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# Data Envelopment Analysis: A knowledge-driven method for mineral prospectivity mapping

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ABSTRACT

This paper describes the application of a proposed method in mineral prospectivity mapping (MPM), i.e. the Data Envelopment Analysis (DEA) technique as a well-known approach in the operational research which involves the representation and integration of the evidential map layers derived from different geo-datasets consisting of the geological, geophysical and geochemical layers of Nowchun Cu–Mo deposit located in the SE of Iran. DEA has proven to be a useful tool for assessing efficiency or productivity of organizations, which in managerial decision making is of fundamental practical importance. Its powerful ranking characteristic for varieties of alternatives in a multiple criteria decision-making problem was used to produce the desired MPM in the region of interest. The outputs were validated by taking into account the twenty-nine boreholes that have been classified into five classes based upon the amounts of Cu grade above an economical cut off value of 0.2% multiplied by its thickness along each borehole. The performance of the proposed method was investigated as well showing its strong applicability in the MPM process while reducing the cost of exploratory drilling in the prospect area.


## 1. Introduction

Mineral prospecting aims to explore new ore occurrences in a region of interest. Distinguishing prospective regions within the study area is one of the main objectives in mineral exploration. Various thematic geo-datasets (e.g., geological, geophysical and geochemical data) are gathered, analyzed and integrated for mineral prospectivity mapping (MPM) to delineate new prospective areas. Therefore, MPM is a multiple criteria decision-making (MCDM) task that produces a predictive model to outline prospective areas. Various MPM approaches are available which can be categorized into data- and knowledge-driven ones (Pan and Harris, 2000; Carranza, 2008). In data-driven techniques, the known mineral deposits are used as ‘training points' to establish spatial relationships between the known deposits and particular geological, geochemical and geophysical features (Carranza et al., 2008a,2008b). The relationships between evidential maps and the training points are quantified and used to establish the importance of each evidence map (Carranza and Hale, 2002a) and are finally integrated into a single MPM (Nykänen and Salmirinne, 2007). Examples of such methods of MPM include weights of evidence (Agterberg et al., 1990; Carranza and Hale, 2002b), logistic regression (Agterberg and Bonham-Carter, 1999; Carranza and Hale, 2001; Mejía-Herrera et al., 2014), neural networks (Harris et al., 2003; Nykänen, 2008; Abedi and Norouzi, 2012), evidential belief functions (Carranza and Hale, 2002c; Carranza and Hale, 2003; Carranza et al., 2005, 2008a), Bayesian classifiers (Porwal et al., 2006; Abedi and Norouzi, 2012), support vector machines (Zuo and Carranza, 2011; Abedi et al., 2012a), clustering methods (Abedi et al., 2013a) and random forest method (Rodriguez-Galiano et al. 2014; Carranza and Laborte, 2015). The other techniques, in which a geoscientist's opinions are applied, are called the knowledge-driven approaches and include methods such as the use of Boolean logic (Bonham-Carter et al., 1989), index overlay (Carranza et al., 1999), the Dempster–Shafer belief theory (Moon, 1990; Carranza et al., 2008b), fuzzy logic (Abedi et al., 2013b), wildcat mapping (Carranza and Hale, 2002d), and outranking methods (Abedi et al., 2015, 2013c, 2012b,c).

Selection of high potential zones for exploratory drillings by incorporating diverse criteria and alternatives is developed in this study. In addition the results of application of a new proposed approach that is called Data Envelopment Analysis (DEA) is investigated. This is the first attempt in ore exploration that the DEA is applied for MPM to delineate prospective areas in a region of interest. The proposed method can appropriately deal with multiple criteria and alternatives without knowing a priori relationship among them. By sensitivity analysis of produced MPM using leave-one-out layers of exploratory geo-datasets the importance and relative weight of evidential layers are demonstrated. DEA

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evaluates the given set of alternatives by several decision making criteria. Herein after a brief introduction of the DEA, thirteen different raster-based evidential layers derived from different geo-datasets (geological, geophysical and geochemical) are integrated for the real data pertaining to the Nowchun porphyry Cu–Mo deposit located in Kerman, central Iran. This region has been previously studied in the variety works (Abedi and Norouzi 2012; Abedi et al., 2012a, 2012b, 2012c; Daneshvar Saein et al., 2012; Abedi et al., 2013a, 2013c; Daneshvar Saein et al., 2014) by examination of divers integration methods in MPM. The main objective of this study is to investigate the applicability of the proposed method in MPM process. Finally, 29 boreholes were used for validation of the generated MPM.

## 2. Methodology

The summary procedure of the applied DEA method to prepare MPM is shown in Fig. 1. The steps of the proposed algorithm are listed below,

**Step 1:** Preparing the geo-data sets and collecting the required data.
**Step 2:** Processing the exploratory data and constructing the layers of information.
**Step 3:** Defining the obtained layers as input and output indicators of DEA. If low values of the evidential layers correspond to high potential zone in MPM, these layers are considered as input data $X$ that must be minimized, and likewise if high values of the evidential layers correspond to high potential zone they should be maximized as output data $Y$.
**Step 4:** Applying graph supper efficiency through DEA-crs method for assessing and ranking of alternatives in order to localize high potential zones for exploratory drilling.
**Step 5:** Mapping graph supper efficiency acquired from previous step.
**Step 6:** Reclassifying produced map based upon its statistical parameters (mean and standard deviation) and constructing final MPM.

