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# An Indicator-based Geostatistical Assessment of the Global Vermiculite Reserves at Palabora Mining Company

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The Palabora Phosphate and Vermiculite Mining Department of the Palabora Mine in Mpumalanga, South Africa, operates two shallow openpit mines from which vermiculite ore in the form of thin, flat flakes is recovered.

The Company supplied data on 366 samples that had been collected in the 1960s from trenches dug on the surface of the vermiculite deposit. The Company required a rough indication, from the data supplied, of the value, grade distribution, optimum drilling distance for exploration, and techniques for the accessing of values without the need for further drilling. Finally, it wanted to know whether the data set was reliable enough to form the basis for the prediction of block values.

This paper describes the geostatistical study undertaken on the data for the vermiculite deposit. It includes initial statistical analysis; reserve estimation, both global and local; and the optimum drilling pattern to be used in exploration sampling in the mine. Owing to the complexity of the data, which related to three mineral populations, multiple-nested indicator kriging was employed using Geostokos Toolkit, a program developed by Dr Isobel Clark at the University of the Witwatersrand

The technique worked well in the evaluation of the vermiculite deposit, and is recommended for deposits of mixed populations that are very difficult to separate.

#### Introduction

One of the more difficult problems frequently facing geologists and mining engineers is that of estimating ore reserves for a mineral deposit using the data sampled by exploration and development drilling. Ore-reserve estimations are usually required not only for the orebody as a whole (global estimation), but also for individual blocks within it (local estimation) to allow adequate grade control during mining. Unless the tonnage and grade of a mineral deposit are known with certainty, it would not be regarded as an orebody, and satisfactory mine planning could not proceed. If a mining operation is considered to consist of mining, milling, smelting, and marketing and, further, if these aspects are considered to have a fixed cost at any particular time, then, given a fixed metal price at that time, there must be a cut-off grade for the ore in the mineral deposit under study. Given such a cut-off grade, it then becomes a matter of comparing each block grade and declaring that block to be either ore or waste. However, one must have a block estimate in the first place to compare with the cut-off grade. This is why block estimation is so vital. Modem mining operations are so cost oriented that there is considerable pressure on the accuracy of both global and block estimations.

Palabora Mining Company, in Phalaborwa, Mpumalanga, South Africa (Figure 1), would like to start mining operations on an abandoned mica deposit known as the Vermiculite Operations Department (VOD). The deposit was abandoned for over 30 years while the market conditions, technical problems, political situation, and other factors were not favourable for vermiculite mining.

After 30 years of shut down, interest in the property has been revived. The Company, a member of the international Rio Tinto Zinc (RTZ) group, would like to mine this vermiculite deposit mainly because of the improvement in the market conditions, technological changes, and political favourability. Information relating to the deposit and the old mining procedures like the mean grade, degree of oxidation, depth of oxidation, size distribution, etc. does not exist, or even if it does, cannot be trusted. The drilling and sampling procedures, and probably the crude metallurgical processes by which the old data were collected and treated, appear dubious, and questions therefore arise about the validity of such information. The only information that is believed to have integrity are the data for 366 samples that were collected along trenches on the surface of the deposit, and then assayed and the values kept in computer archives in the technical department at the head office of the Company in Johannesburg.

Technically, it has been proved feasible to mine this vermiculite deposit (VOD) but, as with any mining venture, the Company would not like to commit money to the operation unless it is economically feasible. Before the Company spends large sums of money on exploration drilling and consequent mining, it would like to obtain a rough indication, based on the data available, of the value, grade distribution, and optimum drilling distance for exploration; the techniques that can be employed to access the values without the need for further drilling; the mining method selective enough for the peculiar nature of the vermiculite deposit; whether the data can reliably be used for block estimation; and the general economic viability of the project. New geostatistical methods have been developed to solve these types of problems, and RTZ therefore called on the technical assistance of the Mining Engineering Department at the University of the Witwatersrand.

In August 1994, after a computer disk containing the sample data had been received from RTZ head office, a brief statistical analysis was made and, in September 1994, a visit was paid to the mine. Work started immediately after that at the Mining Engineering Department

with a proprietary software package called Geostokos Toolkit, which had been developed by Dr Isobel Clark of the Department. This toolkit package is interactive and well-documented, has the anisotropic option built in, and outputs prediction and standard error values for easy contouring.

#### The Mine

Palabora Mining Company has one of the largest surface mining operations in South A frica. The mine has two major surface operations – for copper and vermiculite – and has been in operation since 1954. Vermiculite is the alteration product of phlogopite, which is a species of mica. In this paper, mica has been used synonymously with vermiculite. Micas normally take the form of numerous flakes adhering together naturally to form books. The individual flakes, which are very thin (about 20  $\mu$ m), are pliable, resilient, and tough, and have smooth surfaces. When heated, vermiculite expands to about 30 times its original size.

