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Mitigating uncertainties in mineral exploration targeting: Majority voting and confidence index approaches in the context of an exploration information system (EIS)

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ABSTRACT

Various mineral prospectivity modelling (MPM) approaches are available for targeting mineral deposits, each method capable of predicting areas of high prospectivity. Given the diversity of MPM approaches, the modelled areas of high prospectivity can differ across different MPMs. However, rather than a negative, different MPM outputs can benefit mineral exploration targeting because each method has its advantages. Rather, the problem lies in the lack of consensus over how to best select and delimit mineral exploration targets from different MPM results. Here we aim to address the challenges outlined above whilst quantifying and mitigating the effects of inherent uncertainties. We first generate eleven different prospectivity models utilising deep learning, machine learning, fuzzy logic, and geometric average integration methods. Then, we adopt a majority voting ensemble technique to incorporate and combine the predictions of each prospectivity model. Next, we propose a confidence index designed to mitigate uncertainty associated with our multi-technique approach to MPM. The confidence index quantifies variation in prospectivity values for each cell of the MPM target area. The conjunction of a confidence index and majority voting model facilitates consistent and robust algorithm-driven extraction of exploration targets based on an ensemble of prospectivity models.

1. Introduction

Over the past few decades, various mineral prospectivity modelling (MPM) methods have been developed, each capable of identifying areas that are highly prospective for a chosen mineral deposit type and, thus, aiding mineral exploration targeting (e.g., Yousefi et al., 2021). The diversity in weighting methods and integration approaches can result in a variety of MPM outputs that not only make the selection of exploration targets a more challenging task but also serve to propagate uncertainty into target selection (e.g., Burkin et al., 2019; Yousefi et al., 2021). To mitigate this issue, generating sound targeting models, validating them against the locations of the known targeted mineral deposits, and selecting targets from the 'best performing' model is common practice (e.g., Bonham-Carter, 1994; Kreuzer et al., 2020; Yousefi et al., 2021). Whilst the various approaches to MPM are being continuously improved (Nykänen, 2008; Nykänen et al., 2008; McCuaig et al., 2010; Hagemann et al., 2016a, 2016b; Yousefi et al., 2019, 2021; Yousefi and Hronsky, 2023; Yousefi et al., 2023a; Mostafaei et al., 2024), significant uncertainty remains concerning how to best select mineral exploration targets from the models generated. For instance, exploration data can be weighted using statistics, expert knowledge, user-defined functions, and logistic functions (e.g., Bonham-Carter, 1994; Pan and Harris, 2000; Harris et al., 2015; Yousefi et al., 2021). Weighted predictor maps can be integrated using a variety of methods such as statistical functions, fuzzy operators, supervised machine learning, supervised deep learning, unsupervised deep learning, and geometric average function (e.g., Bonham-Carter, 1994; Carranza, 2008; Yousefi and Carranza, 2015b; Zuo and Wang, 2020; Rahimi et al., 2021; Yousefi et al., 2021, 2023a, b; Bahri et al., 2023; Ghasemzadeh et al., 2023). However, choosing the most appropriate method(s) remains challenging. The holistic nature of

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the currently available MPM techniques confers an advantage that all can be used for most targeting exercises. However, choosing an appropriate MPM method often relies on the practitioner's prior experience rather than the types and quality of the available input data or the targeted deposit type. Whilst most methods are statistically adequate, the resulting prospectivity values differ, causing problems with benchmarking a reliable and proven methodology for mineral exploration targeting that is appropriate for real-world decision-making.

Generally, uncertainty in the natural sciences can be considered either aleatory or epistemic (Quigley et al., 2019). Aleatory uncertainty (also known as stochastic or statistical uncertainty) derives from the natural variation of inputs and parameters (e.g., minor imprecisions of geochemical assays or GPS coordinates). Aleatory uncertainty cannot be reduced even as more data are gathered. In contrast, epistemic (or systematic) uncertainty, which stems from an incomplete knowledge, can (at least theoretically) be reduced by obtaining additional information about the object or system in question. In mineral exploration targeting, incomplete knowledge manifests itself in many forms. Pertinent examples are (i) geological processes, which cannot be observed directly and, as such, have to be modelled or inferred, or (ii) prospective bedrock under thick post-mineral cover, where exploration targeting requires interpolation and/or extrapolating of sparse geological, geochemical and geophysical data. In MPM, epistemic uncertainty is addressed by interpolation using, for example, kriging, natural neighbour algorithms or other statistical techniques to substitute for spatial knowledge gaps.