### 2.1. The DEA method

DEA as a non-parametric performance evaluation method with diverse aspects of application within various disciplines is a useful tool for assessing efficiency of organizations (Akcay et al., 2012). DEA defined as "a mathematical programming model applied to observational data and a new way of obtaining experimental estimates of relations such as the production functions and/or efficient production possibility surfaces" by Charnes et al. (1978). For a set of Decision Making Unites (DMUs) in terms of multiple inputs and outputs presuming neither a specific form of relationship between inputs and outputs, nor fixed weights for the inputs and outputs of a DMU can be traditionally compared. DEA has enabled

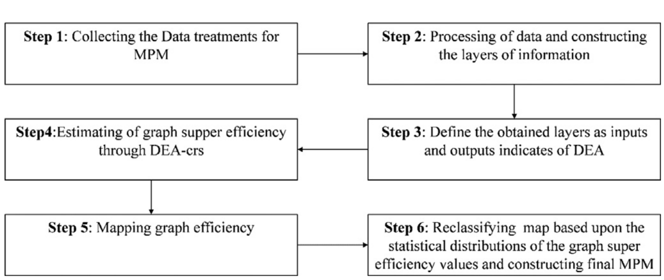


**Fig. 1.** The summary procedure of applying DEA method to generate MPM.

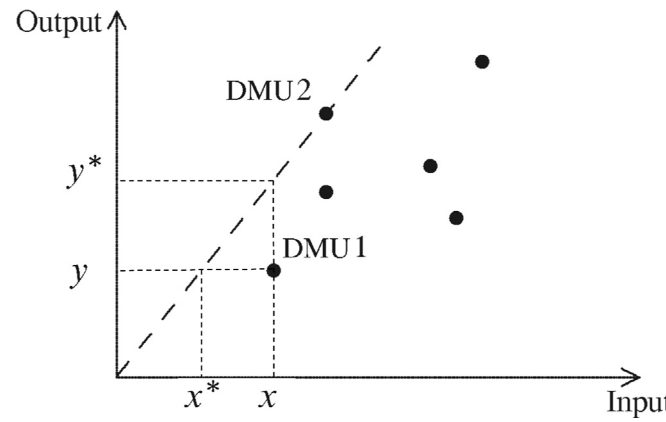


**Fig. 2.** Farrell efficiency in one-input/one-output example (reproduced from Bogetoft and Otto (2011)).

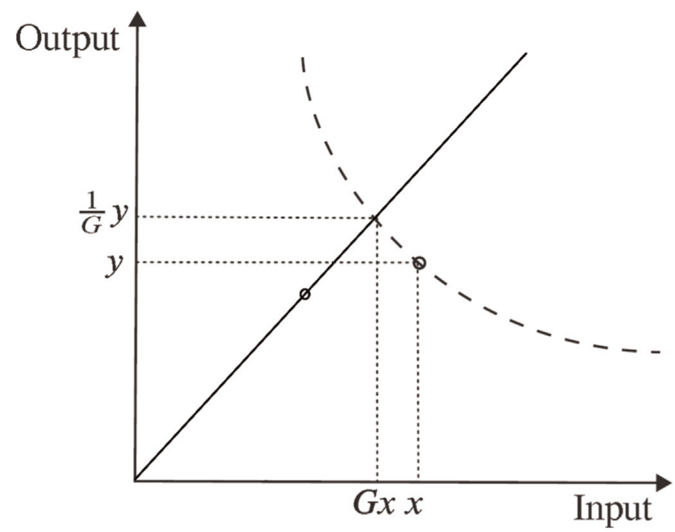


**Fig. 3.** Graph efficiency measure (reproduced from Bogetoft and Otto (2011)).

its use in cases which have been resistant to other methods because of the complex and often unknown nature of the relationship between the multiple inputs and outputs involved in many activities. DEA measures the relative efficiencies of DMUs with multiple inputs and outputs and provides an *efficiency score* between 0 and 1 (or $>1$, in supper efficiency case) for each DMU involved in the analysis. The efficiency score for a DMU can be determined by computing the ratio of its total weighted outputs to its total weighted inputs. DEA assigns weights to the inputs and outputs of a DMU that gives it the best possible efficiency (Cooper et al., 2006). To compute the efficiency scores of each DMUs for a DEA model with $n$ different DMUs (or $n$ alternatives in MCDM problems), $n$ different programming optimization models have to be solved.

A basic DEA model can provide important metrics and benchmarks for monitoring the comparative performances of DMUs in a group. It compares each DMU with only the "best" DMU. An *efficient frontier* or *envelopment surface*, drawn over the "best" DMUs, is the critical component of a DEA model. It can be formed through efficient DMUs with efficiency scores of 1 (or max efficiency in supper efficiency case). The efficiency score of a DMU is basically the distance between a DMU to this efficient frontier. The efficiency scores of the inefficient DMUs are calculated in accordance with such distance presented as a Pareto ratio (Akcay et al., 2012).

Bogetoft and Otto (2011) described efficiency as generally a question of using minimum inputs to produce maximum outputs.