simulation approach for modelling lithological domains for a Brazilian iron ore deposit. They state that delineation of litho units is conventionally based on vertical and horizontal sections interpreted by a mine geologist, and in more advanced cases, geostatistical methods such as IK and/or simulations are used which allow to automate the modelling process. These methods are probabilistic and use variogram models to represent the geological continuity of each litho unit.

IK is an estimator applied on a set of variables whose values are modified according to a nonlinear transform, and it transforms each value of the set of variables into indicator values[7]. The main advantage of IK is that it is nonparametric and the distribution function can be estimated, which makes it feasible to determine the uncertainties and infer the attribute values where there are no samples[8].

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A good knowledge of grade distribution within an ore body is essential to assess the economic feasibility of mine production. The geostatistical evaluation of ore deposit avoids economic failures[9]. In the present study, spatial modelling of litho units is investigated and IK is used for assigning the litho types in the block model. A comparison is made between the estimates of IK model and geological cross-section model for different lithological units and also with exploratory data. The delineation of litho units and evaluation of grade distribution in hematite iron ore deposit is presented.

The Bailadila iron ore deposit trends in NE–SW direction with moderate to steep southeasterly slope and forms a cliff towards the north. The deposit has a strike length of 1600 m and width that varies between 120 and 975 m. The enriched ore within the banded iron formation (BIF) is concentrated in synclinal structures as swelled portions[10].

The Bailadila iron ore series consists of iron ore, BIF, ferruginous shales, phyllites, tuffs and quartzites. Metabasaltic traps with tuffs and cherts underlie the above suit of rocks (i.e. Bengpal series), and granite and gneissic rock formations underlie the Bailadila iron ore deposit. The basal metabasaltic lavas, dolerite intrusions are encountered along the eastern foothills of the range. Metasedimentary sequence of Bailadila group is divided into three subgroups, which comprise of five stratigraphic formations, namely Bhansi metabasalts and metapelites, Bacheli metasiliciclastics (feldspathic quartzite), East Ridge shale/slate, Loha conglomerates and shales, and Kailash Nagar Formations in ascending order[11].

The iron ore data were obtained from 4537 samples of 93 vertical boreholes (Figure 1) drilled for exploration purpose. The boreholes were spaced in a grid pattern with a spacing of 60–120 m (average 100 m) between each borehole. The depth of boreholes varies from 13.75 to 169.25 m, with an average depth of 97.5 m. The iron ore is associated with eight different lithologies such as steel grey hematite (SGH), blue grey hematite (BGH), laminated hematite (LH), lateritic/limonitic ore (LO), blue dust (BD), banded hematite quartzite (BHQ), shale (Sh) and transition zone (TZ). For the purpose of block modelling, the deposit was discretized into various blocks with the size of each block being 25 × 25 × 12 m (length × width × height). Although data on Fe, SiO_2, Al_2O_3 and LOI variables are available, we have chosen only Fe content for geostatistical characterization of the ore deposit in the present study.

Statistical analysis of the data was undertaken to understand the distribution of sample grades. Fe content was chosen as a regionalized variable for grade estimation. The basic statistical parameters and frequency distribution (histogram) of the raw data are shown in Figure 2. It can be seen from the figure that Fe is skewed towards the left side, which may be due to higher amount of silica in a few samples. Further, basic statistics and histograms (Figure 3) of the assay data of Fe variable were calculated for each litho type.

Compositing is a procedure in which sample assay data are combined by computing a weighted average over longer intervals to provide a smaller number of data with greater length for use in developing the resource estimates. Irregular length assay samples are composited to

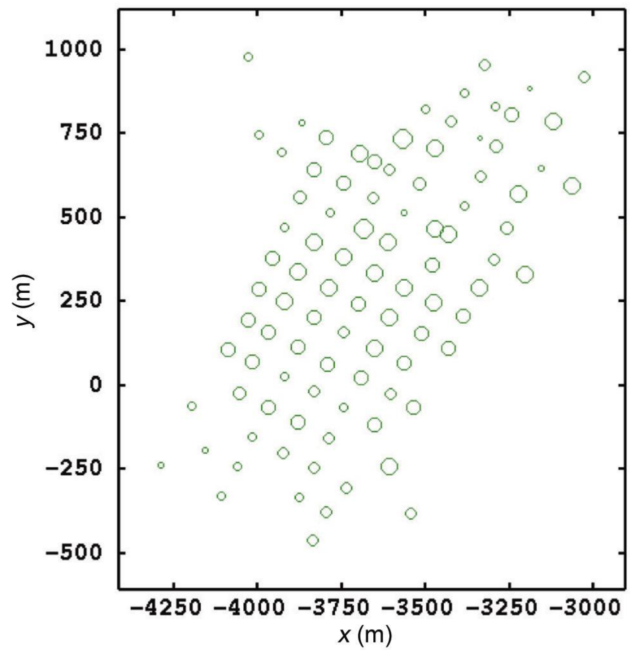

Figure 1. Distribution of exploratory boreholes in the study area. Boreholes are located in regular grids with an average spacing of 100 m.