The Vermiculite Operations Department (VOD) of the Company operates two shallow openpits from which the vermiculite ore is recovered. The mining operation is notoriously difficult because of the sporadic and unpredictable distribution of all the economic minerals. The vermiculite ore was mined from the start by opencast methods, the bench height being maintained at 5 m. The vertical blastholes are spaced at 3 m, with a burden of 2,5 m. The holes are of standard diameter (65 mm), drilled with a truck-mounted pneumatic drill. The explosive is a blend of granular ammonia nitrate and fuel oil. In dry holes, the detonation is by electrical detonators connected in series; in wet holes, blasting is effected by high-explosive primer cartridges set off by detonating fuse. The powder factor is satisfactory at 6,5 t per kilogram of explosive. After blasting, the vermiculite ore is loaded into trucks and transported to the plant, where it is crushed and dried before being passed through an air stream. Here, the light vermiculite flakes are winnowed off, leaving the host rocks to be discarded as waste. Vermiculite is light, and has excellent thermal-, electrical-, and sound-insulating properties. It is used in fireproofing, and in acoustical and decorative plasters, as well as in horticulture.

# **Physical and Geological Characteristics**

There are two known deposits of vermiculite in the mine. These are the Palabora phosphate and vermiculite (PP&V) deposits and the deposit of Vermiculite Operations Development (VOD), and they are found in the Palabora Complex (Figure 2). The vermiculite ore in this deposit forms a surface layer that decreases in grade downwards into rocks containing too much phlogopite, which is an undesirable contaminant of the vermiculite concentrate. The deposit¹ does not extend for more than 2 km². The phlogopite is a characteristic component of ultrabasic rock in alkaline and carbonatite complexes. The early intrusion of the ultrabasic rock was followed by a final alkaline phase of intrusion that has resulted in many bodies of syenitic rocks scattered over a wide region around central ultrabasic pipes. The areas of pyroxene pegmatoid and serpentine pegmatoid are underlain by phlogopite rocks in which much of these minerals has a coarse grain structure. The phlogopite is almost completely altered to

vermiculite to a depth of not less than 50 m below the surface. Underlying this altered zone is unaltered phlogopite, which might continue to a greater depth.

#### The Dataset

As mentioned earlier, the sample data for the VOD deposit used in this study related to 366 samples obtained some 30 years before. The samples were taken along trenches on the surface of the deposit. The sampling did not seem to have followed a logical pattern, as was later revealed by the scatterplot of the mica data. The sampling distance, though not constant, was found from the scattergram to range from about 1 m to as high as 20 m. The support was also not constant since a shovel was used to pick the samples at random from the trenches. The information in the database included the following:

- \* coordinates of sample points in two dimensions
- \* percentage grade of vermiculite
- \* percentage grade of phlogopite
- \* total percentage grade of mica
- \* proportion of size classification for every grade.

#### **Statistical Studies**

The first step in any geostatistical analysis is the data survey, which enables the detection of anomalies in the data that could affect the accuracy of the estimation. Global and local histograms, averages, and variances are among the statistics computed. All these parameters give a rough idea of the statistical nature of the deposit.

The preliminary statistical analysis, involving the computation of basic summary statistics and the construction of histograms, was conducted for mica grade. A scattergram was drawn to show the specific location of the trench samples (Figure 3). The sample density varied, some areas being closely sampled, and others somewhat sparsely sampled. From the scattergram, the area under study extends roughly between 1500 and 3300 in a north-south direction and 2400 to 3700 in an east-west direction, an area of approximately 1800 m x 1300 m. Although most of the data followed a northeast-southwest direction, no grid sampling was done. The samples appear to be concentrated in the centre of the western part of the study area, which may indicate an orebody extending to this part of the deposit.

The histogram for the mica samples (Figure 4) indicates some positive skewness, with erratically high class frequency in the lower-grade area, and in between. The high coefficient of variation (0.75) indicates that the deposit is irregular. Figure 5 shows the lognormal histogram. It is very obvious from these diagrams that the samples follow neither a normal nor a lognormal distribution. Instead, it appears to be a mixed population, with three modes or peaks in both the raw and the logarithmic histograms.

