Geostatistical Clustering, Potential Modeling and traditional geostatistics: a new coherent workflow

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ABSTRACT

Mineral Resource Estimation (MRE) is a crucial procedure for the mining industry. From data collection, geological interpretation and grade modeling through to resource classification, it defines the most important economic asset for a mining entity: the scale and quality of its resources. For over 30 years, geostatistical methods, when aptly chosen and implemented are recognized to be adding value to the MRE process. There is an obvious interest to ensure that these methods are easily understandable and provided within an integrated and secure environment.

The modeling of coherent geological domains is a major area of integrated MRE. The description of the behavior of variables associated with mineralization processes helps delineating spatial envelopes, which facilitate grade interpolation, and fully defines mineralized tonnages. The geological modeling is operated in two steps, first samples are clustered into domains, and then the domain 3D envelopes are interpolated. The Geostatistical Hierarchical Clustering (GHC) is an innovative clustering algorithm that takes into account the spatial dependency between samples. The Potential Field method is a solution for domain modeling that offers the advantage of allowing the assessment of the uncertainties attached to the domain envelopes.

Once the geological domains are shaped, the integrated MRE workflow continues with further geostatistical applications. They entail a complete exploratory data analysis (EDA) including: compositing, declustering, variography and the identification of the main continuity directions on a 3D variogram map. Kriging Neighborhood Analysis (KNA) helps determine the search neighborhood parameters. These parameters and the variogram model are then used to produce a 3D block estimation. With a view to obtain recoverable resources at local scale, the workflow may end with the implementation of non-linear methods such as Localized Uniform Multivariate Conditioning (LMUC), and Turning Bands (TB) conditional simulations for risk analysis.

All the steps of the proposed integrated MRE workflow are illustrated in Minestis software, developed by Geovariances.

INTRODUCTION

Integrated MRE procedure from mining data analysis to resource classification is essential within the resource evaluation framework as it defines the scale and quality of resources. A robust and dynamic workflow of resource evaluation, with a focus on geostatistical solutions, is critical to success in resource modeling and MRE process. This paper presents an innovative workflow to produce a coherent resource evaluation. Details of the underlying concepts presented in this document are given in (Rossi & Deutsch, 2014), other than clustering algorithm and domain modeling method.

A proper integrated MRE cannot be performed without a rigorous modeling of geological domains. Geological modeling involves some parameters (e.g., structural data, lithology, grade, etc.), which are derived from a combination of hard information (e.g., drill holes) and geological knowledge and interpretation. The domain modeling step is usually preceded by a crucial data clustering step which consists in understanding the various domain characteristics and assigning each drill hole sample to a given domain. These two steps ensure a final grade model made of several domains with stationarity of grade profiles in each domain.

Traditional geological modeling methods are based on manual clustering and cross-sectional interpretation. Over the last decade implicit modeling approaches have allowed building and updating geological models in shorter time than traditional methods with more flexibility and dynamism. But the clustering step is still commonly subjective and arduous.

In 2010, the Geostatistical & Geological Domaining Research Consortium (G2DC) was created by Geovariances and Centre de Géosciences de Mines ParisTech with the aim of developing geostatistical methods to complement traditional construction of geological domains and to enable assessment of uncertainty associated with domains. In order to achieve these goals, two main applications where implemented in Minestis: Automatic Domaining and Domain Modeling. This solution combines GHC, a clustering algorithm, and the Potential Field method, a domain modeling method.

Once geological modeling is performed, the next steps of the workflow are based on geostatistical applications used to compute recoverable resource estimation at global and local scales (Rivoirard, 1994). Innovative techniques are used to assist Resource Geologists with a supervised declustering and KNA (Vann et al., 2003).

This paper illustrates this innovative workflow with an application on an iron ore deposit operated by BHP Billiton. All the steps of the proposed workflow are implemented in Minestis software.

METHODOLOGY

Geostatistical Hierarchical Clustering

GHC respects the spatial connectivity of input data, forming subsets, according to the degree of similarity between observations (Romary et al., 2015). GHC is executed in a two-step procedure. First, the data set is organized in a graph (dendrogram), purely based on the data spatial connectivity. The linkage between samples is given by a neighborhood with a given extension and orientation, which determines if two samples are connected. In a second step, the GHC algorithm merges sequentially the two closest clusters based on their similarity (Romary et al., 2012). This step is repeated until the required number of domain is reached. The similarity is based on differences calculated using a set of variables (grades, distance etc.) of a pair of cluster. Weights can be associated to each variable to define their relative importance.