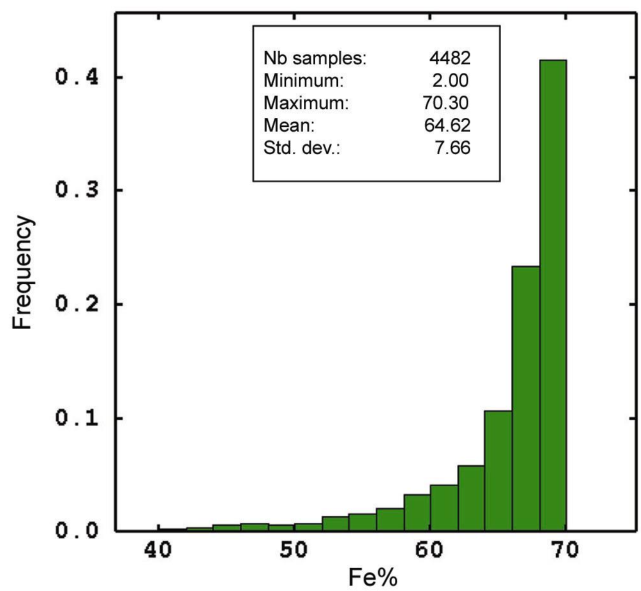

Figure 2. Histogram showing grade distribution of Fe% in the borehole samples. Majority (85%) of the samples exhibit Fe grade >60%; 9% of samples exhibit 50–60%, and the remaining samples exhibit <50% Fe grade.

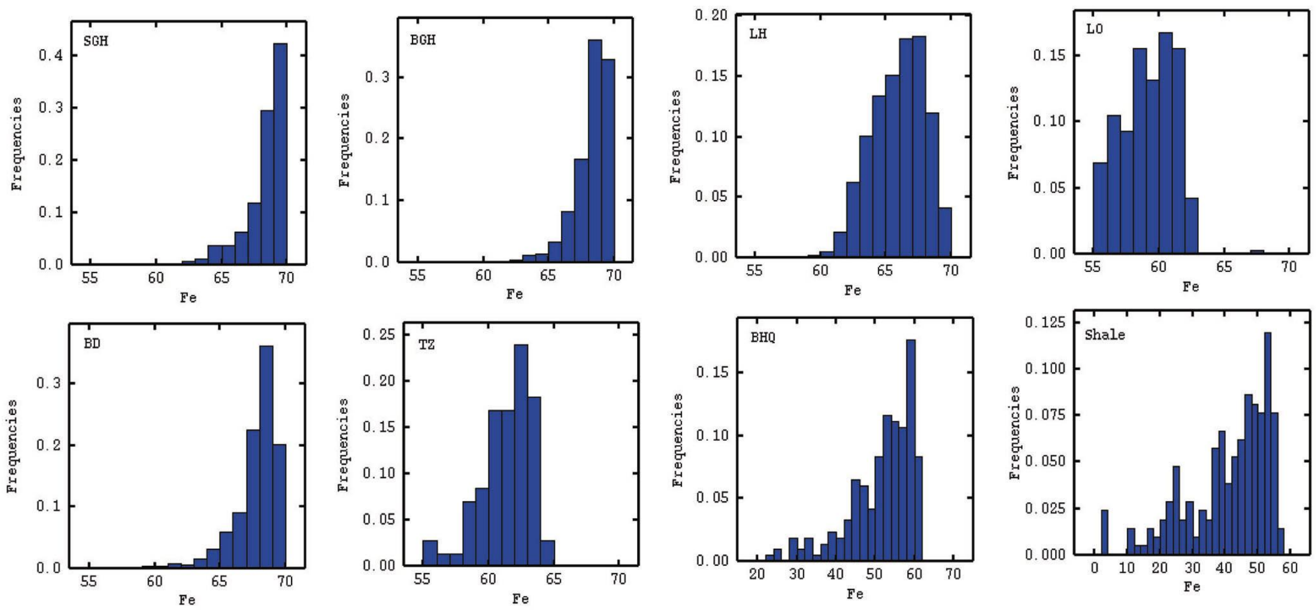

Figure 3. Histograms showing grade distribution of Fe% in the borehole samples of different litho units. Steel grey hematite (SGH), blue grey hematite (BGH), laminated hematite (LH), lateritic/limonitic ore (LO) and blue dust (BD) show very high-grade Fe% varying between 55% and 70%, whereas banded hematite quartzite (BHQ) and shale show low-grade Fe values.

Table 1. Basic statistical parameters of assay data (n = 4482) and composited data (n = 719) of Fe% in different litho units

	Sample		Mean		Standard deviation	
Litho type	Assay	Composited	Assay	Composited	Assay	Composited
SGH	585	65	68.19	67.58	1.49	1.78
BGH	1158	225	68.20	68.05	1.28	1.74
LH	1077	157	65.84	65.25	2.03	2.70
LO	334	35	58.55	60.38	2.80	2.11
BD	833	163	67.69	66.95	1.61	2.51
BHQ	215	38	51.40	53.89	8.27	5.75
Shale	209	36	40.69	45.09	12.71	10.12
TZ	71	6	61.27	60.49	1.90	1.86

SGH, Steel grey hematite; BGH, Blue grey hematite; LH, Laminated hematite; LO, Lateritic/limonitic ore; BD, Blue dust; BHQ, Banded hematite quartzite; TZ, Transition zone.

provide equal-sized data for geostatistical analysis. In this study, assay data were composited to a bench height of 12 m, resulting in 719 composite samples. Litho type assigned to the composited sample is the predominant lithology occurring in the original samples within that composited length. Table 1 presents the summary statistics of assay data and composited values of Fe% for each litho type. It is observed from the composited data that the lithological unit TZ has only six samples, which are not significant for modelling and thus it is ignored for further analysis.