Some authorities<sup>2</sup> have shown that a clearly multi-modal histogram like that in Figure 4 generally reveals the existence of heterogeneous mineralization, the number of populations being equal to the number of modes or peaks. To further test the nature of the data and confirm the behaviour of the population, a cumulative less-than curve was plotted on non-nal

probability paper. This plot, which is illustrated in Figure 6, shows an S-shaped curve, confirming the three populations in the data with two indistinct breaks. The three populations strongly overlap one another. Table I gives the statistical parameters of the data.

The three populations recognized in the data merge strongly into one another. Attempts were made to separate the three populations so that they could be treated separately, but this did not yield satisfactory results: neither a normal nor a lognormal individual population could be achieved. As this could cause problems in the modelling of the semivariograms, multiplenested indicator kriging was adopted to avoid cutting or trimming of the data<sup>4</sup>. This would also make the variogram easy to estimate and model. Indicator kriging removes the impact of abnormally high values in low-grade areas and *vice versa*. In fact, indicator kriging is one of the non-parametric geostatistical techniques that is ideal for the estimation of an irregular mineralization like this.

It was concluded that the vermiculite deposit is made up of three different populations. Clark and Garnett<sup>3</sup> state that there is always geological evidence of a multiple population: two or more distinct periods of hydrothermal infilling of a fracture system or the superimposition of placer deposits constitute repetitious mineralization, reworking of part of the placer deposit, demobilization, etc. These were some of the established traits of the deposit: the deposit had undergone different degrees of oxidation with increasing depth, and there was a different period of intrusion during the mineralization phase, which resulted in many bodies of syenitic rocks over a wide region around a central ultrabasic pipe. Based on this finding, it is recommended that the geologist at the mine should delineate the deposit geologically before any advance work is done.

#### **Geostatistical Studies**

After a fair idea had been obtained of the data in terms of the statistical parameters mentioned earlier, the presence of anomalies that could affect the accuracy of the estimation, and the selection of a suitable geostatistical method, the data could be assessed geostatistically.

# **Trend Analyses**

The distribution of minerals can exhibit very unusual behaviour. At times, there is a rapid increase or decrease in grade over a distance as one moves from one point to another. This behaviour of mineralization is known as trend or drift. Drift can take various forms: linear, quadratic, or cubic. Whatever the case may be, linear geostatistics cannot handle data with drift very well, although there are various ways in which such data can be handled. One of the solutions lies in the area of universal kriging. A test has to be conducted on the data and, if this drift exists, it must be removed before any meaningful geostatistical analyses can be done.

The mica data were analysed for possible trends (Figures 7 and 8, and Table 11), and it was found that the deposit does not show any strong trend. Therefore, the removal of trend, which was considered to be negligible, was not required.

#### **Anisotropism**

There was no reason to expect that the mineralization would exhibit the same behaviour in every direction, i.e. that the mineralization would be isotropic. If anisotropy had existed, the estimation would have been based on the directional semivariogram. By the plotting of semivariograms in several directions, it would be possible to determine any anisotropism, which could be corrected for before the estimation. The mica data were tested for isotropism by the plotting of all the directional semivariograms, based on the indicator values, superimposed on one graph. This composite semivariogram is shown in Figure 12. No structural anisotropy could be detected.

### **Indicator Kriging**

As noted earlier, the complexity of the data required a treatment of multiple-nested indicator kriging (IK), in which the values below a cut-off are removed each time a higher cut-off is applied. The technique is robust in the sense that the estimate does not depend on the actual grade values but on their position relative to the cut-off. The steps involved are highlighted in various papers<sup>5 6</sup> and are therefore not discussed here in detail. In brief, the process consists in the following:

- construction of a histogram/probability plot
- selection of a cut-off grade, preferably where the curve has a sharp turn
- transformation of the data into 0 and 1 values for every cut-off grade selected (1 if they are below the cut-off, and 0 otherwise)
- development and modelling of the indicator variogram separately for every cut-off
- performance of ordinary kriging of the transformed values (0, 1) for each cut-off
- calculation of the mean.

In the study described here, the indicator cut-off values were taken as  $C_1 = 10$  and  $C_2 = 25$ . This was after the application of the rule-of-thumb method in which indicators are chosen so that the data retained are not less than three times the number of cut-off grades selected<sup>7</sup>, as well as the use of the point on the probability plot where there is a distinct turn on the graph. The Geostokos Toolkit also makes it possible to experiment with different cut-off grades to find one that gives a set of useful, easy-to-model semivariograms.