Potential Field Method

The potential field method was conceived to model geological boundaries from geological and mining information. It can integrate structural data, geological maps, drill hole data and the geologist's interpretation. The original method was designed to build single or subparallel interfaces (Lajaunie et al., 1997). The principle of the potential field method is to define the potential field as a scalar function $T(x)$ of any point x in 3D space. The data available to model $T(x)$ are: interface points, which correspond to the points located at the interfaces between domains (e.g., drill hole information); and orientation data: correspond to the structural data (e.g., foliation).

The isopotential surface corresponds to $T(x) = t_k$, where t_k is an unknown value. The points belonging to the interface have the same potential field value and are denoted by x_α: $\alpha = 1,\ldots,m$. Therefore the potential difference between two points on the same interface is equal to zero, $T(x_{\alpha+1}) - T(x_\alpha) = 0$: $\alpha = 1,\ldots,M$, and M represents the total number of increments and is equal to the number of points on the interfaces minus the number of interfaces. The orientation data is denoted by x_β: $\beta = 1,\ldots,n$ and is polarized by the unit vector normal to the interface. This data is interpreted as gradient of the potential field and is equivalent to a set of partial derivatives $\partial T(x) / \partial u_1$, $\partial T(x) / \partial u_2$, $\partial T(x) / \partial u_3$, where u_1, u_2, u_3 are the axes in the 3D space (Chilès et al., 2004). The potential field is defined up to an arbitrary constant, the estimator of the potential field is given by the cokriging estimator

$$T^*(x) - T^*(x_0) = \sum_{\alpha=1}^{M} \mu_\alpha \left(T(x_\alpha) - T(x'_\alpha)\right) + \sum_{\beta}^{N} \nu_\beta \frac{\partial T}{\partial u_\beta}(x_\beta) \tag{1}$$

where μ_α and ν_β are the cokriging weights and solution of the cokriging system. Equation (1) shows that in absence of gradient data the estimator would be zero. Although the potential increments have a nil contribution, the solution of the cokriging system is different if the estimation is performed from the gradient data alone (Renard et al., 2013).

Some control points or Gibbs points (soft data) can be added to assist in the modeling. The control points inside the domain are characterized by $T(x) \leq t_k$ and the control points outside the domain by $T(x) > t_k$. The Gibbs sampler procedure transforms the Gibbs points into pseudo-hard data which can be incorporated into the cokriging process (Chilès & Delfiner, 2012).

A map of the probability to be inside the domain can be computed from the cokriging variance maps. Additionally conditional simulation of potential fields offers a way to access the uncertainty on the domain envelope.

Integrated Mineral Resource Estimation Workflow

Integrated MRE workflow was implemented in Minestis which is a new generation software solution developed by Geovariances aiming at offering a coherent solution to geological domaining and MRE process. This software combines geostatistical solutions, which ensure precision and reliability and provides an efficient platform for data quality control and analysis, geological modeling, recoverable resources estimation, and risk assessment.

The G2DC module assists in the definition and assessment of domain models, with two purposes: to reduce reliance on purely subjective interpretations without quantitative inputs; and to reduce the time expense of model interpretation and updating. The Automatic Domaining of Integrated MRE workflow provides tools to classify borehole samples into domains using GHC and the Domain Modeling based on the potential field method.

Integrated MRE workflow begins with data import and data validation, where the raw data is verified in order to clean possible duplicates and to define detection limits. The next step is the geological modeling solution, starting with an automatic sample clustering into domains according to their grade values and lithology, the process ending up with the assessment of the uncertainties on the domain envelopes using the Potential Field method. Then this workflow provides a complete EDA including: compositing, assisted declustering, automatic variogram fitting and interactive identification of the main continuity directions on a 3D variogram map for the raw and Gaussian variables. The KNA step helps defining the moving neighborhood parameters. Block estimation is then performed by ordinary kriging. The global change of support is applied and the information effect can be taken into account in the recoverable resource estimation procedure. Uniform conditioning and its localization are available to compute recoverable resource estimates at global and local scales and TB simulations can be generated almost simultaneously to assist with risk analysis (Rivoirard, 1994). This workflow is shown on Figure 1.