Geostatistics has been used widely to estimate the grades of various mineral deposits such as iron ore[12–14], copper[15], gold[16], limestone[5]. IK, a nonlinear geostatistical technique and a non-parametric counterpart of 'ordinary kriging', is an estimation technique applied to attributes with non-Gaussian distribution. The attributes are transformed according to nonlinear mapping and codified by means of indicator[8]. IK can be used for both numerical data and categorical data such as Fe grade and lithology. While using IK for categorical data such as lithological type, a series of indicator values corresponding to each lithological type is chosen. These indicator values are used to build up numerically the probability of occurrence for different lithologies at each estimation point. IK process is carried out in three steps as discussed below.

Indicator transformation: Composited data in each of the available sample location are transformed into zeros and ones. It is '1' if the data belong to the particular litho type, and '0' if the data do not belong to that particular litho type. A categorical indicator transformation is carried out for each of the seven lithological units of the

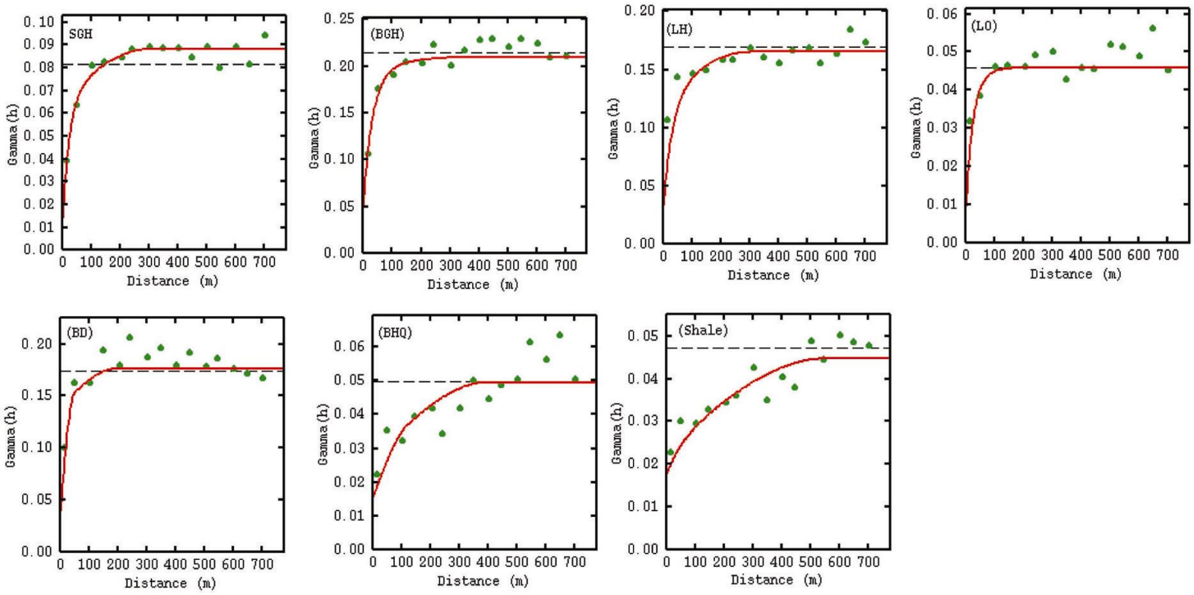

Figure 4. Indicator variogram models for each litho type. The variograms of seven litho units show good spatial structure with low nugget values.

Table 2. Indicator semi-variogram parameters for different litho units

		Structure 1			Structure 2		
Litho type	Nugget effect	Model 1	Sill	Range (m)	Model 2	Sill	Range (m)
SGH	0.008	Exponential	0.060	75	Spherical	0.020	300
BGH	0.050	Exponential	0.150	100	Spherical	0.010	400
LH	0.025	Exponential	0.106	100	Spherical	0.034	300
LO	0.005	Exponential	0.039	75	Spherical	0.001	250
BD	0.030	Spherical	0.110	50	Spherical	0.036	200
BHQ	0.015	Spherical	0.012	125	Spherical	0.022	400
Shale	0.017	Exponential	0.006	150	Spherical	0.021	550

deposit under investigation. At a sample location x in the deposit, for a particular lithological unit L_i, an indicator transformation is designated by the following equation.

$$I_i(x) = 1 \quad \text{if } x \in L_i,$$
$$= 0 \quad \text{otherwise,}$$

where i varies from 1 to 7 lithological units. The composited data are transformed and a different set of indicator data generated for each lithological unit.

Indicator semi-variogram models: Indicator semi-variograms for each lithological unit provide better results in quantifying the spatial variability of the lithology and in characterizing the spatial continuity of samples. However, Soares[17] used single average semi-variogram model for determining lithofacies in a petroleum reservoir as he found that this saves time. Chatterjee *et al.*[5] have also used a single average semi-variogram model for all the lithological units, instead of separate semi-variogram models, assuming the same spatial continuity for all lithological units. As this approach has limitations, we have constructed a separate indicator semi-variogram model for each lithological unit for obtaining a better spatial variability in the deposit. The omni-directional semi-variogram models of each lithological unit are shown in Figure 4. These semi-variograms are modelled with a small nugget effect and using two (exponential and spherical) structures, and the modelling parameters are given in Table 2.

