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Geostatistical simulation to map the spatial heterogeneity of geomechanical parameters: A case study with rock mass rating

Marisa Pinheiro [a,*], Javier Vallejos [b,c], Tiago Miranda [a], Xavier Emery [b,c]

[a] ISISE, University of Minho, Azurém, 4800-058 Guimarães, Portugal
[b] Department of Mining Engineering, University of Chile, Avenida Tupper, 2069 Santiago, Chile
[c] Advanced Mining Technology Center, University of Chile, Avenida Beauchef, 850, Santiago, Chile

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ABSTRACT

A better characterization of complex rock masses is essential in geotechnical engineering, as the empirical systems widely used for this purpose have significant limitations and do not provide adequate answers for risk analysis. Geostatistics offers a set of tools that allow not only predicting the rock mass properties, but also mapping their heterogeneity at different spatial scales and quantifying the uncertainty in their actual values. In this paper, two geostatistical approaches are compared for modeling the Rock Mass Rating (RMR), which is used to geomechanically characterize the rock mass in geotechnical works. The first approach consists of the direct simulation of the RMR values, based on a Gaussian spatial random field model. In contrast, the second approach uses the truncated Gaussian model to separately simulate the individual parameters of the RMR, which subsequently are summed to obtain the final RMR value. The computation time, practical implementation, level of details and post-processing outputs that can be obtained from both approaches are analyzed. Besides the RMR mapping and associated uncertainty, the deformation modulus is subsequently obtained based on these maps together with empirical expressions.

1. Introduction

In the current practice of geotechnical works design, the geomechanical parameters of the rock formations are set based on campaigns of in situ and laboratory characterization works and tests. According to the results of these campaigns, a geotechnical zoning is established and a set of geomechanical parameters is assigned to each zone. This is a highly subjective exercise, but its output is of utmost importance for the next stages of geotechnical design. However, this approach does not properly account for the intrinsic spatial variability and high heterogeneities that can be found in many rock masses, which can have a significant impact on the structure behavior. In this sense, there is a lack of an approach that allows reducing the subjectivity of geotechnical zoning and that explicitly considers the spatial variability and heterogeneities many times present in rock masses.

The recourse to geostatistical models can be a mean to foster the development of such an approach. Indeed, in these models, the geomechanical parameters are viewed as outcomes (realizations) of spatial random fields, the properties of which can be inferred from the available in situ measurements and laboratory tests. Kriging techniques (Matheron, 1971) can be used to predict the values of the parameters of interest at any specific location, based on the information available at neighboring locations and on the spatial correlation structure of the underlying random fields. These techniques aim to minimize the expected squared error between predicted and true values, but, in return, they provide over-smoothed maps that do not reflect the actual variability of the true parameters. To avoid this drawback, conditional simulation techniques have been developed to construct numerical models that reproduce the spatial variability at all scales and allow a better understanding of the rock mass heterogeneities (Journel, 1974; Chilès and Delfiner, 2012). Unlike kriging that provides a single prediction for each parameter of interest, simulation yields as many case scenarios as desired, which are helpful to assess the uncertainty in the actual (unknown) parameter values at any specific location or jointly over several locations.

Numerous authors already applied geostatistics to estimate or to simulate properties such as lithology faces (Rosenbaum et al., 1997), Rock Quality Designation (RQD) (Esfahani and Asghari, 2013; Ozturk and Simdi, 2014; Ozturk and Nasuf, 2002), Rock Mass Rating (RMR) (Ryu et al., 2003; You, 2003; Oh et al., 2004; Stavropoulou et al., 2007; Exadaktylos and Stavropoulou, 2008; Jeon et al., 2009; Egaña and Ortiz, 2013; Ferrari et al., 2014), joint frequency (Ellefmo and Eidsvik, 2009) or Geological Strength Index (GSI) (Ozturk and Simdi, 2014; Deisman et al., 2013).

Hereunder, the system used for simulation is the Rock Mass Rating (RMR) proposed by Bieniawski (1989). This system allows classifying the rock mass in five classes (very good, good, fair, poor, very poor) using a continuous scale that varies from 0 to 100 obtained after weighting six individual parameters regarding the rock mass and its

* Corresponding author.
E-mail address: marisamotapinheiro@gmail.com (M. Pinheiro).

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discontinuities. The referred parameters are: a) Uniaxial compressive strength of rock material (P1); b) RQD (P2); c) Discontinuity spacing (P3); d) Condition of discontinuities (P4); e) Groundwater conditions (P5); f) Orientation of discontinuities (P6). In this work, the sixth parameter (P6) will not be used because it does not depend only on the characteristics of the rock discontinuities but also on their relation with the structure and this is unknown. The RMR under consideration is therefore the so-called basic RMR, which is obtained considering only the contribution of parameters P1 to P5.