Whilst aleatory uncertainty has been demonstrated to significantly impact geoscientific models (e.g., in 3D geomodelling: Wellmann et al., 2010; Lindsay et al., 2012, 2020), epistemic uncertainty arguably has greater impact on regional-scale MPM. Aleatory errors, as pertaining to MPM, are typically minor (e.g., GPS: $\pm$ 5 m) and commonly have a lesser impact on the results, especially when multiple modelling approaches are utilised. As such, our focus is on epistemic uncertainty.

In this paper, we adopt a majority voting ensemble technique (e.g., Lam and Suen, 1997; Sun and Li, 2008; Usman et al., 2016) to optimise and aggregate the positive aspects of different prospectivity models, each constrained by the same input data, into a single output. We introduce a confidence index designed to mitigate the problem of divergence in the modelled prospectivity values, which differ from model to model for any given area unit of the study area. The proposed procedure not only enhances decision-making in MPM but also lends itself for use in and to augment an exploration information system (EIS) (Yousefi et al., 2019, 2021), an exploration targeting support tool designed to better integrate the conceptual mineral deposit model (i.e., the critical and constituent processes of the targeted mineral system) with data available to support exploration targeting.

2. Deposit model, study area and input dataset

Porphyry-Cu deposits form in subduction-related magmatic arcs along convergent plate margins and are associated with intrusive complexes (Sillitoe, 2010). These ore deposits contain copper-bearing minerals in trap sites within host rocks or as open-space fill as veins or in breccias. Fractures in the spaces around porphyry-Cu deposits provide channels for the entry of external ore-bearing fluids into the outer parts

