

Research article

Comparison of geostatistics and artificial intelligence methods for 3D modeling of epithermal gold mineralization in the Zailik region, northwest of Iran

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| <i>Keywords</i> | <i>English Extended Abstract</i> |
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| kriging artificial neural network firefly algorithm particle swarm optimization Zailik | Summary For the three-dimensional modeling of the S01 vein from the Zailik exploratory area, the sampled data of the trenches and boreholes of this vein were used, and the gold grade was estimated using ANN, ANN-PSO, and ANN-FFA methods. To check the accuracy of the |

modeling, it was compared with the estimate of grade using the ordinary geostatistical kriging method, as well as the geological evidence of the area, such as lithology and alteration.

Introduction

Due to the lack of essential mathematical models to describe the magma migration and subtraction, the mineralizing in rocks, and the need to identify the anomalies associated with real mineralization from its false types, it is necessary to specific modeling for each mineral mass. Modeling is indispensable because after modeling, first of all, the ore reserve is calculated by the product of the block volume and the specific weight of the rock, and the tonnage-grade diagram is drawn (determining the economic limit grade), and according to the conventional classification systems, the type of ore deposit is specified. Another advantage of modeling is saving money and time instead of carrying out excess sampling in the exploration area [1]. Estimation operations are used to perform modeling and pattern recognition; when a data analyst model encounters a set of data, it must be able to estimate these data, which requires choosing the best estimator model to solve a specific problem. In new methods, achieving optimal modeling will only be possible with the simultaneous use of geological sciences, mathematics (statistics and probabilities), and computer engineering (artificial intelligence). This research aims to combine machine learning algorithms (support vector machine) and meta-heuristic optimizer algorithms (firefly algorithm and particle swarm optimizer) to perform three-dimensional block modeling and prepare Au-grade distribution maps in the Zailik region in the northwest of Iran. In this article, to model the S01 vein gold reserve in three dimensions, the combination of trenches and borehole sample data was used to obtain the Au grade distribution map using geostatistics and artificial intelligence methods. In the above modeling, comparing and evaluating the mathematical and numerical criteria, it is necessary to examine the qualitative validation of the predicted models to identify and extract the exploration pattern correctly. Qualitative validation means measuring the conformity of the obtained exploratory modeling with the known mineral deposit datasets that were not used in the preparation of the model [2]. The general process of conducting this research is as follows:

1. Analyzing litho-geochemical data and pre-processing on Au values and corresponding paragenesis values.



2. Prediction and estimation of Au values using the geostatistical method as well as artificial intelligence integrated methods (artificial neural network, firefly, and particle swarm algorithms)
3. Comparison of quantitative evaluation criteria such as coefficient of determination and error function value [3]
4. Qualitative assessments and compliance of the estimated points with the lithology and variation of the Zailik region

Methodology and Approaches

In the Zailik exploratory area, due to the spread and width of the mineral inside the excavated trenches, sampling was done unsystematically with variable distances and lengths (Fig. 1). These samples were analyzed in the laboratory for the gold using the Fire Assay method and for other elements using the ICP-OES method. In addition to determining the grade in each sample, that sample's lithology information and alteration type were recorded. The statistical parameters of the samples taken from this vein are represented in Table 1.

Table 1. Statistical parameters values of Au in vein S01

| Au(ppm) | Raw Data | Out layer |
|----------|----------|-----------|
| Min | 0.005 | 0.050 |
| Max | 54.166 | 10.000 |
| Mean | 1.704 | 1.099 |
| Median | 0.497 | 0.497 |
| S. Dev | 5.477 | 1.653 |
| Skewness | 7.266 | 3.031 |
| Kurtosis | 59.581 | 10.157 |

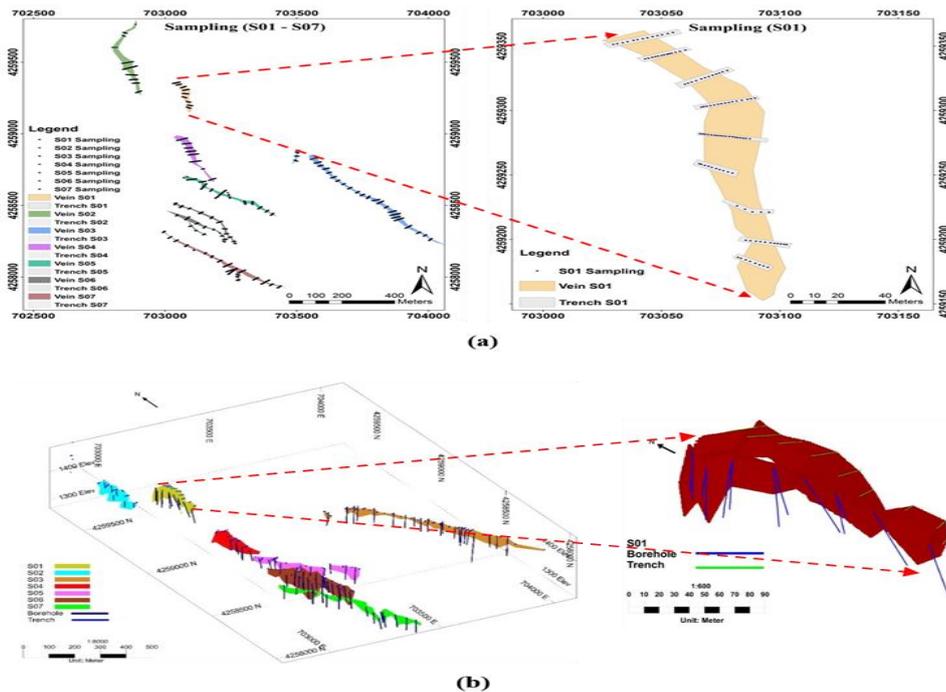


Fig. 1. (a) Location of the samples collected in trenches S07 - S01 (b) Location of boreholes drilled in veins S01 to S07



Results and Conclusions

Modeling in ANN, ANN-PSO, and ANN-FFA methods was done according to the following steps, and its results are shown in Fig. 2.

