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Modelling of the kaolin deposits and reserve classification challenges of Charentes Basin, France

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Abstract

The kaolinitic clays have been exploited for more than a hundred years, in the western part of the Charentes Basin, France, and belong to a paleo-deltaic network. The recent deposits are relatively richer in alumina in comparison with the older ones. The genesis of the kaolin deposits of the Charentes Basin follows simple geological rules, but their detailed geometry has a great complexity, reinforced by the fact that one must distinguish very different clay qualities. The exploitation of the complex deposits which are buried in the deeper level needs the more powerful tools. The paper aims at analyzing the adequacy of the traditional method used in the exploitations of the kaolin deposits of the Charentes Basin in comparison with another method based on geostatistics to define criteria of selection and classification of reserves.

Keywords: *Kaolin, Modeling, Geostatistics, Simulation, Classification.*

1. Introduction

Clays and clay minerals are very important industrial minerals. There are over one hundred documented industrial applications of clay materials [1]. The group of kaolinite is the 1:1 clay mineral layer type. Kaolin predominantly comprises mineral kaolinite, a hydrated aluminium silicate. Other kaolin minerals are dickite, nacrite, and halloysite. The chemical formula of kaolinite is $Si_4O_{10}Al_4(OH)_8$ [2]. Kaolin is one of the most important industrial clay minerals in several markets including the paper industry, ceramics, paints, refractories, plastics, rubbers, ink, fibreglass and many other uses [3].
Competitions for new markets make clients more demanding and require new approaches for quality control of the mining process. The technological properties of kaolins are largely dependent on a number of factors. Regarding the end use of kaolin, some properties are more important than others. Factors such as crude clay quality, cost of processing, processed clay quality, and availability of the equipment imply the decision on the application of kaolin. In most cases the decision to process or extract a particular kaolin deposit or some parts of a deposit for some defined end use as opposed to the other deposits depends primarily on the quality of the raw materials [4]. This shows the key role of selective mining in the kaolin industry.
This paper aims at analysing the adequacy of the traditional method used in the exploitation of the kaolin deposits of the Charentes Basin and in comparison with another method based on geostatistics to define criteria of selection and classification of reserves.

2. Case study

The kaolinitic clays have been exploited for more than a hundred years, in the western part of the Charentes Basin, France. The kaolin deposits are belonging to a paleo-deltaic network.

2.1. Geographical and geological setting

The geological unit called Charentes Basin is composed of Eocene and Oligocene deposits, laid above karstic limestone formations of the Campanian, in the North of the Aquitaine Basin. The kaolin clays of Charentes belong to this mainly continental, tertiary formation often referred to as “siderolithic”, of which the principal outcrop is situated in the South of the Charente Maritime department, about 50 km to the north-east of Bordeaux. The quarries are scattered along a 30-km long, 10-km wide, north-south band (see Figure 1).

