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Mineral Prospectivity Mapping For Podiform Chromite Deposits Using Continuously-Weighted Evidence Maps In Sabzevar Ophiolitic Belt

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Abstract: Multi-criteria decision-making approaches using geographical information system are widely used to solve problems in geoscience. In this paper, logistic transformation, as a data-driven way, was utilized to assign continuous weights to evidential maps of host rocks, structural controls and geochemical data. These three evidence layers were then integrated using fuzzy gamma and geometric average operators. The prediction-area plot and receiver operating characteristic curve confirm that the generated prospectivity models are reliable to be used for selecting exploration targets.

Keywords: Podiform chromite, Fuzzy gamma, Geometric average, Mineral prospectivity mapping.

INTRODUCTION

Diverse exploration methods (i.e., geology, geophysics, geochemistry and remote sensing) have been utilized to prospect podiform-type chromite deposits. Nevertheless, prospectivity analysis of this type of mineral deposits has rarely been implemented. There are various methods for mineral prospectivity mapping (MPM) [1,2]. The purpose of this paper is prospectivity analysis of podiform-type chromite deposits in regional scale (1:100,000) in northeast of Iran. For this end, a continuous weighting method [3] through fuzzy logic MPM was applied. The study area with a surface of ~4200 Km^2 located in Sabzevar ophiolite belt in the central Iranian microcontinent and is a part of the northern branch of Neo-Tethyan ophiolite belt in the Middle East [4].

METHODS

In this paper, of various weighting methods of spatial exploration data, continuous weighting approach was utilized to evade (1) random error resulting from arbitrary judgments of analyst and (2) systematic error resulting from using known mineral deposit in definition of the weights [3,5]. Consequently, the ensuing exploration bias in the generation of exploration targets for further prospecting podiform-type chromite deposit could be modulated.

FINDINGS AND ARGUMENT

There are various types of igneous, metamorphic, sedimentary, hydrothermal and volcano-sedimentary rocks, which exposed in the study area (Figure 1). We first elicited serpentinized units from the Sentinel-2B satellite images. Then, we created a map of distance from the serpentinized rocks. Subsequently, by transforming the distance values into [0, 1] range using a logistic function [3], fuzzified evidence layer of proximity to host rock was obtained (Figure 2A).

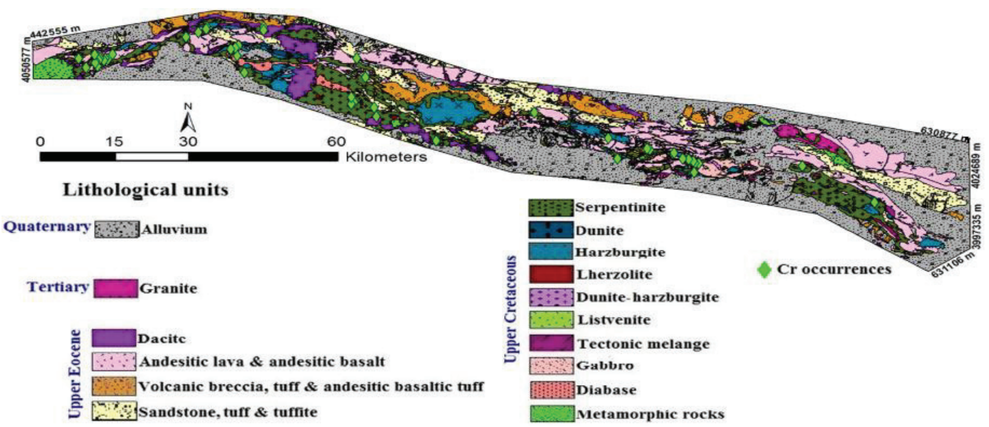

Figure 1. Simplified geological map of the study area and location of known podiform chromite occurrences

For depicting structural controls of the podiform chromite deposits, we recognized and digitalized faults with the aid of ETM$^+$ imagery. Then, we created a map of fault density (FD: total length of faults per pixel in the study area). Eventually, to generate a weighted evidence map of structural controls, the values of FD were fuzzified by using logistic function (Figure 2B).

Geochemical signatures could be applied to prospect podiform chromite deposits. For this, the element contents of Cr, Co, Ni and Cu geochemical indicators were fuzzified using logistic function, through which dispersion patterns of these geochemical signatures are modeled. Due to the close genetic linkage of these elements with chromite deposits, they could reveal signatures of the mineralization. Then, to achieve a stronger geochemical evidence layer, for integrating with other evidential maps, the efficient fuzzified uni-element geochemical signatures [6] were combined using fuzzy "OR" operator (Figure 2C).

