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Combination of geostatistical simulation and fractal modeling for mineral resource classification

Behnam Sadeghi [a,b,*], Nasser Madani [c,d,e], Emmanuel John M. Carranza [f]

[a] Department of Mining Engineering, Faculty of Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran
[b] Young Researchers and Elite Club, South Tehran Branch, Islamic Azad University, Tehran, Iran
[c] Department of Mining Engineering, University of Chile, Santiago, Chile
[d] Advanced Mining Technology Center, University of Chile, Santiago, Chile
[e] CSIRO-Chile International Center of Excellence in Mining and Mineral Processing, Chile
[f] School of Earth and Environmental Sciences, James Cook University, Townsville, Queensland 4811, Australia

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ABSTRACT

The separation, identification and assessment of high-grade ore zones from low-grade ones are extremely important in mining of metalliferous deposits. A technique that provides reliable results for those purposes is thus paramount to mining engineers and geologists. In this paper, the simulated size–number (SS–N) fractal model, which is an extension of the number–size (N–S) fractal model, was utilized for classification of parts of the Zaghia iron deposit, located near Bafq City in Central Iran, based on borehole data. We applied this model to the output of the turning bands simulation method using the data, and the results were compared with those of the application of the concentration–volume (C–V) fractal model to the output of kriging of the data. The technique using the SS–N model combined with turning bands simulation presents more reliable results compared to technique using the C–V model combined with kriging since the former does not present smoothing effects. The grade variability was classified in each mineralized zones defined by the SS–N and C–V models, based on which tonnage cut-off models were generated. The tonnage cut-off obtained using the technique of combining turning bands simulation and SS–N modeling is more reliable than that obtained using the technique of combining kriging and C–V modeling.

1. Introduction

The recognition of geochemical anomalies and their distinction from geochemical background for the identification, delineation, and modeling of mineralized zones is important in mineral exploration, mineral resource classification, and mine planning. Although various factors of mineral deposit formation control the variability in geochemical data, grades of metals in mineral deposits or concentrations of chemical elements in the Earth's crust have been assumed to follow a normal (Gaussian) or log-normal distribution in traditional statistical methods of data analysis (Armstrong and Boufassa, 1988; Clark, 1999; Limpert et al., 2001). However, many scientists and researchers have recognized and advocated that frequency distributions of element concentrations are mostly not normal (Ahrens, 1954a,b, 1966; Bai et al., 2010; He et al., 2013; Li et al., 2003; Luz et al., 2014; Razumovsky, 1940; Reimann and Filzmoser, 2000).

Geostatistical methods have been increasingly used as powerful tools for predicting spatial attributes and for modeling the uncertainty of predictions in un-sampled locations, which are important in mineral resource estimation and ore reserve evaluation (e.g., Chilès and Delfiner, 2012; Emery, 2005, 2012; Emery and González, 2007; Emery and Robles, 2009; Emery et al., 2005, 2006; Maleki Tehrani et al., 2013; Montoya et al., 2012; Ortiz and Emery, 2006). Kriging, as an important geostatistical interpolation method, is a linear and generally robust estimator, but its main disadvantage is its smoothing effect, particularly for highly skewed data. Consequently, if kriging is applied to datasets with non-Gaussian distribution, it is not able to reproduce spatial heterogeneity that is characteristic of many such datasets. In contrast, Gaussian simulation as an alternative technique for kriging provides more precise results (Deutsch and Journel, 1998; Matheron, 1973; Shinozuka and Jan, 1972), and most continuous variables can be simulated by transformation to the Gaussian (or multi-Gaussian) distribution. Gaussian simulation algorithms are divided into two types, exact and approximate algorithm (Emery and Lantuejoul, 2006). Several approximate Gaussian simulation algorithms have been developed, and one of them is called turning bands method (Matheron, 1973). It was first introduced by Chentsov (1957) in a special case of Brownian random functions, but has been extended for the Gaussian simulation of stationary and intrinsic random functions by Emery and Lantuejoul (2006) and also Emery (2008). This method aims at simplifying the

* Corresponding author.
E-mail address: behnamsadeghi.researches@yahoo.com (B. Sadeghi).