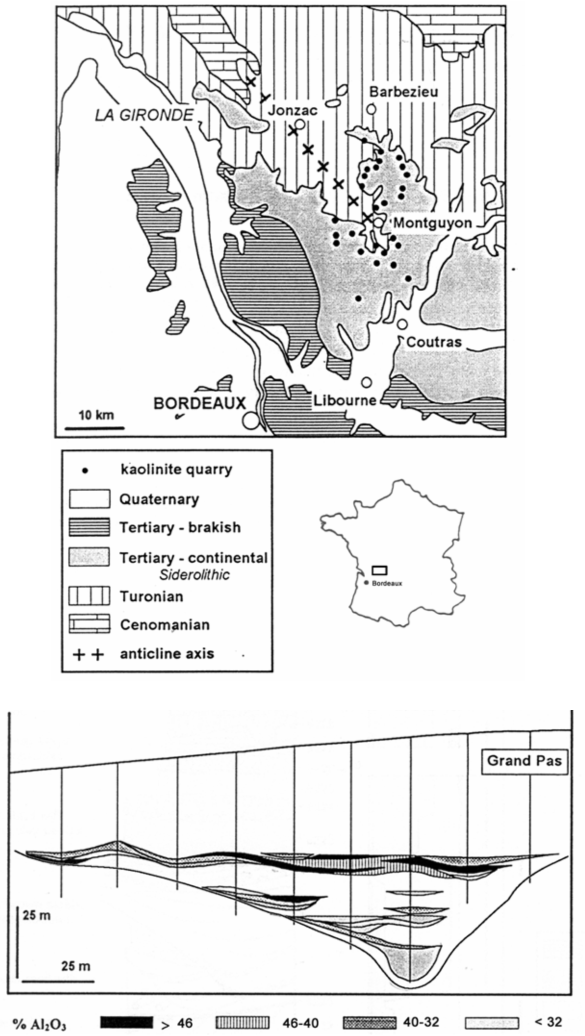


Figure 1. Geological map of the Charentes Basin area (up). Geological section showing the distribution of the kaolinite layers [5]; kaolinite accumulation is clearly related to the paleomorphologies; the upper clay units always become more regular (down). Note that the grade of Al_2O_3 is calculated on fired material (pure kaolinite contains 45.9% of Al_2O_3).

The mineable kaolins are composed of a succession of clays, sands and pebbles. This torrential-stream deposit, laid to the deposition of sandy-clayey materials, with a variable iron content, is due to a lateritic weathering of the French “Massif Central” granites [6-9].

Those complex geometries, with structures smaller than 20 meters, lead to particularly difficult recognition, estimation and exploitation phases. One should also notice important lithology variations. The presence of different criteria depending on the customers leads the mining industry to control several parameters. The AGS Company uses no less than 24 codes and 8 colour codes for its samples description. Those classes are subdivided to take into account the grades in organic matters, iron, titanium, potassium, the colour, the aptitude to flow, etc.

The deposits with thin overburdens have been exploited during the past century and the new deposits are situated in the centre of the basin, where the sediments are thicker. These deposits are found under a relatively thick overburden (more than 30 m in some cases). The ancient sedimented kaolins are affected by a more rigorous paleotopography, some parts of deposits have undergone a post-sedimentation process. The kaolin is rich in alumina due to the presence of gibbsite [10]. This type of clay, called Hyperaluminous, has been known for a long time in the Charentes Basin. What is important is its very high frequency in the recent deposits. These changes in the complexity has caused to set the question of the relevance of the traditional method of kaolin extraction to meet demand requirements.

2.2. Production of kaolin in the Charentes Basin

The variety in geological setting and formation of kaolin deposits of the Charentes Basin allows the commercialization of kaolins for different industrial markets. What is the most important for AGS-Mineraux (Imerys) is the quality of the product. For each range of products, there are predefined specifications consisting in chemical composition and industrial properties, which must be respected. The economic sensitivity to the different qualities is rather low. The production cost penalizes fabrication of high quality products, therefore profit margins do not vary too much, but the diversification of products is an important strategy to reduce the dependence to a particular market and instability, and be more competitive [11].

The selective extraction method permits to reduce the range of variation. It is appreciated by producers who have different categories of products. If only the miners are equipped by sufficient criteria and tools for selection, selective mining will be useful. The present method of exploration in the Charentes Basin is based on the selection of an assumed homogeneous zone around a given core sample; classification of resources is based on the chemical analysis of the core sample. Miners delimit zones on the basis of visual criteria such as variation of colour, feeling of clay and presence of sand and mica. The grade of alumina measured on calcined samples is the first criterion for the kaolin reserve classification. The definition of the classes is performed by AGS-Mineraux particularly for the kaolin deposits of the Charentes Basin.

Over the last years, the stockpiles were made based on this classification for each kaolin quarry. Stockpiles can serve commonly to three purposes: buffering, blending and targeting. The stockpiles are the main tools used to mix the materials and reduce the variation on the input stream [12].

