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3DWofE: An open-source software package for three-dimensional weights of evidence modeling

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ABSTRACT

The shortage of outcropping ore deposits and the inefficiency of traditional mineral exploration methods for discovering deep-seated deposits have increased the necessity of developing three-dimensional modeling methods for in-depth exploration. The 3DWofE is a Python-based open-source software package that provides the tools required for three-dimensional modeling of concealed ore bodies by developing a data-driven prospectivity modeling method called weights of evidence. This software enables users to create three types of models which include posterior probability, uncertainty, and studentized posterior probability. These models can guide exploration geologists through identifying potential regions of target mineralization in depth.

Code metadata

Current Code version	*1.0.0*
Permanent link to code/repository used of this code version	https://github.com/SoftwareImpacts/SIMPAC-2020-39
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/6217621/tree/v1
Legal Code License	*GPL*
Code Versioning system used	*git*
Software Code Language used	*Python*
Compilation requirements, Operating environments & dependencies	*NumPy and pandas libraries*
If available Link to developer documentation/manual	
Support email for questions	e.farahbakhsh@aut.ac.ir

1. Introduction

The importance of exploration in the mineral industry has been increasing in recent years, particularly due to the need of humans for finding new deposits of the materials required to drive the energy transition away from fossil fuels [1,2]. Unfortunately, there has been a marked decrease in the rate of discovery over the recent past [3]. Despite advances in spend and technology, exploration efficiency is in decline, mainly because the easiest deposits have been already discovered. This is also despite advances in mining and processing technology which have allowed much lower quality deposits to be categorized into discoveries. It is likely that metal supply will not meet demand in the future, stymieing global economic growth, particularly in the developing world [4]. Only a few prospects become a mine, therefore to improve the exploration efficiency and to reverse the discovery decline, there is a need to improve exploration methods and decisions, so that deep-seated ore deposits are explored and ore reserves estimated.

The development of three-dimensional modeling methods can significantly further our understanding of the ore deposits concealed in depth from a variety of aspects. The main challenges in three-dimensional modeling are extracting exploration criteria from diverse datasets and integrating available information to guide future blind exploration [5]. In recent years, mineral prospectivity modeling methods have been applied for integrating multiple geoscientific datasets

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in three-dimensional space [6–9]. Among these methods, the weights of evidence method which is a data-driven method based on the Bayes' rule can provide a fully quantitative and informative prospectivity model and fuse all available constraints in a probabilistically rigorous fashion [10]. In general, the weights of evidence represent the degree of correlation between a specific type of mineralization and a particular model under specific conditions known as an evidence [11].

In this paper, we present 3DWofE which is a Python-based open-source software package for ordinary and fuzzy weights of evidence modeling of deep-seated ore deposits in three-dimensional space. This software comprises a number of subroutines with different functions leading to determining positive and negative weights of evidence for continuous and discrete evidential models, and integrating selected evidential models which ends up to creating posterior and studentized posterior probability models. The resultant probability models are used to identify potential regions of mineralization in the modeling space.

2. Weights of evidence method

The weights of evidence method is known as an efficient Bayesian probabilistic method [11,12] which is used for estimating the posterior probability of a specific type of mineralization with the assumption of conditional independence between input evidential models [10]. We update the prior probability of the occurrence of target mineralization using the weights of evidence in the light of input evidential models. These input models can be any type of data such as geological, geochemical or geophysical which are recognized to be associated with target mineralization. An example of the prior probability in a 3D space is the trained model created by interpolating the concentration values of the target element obtained from boreholes.

We can implement the 2D weights of evidence method using available GIS packages [13–15]; however, implementing weights of evidence in a 3D space is challenging. The weights of evidence method is applicable for prospectivity mapping when a number of mineral occurrences are known [12] which can be then extended to known mineralization voxels in a 3D space. We determine the degree of correlation between a particular model created under specific conditions known as an evidence and target mineralization using calculated positive or negative weights [7,8,16,17]. The weights of evidence can be interpreted in geological terms, intuitively, indicating the association between evidential models and the presence/absence of target mineralization. Therefore, we can use an evidential model to assess the contribution of a geological process in the creation and prospectivity of a specific type of mineralization [10]. The 3DWofE makes it possible to determine the fuzzy and ordinary weights of evidence in a 3D space.