Indicator kriging: IK is carried out using the corresponding indicator semi-variogram as a structural function. An IK estimate always lies in the interval [0, 1], and can be interpreted as a probability of the block of a specific litho type[18]. The probability of occurrence of each litho type in all the blocks of the deposit using corresponding indicator data and semi-variogram model is estimated using kriging.

The lithological maps were prepared using indicator kriged estimates as suggested by Deutsch and Journel[7], and Chatterjee *et al.*[5]. In this study, we have assigned a

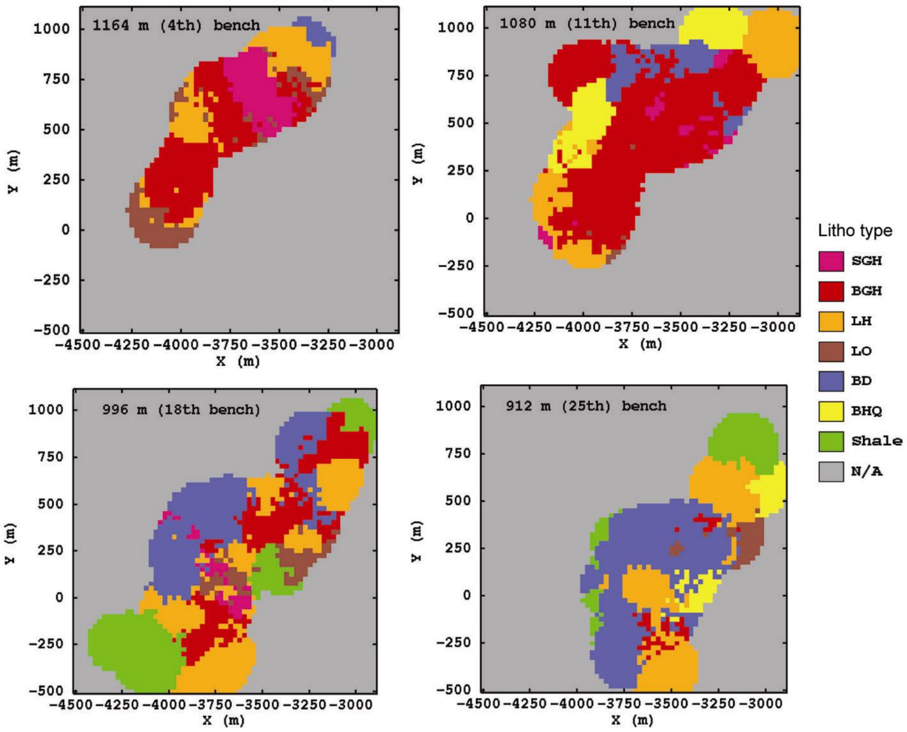

Figure 5. Lithological maps of four mining benches located at 1164, 1080, 996 and 912 m. Majority of the blocks in each bench are categorized into high-grade Fe litho units. Banded hematite quartzite and shale containing low Fe grade are observed in peripheral areas.

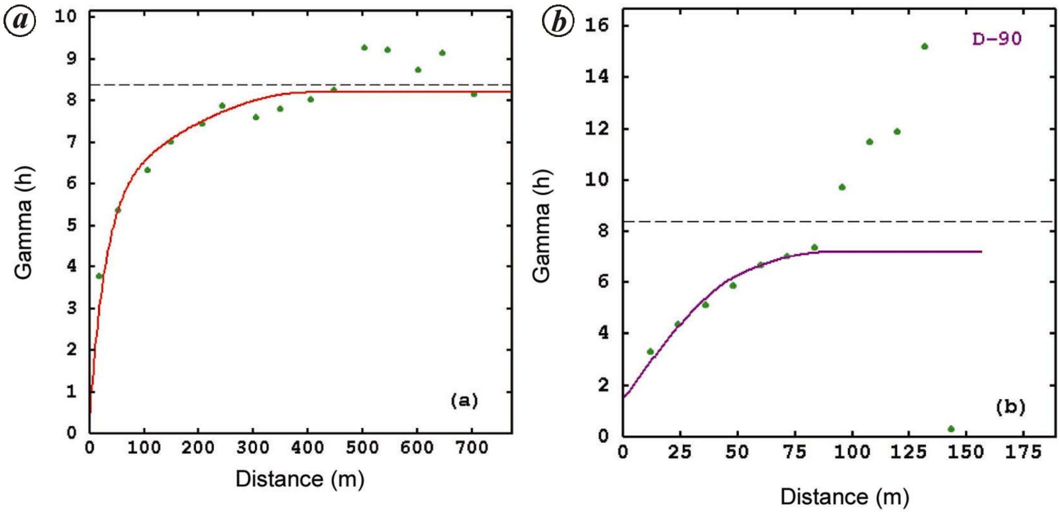

Figure 6. Omni-directional semi-variogram models of Fe% for domain A in horizontal direction (***a***) and vertical direction (***b***). Both the semi-variograms show good spatial structure with nested models. Small nugget effect is observed in both the models.

single litho type to each block based on the maximum probability of occurrence of kriged estimates of seven litho types in that block, and the lithological maps for all the 32 benches were constructed. The lithological maps of four benches at reduced levels (RL) of 1164, 1080, 996 and 912 m are given as an example in Figure 5.

