# ASSESSMENT OF RMR AND ITS UNCERTAINTY BY USING GEOSTATISTICAL SIMULATION IN A MINING PROJECT

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## ABSTRACT

Geostatistical methods have been available for a long time, but have found little application in engineering geology. This paper aims to show the advantages of applying geostatistics in the assessment of geotechnical variables of engineering projects. When compared with standard techniques, such as the inverse distance weighting or averaging of sample data, geostatistics gives a more precise estimation and provides a measurement of the uncertainty in the estimation. The latter may be used during the risk analysis of the projects. For a correct application of geostatistical estimation and simulation techniques, we review the particular features of some geotechnical variables that should be considered. This includes (1) non-linearity, (2) directional behaviour and (3) mixing of multiple populations. To neglect these characteristics may lead to significant errors, not only in geostatistics, also in other techniques normally used in the industry. A methodology is proposed for applying geostatistical techniques to model rock mass quality by using the Rock Mass Rating (RMR), which is a parameter widely used in engineering projects. The methodology is applied to Chuquicamata Underground Project in Northern Chile, which is one of the largest underground mining projects in the world. This project aims to extend the life of the open pit currently in production. Results are compared with the current approach, which consists in defining geotechnical units and averaging the available information within large volumes. The proposed methodology shows a significant improvement in the quality of the local estimation. The results are statistically validated by using a jack-knife technique.

*Key words:* Rock mechanics, geostatistics, rock mass classification, rock mass rating.

## 1. INTRODUCTION

The geotechnical characterization of the rock mass is one of the most relevant aspects for the success of projects in the mining, hydropower and tunnelling industries, among many others. Due to this, a significant investment is placed for data acquisition during the phase of ground investigation. An equivalent effort should be done to manipulate and interpret the data obtained.

In order to study a rock, it is important to distinguish between intact rock and rock mass properties. Intact rock is defined as the rock material found between discontinuities. The rock mass, on the other hand, comprises the total volume of rock, including intact rock and discontinuities, and its mechanical behaviour can be significantly different than that of the intact samples.

Some of the most relevant intact rock properties for an engineering project are density, permeability, rheological behaviour and uniaxial compressive strength (UCS). On the other hand, in order to describe a rock mass, it is also necessary to characterize its discontinuities. This includes the roughness, filling quality and weathering in the discontinuity walls, among others.

In practice, rock mass properties are summarized using a rock mass classification (RMC) scheme (Holland and Lorig 1997; Brown 2003). In addition, since RMC methods are used in engineering projects, they usually consider other parameters such as stress field and water conditions. In large scale projects, the most commonly used schemes are:

1. Rock Mass Rating (RMR) (Bieniawski 1973; 1976; 1989);

2. Mining Rock Mass Rating (MRMR) (Laubscher 1977; 1990);

3. Geological Strength Index (GSI) (Hoek 1994).

In this paper we shall focus our analysis on the RMR. This system consists in a weighted sum of ratings assigned to each of the following parameters: Rock Quality Designation (RQD), Fracture Frequency (FF), Uniaxial Compressive Strength (UCS), Joint Condition (JC) and Underground Water Condition (WC). We will exemplify a methodology to characterize the rock mass behaviour and its uncertainty using geostatistical techniques with this classification scheme. The notions presented are general and could be easily extended to other classification schemes.

The use of geostatistics to model geotechnical variables is uncommon, although some attempts have been made, mainly considering the use of kriging techniques for the estimation of spatially distributed variables. Van de Wall and Ajalu (1997) used block kriging to estimate average values of an indicator of rock strength, namely the hardness, to define the proper sampling strategy in a quarry of construction material. Castaing *et al.*, (1997) used geostatistics to characterize the distribution of fractures in a network to understand the spatial distribution at different scales. Archambault *et al.*, (1997) characterized the asperity of joint surfaces through geostatistical analysis. Gentier *et al.*,

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(2000) studied the relationship between fracture geometry and the damage caused by shear stress. More recently, Ayalew and others (2002) used ordinary kriging to estimate the RQD distribution, associating the estimation standard error as a measure of reliability.

When considering classification of rock masses, only few applications can be found in the literature aiming at the estimation of RMR (You and Barnes 1997; Exadaktylos and Stavropoulou 2008). However, they use a direct estimation of the RMR value through non parametric techniques (indicator kriging) or directly by ordinary kriging. Indicator techniques may be cumbersome to apply, and do not provide a single estimate, but rather, a distribution, thus deciding what to do with the result may not be simple for practitioners. On the other hand, the direct use of ordinary kriging to estimate RMR does not account for the non-linearity of this parameter, and may carry important estimation errors.