The efficiency of blending and homogenisation depends firstly on the mechanisms of mixing. As mixing cannot be complete, it will be more efficient and cost effective if the input is more homogenous with low variations. Not only many industrial properties of kaolin are controlled by its mineralogical composition, but also it is current to observe different industrial behaviours of two input streams with similar chemical compositions but different mineralogical compositions or different crystallographic structures.

Whatever the selection criteria, selection will be perfect if the properties of the ore are perfectly known, at least at the scale of selective mining units. In practice we are not in that situation, so that these properties are evaluated on the basis of the information available prior to exploitation. This states the question of the relevance of the estimation method used. We will examine that question in the very simple case where the objective is to assign blocks to stockpiles defined by grade ranges and the selection criterion is the estimated grade.

3. Assessing the adequacy of estimation methods for classification

The application of geostatistical tools to industrial minerals is very limited. There are some technical limits to the use of these powerful tools [13, 14]. Studies of kaolin deposits are rather rare [15,16, 17].

In this paper, we present a comparison between the traditional method and a method based on linear geostatistics. There are more powerful geostatistical methods for estimating recoverable reserves [18]. But due to their complexity and the lack of familiarity of the present industry with geostatistics, we prefer to focus on simple and easy-to-use tools for that industry.

3.1. Assessment method

There are many studies that compare the results obtained by geostatistical methods with the result of a traditional estimation method. To carry out this kind of study, we need know the actual values of the estimated blocks of the deposit. This is seldom the case and we are not in that situation here. Therefore, a simulated value of the grade is taken as the actual grade in this study.

Two deposits BR-NE and SG[i] were chosen as case studies. SG is classified as a simple deposit of the Charentes Basin due to its low variation of grade and its simple geometry [19]. This deposit has been sampled by a dense and regular drilling grid. Alumina grade varies between 26.9% to 42.5% with an average of 36.1% and a standard deviation of 2.8 %. BR-NE is the north-eastern part of BR deposit, one of the biggest kaolin deposits of the Charentes Basin. It has been explored by a relatively regular but large grid (40m). The geometry of that deposit is complex; it comprises different overlaid levels, with channels, lenses and layer shapes. This deposit is richer, with an average gradeof 42.8%, but it also display large grade variations: the grade varies between 24.2% to 66.9%, with a standard deviation of 5.3%. Details of statistical properties of these deposits can be found in Koneshloo et al. [20]. Figure 2 shows the map of the drill holes and the block within which the estimation will be done.

The process can be summarized as follows (see Figure 3):

- A conditional simulation of alumina content is built for each deposit. By design it honours all known data and mimics the true spatial variability of grade. That conditional simulation is considered as reality. The simulated sub-blocks are 2*2*0.5m in SG deposit and 5*5*0.5m in BR-NE.
- In the first scenario, blocks with a size of 20 * 20 * 0.5m (BR-NE) and 10 * 10 * 0.5m (SG.) are estimated by kriging on the basis on the available drilling data.
- The other scenario is the estimation of each block by the nearest-neighbour method. This is close to the method that is presently in use in the company.
- For each scenario, each block is classified inside the relevant stockpile on the basis of its estimated grade. In this way, the stockpiles are simulated. Then, for each stockpile we calculate the average and the standard deviation of the "true" grade of the sub-blocks sent in that stockpile.
- This process is repeated for 10 conditional simulations, namely for 10 likely "real" deposits, in order that the final results do not depend on a specific realization.
- The "true" average grade of a stockpile in comparison with its predefined grade range res the overall accuracy of the method, and the standard deviation of the grades of the sub-blocks it

contains measures its homogeneity, or more precisely its heterogeneity.

3.2. Geostatistical simulation

Conditional simulations are useful qualitively, to obtain realistic pictures of spatial variability and quantitively, to evaluate the impact of uncertainty on the results of complex procedures [21]. Conditional simulations fall in the scope of so called Monte-Carlo methods. These techniques are based on the interpretation of the regionalized variable (here alumina grade) as a realization of a random function and a modelling of its spatial distribution, honouring the sample values.