Grade models were prepared for the grade attribute Fe using ordinary kriging, and grade was estimated for each block based on neighbourhood samples. As the original data of Fe% are strongly skewed, composited data were categorized into two domains to avoid mixing of populations, based on the characteristics of the geology and

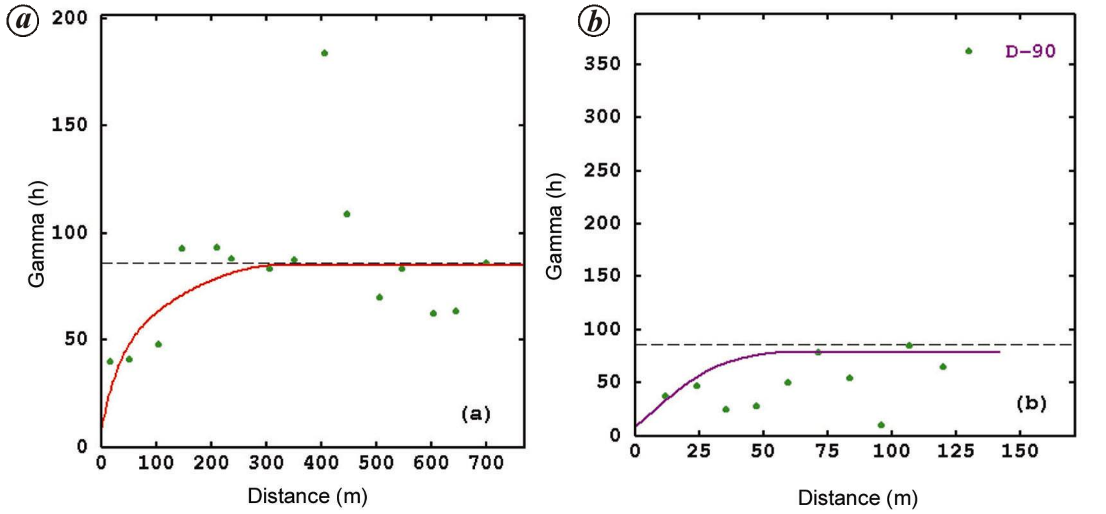

Figure 7. Omni-directional semi-variogram models of Fe% for domain B in horizontal direction (***a***) and vertical direction (***b***). Both the semi-variograms show reasonably good spatial structure with nested models.

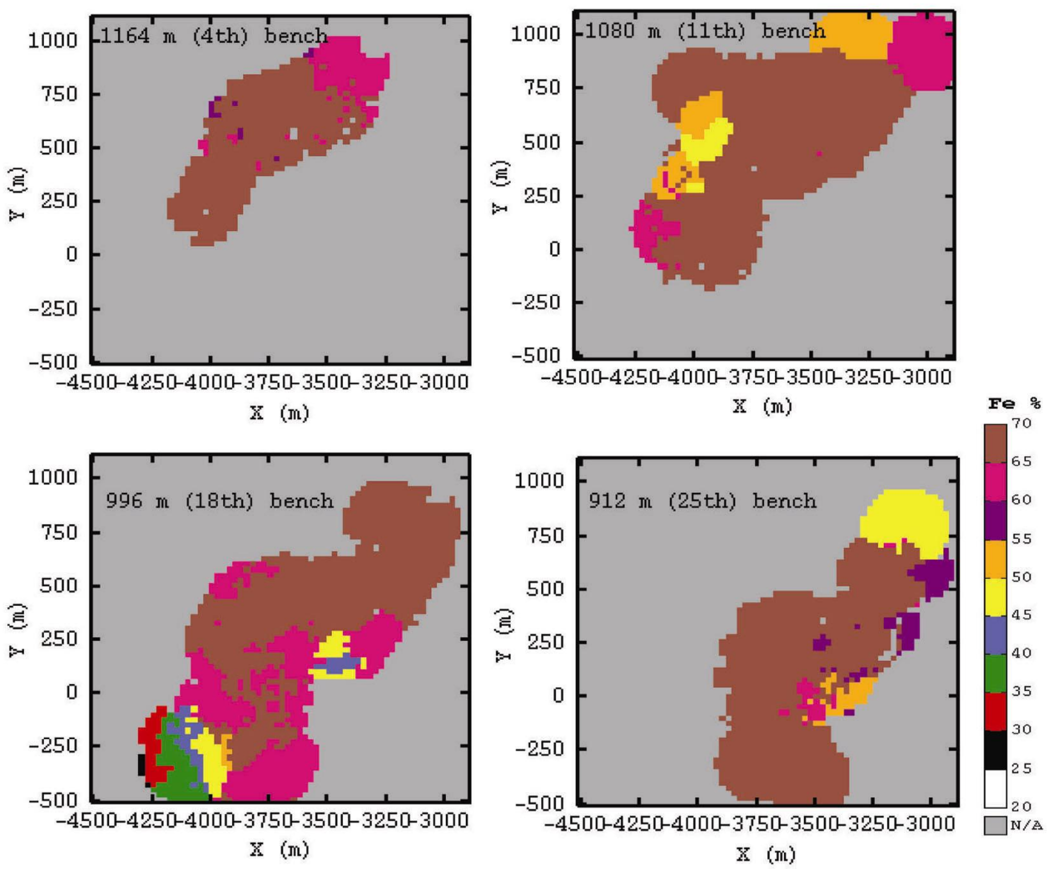

Figure 8. Grade maps of four mining benches located at 1164, 1080, 996 and 912 m based on kriged estimates. Majority of the blocks in each bench have estimated Fe >40% and very few peripheral blocks have estimated grade <40%.