The next section presents two geostatistical approaches to simulate the RMR, depending on whether one considers that the properties are measured on a continuous quantitative scale or on a discrete scale. In the first approach, the most straightforward and usual one, RMR is viewed as a variable measured on a continuous scale (from 0 to 100) and is directly simulated with a multivariate Gaussian algorithm. In contrast, the second approach is more complete, as each one of the five parameters (P1 to P5) is simulated and the results are then summed to obtain the final mapping of RMR. A novelty of this second approach with respect to previous works is the fact that the underlying parameters are considered as variables measured on a discrete scale, which better suits their nature as a ranking and not as a continuous value, and that a specific geostatistical model (truncated Gaussian model) is used for the purpose of simulation. In Section 3, both approaches are applied to a case study and compared in terms of implementation facility, accuracy and level of detail provided in simulating the spatial distribution of RMR. Finally the simulated RMR is converted into deformation modulus (E_m) using empirical formulae.

2. Geostatistical simulation of RMR

2.1. First approach: direct simulation of RMR

In this approach, the RMR is viewed as a variable that continuously varies from 0 to 100 and is simulated directly (Fig. 1a). To this end, the multi-Gaussian random field model is used, through the following steps (Chilès and Delfiner, 2012):

1) First, a representative distribution of the RMR values is calculated, by weighting each data depending on the geometrical configuration of the data locations. This procedure aims at down-weighting the data that are spatially clustered, which contain redundant information (Deutsch and Journel, 1998). In case of a regular sampling design, the data can be assigned the same weights.
2) The RMR data are then transformed into data with a standard Gaussian distribution, accounting for the previously calculated declustering weights. These transformed data are associated with a parent second-order stationary Gaussian random field, which is fully characterized by its auto-correlation function or, equivalently, by its variogram (Lantuéjoul, 2002).
3) The experimental variogram of the Gaussian data is computed and subsequently fitted with a theoretical model. At this stage, the study can be performed in one or more directions of space, in order to identify a possible anisotropy and to better understand the spatial behavior of the data.
4) A Gaussian random field is then simulated at the target locations, conditionally to the available data (i.e., such that the values simulated at the data locations match the data values). In the present case the turning bands algorithm (Emery and Lantuéjoul, 2006) is used for simulation.
5) The simulated Gaussian values are back-transformed to the original scale (RMR).

Similar approaches, which differ in the specific simulation algorithm used at step (4), have been proposed by Ryu et al. (2003); Jeon et al. (2009); Egaña and Ortiz (2013) and Ferrari et al. (2014), among others, for the spatial prediction of RMR and for uncertainty quantification.

2.2. Second approach: simulation of underlying parameters

The second approach is more innovative and consists in simulating all five parameters assigned with their ratings, viewed as discrete variables (i.e., they only assume integer values). The sum of the simulated parameters gives the final value for RMR.

For the parameter simulation, the truncated Gaussian model (Armstrong et al., 2011) is used, which relies on the truncation of

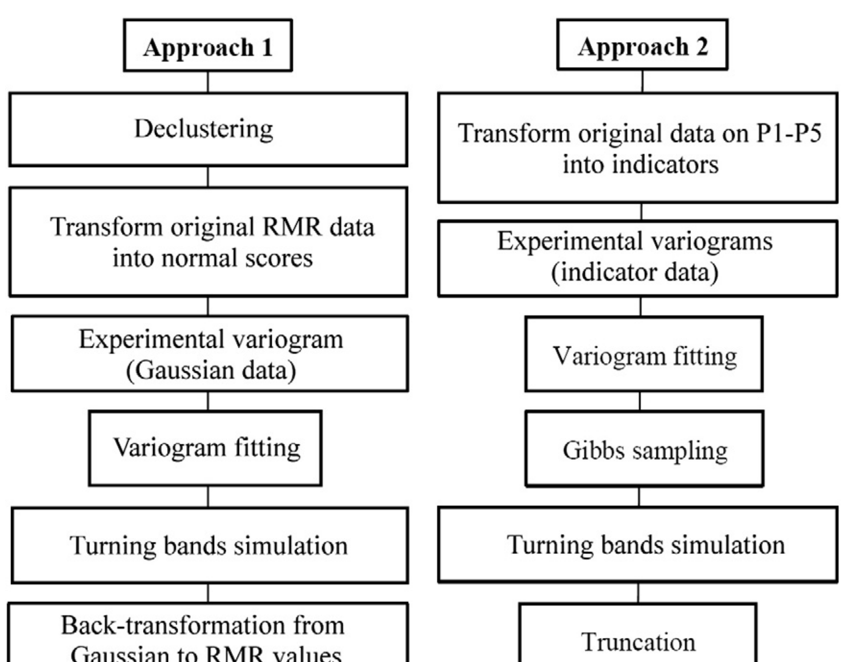

Fig. 1. Flow charts for simulation under the multi-Gaussian model (Approach 1) (a) and the truncated Gaussian model (Approach 2) (b).