## **Indicator Semivariogram**

As already mentioned, the semivariogram is an essential tool in any geostatistical analysis. It provides a graphical and numerical measure of the continuity of mineral values within a deposit. The mica data were used in the calculation and modelling of an indicator semivariogram for two cutoff grades (Figures 9 to 11). Table III shows the sill, range of influence, and nugget effect of the various indicator semivariograms. These semivariograms were calculated and fitted for the north-south and east-west directions. This composite variogram is shown in Figure 12. The overall mineralization present is isotropic. Table III shows the indicator semivariogram parameters for all the cut-offs, and the lognormal semivariogram for the data above 25% vermiculite.

#### **Cross Validation**

The semivariogram parameters were established and confirmed by cross validation. The Z statistic has a mean of 0.0223 and a standard deviation of 0.9752 for the case of C = 25, and -0.005 and 1.4977 for C = 10. Although various researchers rely on the values of cross validation as a confirmation of good models and fit, Clark<sup>8</sup> has shown that this is not confirmatory enough since wrong models have also been proved to have cross-validation statistics of 0 and 1. In indicator kriging, this confirmation is even poorer and more subjective because the values dealt with are one and zero, and the Z statistics would definitely be expected to be around these values, whether the wrong model is used or not. In indicator kriging, therefore, cross validation has a very marginal use.

Following the cross validation of the global semivariogram, the semivariogram parameters that were used in the kriging were established (Table III). The nugget variance reflects the small variability of the grade being examined. The sill (continuity plus nugget variance) is roughly equivalent to the variance of the data set being examined, and the range reflects the distance beyond which the samples are not related to one another.

#### **Global Estimation**

The next stage was the estimation of the overall *in situ* material. As already noted from the scatterplot, the data were very clustered in specific locations and sparse in other areas. Kriging was used in the estimation of all the values. This technique produces a weighted-average estimator, which automatically de-clusters the data to produce an optimal predictor.

The indicator semivariogram parameters were used in the kriging of the whole deposit to give the probabilities of the deposit being mineralized for each indicator value. Ordinary kriging was used for the (10 to 25)% mica. A constant value was allocated for the host rock. Lognormal kriging was used for the values above 25% mica. Table IV gives the probabilities and the error associated with the deposit in each cut-off value.

For the values given in Table IV, the mean from lognormal kriging was calculated from the following formula:

$$e^{g^*+0.5\sigma_k^2-\lambda}$$
,

where  $g^* = \text{mean of the log data}$ 

 $\sigma_{k^2}$  = kriging variance

 $\lambda$  = Lagrange multiplier.

This was done by means of a back transform. The overall mean is given by

$$g = (1 - P_1^*)g_{\text{host}}^* + P_1^*(1 - P_2^*)g_{\text{medium}}^* + P_1^*P_2^*g_{\text{high}}^*,$$

where  $P_I^*$  and  $P_2^*$  are the probabilities of being mineralized in the three indicator cut-off cases, and  $g_{host}^*$ ,  $g_{medium}^*$ , and  $g_{high}^*$  are the mean grades of the various cut-off conditions (host, medium, and high values), which by substitution gives 70.23% mica. It should be noted that, owing to the confidentiality of the values, they have all been multiplied by a certain factor.

#### **Block Estimation**

The next step in the estimation involved the determination of the kriged estimates and kriging standard deviation for vermiculite within each chosen block. The block size chosen in a mine depends on many factors, including the type of deposit, mining methods, the equipment and, above all, the selectivity of mining that is required. The sparsely distributed sampling data did not allow very small blocks to be kriged. The sizes of the blocks therefore depended on the sampling density and the ranges of influence. Any attempt to estimate small blocks from widely spaced sample data proved disappointing. After a number of iterations and a consideration of the kriging variance for various block sizes, a block size of 50 m x 50 m was chosen for kriging.

The kriged estimates (the percentage vermiculite in each block and its associated standard error) were written in a mineral inventory file, which for each block contained the coordinates of the centre of the block, followed by the mean mica content (as a percentage) and the standard error of the estimation.

It must be stated once again that the nature of the data (historical), the sampling method (randomly taken), the sample support (variable), and the grid interval (relatively sparse and definitely concentrated in the rich area) as revealed by the scattergram may not give very accurate results for small-block estimates like these, especially for blocks that are very far from the sampled location. (It should be noted that the search radius was 650 m.) It is therefore suggested that drill-hole samples taken during mining should be monitored, and that the ore grade and quality should be controlled both by a visual evaluation of blasthole chippings and by laboratory assays on a daily basis so that the vermiculite grade in individual blocks can be updated.