One of the most relevant issues with variables whose values change in space is that these variables must be additive if block kriging is to be used for their estimation. In order to illustrate the concept of additive and non-additive variables, let us check the example of pH. This variable corresponds to the logarithm of the concentration of $H^+$ ions. Since pH is non-additive, the average of pH values is different than the logarithm of the average concentration of $H^+$ ions, Eq. (1). The latter is the correct approach, because the arithmetic mean ($< \cdot >$) has to be calculated over an additive variable, in this case the number of $H^+$ ions.

$$< pH > = \left\langle Log(H^+) \right\rangle \neq Log < H^+ > \tag{1}$$

RMR, being a sum of ratings assigned non linearly to several geotechnical parameters, has a similar behaviour than pH. Thus, RMR is not an additive variable, hence it should not be directly estimated by using geostatistical tools. The correct approach to spatial prediction in this case, would be the following:

1. To estimate or simulate each of its parameters (RQD, FF, UCS, JC and WC), which are linear variables.
2. To assign a rating to the estimated or simulated value of each parameter.
3. To obtain the final rating, RMR, as the sum of the ratings obtained in step 2.

Instead of using geostatistical methods, it is usual in the industry to divide the rock mass in different geotechnical units and assign constant values to the geotechnical parameters inside each unit. A geotechnical unit aim to represent a volume with similar geotechnical behaviour of the rock mass. The geotechnical properties inside each unit are commonly assigned by averaging the values obtained during the ground investigation phase. For instance, the average of the UCS tests of all samples located in a given unit, or the average of all the RMR values mapped or estimated in the unit. This corresponds to the zoning and averaging method.

This paper is organized as follows: We start with a review of some important geostatistical concepts to back up our proposed modelling approach. Then the nature of the geotechnical variables is discussed and a methodology is proposed. The methodology is implemented in a real case study, Chuquicamata Underground Project. Also the zoning and averaging method is applied to the same database. The results obtained by both methods are quantitatively compared in order to measure the benefits of using geostatistics. The results are statistically validated by using jack-knife technique. Jack-knife consists in splitting the database in two sets and then using one set to interpolate the values at the locations of the data samples from the other set. Thus, the estimated values can be compared with the real values in order to assess the quality of the estimation.

## 2. THE GEOSTATISTICAL APPROACH

### 2.1 The Geostatistical Framework

Geostatistics was originated to solve prediction problems in gold mines in South Africa (Krige 1952). The apparent random, yet structured behaviour of gold grades triggered the formulation of a probabilistic approach, where the grade value at an unsampled location, $z(\mathbf{u})$, is related to a random variable, $Z(\mathbf{u})$, characterized by a probability distribution. The structured behaviour is accounted for by relating random variables at different locations by means of a random function, $\{Z(\mathbf{u}),\ \mathbf{u} \in D\}$. This random function is characterized by its statistical moments which must be inferred from the available data, that is, the values gathered at sample locations, $\{z(\mathbf{u}_\alpha),\ \alpha = 1, \ldots, n\}$.

The spatial distribution of actual values of the variable within the domain is interpreted as a realization of this random function. The geostatistical paradigm consists on estimating the expected value of the random variables at every location to obtain a map suitable for local optimum prediction or constructing other realizations of the random function to characterize the uncertainty associated to unsampled locations, preserving the spatial relationships between locations. This is achieved through the estimation and simulation techniques that are discussed in the following paragraphs.

### 2.2 Geostatistical Estimation

Estimation is done by considering a linear estimator that depends on the surrounding information available. In geostatistics, this estimator is called kriging and is the best linear unbiased estimator (Journel and Huijbregts 1978; Isaaks and Srivastava 1989). The construction of the kriging estimator is done by successively imposing these features (linearity, unbiasedness, optimality). Variations of the estimate are achieved by imposing a known or unknown mean, and allowing local variations of it (Goovaerts 1997). Kriging is the best estimator in the least squares sense, that is, it imposes the minimization of the error variance. The simple kriging estimate assumes the mean known and constant:

$$Z^*_{SK}(\mathbf{u}_0) = \sum_{\alpha=1}^{n} \lambda_\alpha\, Z(\mathbf{u}_\alpha) + \left(1 - \sum_{\alpha=1}^{n} \lambda_\alpha\right) m \tag{2}$$