- The First step was Data compositing, drawing strings, creating a wire model, and finally creating a block model in the Datamine Studio software.
- The second step was calculating the grade of each of the blocks within the defined search radius using the constructed composite model.
- The third step was entering the grade values of the second-step blocks into artificial intelligence methods to estimate the blocks with specified coordinates and unknown grade values (blocks outside the search radius in the second step).
- The fourth step is assigning the grade values obtained in the previous steps to the corresponding blocks in the Datamine Studio software.

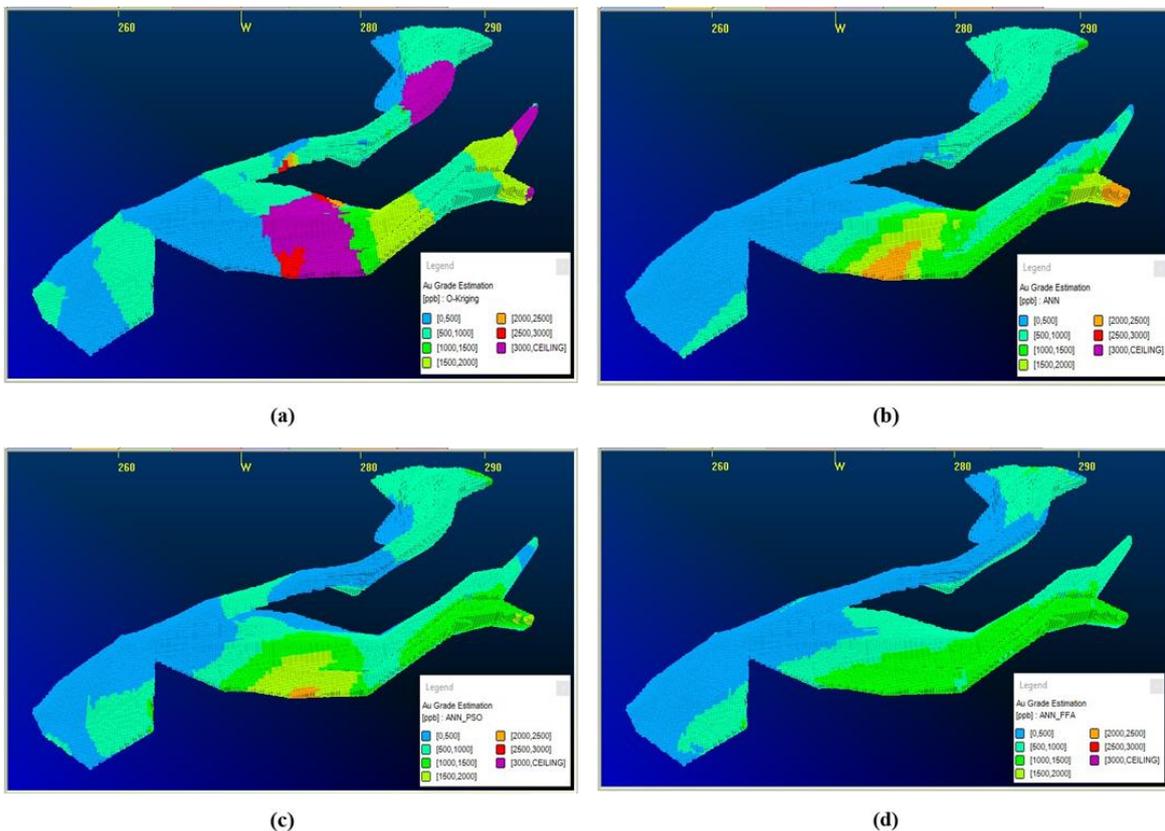
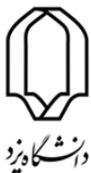


Fig. 2. (a) 3D modeling of Au grade in S01 vein by OK (Ordinary Kriging) method (b) ANN (c) ANN-PSO (d) ANN-FFA

In this research, recognizing the geochemical patterns of Au in the Zailik region appropriately and more accurately distinguishing the anomaly from the background, modeling using geostatistics and artificial intelligence methods (ANN, ANN-FFA, and ANN-PSO) were performed and compared with each other. In artificial intelligence modeling for validation, by quantitatively comparing the accuracy evaluation criteria, it was shown that the ANN-FFA method has the highest coefficient of determination ($R^2=0.66$) and the lowest error value ($RMSE=0.134$) compared to ANN and ANN-PSO methods. The location of the estimated values was compatible with the lithology and alteration related to Au mineralization. To approve the correctness of the modeling done in artificial intelligence methods, the location of the estimated values in these methods



was in good agreement with each other and the area of the estimated values in geostatistical methods. Hence, the estimated anomalies were in the northern and eastern parts of the S01 vein, with a high amount of Au grade obtained in silicate minerals and silicified alteration zones. As a result, according to the obtained layers of information, the creation of a strong silicified alteration zone with high amounts of iron oxides and the formation of scattered alteration halos around this zone (advanced argillic with medium amounts of iron oxide and medium argillic with low amounts of iron oxide), It indicates the formation of a potential and promising anomaly for Au mineralization in the region.

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