# **Optimum Drilling Grid**

Increasing exploration cost-, and the need to reduce the time frame from exploration to production demand formalized procedures in exploration planning and reserve analyses. The exploration planning would involve the selection of the most cost-effective drilling and sampling programme, and flagging of the needs for data of greater relevance and reliability. Every mineral deposit has an optimum drilling grid, being the configuration that will yield the maximum amount of information for the minimum cost of drilling, The method devised and applied in the present study involved the plotting of the standard deviation of the global mean against the number and pattern of drill-holes in a given area. The estimation used the weighted-distance method since data were not available for variograms, and hence kriging, and the error incurred in every pattern and drill-hole was configuration noted. The estimation/variance criteria are independent of the data values, and hence do not affect the results irrespective of the estimation method applied. As the number of holes drilled are reduced, resulting in a wider pattern, the error incurred increases gradually to a point where the error can no longer be allowed to prevail in the estimation. This technique was presented in a graphical form (Figure 13.)

The various drilling patterns were used in the calculation of the vermiculite values in a 175 m x 175 m area, and the variance of the estimation is given in Table V. From the graph of estimation variance against the number of holes, hence grid interval (Figure 13), it can be seen

that little improvement on the precision of the mean would result from the drilling of the entire deposit on a regular 25 m grid, even though this would involve the drilling of additional holes. As the grid distance increases, the error incurred also increases to the point of a 50 m grid, where an increase in the grid has an appreciable effect on the error incurred. It would seem economically sensible, then, for the maximum drilling pattern to be between 40 and 50 m but not exceeding 50 m. This result is not surprising since the grid interval actually falls far within the range of influence of the deposit. Moreover, since the variograms (deposit) were considered to be isotropic, a square grid would be a logical choice.

#### **Block Sizes for Effective Selective Mining**

After an idea had been gained of the optimum drilling grid, it was necessary to find the smallest mining block that can be mined at a time to achieve the high degree of selectivity required. The rule-of-thumb is that the smallest mining block should be a quarter of the optimum drilling grid. A block size of 10 to 15 m square should therefore be considered during mining.

Once again, this finding should not be used in isolation. Some part of the orebody has a very erratic distribution (revealed by the initial statistical analyses), which would demand the mining of smaller blocks. Other areas have a fairly constant distribution, which would demand larger blocks. The recommendation is that blasthole chippings should be constantly assayed for the quality and grade of vermiculite so that, after blasting, areas of similar quality and grade are delineated for mucking and loading separately. In fact, the nature of the deposit dictates that a more bulky style of mining would not be at all suitable.

#### **Coarseness and Size Fraction of Vermiculite**

The average percentage grade of the various sizes of vermiculite (plus 3 to plus 35 mesh) was used in the calculation of the percentage of each size fraction in the deposit. Table VI shows the size fraction, average grade, and coarseness of the vermiculite.

#### **Conclusions**

In conclusion, the initial problems and questions that gave birth to the project described are reiterated.

- What is the maximum drilling pattern?
- What is the overall average grade?
- What about block estimates?
- What is the size fraction of the vermiculite?
- What size of mining block will give the required degree of selectivity?
- Is the dataset reliable enough for block estimates?

The geostatistical technique applied was able to supply answers to RTZ management for use in their economic and financial analyses and mining operations.

The vermiculite deposit at Palabora Mining Company has three different populations, which merge into one another. Geological anomalies like different degrees of oxidation and different phases of mineralization are responsible for the complex nature of the mixed population. Based on this finding, it is recommended that the geologist at the mine should delineate the deposit geologically before any advance work is done. The global mean of the deposit was found, by multiple-nested indicator kriging, to be 70.23% mica, with a 90% confidence level of 1 02

The optimum drilling pattern for exploration was found to be between 40 and 50 m, and 45 m is recommended. Because the deposit is isotropic, a square grid is recommended.

A calculation of the percentage size grade showed that the greatest percentage (26.8%) of vermiculite has a size of more than 35 mesh, while only 12.6% of the vermiculite found in the deposit has a size of less than 3 mesh.

A block estimate of 50 in x 50 in error was obtained, but the drilling grid used for the data collection was relatively sparse, and the block estimate may therefore not be accurate. This may provide a gross margin of potential error in the estimation.

The largest mining block that can be mined to give highly selective mining was found to be 15 in square, but the use of this block size in mining must not be too rigid. The ore grade and quality in each block should be controlled by a combination of visual evaluation and laboratory assay of blasthole chippings.

The data available were not very satisfactory in meeting the challenges of accurate estimation, especially in the block estimations. The sampling intervals were too sparse. Infilling drilling is recommended if meaningful block estimation is to be made. It must be noted that, when a highly selective mining operation is planned, the estimation *of in situ* geological resources is of little help. The challenge is the estimation, at an early exploration stage, of the mineable ore reserve, which, for this vermiculite deposit, has been done successfully. Owing to the paucity of the available data, the estimation techniques applied (kriging) did not perform reasonably well in providing accurate estimates of the grade of small selective mining units from the early, widely-spaced data. Only block sizes as small as 50 in x 50 in could be estimated.