The estimation variance results in:

$$\sigma^2_{SK}(\mathbf{u}_0) = \sigma^2_Z - \sum_{\alpha=1}^{n} \lambda_\alpha\, C(\mathbf{u}_\alpha, \mathbf{u}_0) \tag{3}$$

where $\sigma^2_Z$ is the variance of the population, which is estimated from the sample data, $C(\mathbf{u}_\alpha, \mathbf{u}_0)$ is the covariance between the data located at $\mathbf{u}_\alpha$ and the location of interest $\mathbf{u}_0$, and $\lambda_\alpha$ are the optimum weights to minimize this error variance. This variance gives a basic measure of uncertainty of the estimated value. However, as seen in Eq. (3), it does not depend on the sample values themselves, but only on their locations. Therefore, the kriging variance measures the uncertainty at the estimation location due to the spatial configuration of the available data for its estimation rather than based on the dispersion of the values.

The kriging weights are obtained from solving the following linear system of equations, which arises from imposing the minimization of the error variance:

$$\sum_{\beta=1}^{n} \lambda_\beta\, C(\mathbf{u}_\alpha, \mathbf{u}_\beta) = C(\mathbf{u}_\alpha, \mathbf{u}_0) \qquad \forall \alpha = 1, ..., n \tag{4}$$

## 2.3 Geostatistical Simulation

Geostatistical estimation is at the heart of simulation methods. The idea of simulation is to provide alternate realizations of the random function, recalling that the actual values are interpreted as one possible realization of it. Therefore, each resulting realization performs like the actual deposit and can be used for risk assessment and uncertainty quantification. The main difference between estimation and simulation is that the former looks for the best local estimate, while the latter is concerned with reproducing the spatial characteristics that relate multiple locations.

There are several approaches to simulate a random function, most of them are based on a multigaussian assumption that relieves the inference of the probability distribution characterizing every location. Under this assumption, the random variable $Z(\mathbf{u})$ can be linked to a Gaussian shaped probability distribution, whose expected mean and variance are identified with the simple kriging mean and kriging variance (Eqs. (1) and (2)). Simulated values are directly drawn from this local distribution and the spatial correlation is imposed through a Bayesian framework, by sequentially conditioning the inference of the probability distribution at a given location on the previously simulated values at other locations (Journel 1974; Deutsch and Journel 1998). Since most variables are non-Gaussian, this approach is implemented after a transformation of the distribution into a standard Gaussian distribution. The application of this method requires the following steps:

1. First, distinct statistical and geotechnical populations should be defined in order to group data with similar characteristics into subsets, called geotechnical units. The analyses are done for each set separately. Each population should contain a large enough number of sample data in order to allow for statistical inference of the moments of the random function. Furthermore, each estimation unit should be spatially delimited to a specific volume, within which the estimation or simulation is performed.
2. For each estimation unit, the representative data distribution must be transformed into a standard Gaussian distribution. This may require correcting for non representative spatial sampling through declustering (Deutsch 1989).
3. The transformed variable should be checked to ensure that it does not violate the multigaussian assumption (Goovaerts 1997).
4. A three-dimensional variogram model of the continuity is required in each estimation unit. It is obtained by computing and fitting a model to the experimental variogram or covariance function of the transformed variable. Any anisotropic behaviour should be characterized at this stage.
5. Simulation proceeds by defining a grid and visiting the nodes in a random path for each estimation unit.
6. At every node simple kriging is done considering the informed nodes and data belonging to the same subset within a neighbourhood. A simulated value is generated from this distribution by Monte-Carlo drawing using a Gaussian distribution function with mean and variance as per the kriging result.
7. This new value is used as conditioning information in all subsequently visited nodes.
8. Once completed, the simulated values are back transformed to the original distribution within each estimation unit.

Multiple realizations can be generated by changing the random path and drawn values in each conditional distribution. Each realization provides a plausible image of the true distribution of the attribute. They can be used to assess the joint uncertainty (several points at a time) for a given process.

Realizations must be validated to ensure they reproduce the essential statistics of the data (histogram and variogram).

Other methods to simulate multigaussian random functions exist and could be used alternatively (see for example Chiles and Delfiner 1999).

Simulation trades off the local precision obtained in kriging to reproduce the spatial continuity of the variable. The distribution of simulated values at every unsampled location provides a measure of uncertainty and, contrary to the kriging variance, this uncertainty is data value dependent. This is highly convenient in most applications where some relationship is seen between variability and local mean.