grade variation. Domain A8 – consisting of samples of lithological units SGH, BGH, LH, LO and BD, and domain B – consisting of samples from lithological units BHQ and shale. Omni-directional semi-variograms in the horizontal and vertical directions for both the domains were calculated and shown in Figures 6 and 7. The parameters used in modelling these semi-variograms are shown in Table 3. Grade estimation was carried out for

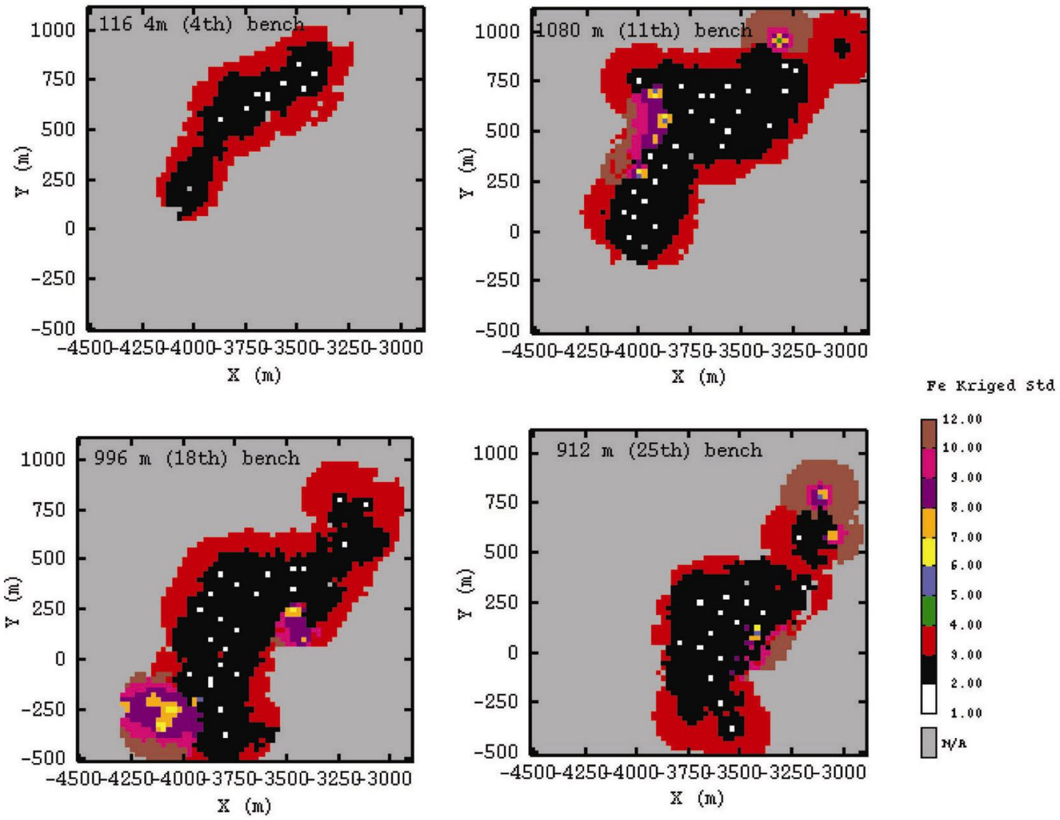

Figure 9. Kriged standard deviation maps for the benches located at 1164, 1080, 996 and 912 m. The central part of each mining bench has a very low grade varying between 1 and 3%. High variation in estimated grade is observed only in peripheral areas.

Table 3. Domain-wise semi-variogram parameters of Fe% in horizontal and vertical directions

Domain	Direction	Model 1	Model 2	Range 1	Range 2	Sill 1	Sill 2	NE
A	Horizontal	Exponential	Spherical	90	400	5.4	2.3	0.5
	Vertical	Spherical	Spherical	50	90	2.1	3.6	1.5
B	Horizontal	Exponential	Spherical	100	325	40	36	9
	Vertical	Spherical	Spherical	35	60	24	46	9

Domain A, SGH, BGH, LH, LO and BD; Domain B, BHQ and shale.

Table 4. Summary of estimated grade of Fe% in different litho units

Litho type	Blocks estimated	Krig Fe%	Standard deviation
SGH	1771	67.29	1.12
BGH	12,018	67.83	1.27
LH	9001	64.96	2.49
LO	977	60.52	1.82
BD	9515	66.57	1.69
BHQ	3010	53.65	4.34
Shale	2614	45.78	5.02

each block using the composites of litho types of that particular block and the corresponding variogram model.

Summary of kriged grades of Fe% for different litho units is shown in Table 4. Based on kriged estimates of Fe grade, grade maps were generated for the 32 benches of the total deposit. Grade maps and kriged standard deviation maps of four benches, viz. 1164, 1080, 996 and 912 m are shown in Figures 8 and 9. The correlation coefficient between kriged grades and kriged standard deviation of Fe was calculated.