Figure 1: Integrated Mineral Resource Estimation Workflow.

RESULTS AND DISCUSSION

A real 3D data set is used to illustrate the innovative workflow of Minestis software. It was kindly provided by BHP Billiton. The raw data consists of about 1 800 vertical drill holes with 90 000 samples. Each sample interval includes assay for 10 grade variables, 15 spectral measurements, and a categorical variable. The example focuses on using the information from drill holes to perform geological modeling and recoverable resource estimation of Fe.

The data set has been imported and validated. The dissimilarity between the clusters is based on the Euclidian distances with 5 numerical variables (Fe, Al_2O_3, SiO_2, and spectral measurements of hematite and goethite) and a categorical variable (weathering). A weight is attributed to each variable based on the relevance of each variable to the overall domaining rationale. The Fe grade is the most important variable in the automatic domaining. Three clusters are defined: high grade (HG), low grade (LG) and waste (W) (Figure 2). The clustering reveals a nested organization of the HG, LG, and waste domains (Figure 3).

Domain modeling is performed for HG and LG. The variogram anisotropy and u, v, w ranges are based on the output of GHC. The ranges are based on the expected extension of the orebody from an interval of HG or LG. The results of domain modeling are presented in Figure 4 and Figure 5.

Once the envelopes have been defined for HG and LG, the drill holes are composited and the declustering weights are calculated for Fe grade. The Fe variogram models are fitted (Figure 6) and the global change of support applied for each domain.

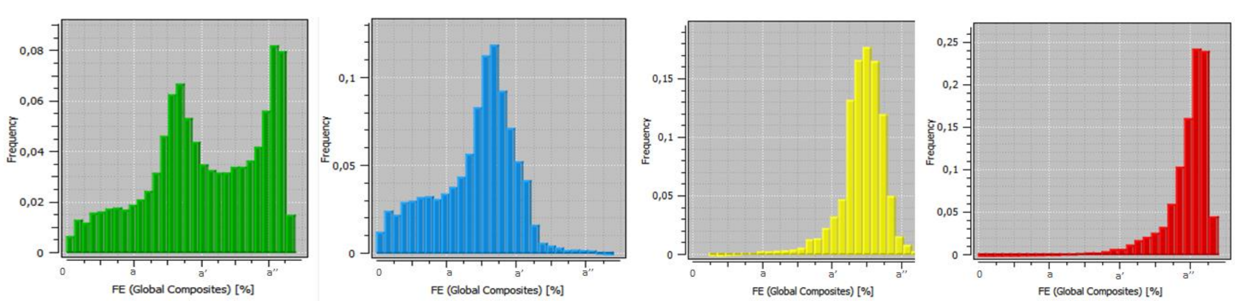

Figure 2: Histogram of % Fe grade from global data (green), waste samples (blue), low grade (yellow) and high grade (red).

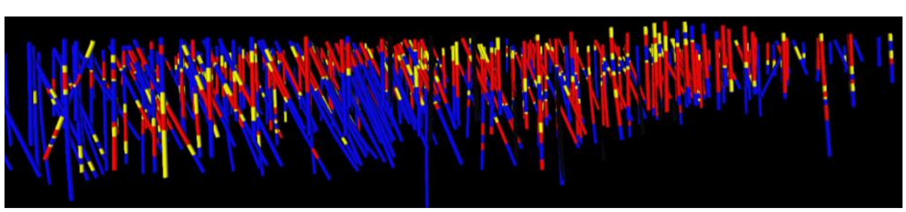

Figure 3: 3D view of drill holes, classified by GHC algorithm. In red the samples of high grade domain; in yellow the samples of low grade domain; and in blue the samples of waste.