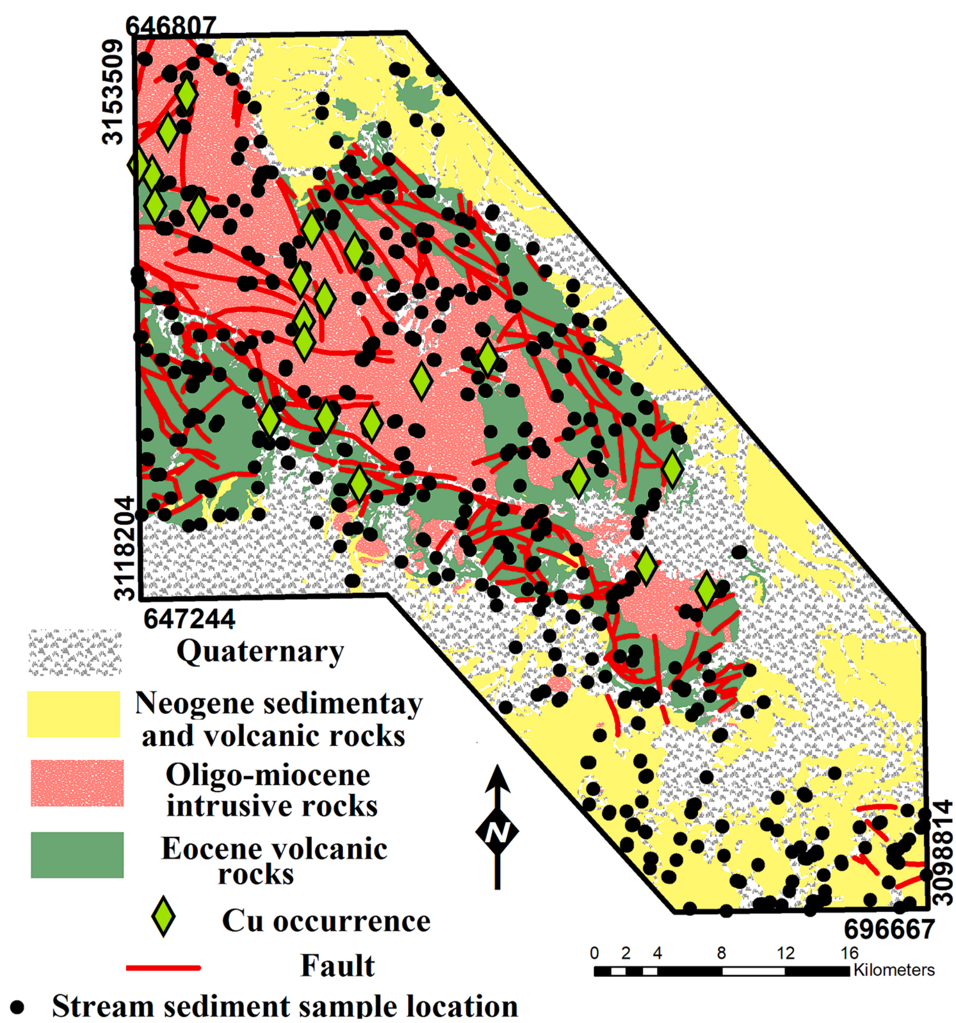

Fig. 1. Simplified geology map of the study area superimposed by point symbol representing the location of stream sediment samples.

of the hydrothermal system (e.g., Yousefi and Hronsky, 2023), causing alteration (e.g., Sillitoe, 2010). Therefore, different wall rock alteration types are common geological features within and around porphyry-Cu mineralization systems.

The study area measures ~ 1620 km^2 and covers parts of a 1:100,000 scale geological map of Nagisan (provided by the Geological Survey of Iran; GSI) in the southern part of the Urumieh–Dokhtar Volcanic Belt, Iran. Geological details of the Urumieh–Dokhtar Volcanic Belt can be found in Alavi (1980) and Berberian et al. (1982). Fig. 1 shows the simplified geological map of the study area with 22 known porphyry Cu deposits and occurrences. We used these deposits as a set of positive samples to train the artificial intelligence algorithms and test the performance of the generated models.

We used stream sediment geochemical data comprising 545 samples of −80 mesh fraction, collected and analysed by GSI, in our porphyry Cu deposits analysis. The samples were analysed by the inductively coupled plasma optical emission spectrometry method. In this study, according to data availability and quality, we only utilized Cu stream sediment data to generate geochemical evidence layer as an important indicator of the targeted deposits. As illustrated in Fig. 1, the known porphyry Cu deposits are hosted by mainly Oligo-Miocene intrusive rocks. Faults deform these rocks. The intrusive systems are surrounded by sedimentary Neogene and Quaternary units. The Quaternary units, covering a small part of the eastern study area, were not sampled.

3. Methods and results

3.1. Mineral prospectivity modelling (MPM)

3.1.1. Predictor maps

We generated five maps of exploration evidence features and proxies according to the mineral system model and the ensuing district-scale exploration criteria of porphyry-Cu ore formation applied for targeting these types of mineral deposits. Data availability was considered with the history of exploration programs in the Urumieh–Dokhtar Volcanic Belt. The exploration features are: (i) fault density (FD), (ii) Cu element content in stream sediments, interpolated using inverse distance weighting; (iii) distance to argillic alteration, (iv) distance to iron oxide alteration and (v) distance to intrusive contacts. The alteration features were mapped using ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) imagery supplied by the National Iranian Copper Industries Company. The values in the maps were then weighted using logistic functions (Fig. 2), a well-known continuous weighting approach (Yousefi and Carranza, 2015a; Yousefi and Nykänen, 2016; Almasi et al., 2017; Yousefi and Hronsky, 2023). It has been demonstrated in multiple studies that the application of continuous weighting methods using logistic functions improves the reliability of exploration targeting models when compared with classified weighted exploration evidence data (e.g., Yousefi and Carranza, 2015b, 2017; Yousefi and Nykänen, 2016; Mao et al., 2019). The weights in these maps have been obtained through a transformation using logistic fuzzification functions and lie within 0 and 1. Thus, the weighted maps are ready to be combined using our variety of integration approaches and functions. Given that this paper proposes to benefit from the advantages of different prospectivity modelling approaches, we combined the generated weighted layers using three machine learning approaches, two deep-learning methods, five fuzzy operators, and the geometric average function.