Finally, the three fuzzified evidence maps, i.e., weighted evidence layers of FD, proximity to host rocks, and geochemical signature were integrated with fuzzy gamma (=0.9) and geometric average operators to delineate target areas for further exploration (Figure 3).

After generating the fuzzy and geometric average prospectivity models, we utilized the prediction-area (P-A) plot and receiver operating characteristic (ROC) curve to appraise the models. In this regard, we utilized two following criteria; 1) normalized density, Nd [7], and (2) area under the receiver operating characteristic curve, AUC [8]. For this, we used 46 mineral deposit locations (MDLs) and 46 non-deposit locations (NDLs) in the study area for evaluating the efficiency of the generated prospectivity models. The N_d and AUC criteria were adjusted in P-A plot [7] and ROC curve, respectively, for selecting more efficient prospectivity model. In a P-A plot, the two curves namely prediction rate curve of MDLs and occupied area

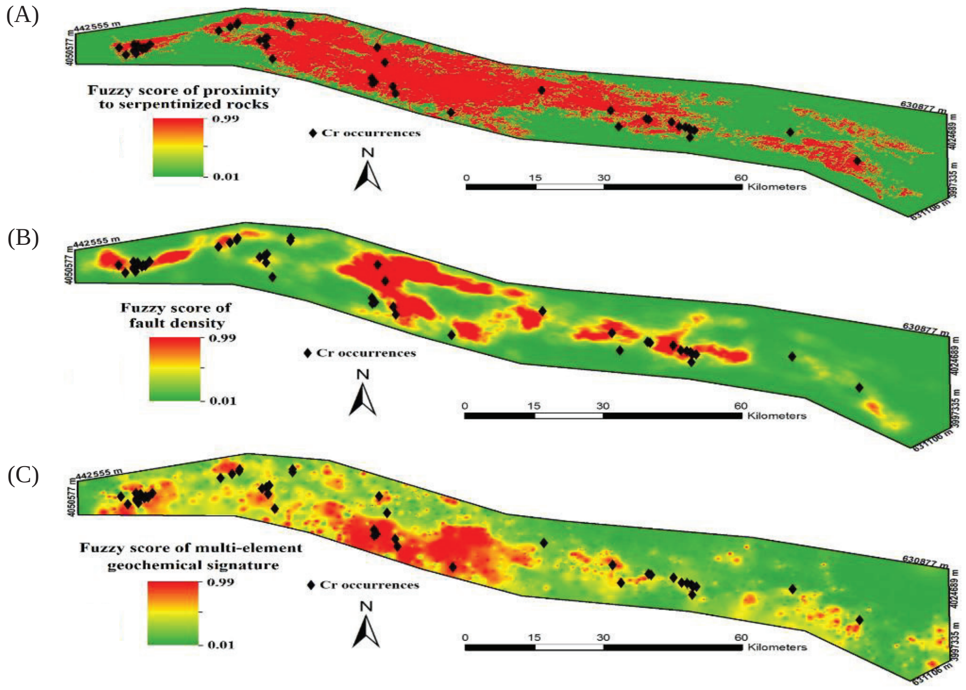

Figure 2. Continuously weighted evidence layer of A: proximity to serpentinized rocks, B: fault density and C: multi-element geochemical signature

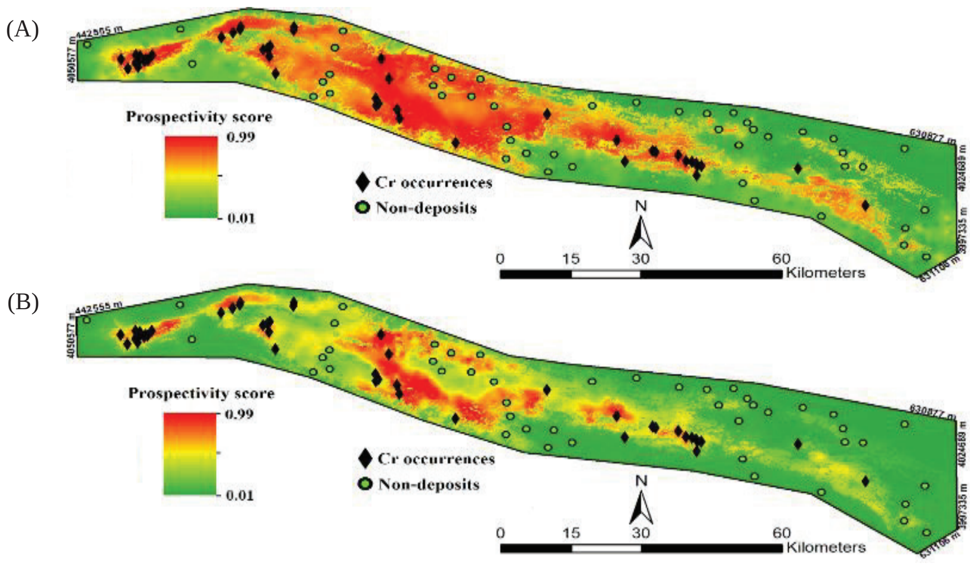

Figure 3. Exploration targeting model of A: fuzzy gamma (=0.9) and B: geometric average

