

A Computational Optimized Extended Model for Mineral Potential Mapping Based on WofE Method

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Abstract: The multivariate fuzzy-c-means classifier is used to model extended weight of evidence (WofE) considering predictor maps. Approaches to mineral potential mapping based on WofE modeling generally use binary maps, whereas, real-world geospatial data are mostly multi-class or fuzzy-class in nature. The consequent reclassification of fuzzy-class maps into binary maps is a simplification that might result in a loss of information. This research thus describes an extended WofE modeling for predicative mapping of gold deposit potential in Tourd-chah Shirin metallogenic zone, Semnan province, in north of Iran to demonstrate optimization of mineral potential information by using fuzzy-class predictor maps, as applied to the study area. The optimization of an extended WofE model using fuzzy-class predictor maps for the study area results in demarcation of the high, moderate and low favorability zones. Optimization was also obtained by constraining simple WofE model using only binary predictor maps with different levels of uncertainty for study area. A comparison between the results of the extended WofE model and field data indicates that little correlation exists between these two results.

Key words: Weights of evidence, Computational model, Fuzzy-c-means, Gold Deposit

INTRODUCTION

A Geographical Information System (GIS) is a computer based system which integrates the data input; data storage and management, data manipulation and analysis and data output for both spatial and attribute data to support decision-making activities Malczewski^[5]. After over 40 years of development, GIS have been applied to serve important roles in many fields, such as environmental monitoring, resources management, applications in commerce and business fields and different utilities. The ultimate purpose of GIS is to make evaluations or predictions with different specific data integration models to combine spatial and attribute data from various sources to provide support for decision-makers.

According to Bonham-Carter^[1], the data integration models in GIS are divided into two categories, data-driven and knowledge-driven model based on different methods for estimation of weights of different evidential maps. In data-driven models, the weights are calculated by using statistical methods and data of evidences in a training area to estimate the spatial relationships between the evidential maps and the final response maps. Data-driven models include Logistic

Regression, Weights of Evidence, Neural Network and so on and the weights in those models are calculated from training data. While, the weights are estimated based on experts opinions in knowledge-driven models. The knowledge-driven models include Fuzzy Logic, Dempster-Shafer Belief Theory and their weights are given with experts' opinions.

Weights of evidence model is used to predict a hypothesis about occurrence of an event based on combining known evidence in a study area where sufficient data are available to estimate the relative importance of each evidence by statistical methods. In the case of mineral resources assessment, the evidence consists of a set evidential datasets (maps) and the models are used to predict the hypothesis about the occurrence of a given type of deposit in a study area. The weights are estimated from the measured association between known mineral occurrences and the values on the evidential maps. Based on combination of the evidential maps selected, the final result is extracted as a mineral potential map with a single index representing probability of occurrence of the given type of mineral deposit.

The purpose of this research is to demonstrate working of weights of evidence model with using an

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application in the predication of Gold mineral occurrence in the Moalleman zone in Iran. The objectives of this research are: (1) to study the model for prediction of gold deposits in the study area and (2) to evaluate analysis result of application of this model.

In this research, a procedure for prediction of gold deposits using weights of evidence model in GIS and fuzzy c-means clustering together to integrate different evidential datasets, such as geological data, geophysical data, remote sensing and so on, described the results are evaluated.

APPLICATION TO GOLD POTENTIAL MAPPING IN TORUD-CHAH SHIRAN PROVINCE

The Torud-Chah Shiran range lies in the central to eastern portion of the Alborz mountain system, a mountain chain of complex tectonic, magmatic and stratigraphic history (summarized by Alavi, 1996). On the basis of regional tectonic considerations, Alavi^[9] suggested that the Torud-Chah Shiran range and volcanic rocks in the adjacent areas are related to Eocene magmatism in the Central Iran magmatic zone to the south and not to the volcanic rocks of the Alborz magmatic belt to the west. The distribution of Tertiary igneous rocks shows that the western portion of the Alborz arc merges with another Tertiary calc-alkaline magmatic belt, the Urumieh-Dokhtar zone, which runs parallel to the main northwest-trending Zagros thrust. Recently, Hassanzadeh^[10] suggested that the two belts were once a single arc but separated by intra-arc extension that started in the late Eocene. Based on the latter view, the Alborz magmatic belt includes Torud-Chah Shiran and represents the northern half of the proto-arc. This arc is characterized by thick accumulations of early to middle Eocene submarine green tuffs (equivalent to the Karaj Formation of central and western Alborz), followed by late Eocene, to possibly early Oligocene, submarine to subaerial lava flows which locally include nepheline-normative and shoshonitic rocks. A series of silica-saturated volcanic rocks occur locally. The intra-arc spreading formed sedimentary basins between the Alborz range and Central Iran, an area characterized by Oligocene mafic-alkaline magmatism Hassanzadeh^[10]. Chemical compositions of volcanic rocks presented below indicate that Torud-Chah Shiran rocks have a typical arc signature, consistent with this proposed interpretation.