The turning bands algorithm [22] provides fully consistent simulations of Gaussian variables. Since it is designed for Gaussian variables, the grades are first transformed into normal-distributed grades. At the end of the simulation process, the inverse transformation is applied. The whole process is fully operational, even in a multivariate environment [23].

The generation of conditional simulations is based on the variogram of the normal-transformed grade. The experimental variograms are shown in Figure 4 (bottom) and the parameters of the variogram models are given in Table 1 (variable G.Al_2O_3).

3.3. Kriging

Kriging and especially ordinary kriging is now widely used in geosciences [24]. This optimal linear estimator requires the variogram of the original grade. The experimental variograms and the variogram models are shown in Figure 4 (top) and Table 1 (variable Al_2O_3).

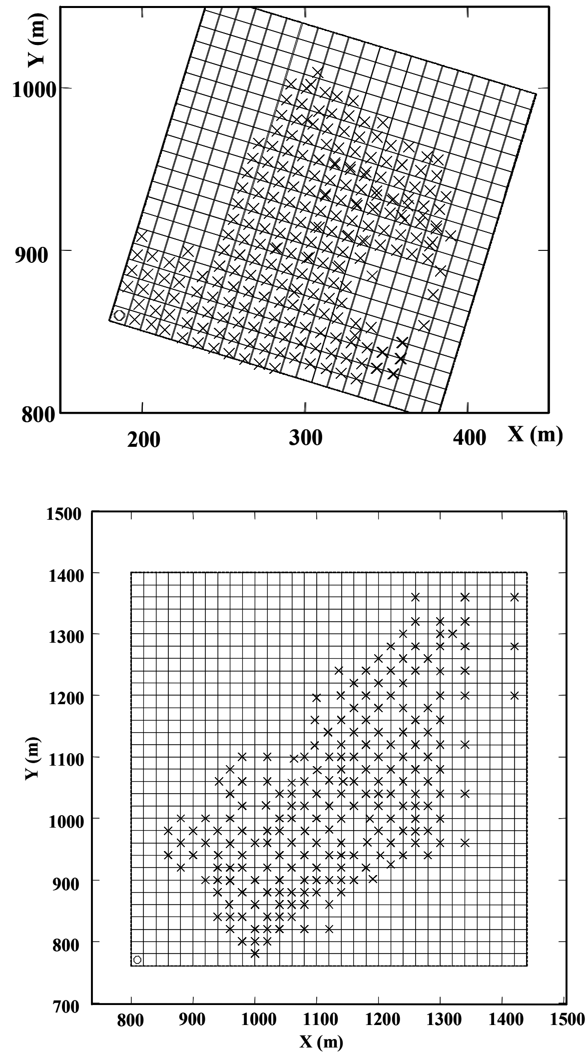


Figure 2. Location of the drill holes and the blocks to estimate the SG deposit (a) and the BR-NE deposit (b). The maps do not have the same scale