A comparison was made between the results of the estimated grades obtained from geological cross-section model and IK approach in order to test and validate the estimated Fe grade for each litho type. As suggested by Keogh and Moulton[18], the resulting model grade distributions were compared with input composited grade distributions and raw data, i.e. borehole data to test whether estimated results are in line with the original data (Table 5 and Figure 10). Isatis software (version 2013) was employed in computing the statistical and geostatistical parameters and graphical outputs.

The basic statistics of exploratory borehole data reveal that the overall Fe content is high in the deposit with

Table 5. Comparative results of estimated grades and exploratory data for Fe%

	Estimated grades		Exploratory data	
Litho type	Geological cross-section model	Indicator kriged model	Composited data	Assay data
SGH	67.11	67.29	67.58	68.19
BGH	67.34	67.83	68.05	68.20
LH	65.95	64.96	65.25	65.84
LO	65.10	60.52	60.38	58.55
BD	67.01	66.57	66.95	67.69
BHQ	43.45	53.65	53.89	51.40
Shale	36.24	45.78	45.09	40.69

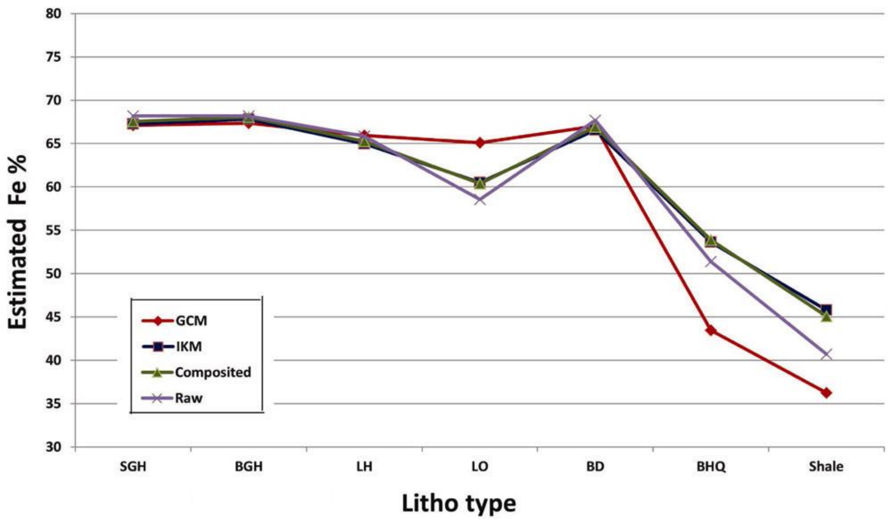

Figure 10. Comparative Fe kriged grade results obtained from both the methods – geological cross-sectional model (GCM) and indicator kriging model (IKM). The estimated grades match perfectly in all the litho units of SGH, BGH, LH and BD, except in LO where conventional estimation model differs from the remaining methods.

an average Fe grade of 64.62%. The histogram shows that majority (85%) of the boreholes exhibit Fe grade >60% and very few boreholes (6%) have Fe grade <50% (Figure 2); this may be due to high silica/alumina content in the samples.

It is observed in both assay and composited data that Fe grade variability is high in the litho types BHQ and shale compared to other litho types, viz. SGH, BGH, LH, LO and BD (Table 1 and Figure 3). This may be due to low Fe values in litho units BHQ and shale because of the presence of high impurities like silica and alumina, whereas other litho types consist of moderate to high Fe content (45–70%). Keogh and Moulton[18] have also reported similar observations in the Hamersley iron ore deposits of the Pilbara region in Western Australia.

The indicator semi-variogram models of each lithological unit (Table 2 and Figure 4) show good spatial structure with an average range of around 350 m. It is observed from the lithological maps of 32 benches that the low-grade Fe bearing litho units BHQ and shale occur mostly in the peripheral blocks, whereas high-grade Fe-bearing litho units occur in the middle portion of the deposit (Figure 5).

It is observed from the semi-variogram models of Fe% that both the horizontal and vertical directions show good spatial structure with a small nugget effect in domain A. Anisotropy is observed in both the directions ranging 400 and 90 m respectively (Table 4 and Figure 6). On the other hand, the horizontal and vertical semi-variograms of domain B are less structured (Figure 7), which may be due to low-grade Fe values and the presence of impurities like silica and alumina.

The kriged results of each lithological unit (Table 4) indicate that the litho units SGH, BGH, LH and BD in domain A exhibit Fe grade >65%, but LO has Fe grade of 60.5%. Grade maps show that the Fe grade is distributed mostly between 65% and 70% and partly between 60% and 65% in the entire deposit, with overall grade of 64% (Figure 8). The medium grade (50–60%) Fe is scattered in pockets and low grade (40–50%) Fe occurs only in the peripheral areas of the deposit. It is also inferred that the central part of the ore body has a very less kriged standard deviation compared to peripheral areas (Figure 9). The kriged grades of Fe and kriged standard deviation show strong negative correlation (–0.83), which indicates that most of the estimated grades of Fe have less error of estimate. Further, this suggests that IK model estimates are accurate and reliable.

On comparison of the results of both IK model and geological cross-sectional model (Table 5 and Figure 10), it is observed that the estimated mean grades of litho units SGH, BGH, LH and BD are the same, whereas estimated mean grade of litho unit LO is a little higher (4.6%) in case of the geological model than the IK model. On the other hand, a significant difference in the estimated grades of the litho units BHQ and shale is observed. However, these two litho units are considered as waste in mining practice. It is further observed that the results obtained from IK modelling are in accordance with the original drilling data and also composited data.