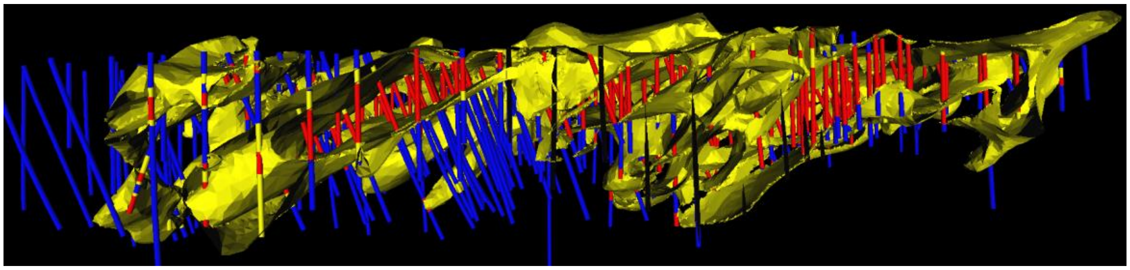

Figure 4: 3D view of drill holes and the boundary wireframe of low grade domain. In red the drill holes of high grade domain; in yellow the drill holes of low grade domain; and in blue the drill holes of waste.

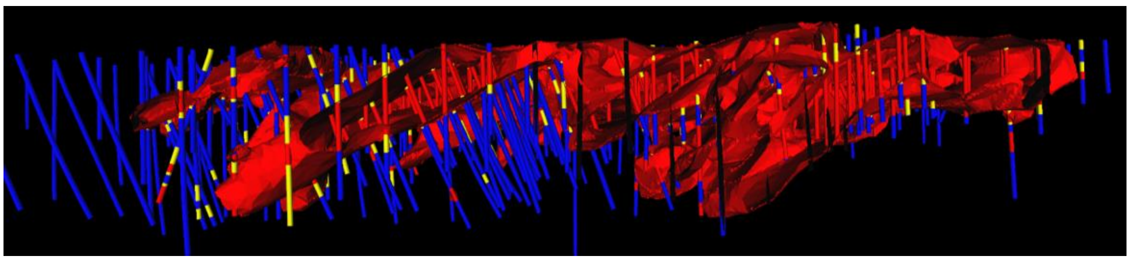

Figure 5: 3D view of drill holes and the boundary wireframe of high grade domain. In red the drill holes of high grade domain; in yellow the drill holes of low grade domain; and in blue the drill holes of waste.

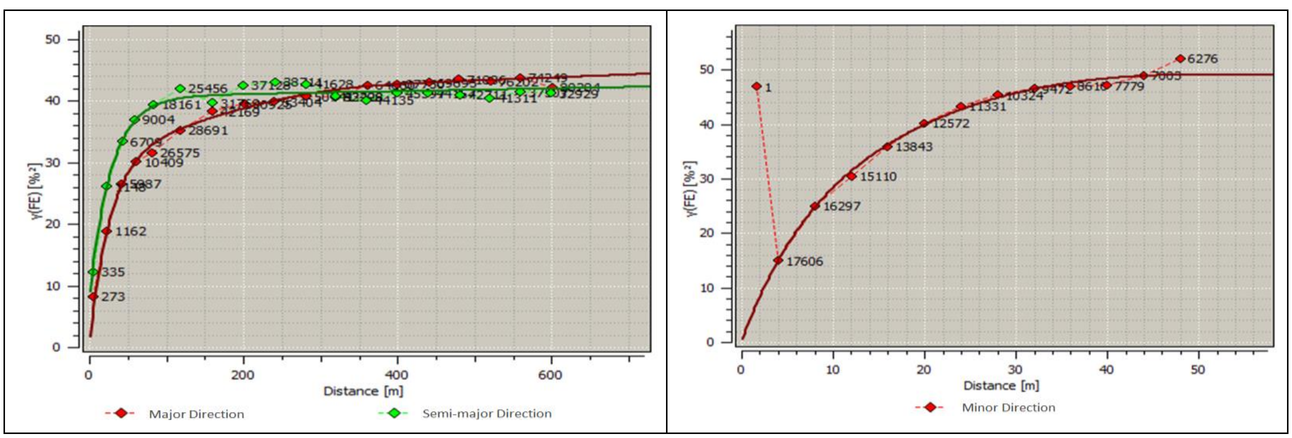

Figure 6: Experimental and modelled variograms of Fe variable in HG (composite3 m). Major direction (left- red); Semi-major direction (left-green); and Minor direction (right-red).