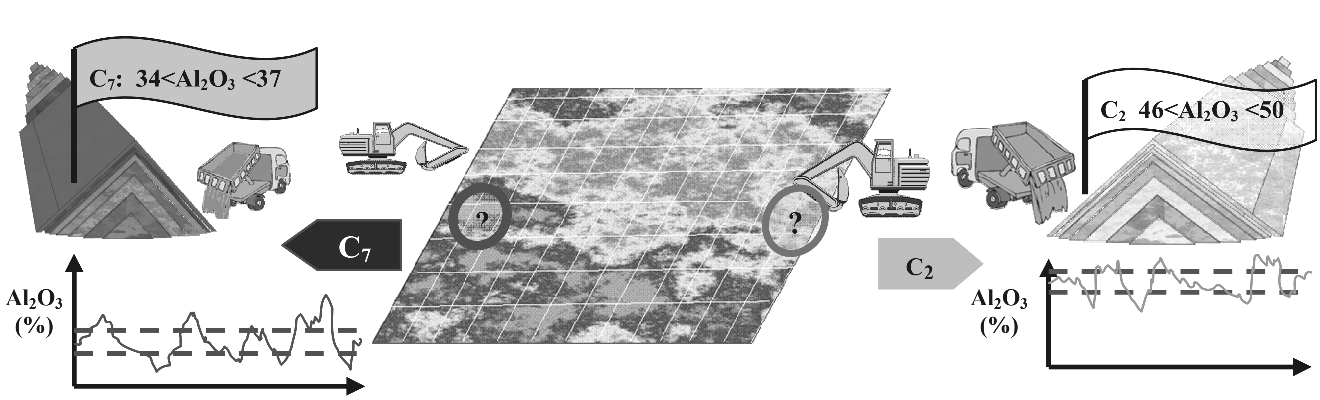


Figure 3. Schema of the procedure of stocks simulation

Indicator of kaolin is defined for the estimation of the presence of kaolin in the deposit. In the definition of the indicator, only the commercial kaolins are taken into account. The experimental variogram of this indicator has been calculated and modelled (Table 1, variable Indic.). Its kriging has been used to define the zone within which the kriging and simulation of grade are carried out.
The variograms show a structural anisotropy, also called zonal or stratified anisotropy. Long-range spherical or linear models are used to model this anisotropy. In the SG deposit horizontal directional variograms show a geometric anisotropy parallel to the axes of the drilling grid. The first spherical model of the variogram of grade represents a smaller part of the total sill in SG than in BR-NE deposit. Note that the ranges are very close to the respective drill hole spacings.

3.4. Nearest neighbour method (NNM)

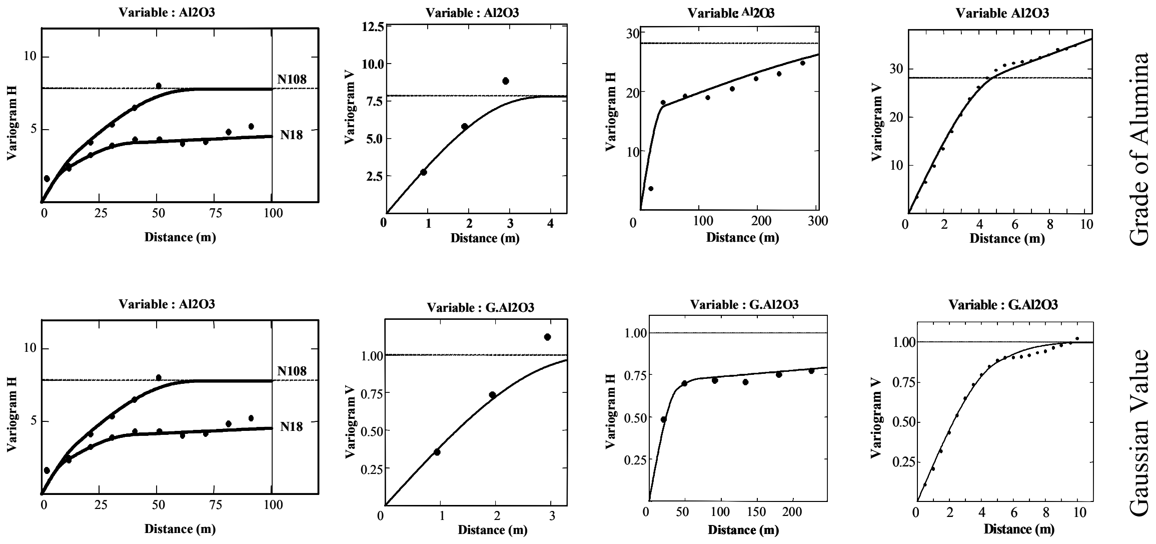
In this method the value of the nearest sample to the centre of a sub-block is assigned to it. To avoid an exaggerated vertical interpolation and regarding the stratified nature of the sedimentary kaolins the search area is defined with a limited vertical radius.
The detail parameters used for the simulation and the estimation can be found in reference [19].