In this communication an application of nonlinear geostatistical IK approach[19] for assigning litho types of a block model in a mineral deposit is presented. In assigning the litho types in the block model, two approaches – geological cross-sectional model and IK model – are addressed. Our results suggest that both the methods give almost similar results of grade estimation of all lithological units, except LO; however, the estimated grade of LO is in accordance with the original raw data.

Further, it is suggested that the IK approach is more suitable to assign the litho types in block model, and serves as an alternative approach to the traditionally used geological cross-sectional model. The advantage of the IK model is that it captures the spatial variability of lithological units, which is not possible using the conventional methods.

The absolute performance of these methods could be tested with mine production data. We could not test this with actual mine data as mining is yet to be commissioned in the study area. In the absence of mining data, we plan in future to conditionally simulate the iron grade values on a dense grid and then to average these realizations into smaller sized blocks from which the grade can be calculated. The results obtained in the present study can be compared with simulated values and be validated.

1. Armstrong, M., *Basic Linear Geostatistics*, Springer-Verlag, Berlin, 1998, p. 256.
2. Henstridge, J., Nonlinear modelling of geological continuity. In Proceedings of a One Day Symposium: Beyond Ordinary Kriging, Geostatistical Association of Australasia, Perth, Australia, 1998, pp. 41–49.
3. Emery, X. and Gonzalez, K. E. Probabilistic modelling of lithological domains and its application to resource evaluation. *J. South Africa Inst. Min. Metall.*, 2007, **107**, 803–809.
4. Glaken, I. M. and Snowden, D. V., Mineral resource estimation. In *Mineral Resource and Ore Reserve Estimation. The AusIMM Guide to Good Practice* (ed. Edwards, A. C.), The Australasian Institute of Mining and Metallurgy, Melbourne, Australia, 2001, pp. 189–197.
5. Chatterjee, S., Bhattacherjee, A., Samanta, B. and Pal, S. K., Ore grade estimation of a limestone deposit in India using an artificial neural network. *Appl. GIS*. 2006, **2**, 2.1–2.20; doi: 10.2014/ag060003
6. Pasti, H. A. Costa, J. F. C. L. and Boucher, A., Multiple-point geostatistics for modelling lithological domains at a Brazilian iron ore deposit using the single normal equations simulation algorithm. *Quant. Geol. Geostat.*, 2012, **17**, 397–407.
7. Deutsch, C. V. and Journel, A. G., *GSLIB Geostatistical Software Library and User's Guide*. Oxford University Press, New York, 1998, p. 369.
8. Mendes, R. M. and Lorandi, R., Indicator kriging geostatistical methodology applied to geotechnics project planning. IAEG2006 Paper no. 527, The Geological Society of London, 2006, pp. 1–12.
9. Matheron, G., Principles of geostatistics. *Econ. Geol*., 1963, **58**, 1246–1266.
10. Mukherjee, A., Mondal, R. P., Wadhwa, R. and Prabhakhar, G., Disposition of banded iron formation of Bailadila Range, South Bastar Dantewada Dist, Chhattisgarh: its implications on exploration. *J. Appl. Geochem*., 2010, **12**, 469–477.
11. Khan, M. W. Y. and Bhattacharya, T. K., A reappraisal of the stratigraphy of Bailadila Group, Bacheli, Bastar District, MP. *J. Geol. Soc. India*, 1993, **42**, 549–562.
12. Sarkar, B. C. and Roy, I., A geostatistical approach to resource evaluation of Kala iron ore deposit, Sundergarh Dist, Orissa. *J. Geol. Soc. India*, 2005, **65**, 553–561.
13. Asghari, O., Soltni, F. and Hassan, B. A., The comparison between sequential Gaussian simulation (SGS) of Choghart ore deposit and geostatistical estimation through ordinary kriging. *Aust. J. Basic Appl. Sci*., 2009, **3**, 330–341.
14. Marzeihe, S. K., Hassan, M., Hossein, H. and Parvizz, M., Determining the best search neighbourhood in reserve estimation, using geostatistical method: a case study anomaly no. 12A iron deposit in central Iran. *J. Geol. Soc. India*, 2013, **81**, 581–585.
15. Emery, X. and Ortiz, J. M., Estimation and mineral resources using grade domains: critical analysis and a suggested methodology. *J. South Africa Inst. Min. Metall.*, 2005, **105**, 247–255.
16. Guibal, D., *Recoverable Reserves Estimation of an Australian Gold Deposit in Geostatistical Case Studies*, Reidel Publishing Company, 1987, pp. 149–168.
17. Soares, A., Geostatistical estimation of multi-phase structures. *Math. Geol.*, 1992, **24**, 149–160.
18. Keogh, A. and Moulton, M., Median indicator kriging – a case study in iron ore. In Proceedings of a One-Day Symposium: Beyond Ordinary Kriging, Geostatistical Association of Australasia, Perth, Australia, 30 October 1998, pp. 106–120.
19. Vann, J. and Guibal, D., An overview of nonlinear estimation. In Proceedings of a One-Day Symposium: Beyond Ordinary Kriging, Geostatistical Association of Australasia, Perth, Australia, 30 October 1998, pp. 6–25.

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