The simulation output can be processed to infer the distribution of a given response to a process. For instance, the models could be used to estimate the expected rock support in the caverns and tunnels. Each realization will lead to different support requirements. Over a large number of realizations and given a decision about the acceptable risk, the support may be designed to ensure that in 90% of the cases, there is no risk of instability.

# 3. GEOTECHNICAL VARIABLES

The nature of geotechnical variables is usually neglected. In order to consider it, we will review some important variables, their nature and consequences in the modelling process.

Consider classification of the rock mass using the RMR methodology. The final rating at any location is given by a sum of ratings assigned to several parameters. The following corresponds to the RMR (1989):

(a) Uniaxial Compressive Strength (UCS) [0-15 points]: It is the maximum stress that a sample of intact rock can resist under uniaxial compression. Its value depends mainly on the nature and composition of the rock, but also on the porosity, degree of weathering, and water content.

(b) Discontinuity Spacing (DS) [5-20 points]: It is usually calculated as the inverse of the fracture frequency (FF), which measures the number of discontinuities per meter, including fractures, dykes, faults and others, obtained by geotechnical mapping. Higher values of DS imply less discontinuities, hence a better rock mass quality.

(c) Rock Quality Designation (RQD) [3-20 points]: It is the percentage of the drill core that is recovered in intact pieces longer than twice its diameter. A higher FF usually leads to a lower RQD. Some correlation should be expected between FF and RQD.

(d) Joint Condition (JC) [0-30 points]: Some discontinuities worsen the rock mass quality more than others, depending on properties such as the separation, persistence, surface roughness and alteration, and the filling material. JC summarizes these properties.

(e) Water Condition (WC) [0-15 points]: The presence of water under pressure in the joints of a rock mass reduces its strength and therefore must be considered when characterizing the rock mass.

This classification system allows categorizing the rock mass into five quality classes ranging from very good (RMR > 81) to very poor (RMR < 20).

Some of these variables are peculiar in the sense that they are non-additive or have a behaviour that depends on the direction in which they are measured.

As discussed previously, non-additive variables are those whose linear average lacks of physical sense (Howson 2004). Usually, this problem arises with variables that are a non linear function of other parameters. This is the case of the RMR which is the sum of several ratings non linearly assigned from others components: UCS, RQD, JC, FF and WC. However, each of these components is an additive variable and therefore, can be directly averaged and modeled with geostatistical techniques.

Variables with directional behavior can be exemplified by FF and RQD. Depending on the direction of the drillhole or the scanline survey, the fracture frequency and the RQD may probably change. Notice that this concept is different than geostatistical anisotropy. The same directional behaviour is valid for the other variables. Since RMR depends on each of these variables, it also has a directional behavior. Unfortunately, the information available in the geotechnical databases not always allows to consider this effect in the data interpretation.

Under the framework of the random functions, the data used for estimation and simulation should belong to a consistent statistical and geotechnical population. This allows pulling together data for statistical inference. Some geotechnical variables, especially those associated to discontinuities are the result of several phenomena intermingled: Joints produced by intrusion of a body are different than those produced by weathering; however, they both count equally when assessing FF. There is a mixing of populations that cannot be discerned. This translates into poor spatial correlation, but is unavoidable.

Most of these particularities of geotechnical data are not properly handled by standard methods such as zoning and averaging. This may lead to significant errors.

Finally, it is important to mention that there is a significant degree of subjectivity in the geotechnical characterization of specimens. This leads to unavoidable uncertainty, which should be considered in the decision making processes.

## 4. PROPOSED METHODOLOGY

The proposed approach to model geotechnical variables starts considering a separation of the entire domain into consistent geotechnical units, where the rock mass is expected to have a similar geotechnical behaviour.

Within each geotechnical unit, work is done independently. For the case of RMR, the variables to be modelled are: Uniaxial Compressive Strength (UCS), Fracture Frequency (FF), Rock Quality Designation (RQD), Joint Condition (JC) and Water Condition (WC).

The necessary steps are:

1. Data preparation: Consists in preparing the database for the subsequent analysis. Data has to be divided and grouped for each geotechnical unit. Additionally, for each geotechnical unit the database is split into two subsets. On one hand, 80% of the data (first subset) are kept as the modelling subset, while the additional 20% (second subset), which has been randomly selected, is taken aside for a posterior validation, through jack-knife. The relation 80% / 20% is subjective, although commonly used in the industry. Other relations could be used as long as the number of estimated vs. actual values is considered meaningful for validation purposes.
2. Exploratory data analysis: Basic statistics and displays are prepared for each variable within each geotechnical unit. This allows checking the consistency in the definition of geotechnical units and verifying the presence of trends in the variables. Since geostatistical simulation is to be used in the next step, declustering to correct for spatial bias and normal score transformation of the representative distribution of each variable is done for every unit.
3. Variogram analysis: The spatial correlation of each variable within the geological units is assessed by calculating experimental variograms in different directions. If the correlation shows a consistent behaviour in all directions, an omnidirectional variogram is calculated and modelled with licit nested structures.
4. Simulation: Each variable is simulated over a lattice of points using sequential Gaussian simulation (Deutsch 1998; Goovaerts 1997). The simulated realizations are conditioned to the available sample data. They reproduce the spatial continuity and the histogram of each variable within the geotechnical units. Thus, the maps generated have a spatial correlation between the points that mimic the correlation found in the samples. The pool of realizations provides a range of plausible distributions of the actual values within the domain, and can be used for uncertainty quantification and risk assessment.
5. Validation of the simulated results: The resulting realizations are checked to ensure that, on average, the reproduction of the histogram and variogram are adequate. Additionally, the realizations must honour the sample data values at their locations.
6. Post processing: This is possibly one of the most important aspects of the methodology. Since RMR is a sum of ratings associated non linearly to the actual geotechnical attributes measured in rock specimens at a limited number of locations, the uncertainty assessment must be done similarly, that is, at every point of the lattice, the rating associated to the simulated value of each attribute must be calculated. Each reali-

zation of the RMR is computed by assigning a rating to each one of the simulated values of each variable at every location. This can be repeated for all realizations. To obtain an estimated model of RMR, the simulated RMR values obtained before are averaged to obtain the estimated RMR value over the grid of points.

7. Comparison of results: Since 20% of the samples points were left aside for validation, and at each one of these points an estimated value has been obtained based on the 80% of remaining samples, a statistical comparison is done by computing the relative error (RE), which is the absolute error divided by the average value of the variable

## 5. CASE STUDY

The methodology is applied to the data of Chuquicamata Underground project. This project provides the continuity to the production of the open pit that has been in operation for almost a century.

Chuquicamata, from Codelco Chile, the Chilean government-owned mining company, is located in northern Chile and has extracted over 2,530 million tons of ore with a mean grade of 1.53% Cropper (Cu), since 1915. The open pit is expected to end its production in 2018, with a final depth of over a thousand meters. Over 2,600 millions tons of resources with a mean grade of 0.83% Cu are still available under the pit, some of which will be recovered by caving methods at a rate of 140,000 tons per day.

Caving methods take advantage of gravity to break the rock mass and move the rock towards the haulage system. It is important to characterize the rock mass properties in order to predict the expected infrastructure stability — which includes more than 1000 km of tunnels — ore subsidence and final granulometry of the ore fragments. A poor prediction of the rock mass performance translates into raising costs during operation due to contingencies that will have to be addressed to ensure a continuous production.

The case study considers 3 geotechnical units, mainly defined by the alteration degree of the rock mass, which was assessed by looking at the mineralogical proportion of alteration mineral species. The units used are:

1. PEK: East Potassic Porphyry, which means a potasic porphyry located at the east side of the mine.
2. Q > S + PES: East Sericitic Porphyry + Quartz more abundant than Sericite, which means the union of two bodies, PES (*i.e.* a sericitic porphyry located at the East side of the mine) plus the area where the quartz is more abundant than the sericite.
3. Q < S: Quartz less abundant than Sericite, which means more sericite than quartz, i.e. highly altered zone.

All the geotechnical variables available for each unit were estimated in the field by following the criteria given Bienawsky (1989). For the RMR calculation, the DS values were calculated as the inverse of the FF values. As an example of the data distribution, Fig. 1 shows the JC values in each one of the geotechnical units. The data was divided according to each unit and split randomly into two subsets, 80% and 20% as described in Step 1 of the methodology. Then the exploratory analysis was carried out (Step 2) for each unit, basic statistics of the complete dataset (Table 1), graphical displays and maps are computed to ensure the data consistency. It is important to highlight that the statistics of both sets, 20% and 80%, in this case shown to be the same. The analysis continues with the quantification of the spatial correlation, through the computation of experimental variograms on the normally transformed variables and subsequent fitting of licit