4. Results and discussion

Statistical comparison shows a good correlation between the kriged block values and the estimates obtained by the nearest neighbour for SG deposit (r^2 =0.69). This leads to a similar classification of reserves and targeting for both scenarios. Table 2 compares the accuracy of targeting by these methods. Both show good results except for the poorest and richest parts of the deposit. However, Table 3, shows that the standard deviation of the "true" grades of the sub-blocks sent to a stock is reduced when using kriging for targeting the sub-blocks. Only in 8 cases out of 60 possible stocks (6 grade classes and 10 conditional simulations) NNM presents a lower variance than kriging.
These results show why the traditional method remains acceptable for a continuous and simple deposit such as SG. On the other hand they also confirm the improvement brought by kriging for a more precise targeting. As shown in Table 4, the same procedure leads to very different results for BR-NE deposit. In a large majority of cases (62 out of 90), the "true" average grades of the stocks defined on the basis of the NNM estimates are out of the predefined ranges. When targeting is done on the basis of the kriged estimate, there are only 6 such inconsistent cases.The correlation between the estimated grades by both methods is weak and the coefficient of correlation is only equal to 0.42. The assigned values to each sub block on the basis of the kriged block estimate are have a correlation of 0.58 with their real (simulated) values. With the NNM estimate, this correlation is weaker (combien?) and the dispersion around the line of regression is larger (r^2 =0.43). Moreover the dispersion of the grades in each stock is lower when the stock has been built on the basis of kriging than NNM. Another criterion that can be used to examine the adequacy and quality of the estimators is the slope of the regression line of estimated and real values. Rivoirard [25] presents this criterion for choosing the suitable

Table 1. Variogram models used for simulation and estimation for SG and BR-NE deposit.

Deposit	Variable	Model of variogram
SG Deposit	Al_2O_3	$\begin{cases}\gamma_{N18}(h)=1.2*Sph.(h/10)+2.6*Sph.(h/40)+4*Sph.(h/800)\\ \gamma_{N108}(h)=1.2*Sph.(h/15)+2.6*Sph.(h/60)+4*Sph.(h/70)\\ \gamma_V(h)=1.2*Sph.(h/3)+2.6*Sph.(h/4)+4*Sph.(h/4)\end{cases}$
	$G.Al_2O_3$	$\begin{cases}\gamma_{N18}(h)=0.20*Sph.(h/15)+0.15*Sph.(h/40)+0.65*Sph.(h/800)\\ \gamma_{N108}(h)=0.20*Sph.(h/25)+0.15*Sph.(h/60)+0.65*Sph.(h/70)\\ \gamma_V(h)=0.20*Sph.(h/3)+0.15*Sph.(h/4)+0.65*Sph.(h/4)\end{cases}$
	Indic.	$\begin{cases}\gamma_H(h)=0.16*Sph.(h/20)+0.09*Sph.(h/100)\\ \gamma_V(h)=0.16*Sph.(h/1.5)+0.09*Sph.(h/6)\end{cases}$
BR-NE Deposit	Al_2O_3	$\begin{cases}\gamma_H(h)=16*Sph.(h/40)+6*Sph.(h/400)+6.15*Lin.(h/400)\\ \gamma_V(h)=16*Sph.(h/1.5)+6*Sph.(h/6)+6.15*Lin.(h/4.5)\end{cases}$
	$G.Al_2O_3$	$\begin{cases}\gamma_H(h)=0.5*Sph.(h/40)+0.2*Sph.(h/70)+0.3*Sph.(h/1200)\\ \gamma_V(h)=0.3*Sph.(h/5)+0.2*Sph.(h/7.5)+0.3*Sph.(h/10)\end{cases}$
	Indic.	$\begin{cases}\gamma_H(h)=10^{-3}*(90*Sph.(h/10)+70*Sph.(h/30)+47*Sph.(h/180)+30*Sph.(h/400))\\ \gamma_V(h)=10^{-3}*(90*Sph.(h/1)+70*Sph.(h/4)+47*Sph.(h/8)+30*Sph.(h/10))\end{cases}$



(a).SG deposit (b).BR-NE deposit

Figure 4. Horizontal and vertical variograms of natural grade (top) and Gaussian-transformed grade (bottom) grade for SG deposit (a) and BR-NE deposit (b).