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Gaussian simulation problem in multidimensional spaces, using simulations in one dimension and spreading them to 2-D or 3-D spaces. This method is extremely fast with parallelizable computations and one can simulate as many locations as desired. The Gaussian simulation also exactly reproduces the desired covariance model (Chilès, 1977; Chilès and Delfiner, 2012; David, 1977; Delhomme, 1979; Emery and Lantuejoul, 2006; Journel and Huijbregts, 1978; Mantoglou and Wilson, 1982). However, the turning bands method is like conventional geostatistical methods because it also operates on the basis of classical statistical parameters such as mean, percentile, and standard deviation and requires normalization of data that may not actually distort the real spatial distribution of geochemical data. For example, geochemical data

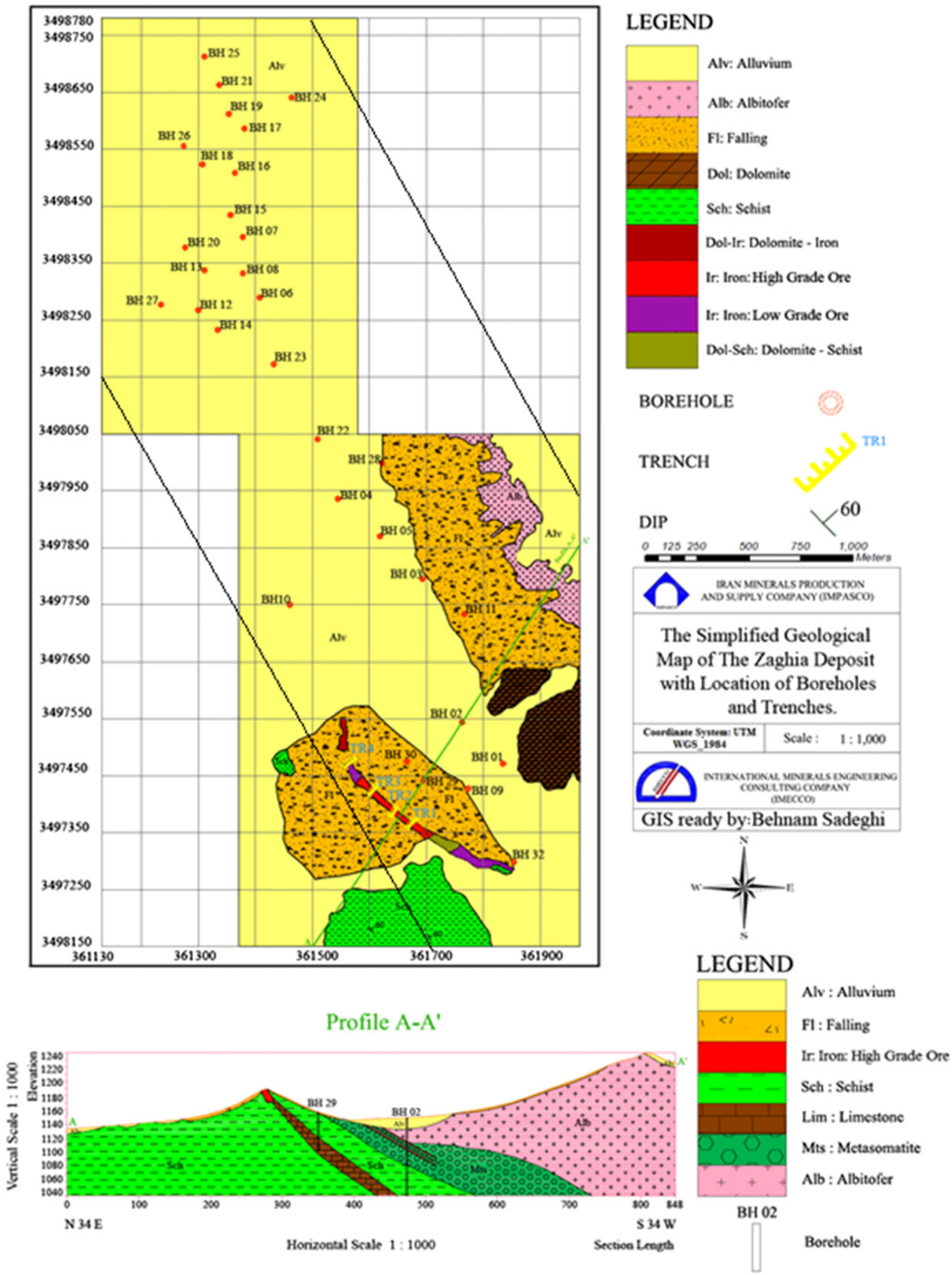

Fig. 1. Geological map of the Zaghia deposit with the locations of boreholes and trenches (from Sadeghi et al., 2012). The two slanting black lines represent boundaries of the study area.