The continuous models such as geochemical or geophysical models need to be converted into binary models or classified before calculating the weights of evidence. The weights are calculated for each class and later used for determining fuzzy weight and contrast. The fuzzy and ordinary weights of evidence along with other parameters such as contrast are calculated as described in past studies [11,18,19]. The posterior probability model is created by integrating input evidential models which is based on Bayes' equation in a log-linear form while assuming that conditional independence holds [11,18].

It is challenging and vital to identify and quantify the uncertainty of geological or prospectivity models [20,21]. We calculate the effects of uncertainty due to missing information using the weights of evidence method [11]. The 3DWofE is able to create the uncertainty model by adapting the approach described before [11,12,18,19,22] and the variance of the posterior probability is determined using the variance of the weights at each voxel. The studentized posterior probability refers to the ratio of the posterior probability to the corresponding standard deviation which equals the square root of total variance at each voxel. The studentized posterior probability acts as a measure of the relative certainty of the posterior probability. Due to a lack in confidence in the results, the voxels where the studentized value falls below some threshold can be masked out.

3. Key features of 3DWofE

3.1. Ordinary and fuzzy weights of evidence

There are a variety of geoscientific data which are used for creating evidential models at the early stage of mineral prospectivity modeling. In general, the evidential models are categorized into continuous and discrete models. The discrete models are usually created using qualitative data such as lithological and alteration data, and each unit of these models can be considered as a separate binary model for calculating the ordinary weights of evidence. The continuous models are created using quantitative data such as geochemical and geophysical data, and there are two ways to deal with this type of models. First, we can consider a specific threshold for each continuous model and convert it into a binary model for calculating the ordinary weights of evidence that causes loss of information. Second, we can classify each model and determine the fuzzy weight of evidence for each class, separately, which increases the reliability of final probability models. The proposed software is able to work with both types of the models and to determine ordinary and fuzzy weights of evidence for a variety of evidential models.

3.2. Uncertainty

The weights of evidence method enables the user to determine the effects of uncertainty on the weights and caused by missing information. This leads to a quantified model of the uncertainty which plays an important role in decision making. The variances of the weights are the main factors that help to model the uncertainty associated with the posterior probability and to generate the studentized posterior probability model which acts as a measure of the relative certainty of posterior probability. In addition to the posterior probability model, 3DWofE is able to provide an uncertainty model and a studentized posterior probability model leading to a more reliable estimation of target mineralization in depth.

3.3. Integration

We usually remove some of the evidential models from the modeling process due to the low correlation with target mineralization or violating conditional independence, and choose the integration method based on selected evidential models. The 3DWofE provides a normal and a hybrid solution for integrating input models. If selected evidential models are all binary, we use a normal solution and if they are a combination of both binary and classified models, we use a hybrid solution. The latter is able to minimize the loss of information and provides a more reasonable model by integrating ordinary and fuzzy weights of evidence.

4. Impact overview

The 3DWofE has been originally created for three-dimensional weights of evidence modeling of concealed ore deposits and detecting potential regions of mineralization in depth. In a recent study, this software has been used for modeling a deep-seated porphyry Cu deposit in southeast Iran [23]. Based on the results, the posterior and studentized posterior probability models shown in Fig. 1, predicted more than 60% of target mineralization in less than 40% of the modeling space, although the prediction rate relies significantly on the input