Table 2. Comparison of the accuracy of targeting with referring to the two different criteria of selection in SG deposit

Classes	Selection criteria: Results of NNM									
	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Sim10
]30	30.89	30.44	30.99	31.66	31.14	30.89	30.44	30.99	31.66	31.14
[30,34[	33.04	32.98	33.21	33.30	33.16	33.04	32.98	33.21	33.30	33.16
[34,37[	35.68	35.51	35.61	35.62	35.58	35.68	35.51	35.61	35.62	35.58
[37,40[	38.12	38.10	38.10	38.08	38.09	38.12	38.10	38.10	38.08	38.09
[40,42[	40.13	40.10	40.08	40.14	39.88	40.13	40.10	40.08	40.14	39.88
[42,44[	41.70	41.70	41.29	41.49	41.76	41.70	41.70	41.29	41.49	41.76
Classes	Selection criteria: Results of Kriging									
	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Sim10
]30	30.61	28.43	29.70	29.60	30.41	30.61	28.43	29.70	29.60	30.41
[30,34[	32.76	32.78	32.92	33.07	32.88	32.76	32.78	32.92	33.07	32.88
[34,37[	35.58	35.37	35.54	35.55	35.51	35.58	35.37	35.54	35.55	35.51
[37,40[	38.29	38.24	38.23	38.20	38.24	38.29	38.24	38.23	38.20	38.24
[40,42[	40.32	40.54	40.49	40.42	40.13	40.32	40.54	40.49	40.42	40.13
[42,44[	40.86	41.77	41.48	41.37	41.10	40.86	41.77	41.48	41.37	41.10

neighbourhood by a cross validation approach. The slope of regression for the supposed real values (simulated) by the kriged values is 0.95 for SG deposit and 0.92 for BR-NR. These values are to close to 1, which is the slope of the ideal estimator. The slope of regression for nearest neighbour method is 0.83 for SG deposit and only 0.42 for BR-NE.

These results show clearly why the traditional method encounters real problems of accuracy and homogeneity of the stream feed. This is not a surprise. Indeed, in assigning the grade of the nearest sample to a block, NNM methods reproduces the distribution (histogram) of sample grades to the scale of block grades, whereas it is obvious that block grades are less dispersed than sample grades: if a very high (resp., low) grade can be seen in a core sample, this can hardly be the case at the scale of a block. The consequence is that blocks estimated rich are poorer than expected, and blocks estimated poor are richer than expected. NNM is an unbiased estimator, but it is not condititional unbiased. This effect can be also observed with kriging but it is much less pronounced than with NNM. This is partly due to the smoothing effect of kriging (this explains why the kriged estimates are always larger than 30%).

The results can be summarised as follows;

- The drilling grid is too large to safely evaluate BR-NE deposit due to a very important grade variability. The data geometry and a weak spatial auto-correlation between the data are not in favour of a fairly accurate estimation by kriging, and far less by the nearest neighbour method.

- The conditional simulation of the sub-blocks of SG deposit show that this deposit seems very continuous. In that case the traditional method, based on NNM, encounters no serious problem. However, a selection based on kriging is an improvement.