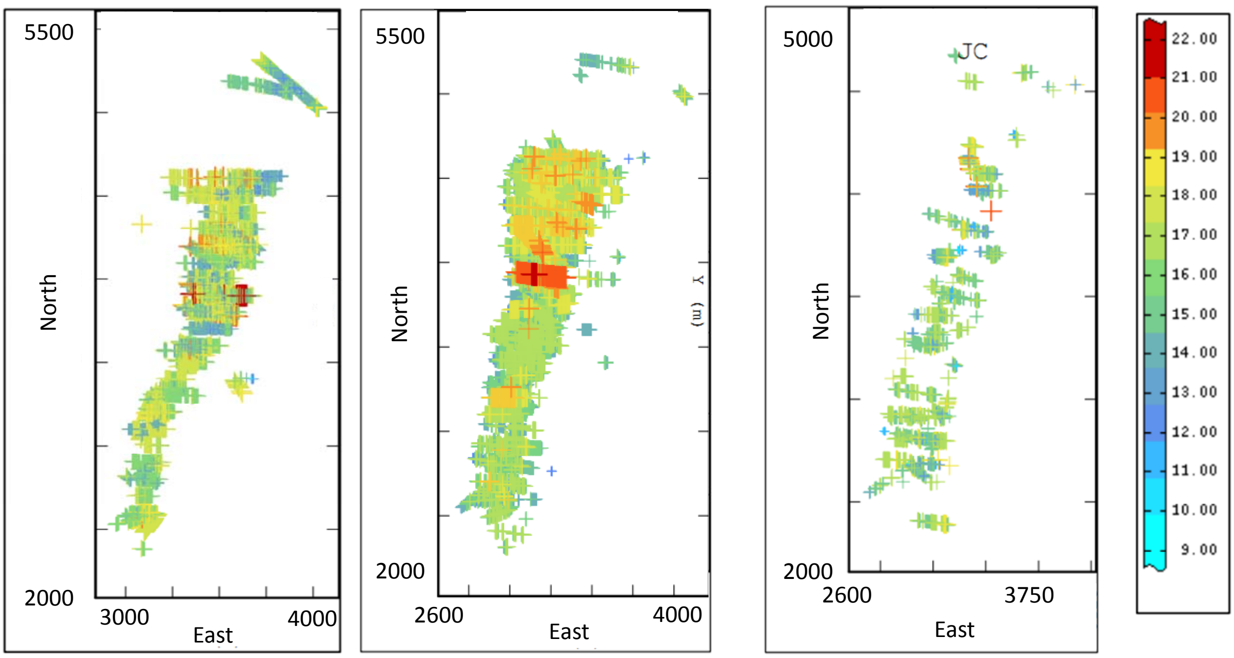


Fig. 1 Plan view of the JC samples available for each geotechnical unit: PEK (left), Q > S + PES (centre) and Q < S (right)

**Table 1 Basic statistics of the modelling variables, for each geotechnical unit and global statistics**

| | | | Variable | | | | |
|---|---|---|---|---|---|---|---|
| | | | UCS (MPa) | FF | RQD (%) | JC | RMR |
| Geotechnical Unit | Q < S | Number of samples | 3293 | 3270 | 3236 | 3250 | 802 |
| | | Mean | 61 | 7 | 82 | 15 | 61 |
| | | Standard deviation | 35 | 10 | 25 | 2 | 9 |
| | Q > S + PES | Number of samples | 20031 | 19864 | 19921 | 19869 | 3913 |
| | | Mean | 91 | 3 | 94 | 16 | 69 |
| | | Standard deviation | 43 | 3 | 12 | 2 | 6 |
| | PEK | Number of samples | 12725 | 12609 | 12490 | 12479 | 2595 |
| | | Mean | 130 | 2 | 94 | 16 | 71 |
| | | Standard deviation | 42 | 3 | 10 | 2 | 6 |
| General | | Number of samples | 36049 | 35742 | 35647 | 35597 | 7310 |
| | | Mean | 104 | 3 | 93 | 16 | 69 |
| | | Standard deviation | 49 | 4 | 14 | 2 | 6 |

nested models (Step 3). These variograms characterize the spatial continuity of the variables, hence indicating the information quantity provided by the samples to estimate the parameters (mean and variance) of the local uncertainty distributions, from which the simulated values are drawn. As an example, Fig. 2 shows the computed variogram for RQD in the geotechnical unit Q > S + PES. As shown in the figure, there in the experimental variogram (left), there is an absence of anisotropy and then an omnidirectional variogram is calculated to fit an isotropic model (right), considering exponential variograms structures in addition to a nugget effect.

One hundred realizations of the four variables on the corresponding geotechnical units are generated using Gaussian simulation over a point grid with spacing of 25 × 25 × 25 m (Step 4). Figure 3 depicts one realization of the JC parameter. The models are combined to obtain the realizations over the entire domain.

