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# Indirect rock type modeling using geostatistical simulation of independent components in Nohkouhi volcanogenic massive sulfide deposit, Iran

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ABSTRACT

Geological modeling is a useful tool for host rock reconstruction in volcanogenic massive sulfide (VMS) deposits. In this paper, we have proposed two rock type models for Nohkouhi copper deposit, which is a siliciclastic felsic volcanogenic massive sulfide in Central Iran zone. In the deposit, copper mineralization is hosted by different copper grade rocks consisting of Black shale and Rhyodacite. Moreover, in the Black shale, the copper grade distribution directly corresponds to the Rhyodacite. Geochemical factors of the rock types distinguished using ICA. Scores of the IC1 via Scores of the IC2 indicated the best discrimination between the Black shale and Rhyodacite. Our manually constructed class boundary provided a bivariate discriminant line that can be used to determine the rock types. Scores of the ICs are simulated using sequential Gaussian simulation (SGS). The discriminant line is used to classify each node of the grid to the rock type for each pair realization. Also, sequential indicator simulation (SIS) is applied to the Black shale and Rhyodacite on account of their wide range of geometries and assumed deterministic geological model.

In order to model the deposit, we have compared two methods comprising direct simulation of rock type (using sequential indicator simulation) and indirect simulation of rock type (using independent component analysis). The experimental results indicated that direct simulation, could be employed for both resource evaluation and knowledge of the geological model. Besides, the indirect simulation produces a model which cannot be used for resource evaluation stage; however, it is helpful with respect to the basic understanding of the geology of the deposit. Our two models showed 96% agreement with each other. Also, ICA chemically presented a key relations between Black shale and Rhyodacite.



## 1. Introduction

Geological modeling is an integrated multidisciplinary set of approaches typically identified by geology and statistics (Liu et al., 2015). These models fall into two broad classes: empirically and geostatistically conditioned models. Geostatistical simulation algorithms have been presented in the past decades in order to model complex geological structures, such as rock units or facies in ore deposits and petroleum reservoirs (Talebi et al., 2014). These algorithms are divided into two categories: object-based algorithms and pixel-based algorithms.

The most popular object-based algorithm is Boolean simulation (Lantuéjoul, 2013). Examples of the pixel-based algorithms include sequential indicator simulation (Alabert, 1987; Journel and Gomez-Hernandez, 1993) truncated Gaussian simulation (Journel and Isaaks, 1984; Matheron et al., 1987), and plurigaussian simulation (Le Loc'h et al., 1994; Armstrong et al., 2011).

Sequential indicator simulation (SIS) is in essence the same as the sequential Gaussian simulation (SGS), except that instead of simulating a Gaussian variable, an indicator variable or an indicator transform of a continuous variable is simulated (Bierkens and Burrough, 1993; Goovaerts, 1996). Based on indicator semi variograms, SIS build up a CDF from facies membership probabilities at each grid node. Then select a facies at random from the CDF SIS realizations generate geobodies which are geologically unrealistic, because each realization contains both reliable geological information and noise that is displayed as unlikely types. Yamamoto et al. (2015) proposed an alternative method for post-processing realizations of sequential indicator simulation.

Independent component analysis (ICA) is a type of analysis in the process of source signal separation introduced by Jutten and Herault (1991) and defined clearly by Comon (1994). Independent component analysis (ICA) is a statistical and computational technique designed for revealing the hidden sources and factors that underlie the distribution

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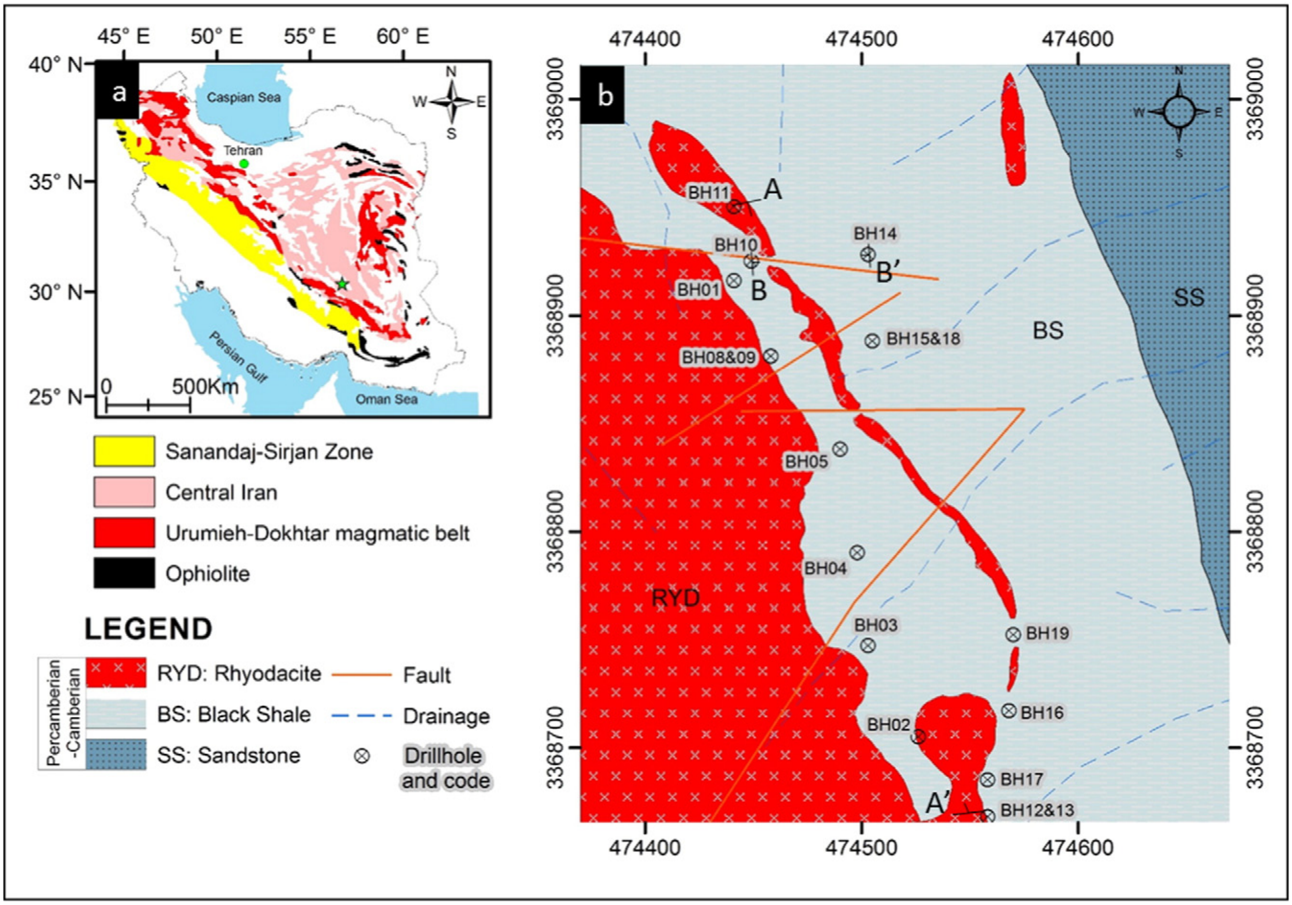