It is recommended that mining should be strictly controlled on an hour-to-hour basis, blasthole-sample values being used to update the grade of each block. Blasting should be mildjust to shake the deposit-so that the pile of broken ore is subdivided into loading 'blocks' based on similarities in grade and quality that can be loaded separately one from another to avoid waste contamination. Because of the nature of the ore distribution, bulk mining is not recommended.

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#### References

- 1. SCHOEMAN, J.J. Mica and vermiculite in South Africa. J. S. Afr. Inst. Min. Metall., vol. 89, no 1. 1989.pp.24-35.
- 2. JOURNEL, A.G., and HUIJBREGTS, C.J. *Mining geostatistics*. London, Academic Press, 1978. chap. 6, pp.481-482.
- 3. CLARK, I., and GARNETT, R.H.T. Identification of multiple mineralization phases by statistical methods. *Trans. Instn Min. Metall. (Sect. A Min. Ind.)*, vol. 83. 1974. pp. A43-A52.
- 4. DEUTSCH, C. Mineral inventory estimation in vein type gold deposit: case study on the Eastmain deposit. *CIM Bulletin*, vol. 82, no. 930. 1989. pp. 62-67.
- 5. CHAOUAI, N.E., and FYTAS, K. A sensitivity analysis of search distance and number of samples in indicator kriging. *CIM Bulletin*, vol. 84, no. 948. 1991.pp.37-43.
- 6. FYTAS, K., CHAOUAI, N.E., and LAVIGNE, M. Gold deposit estimation using indicator kriging. *CIM Bulletin*, vol. 83, no. 934. 1990. pp. 77-83.
- 7. JOURNEL, A.G. The lognormal approach to predicting local distribution of selective mining unit grades. Advances in mathematical geology. *J. Int. Assoc. Math. Geol.*, vol. 12, no. 4. 1980. pp. 283-303.
- 8. CLARK, I. The art of cross validation in geostatistical application. *Proc. 19th APCOM symposium, 1986.* 212 pp.

## **Tables**

# Table I Statistical parameters of the mica data

Number of samples (n)	366
Maximum value $(X_{max})$	76
Minimum value $(X_{\min})$	0.35
Sample mean, g	22.16
Sample variance (s <sup>2</sup> )	280.64
Standard deviation (s)	16.75
Coefficient of variation (cv)	0.76
Chi squared (X <sup>2</sup> )	234.24
Degrees of freedom (v)	62

#### Table II Analyses of variance

	lution of linear equation is:							
VA	ALUE = 0.37524E+0.2	+	-0.12990-01 X	+	0.93117E-02 Y			
So	lution of quadratic equation is	s:						
VA	LUE = -0.36456E+03	+	+ 0.16772+00 X		0.12355+00 Y			
	+ -0.39309E-04 X <sup>2</sup>	+	0.23288E-04 XY	+	-0.38125E-04 Y <sup>2</sup>			
So	lution of cubic equation is:							
VA	LUE = -0.17924E+05	+	0.17100E+02 X	+	0.19169E+01 Y			
	+ -0.71102E-02 X <sup>2</sup>	+	0.30384E-02 XY	+	-0.26136E-02 Y <sup>2</sup>			
	+ 0.10569E-05 X <sup>3</sup>	+	0.16351E-06 Y <sup>3</sup>	+	-0.92384E-06 X2Y			
	+ 0.48377E-06 X	Y <sup>2</sup>						
Source	Sum of squares		d.f.	N	Mean square	F-ratio		
Linear residual	6702.83		2	3351.41		12.66		
	95024.19		359		264.69			
Quadratic	30243.47		5		6048.69	30.12		
difference	23540.64		3		7846.88	39.08		
residual	71483.55		356		200.8			
Cubic	74479.34		9		9		8275.48	106.91
difference	44235.88		4		11058.97	142.87		
residual	27247.67		352		77.41			

Percentage of total sum of squares: Linear component = 6.59 Quadratic component = 29.73 Cubic component = 73.21

Table III Indicator semivariogram parameters

Indicator cut-off value	Semi- variogram model	Nugget effect	Sill	Range of influence
10	Spherical	0.04	0.24	750
25	Spherical	0.14	0.16	650
Values above 25%	Spherical	0.06	0.01	300
(log-normal kriging)				