curve are depicted in a scheme versus their corresponding prospectivity scores. ROC curve is a plot of true positive rate (Sensitivity) on the y-axis versus false positive rate (1-Specificity) on the x-axis. Consequently, the ROC curve requires both MDLs and NDLs for evaluating the efficiency of the prospectivity models. We selected the NDLs respecting three following issues; 1) far away from the MDLs, 2) randomly distributed, and 3) not located on the host rocks. Targeting models with a N_d higher than 1 [7] and an AUC higher than 0.5 [8] could be utilized to select target areas for further exploration of deposit-type sought in the study area. The P-A plots and ROC curves corresponding to the prospectivity models generated are shown in Figure 4. Based on the ROC curves (Figure 4A), the AUC value for both prospectivity models is 0.91, indicating the effective performance of the generated models. Based on the intersection points in Figure 2, 78% of the mineral deposits are predicted in 22% of the study area (Figure 4B) for the fuzzy gamma prospectivity model, while 70% of the mineral deposits are predicted in 30% of the study area (Figure 4C) for the geometric average prospectivity model. Thus, the N_d value for the fuzzy gamma and geometric average prospectivity models is 3.54 and 2.33, respectively. These comparisons demonstrated that the former model is better than the latter model in terms of generating reliable target areas and, thus, could be utilized to select target areas for further exploration of deposit-type sought in the study area.

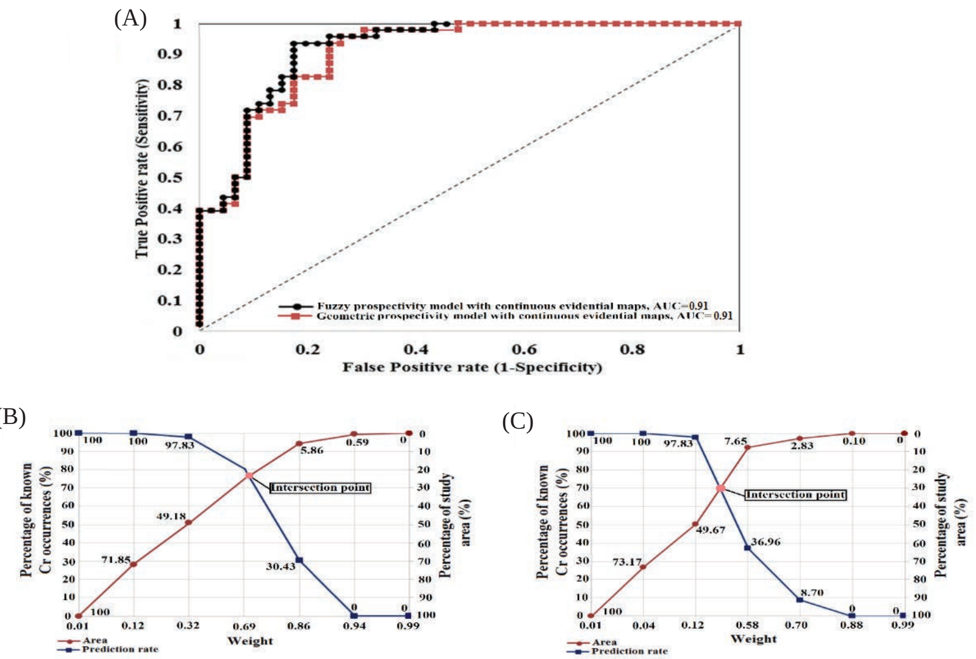

Figure 4. A: Receiver operating characteristic curve of the exploration targeting models generated, B: Prediction-area plot for the fuzzy gamma exploration targeting model and C: Prediction-area plot for the geometric average exploration targeting model

CONCLUSIONS

In this paper, prospectivity analysis of podiform chromite deposits was carried out by using logistic-based continuous weighting method without using known deposit locations as training sites to defeat exploration bias and errors. According to the value of N_d and AUC, the performance of the prospectivity models of fuzzy gamma and geometric average are efficient. Consequently, the exploration targets generated are reliable and could be used efficiently for further exploration programs.

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