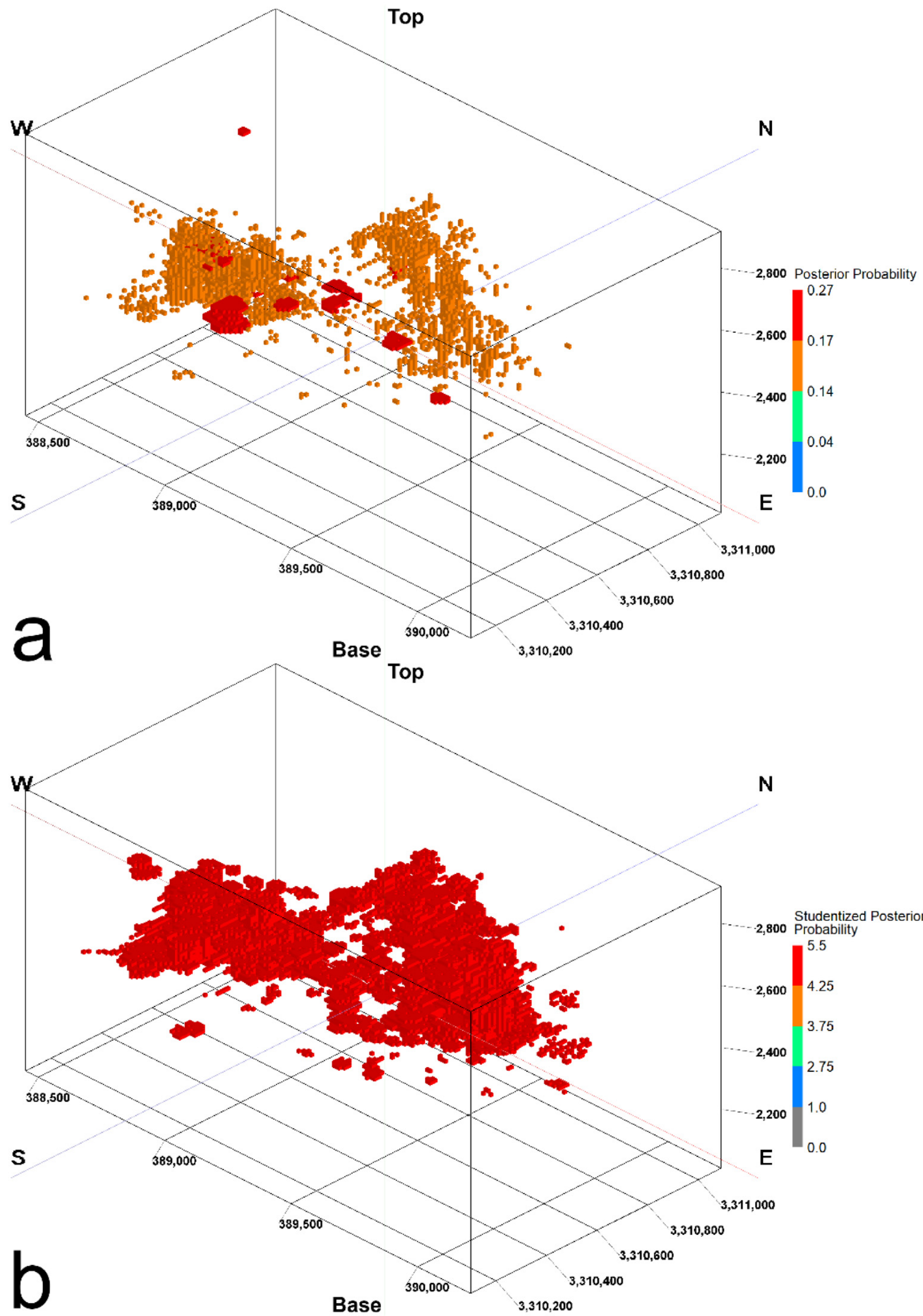

Fig. 1. (a) Posterior probability, and (b) studentized posterior probability models of a deep-seated porphyry Cu deposit created using 3DWofE [23].

evidential models and the extent of modeling space. The results show the efficiency of 3DWofE in modeling the target ore body which implies that using the posterior probability and studentized posterior probability models, we can minimize the risk of further exploration and optimize the process of selecting new locations for drilling. The flowchart presented in Fig. 2 shows the steps that have to be taken for creating probability models and a guide to use 3DWofE.

5. Potential improvements

Currently, the 3DWofE comprises a number of subroutines that each provide the required inputs of other subroutines. Some of the subroutines need individual values to be inserted for specific parameters such as a threshold which is needed in the process of determining the weights of evidence for continuous models which makes using the 3DWofE complicated. We are planning to provide the subroutines in Jupyter Notebook for the ease of use and minimizing the ambiguities during the process of modeling. Also, providing separate packages for normal and hybrid solutions for implementing the three-dimensional modeling would result in more user-friendly packages. A simple graphical user interface can further increase the popularity of the package among the community and encourage companies and beginner users to use this package.