Table IV
Kriging probabilities

Indicator cut-off	Total no. of samples	Average	Probabilities	Error of probabilities
10	357	4.67	0.745	0.38
25	250	16.67	0.57	0.32
>25	139	40.21	Log mean 3.6	Log variance 0.12

Table V
Grid distance and estimation variance

Grid distance	Number of holes	Estimation variance		
25	64	6.20		
50	25	7.10		
75	16	8.36		
100	9	10.88		
125	4	16.70		

Table VI Percentage size fraction of vermiculite

Parameter	Size fraction, mesh no.					
	Plus 3	Plus 6	Plus 10	Plus 20	Plus 35	Total mica
Aperture, µm Average grade, % Coarseness, %	4750 2.7 12.6	2800 3.4 15.6	1700 4.4 20.1	710 5.4 24.9	425 5.9 26.8	21.9 100

# **Figures**

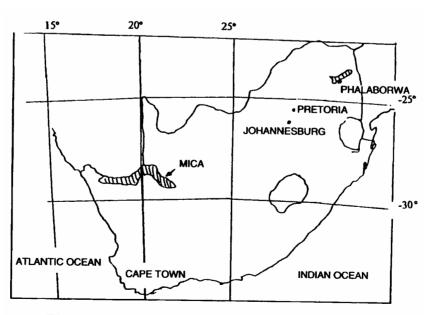


Figure 1. Location of the Palabora Mining Company at Phalaborwa

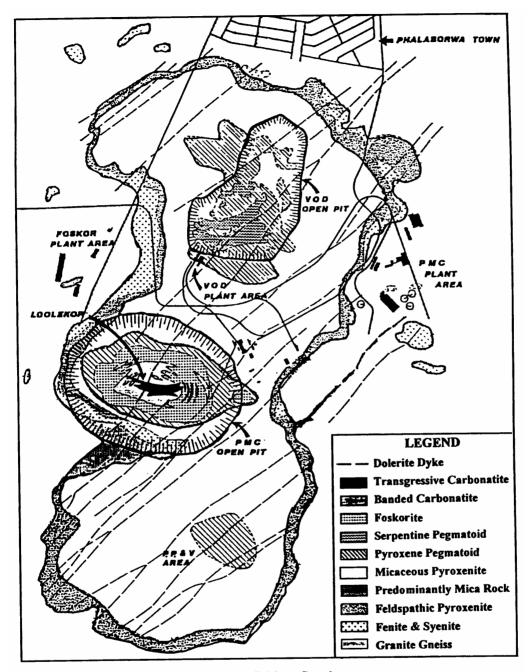


Figure 2. The Palabora Complex

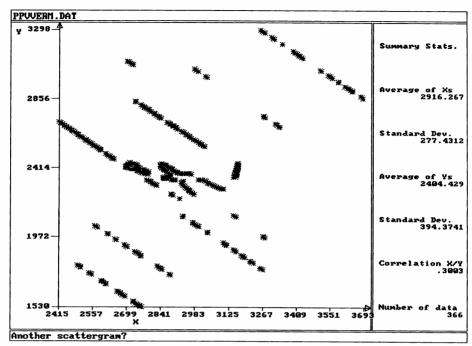


Figure 3. Scattergram for vermiculite

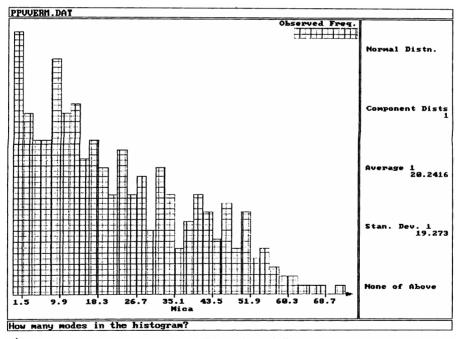


Figure 4. Histogram for vermiculite

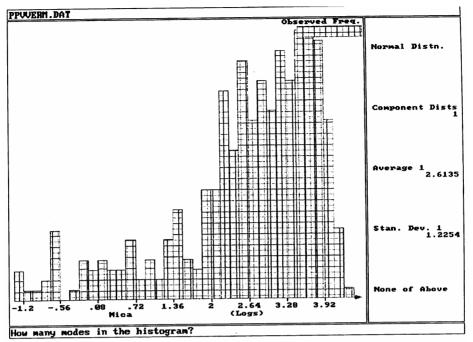


Figure 5. Histogram for vermiculite (logarithms)