The Torud-Chah Shirin mountain range hosts many mineral showings and abandoned mines, particularly epithermal base metal veins. In addition to Gandy (Au-

Ag-Pb-Zn) and Abolhassani (Pb-Zn-Ag-Au), other occurrences include Cheshmeh Hafez (Pb-Zn), Chalu (Cu), Chahmosa (Cu) and Pousideh (Cu). Other types of deposits in this range include placer gold, an underground mine for turquoise at Baghu, skarn deposits and Pb-Zn deposits in carbonate rocks. Gold is probably the product of weathering of nearby quartz sulfide veins hosted by andesitic volcanic rocks. The presence of tourmaline in the wall rocks of these veins may indicate proximity to a porphyry system. An abandoned iron skarn deposit is located at the contact of Cretaceous limestones andesitic lava flows and a quartz monzonite stock 2 km northwest of the study area. Reshm and Khanjar are abandoned Pb-Zn mines located 15 and 10 km, respectively, west of the study area. Ore in these localities occurred principally as veins in Cretaceous dolomitic limestones and consisted of quartz, calcite, galena, sphalerite and pyrite Shamanian^[11].

COMPUTATION OF WOFE

A weight of evidence analysis is used to quantify the spatial correlations between the geological features, representative of deposit recognition criteria and know mineral occurrence (20 mineral occurrences for study area). Four maps representing geological map, hydrothermal alteration, geophysical and structural features are created and used for weights of evidence analysis. Distance maps showing buffer zone for faults at distances 100-500 m (in increments of 100 m) and for alteration at distances 500-2000 m (in increments of 500 m) away from the outline of geological features are constructed and weights of evidence (W^+ , W^-), contrast C and studentized value of C are calculated to select the optimum distance that have the best spatial correlation with the known mineral occurrences.

Weights of evidence analysis of the four evidential maps are shown in Table 1.

CLUSTERING STUDENT(C) BY FUZZY C-MEANS METHOD

After calculation of weights of evidence for evidential maps, intersected four evidential maps with use of Arc Info to generate a map by 795 features of polygons. Each polygon has four values (Sig C) from each evidential map (Table 2 shows some of values). In order to generate a potential map of gold from study area, classifications student C in 7 classes (Table 2) (repetitive clustering of the data using different number of clusters to reach an optimal solution) were carried out by means of FCM Bezdek^[12].

The polygons by the membership values close to 1 are strong representatives of the high probability, result shown in Fig. 1. Also favourability map generated by binary predictor maps shown in Fig. 2.

Table 1: Weights of evidence analysis of evidential maps

Faults						
Buffer (meter)	Area (km ²)	Point	w ⁺	w ⁻	C	Student C
500	62.10	2	0.370	-0.09	0.471	0.593
400	74.40	1	0.043	-0.51	0.550	0.528
300	94.10	4	0.666	-0.27	0.939	1.472
200	120.4	1	0.159	-0.10	0.260	0.250
100	142.4	3	0.050	-0.01	0.060	0.062
Alteration						
2000	88.30	0	0.000	0.182	0.000	0.000
1500	99.00	6	0.279	-0.160	0.439	0.874
1000	111.6	2	0.001	-0.140	0.150	0.300
500	130.6	12	0.728	-0.640	1.369	2.918
Geology						
Name						
dp	14.7	2	1.320	-0.080	1.403	1.753
E sp	29.0	3	1.009	-0.110	1.122	1.697
Etv	199.9	11	0.325	-0.320	0.648	1.365
E v.br	16.0	1	0.458	-0.020	0.478	0.451
Ela	3.0	0	0.000	0.000	0.000	0.000
Etr	57.7	2	0.160	-0.020	0.180	0.237
Geophysics						
Intensity						
90%	95.5	2	0.985	-0.070	1.057	1.408
80%	421.7	10	1.112	-0.490	1.598	3.630
70%	186.8	9	1.846	-0.500	2.345	5.237
50%	4.4	0	0.000	-0.010	0.000	0.000
40%	313.9	0	0.000	0.118	0.000	0.000

High favorability areas in potential map based on fuzzy-class, which occupy 4% of the study area, contain 68% of the known base-metal deposits. While High favorability areas in potential map based on binary Predictor maps, which occupy 18% of the study area, contain 52% of the known base-metal deposits.