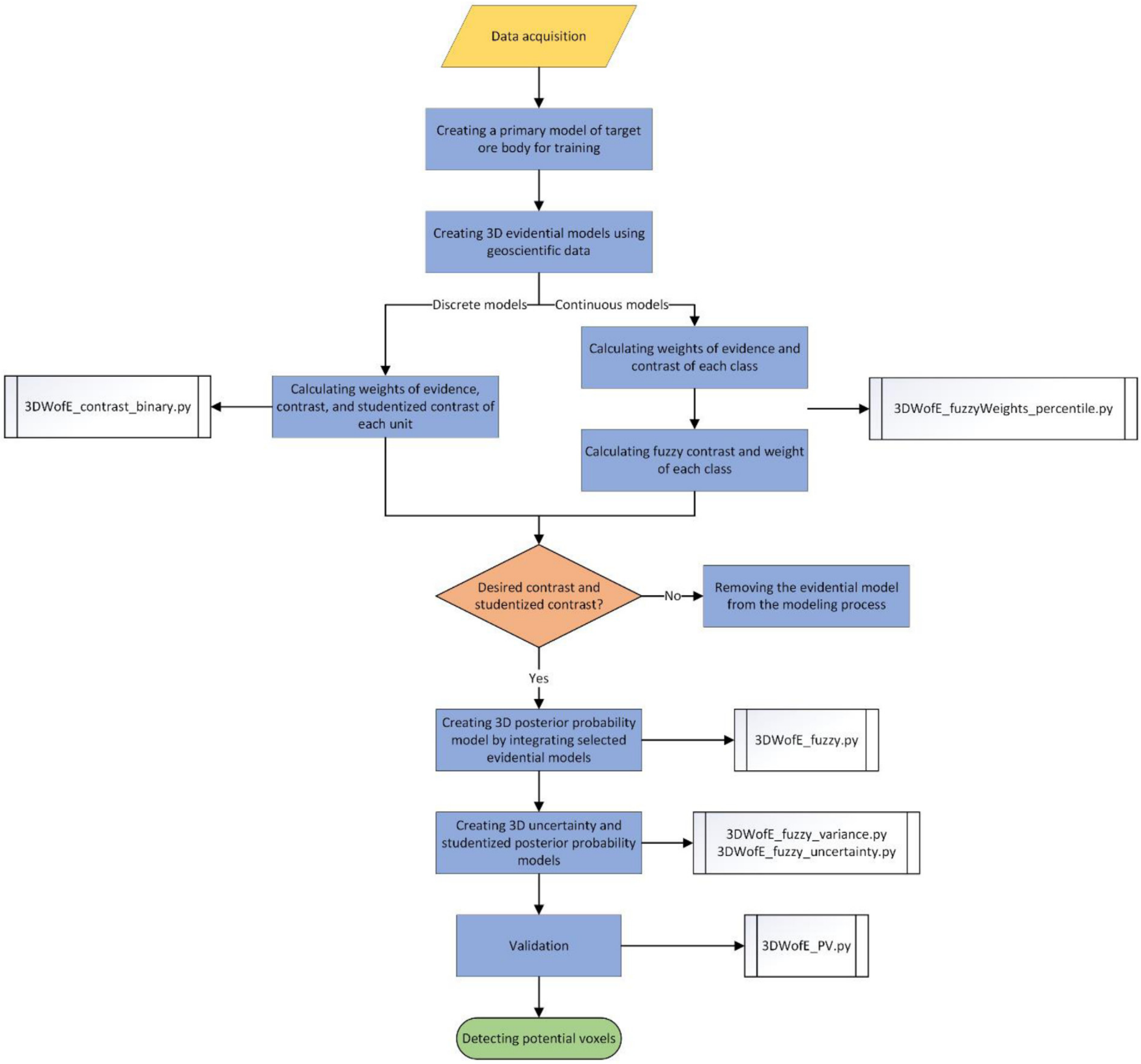

Fig. 2. Methodology flowchart for three-dimensional weights of evidence modeling of an ore deposit. The relevant subroutines are shown beside each step.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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