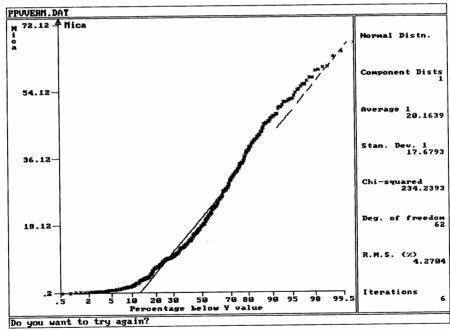


Figure 6. Probability plot for vermiculite

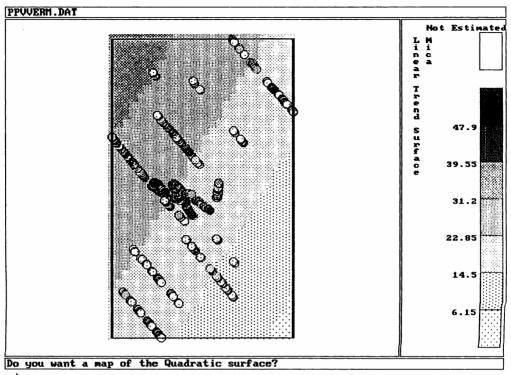


Figure 7. Linear trend surface

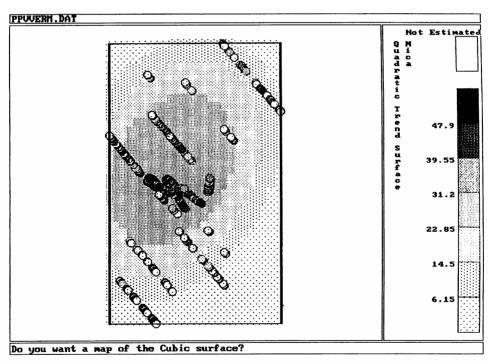


Figure 8. Quadratic trend surface

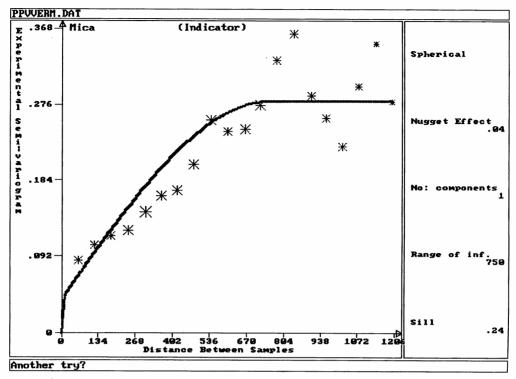


Figure 9. Indicator variogram, C = 10

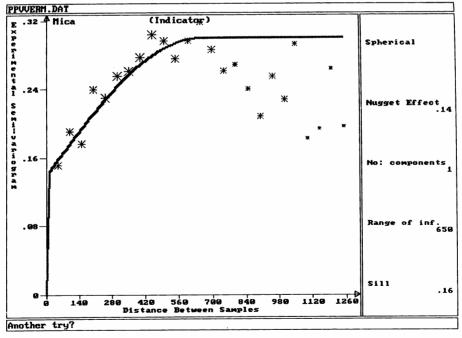


Figure 10. Indicator variogram, C = 25

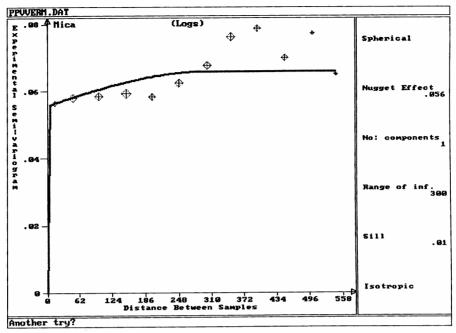


Figure 11. Variograms of logarithms

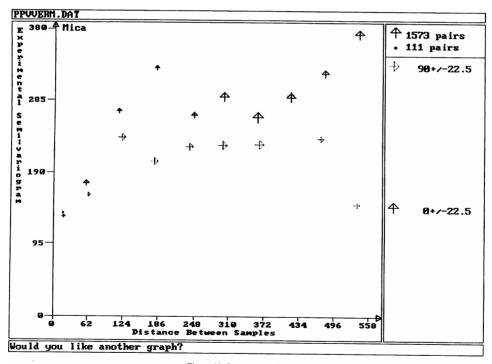


Figure 12. Composite variogram

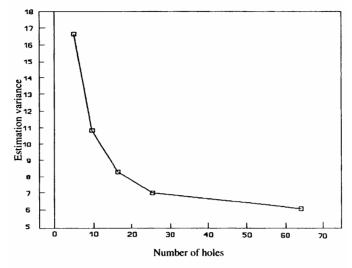


Figure 13. Graph of estimation variance against number of drill-holes