RMR is calculated by adding the ratings of each variable, for each one of the realizations (Step 6). Due to the arid climate of the project area, WC is not expected to have a significant role in this project and for the purpose of this study is assumed to be zero. The expected RMR value can be computed as the average value over all 100 realizations. Other measures can characterize each location, such as the probability of exceeding a given rating, or the variance in the RMR value, which might suggest further data gathering to reduce the uncertainty. Figure 4 shows the results for the RMR in the geotechnical unit Q > S + PES, including estimated RMR, variance and the probability of exceeding a given number, in this case RMR > 70.

In order to demonstrate the value of the presented methodology, the expected RMR value inferred from the realizations, is compared at the locations of the validation samples left aside for this purpose (Step 7). These are also compared to the averaging commonly done for characterizing the geotechnical units. Results are presented in Table 2, in terms of relative errors. Differences are significant and justify the effort for improving the models for geotechnical characterization.

**Table 2 Relative errors for each method computed for the validation locations by jack-knife. The estimated value of each parameter is compared to the actual sample value**

| | | RQD | UCS | FF | JC | RMR |
|---|---|---|---|---|---|---|
| PEK | Geostatistical simulation | 5.2 | 4.4 | 47.5 | 3.4 | 0.61 |
| | Zoning and averaging | 6.7 | 26.7 | 71.1 | 10.5 | 6.90 |
| Q > S + PES | Geostatistical simulation | 5.9 | 8.7 | 47.4 | 3.6 | 0.67 |
| | Zoning and averaging | 7.7 | 34.1 | 68.0 | 10.3 | 6.74 |
| Q < S | Geostatistical simulation | 19.2 | 11.5 | 58.4 | 4.1 | 1.20 |
| | Zoning and averaging | 28.1 | 43.3 | 97.1 | 11.8 | 11.00 |

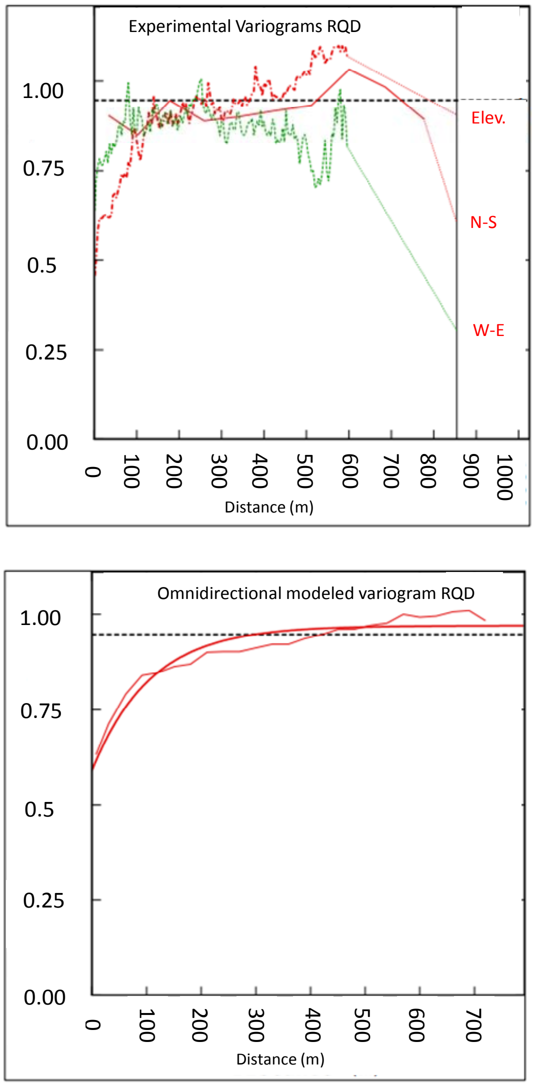


**Fig. 2 Variograms for the RQD in the geotechnical unit Q > S + PES. Experimental variogram (up) and omnidirectional variogram fitting an isotropic model (down)**