**Fig. 1.** (a) The location of Nohkouhi deposit in the structural map of Iran (Green stars; Simplified from Nogole-Sadat and Almasian, 1993), (b) Geological and structural map of the Nohkouhi deposit.

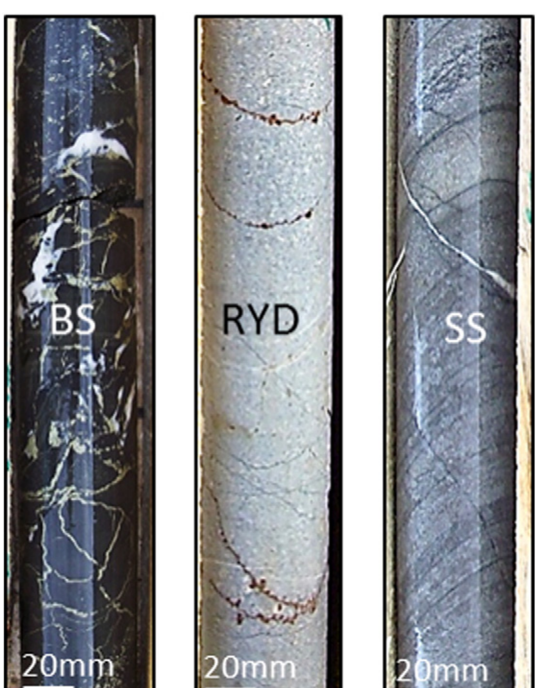


**Fig. 2.** Representative photographs of classes used for lithofacies modeling; abbreviation BS = Black shale RYD = Rhyodacite SS = Sandstone.

of multivariate observations. ICA is based on higher order statistics and decorrelates the input data as well as making the result factors independent from each other (Hyvärinen et al., 2004). ICA algorithms have been presented in three main approaches (Prank et al., 1999). The base of the first approach is batch computations minimizing or maximizing some relevant criterion functions (Cardoso, 1992; Comon, 1994). The second approach is based on stochastic gradient methods including adaptive algorithms (Amari et al., 1996; Bell and Sejnowski, 1995; Delfosse and Loubaton, 1995; Hyvärinen and Oja, 1996; Jutten and Herault, 1991; Moreau and Macchi, 1993; Oja and Karhunen, 1995). The third class of algorithms is based on a fixed-point iteration scheme to estimate the non-gaussian independent components (Hyvärinen and Oja, 1997).

ICA has been used in many different fields such as face recognition (Bartlett et al., 2002; Déniz et al., 2003; Draper et al., 2003; Kim et al., 2005), image classification (Chen and Zhang, 1999; Lee and Lewicki, 2002; Bigdely-Shamlo et al., 2008), text classification (Pu and Yang, 2006), seismic signal processing (Acernese et al., 2003), and hyperspectral data processing (Chiang et al., 2000; Fiori, 2003; Nascimento and Dias, 2005; Gholami et al., 2012).

Iwamori and Albarède (2008) and Iwamori et al. (2010) used Fast ICA to extract independent features of isotopic data of oceanic basalts to illuminate global geochemical structure and mantle dynamics. Yu et al. (2007, 2012) and Zhang et al. (2007) applied an improved Fast ICA algorithm to analyze regional multi-element concentration data for mineral prospecting.

Liu et al. (2014) applied Fast ICA to the soil geochemical data of for geochemical anomaly detection in Dachaidan area in China. Yang and Cheng (2015a) discussed mathematical models of PCA and ICA and examined the differences and similarities between these two models. Yang and Cheng (2015b) compared PCA and ICA in stream sediment