Table 3. Comparison of the precision of targeting with referring to the two different criteria of selection in the SG deposit

Classes	Selection criteria: Results of NNM									
	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Sim10
]30	2.02	2.13	1.83	2.12	2.15	2.02	2.13	1.83	2.12	2.15
[30,34[	2.05	1.98	1.98	1.93	2.06	2.05	1.98	1.98	1.93	2.06
[34,37[	1.97	1.96	1.89	1.98	1.94	1.97	1.96	1.89	1.98	1.94
[37,40[	1.64	1.71	1.65	1.61	1.65	1.64	1.71	1.65	1.61	1.65
[40,42[	1.24	1.43	1.21	1.25	1.42	1.24	1.43	1.21	1.25	1.42
[42,44[	0.77	0.92	0.95	0.88	0.66	0.77	0.92	0.95	0.88	0.66
Classes	Selection criteria: Results of NNM									
	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Sim10
]30	1.70	1.46	1.69	1.95	1.80	1.70	1.46	1.69	1.95	1.80
[30,34[	1.94	1.89	1.83	1.82	1.96	1.94	1.89	1.83	1.82	1.96
[34,37[	1.93	1.96	1.87	1.94	1.90	1.93	1.96	1.87	1.94	1.90
[37,40[	1.54	1.57	1.52	1.54	1.56	1.54	1.57	1.52	1.54	1.56
[40,42[	1.37	1.32	1.04	1.24	1.53	1.37	1.32	1.04	1.24	1.53
[42,44[	0.72	0.71	0.61	1.00	0.61	0.72	0.71	0.61	1.00	0.61

Table 4. Comparison of the accuracy of targeting with referring to the two different criteria of selection in the BR-NE deposit

Classes	Selection criteria: Results of NNM									
	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Sim10
]30	36.20	36.48	36.97	37.15	38.21	38.09	36.64	35.15	37.55	39.54
[30,34[	40.07	39.52	39.17	39.27	40.43	38.00	39.64	39.17	38.42	38.99
[34,37[	40.66	39.93	39.38	40.12	40.51	39.96	39.82	39.43	40.34	39.62
[37,40[	41.09	41.16	40.28	40.69	40.98	41.00	40.42	40.09	40.29	40.52
[40,42[	41.37	41.36	40.81	41.21	41.43	40.92	41.06	40.89	41.07	40.72
[42,44[	42.66	42.51	42.36	42.48	42.63	42.51	42.48	41.98	42.69	42.31
[44,46[	44.82	44.69	44.38	44.49	44.36	44.52	44.34	43.68	44.49	44.08
[46,50[	45.32	45.89	45.65	45.92	45.57	46.09	45.51	45.04	45.84	45.34
[50	48.36	48.53	47.90	48.02	48.50	48.29	49.46	47.87	49.16	47.74
Classes	Selection criteria: Results of kriging									
	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	Sim8	Sim9	Sim10
]30	*	*	*	*	*	*	*	*	*	*
[30,34[	33.05	30.77	34.35	32.60	34.30	35.58	33.12	30.87	33.43	34.12
[34,37[	36.24	36.37	35.13	36.56	37.19	35.84	36.22	35.76	36.62	36.90
[37,40[	38.90	38.82	38.30	38.82	39.49	38.79	39.02	38.56	38.81	38.53
[40,42[	41.21	41.01	40.62	40.85	41.19	40.80	40.79	40.37	40.83	40.63
[42,44[	43.19	42.99	42.76	42.89	42.85	42.89	42.70	42.49	42.79	42.60
[44,46[	44.86	45.26	44.49	44.81	44.80	44.77	44.81	43.96	44.69	44.39
[46,50[	47.11	46.82	46.38	46.55	46.47	46.83	46.52	45.43	47.07	45.98
[50	51.41	51.26	50.64	51.01	51.73	50.67	51.71	50.48	52.11	50.76

- Kriged values present a better correlation with "real" (simulated) values, in comparison with the result of the nearest neighbour method.
- The use of kriging allows a better classification of reserves, with regard to honouring the class limits and ensuring a low variance inside each class.

5. Conclusion

The application of geostatistical tools is less common in the case of industrial minerals than in the domain of metallic resources. This kind of study the improvement that can be brought by geostatistics to the companies who work in the industrial minerals sector.

The exploitation of the complex deposits which are buried in deep levels needs the most powerful tools. Geostatistics helps us to acquire necessary knowledge on the in situ variations of grade, which is survival for selective mining. As this paper shows, it more efficient than the traditional method for targeting and classification.

6. Aknowledgements

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