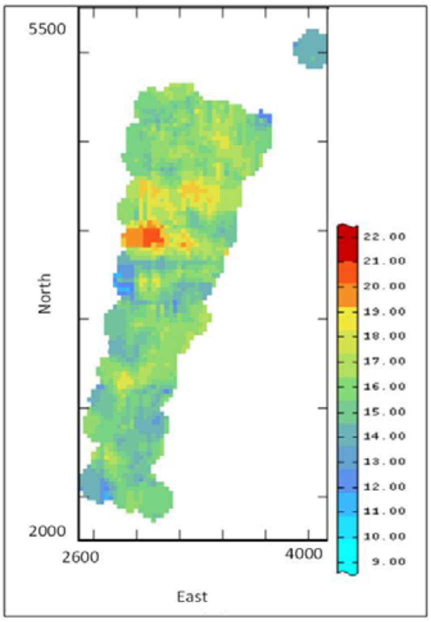


**Fig. 3 A plan view of one of the realizations of joint condition parameter**

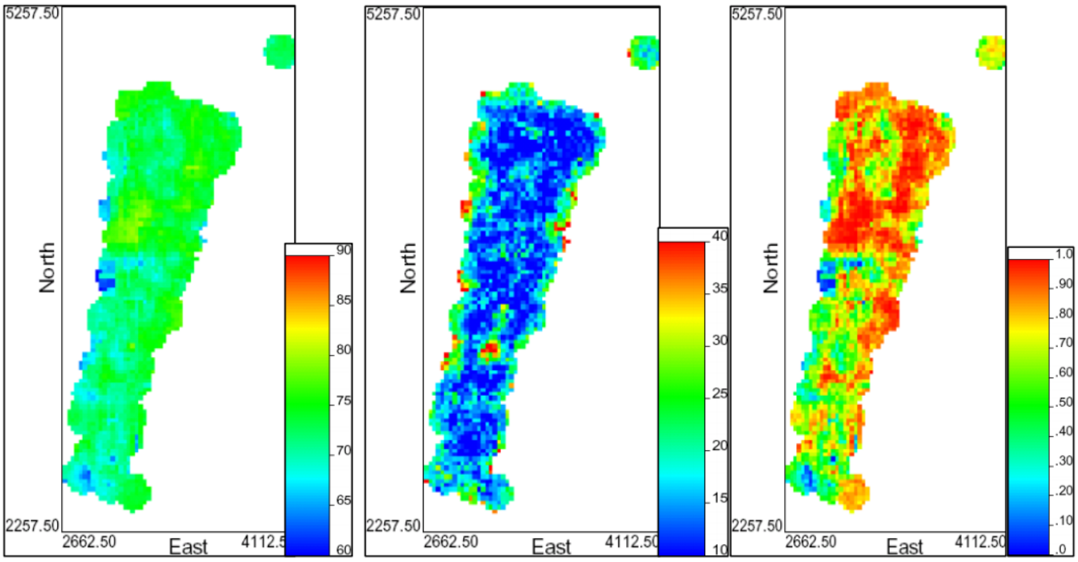


**Fig. 4 Plan view of the results for the geotechnical unit Q > S + PES. Estimated RMR (left), variance (centre) and probability of RMR > 70 (right)**

## 6. CONCLUSIONS

The geotechnical behaviour may significantly impact in the costs and performance of projects in the mining, hydropower and tunnelling industries, among others. Thus, the prediction of the geotechnical variables is one of the most relevant requirements of such kind of projects and an important effort should be done not just during the ground investigation phase, but also in the database processing and interpretation. In this stage it is important to consider the peculiarities of the geotechnical variables, which may include non-additive nature, directional behaviour and mixing of multiple statistical populations.

In this paper, we presented a methodology based on geostatistical techniques which provides an interesting alternative to more traditional approaches. The proposed approach considered the use of Gaussian simulation to characterize all variables involved in the calculation of RMR (rock mass rating) at a point support. At every location, the rating was calculated and the classification was obtained by adding the ratings associated to the different variables for each simulated model. The pool of RMR values obtained over multiple realizations provides a measure of the certainty of the classification and could be used for sampling network design, or simply, for risk analysis.

The proposed method outperformed the more frequently used approach of averaging all available data over a volume and assigning that value as a constant attribute to the entire geotechnical unit. Some of the advantages of the proposed approach are:

(a) It gives a more precise estimation (lower relative error) by taking into account and using the spatial continuity of the variables.

(b) Besides the estimation, the methodology provides a measure of the uncertainty. This can be used for risk analysis or for the design of site investigation plans.
(c) It provides a consistent, repeatable and auditable approach to construct a spatial model of rock mass quality for mine design purposes.

Overall, the proposed approach leads to a better model. In general, as data are more heterogeneous spatially, any local interpolation method done over restricted neighbourhoods will provide a better result than zoning into geotechnical units and averaging.

We publish this work in the hope of encouraging geotechnical engineers and geologist to explore geostatistics as an alternative to the techniques that are in use today.

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