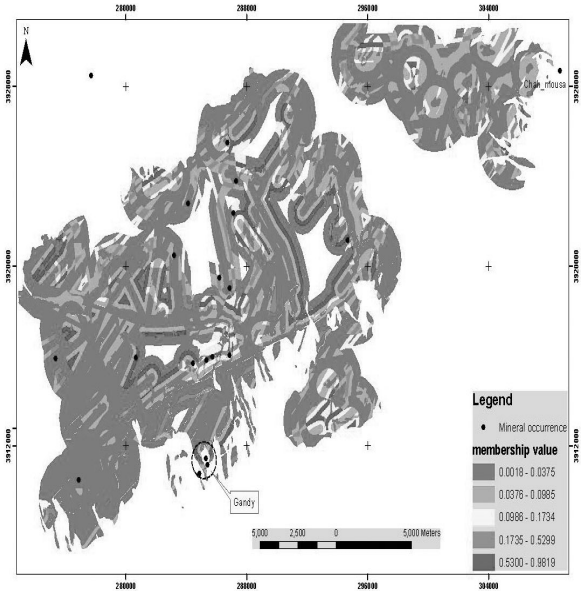


Fig. 1: Potential map of gold mineral, generated by Fuzzy c-means method

Table 2: Some of classifications of Sig C in 7 classes by Fuzzy c-means clustering (C (i), i = 1...7)

Polygon Number	Sig C Alteration			Sig C geology		Sig C Faults			Sig C Geophysics		
	C4	C5	C6	C7		C1	C2	C3			
1	2.91	0.45	1.47	0.00	0.05	0.02	0.01	0.02	0.87	0.02	0.01
2	2.91	0.45	1.47	3.63	0.05	0.04	0.41	0.15	0.07	0.16	0.12
3	2.91	1.69	0.06	3.63	0.09	0.32	0.07	0.10	0.16	0.15	0.11
4	2.91	1.69	0.06	0.00	0.08	0.20	0.09	0.11	0.12	0.18	0.22
5	2.91	1.69	1.47	1.40	0.10	0.52	0.04	0.07	0.18	0.09	0.00
6	2.91	1.69	1.47	0.00	0.04	0.07	0.13	0.08	0.06	0.11	0.51
7	2.91	0.23	0.06	1.40	0.11	0.08	0.05	0.16	0.35	0.20	0.05
8	2.91	0.23	0.25	1.40	0.08	0.07	0.10	0.22	0.16	0.29	0.08
9	2.91	0.23	1.47	1.40	0.07	0.04	0.01	0.03	0.80	0.02	0.03
10	2.91	0.23	1.47	3.63	0.05	0.15	0.36	0.14	0.07	0.16	0.07
11	2.91	0.45	0.06	0.84	0.13	0.05	0.06	0.25	0.31	0.20	0.00
12	2.91	0.45	0.06	1.40	0.00	0.00	0.00	0.00	0.00	0.02	0.98
13	2.91	0.45	1.47	0.00	0.17	0.04	0.02	0.07	0.63	0.06	0.01
14	2.91	0.45	0.25	3.63	0.06	0.04	0.50	0.17	0.07	0.15	0.01
15	2.91	1.69	0.25	1.40	0.04	0.07	0.13	0.08	0.06	0.11	0.51
16	2.91	0.23	0.25	3.63	0.08	0.07	0.10	0.14	0.16	0.20	0.25
17	2.91	0.45	0.06	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.98
18	2.91	0.00	0.06	0.00	0.11	0.06	0.05	0.18	0.34	0.19	0.07
19	2.91	0.45	0.06	0.00	0.11	0.06	0.05	0.19	0.36	0.18	0.05
...
793	0.3	1.36	1.47	1.40	0.02	0.01	0.78	0.07	0.02	0.06	0.04
794	0.3	0.45	0.25	5.23	0.03	0.88	0.01	0.02	0.03	0.02	0.01
795	0.3	0.00	0.52	5.23	0.02	0.02	0.75	0.06	0.02	0.07	0.08

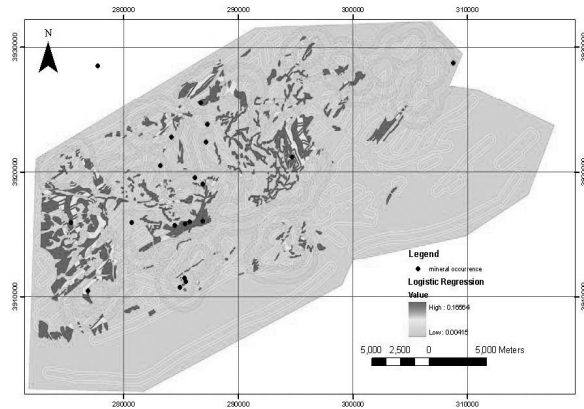


Fig. 2: Potential map generated by binary predictor maps

As this results in the fuzzy map decrease favorability area and increase percent of known mineral deposits in high favorability area than potential map based on binary predictor maps. Similarly, confidence value shows fuzzy map is reliable for mineral exploration in study area.

CONCLUSION

According to the requirements on weights of evidence model, each evidential map need convert to binary pattern (commonly method for generate a binary pattern use of highest student C value in each map for cutoff), which cause losing some useful information in the continuous evidences after data converting. To remove this problem, we have used fuzzy weights of evidence method, based on a fuzzy membership function and WofE. This fuzzy weights of evidence method minimize losing information due to data conversion, also optimize the potential map.

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