Some neighborhood parameters are tested using KNA, with the same rotation used in the variogram anisotropy (Figure 6) and u, v, w ranges are of 120m, 120m, 12m. Four alternative neighborhoods are assessed with or without vertical splitting of the angular sector and radius values modified at 80% or 120% from the original values. The choice of the best configuration is based on kriging efficiency, slope of regression of Z|Z*and the weight assigned of the mean (Table 1). The retained neighborhood has vertical split and radius increase of 120%. The same process is repeated for LG.

Table 1: Parameters tested in KNA of high grade domain.

Test	Vertical split	Ellipse size	KE mean	Slope mean	Weight of the Mean	Mean sum of positive weight
1	yes	1.00	0.4819	0.5728	0.5154	1.0029
2	yes	0.80	0.3502	0.5007	0.5636	1.0015
3	yes	1.20	0.5619	0.6220	0.4792	1.0044
4	no	1.00	0.4636	0.5546	0.5178	1.0011

The 3D estimations in HG and LG domains have been realized using 3 methods: ordinary kriging of $10x10x4m^3$ panels, LUC and TB of $5x5x4m^3$ SMU (Selective Mining Unit). Panel and SMU sizes were chosen as a test only; they do not necessarily reflect their real sizes. The estimation results are presented in Figure 7.

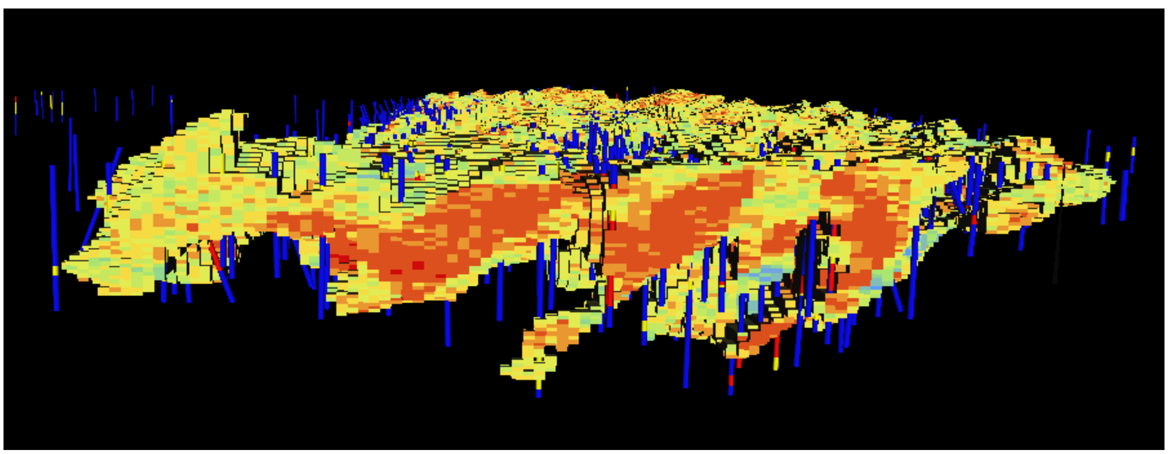

Figure 7: 3D view of Fe grade simulation for HG and LG domain by localized uniform conditioning.

CONCLUSION

The Geostatistical Hierarchical Clustering (Automatic Domaining) and Potential Field (Domain Modeling) methods implemented in Minestis save not only time for the Resource Geologist but also introduce scientific rigor to a traditionally subjective procedure. The clustering method can easily integrate many variables, such as grade, structural data, lithology, etc.; and to control the cluster analysis, the weight assigned to each variable can be modified. The Potential Field method considers the geostatistical behavior of variables to define spatial envelopes which facilitate grade interpolation within stationary zones. This geological modeling approach is flexible and in case new data is acquired, an update can be performed without changing the input domaining parameters. In addition, it calculates the error variance at any location and the probability to be in the domain. The global uncertainty on the domain volume can be produced by conditional simulations.

Sound geostatistical procedures like declustering analysis and KNA, help to ensure that a robust 3D block estimation is obtained. With a view to generate recoverable resources at local scale, the workflow may end with the implementation of non-linear methods such as LMUC, and TB conditional simulations for risk analysis. The Integrated MRE workflow implemented in Minestis offers the geostatistical solutions, covering the best practice facets of resource modeling and MRE procedure.

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