3.1.2. Machine learning integration

We integrated the layers shown in Fig. 2 using support vector machine, random forest, and extreme learning neural network to utilize the positive sides of supervised machine learning methods and training point sets. These supervised methods were trained using 22 Cu occurrences as positive samples and 22 non-deposit locations as negative samples, where mineral deposits are predicted as unlikely to be present (e.g., Abedi et al., 2012; Zuo and Carranza, 2011; Zhang et al., 2016; Zuo and Wang, 2020; Rahimi et al., 2021). The negative point samples were randomly selected out of polygon and line features, which were applied as exploration evidence in this study. The generated prospectivity models have been shown in Fig. 3. Machine learning methods attempt to find locations similar to positive and negative samples, i.e., deposit and non-deposit sites, and return the locations, respectively, as prospective and non-prospective areas and the range of prospectivity between them. This means the outcomes of prospectivity modelling using this category of techniques are strongly affected by the spatial position of the positive and negative training sites (e.g., Prado et al., 2020; Rahimi et al., 2021). Dispersion of deposit sites and their number depends on the number of previous exploration programs, and there needs to be a consensus on a sufficient number of deposit sites to be used in the integration process while respecting the expansion of the area under study.

Furthermore, the selection of negative sites has been a challenging task and gives uncertainty. Despite the dependency of supervised machine learning methods on training set, a considerable disadvantage, supervised methods are also very effective at finding locations similar to the positive samples, which is a significant advantage. If there are undiscovered mineral deposits in a study, including exploration evidence and signals dissimilar to those positive examples in and around the discovered deposit sites, it will be challenging to recognize them as exploration targets.

3.1.3. Supervised and unsupervised deep learning integrations

Deep learning approaches help to reveal patterns in spatial exploration data (e.g., Xiong et al., 2018; Yousefi et al., 2021; Agha Seyyed Mirzabozorg and Abedi, 2023). The abnormal patterns can represent natural phenomena, e.g. mineralization, which is a positive side of deep learning integration approaches. Given that unsupervised deep learning methods identify patterns without using known deposit sites as training points, they have the ability of discovering new mineral deposits that may show exploration evidence not completely similar to those in the known deposit locations. Lack of dependency to training samples is also a positive point where we don't have many known sites, which is the usual case for prospectivity modelling practices. In contrast, the negative side of unsupervised deep learning method is not using training samples and losing the advantages they bring. Supervised deep learning methods benefit the advantages of both training data and pattern recognition, and so, suffer from the same disadvantages of machine learning and unsupervised deep learning. In this paper, we benefited from two deep learning integration approaches: an auto encoder network (Fig. 4a, an unsupervised approach) and a convolutional neural network (Fig. 4b, a supervised deep learning method).

3.1.4. Fuzzy operators

Fuzzy operators (An et al., 1991) for instance "AND", "OR", "sum", "product", and "gamma" have been widely applied to combine layers of fuzzified exploration data, ranging between 0 and 1, in the prospectivity analysis procedure (e.g., Bonham-Carter, 1994; Carranza, 2008; Abedi et al., 2017; Yousefi and Carranza, 2015a; Ghasemzadeh et al., 2019, 2022a). Their advantages and disadvantages have been also reported by Yousefi (2017a). In this study, we combined the same evidence maps in Fig. 2 using the five fuzzy operators to generate the ensuing five prospectivity models in Fig. 5.

3.1.5. Geometric average integration

'Geometric average' is an integration function that combines a set of uncertain variables, e.g., exploration evidence layers (Yousefi and Carranza, 2015b). The geometric average is calculated by taking the nth root of the product of n variables. The main advantage of this integration function comes from the nature of the function itself, which treats uncertainty where there are vaguely known variables (Yousefi and Carranza, 2015b). The geometric average has been widely applied in multi-criteria decision-making problems of other fields, in which the values

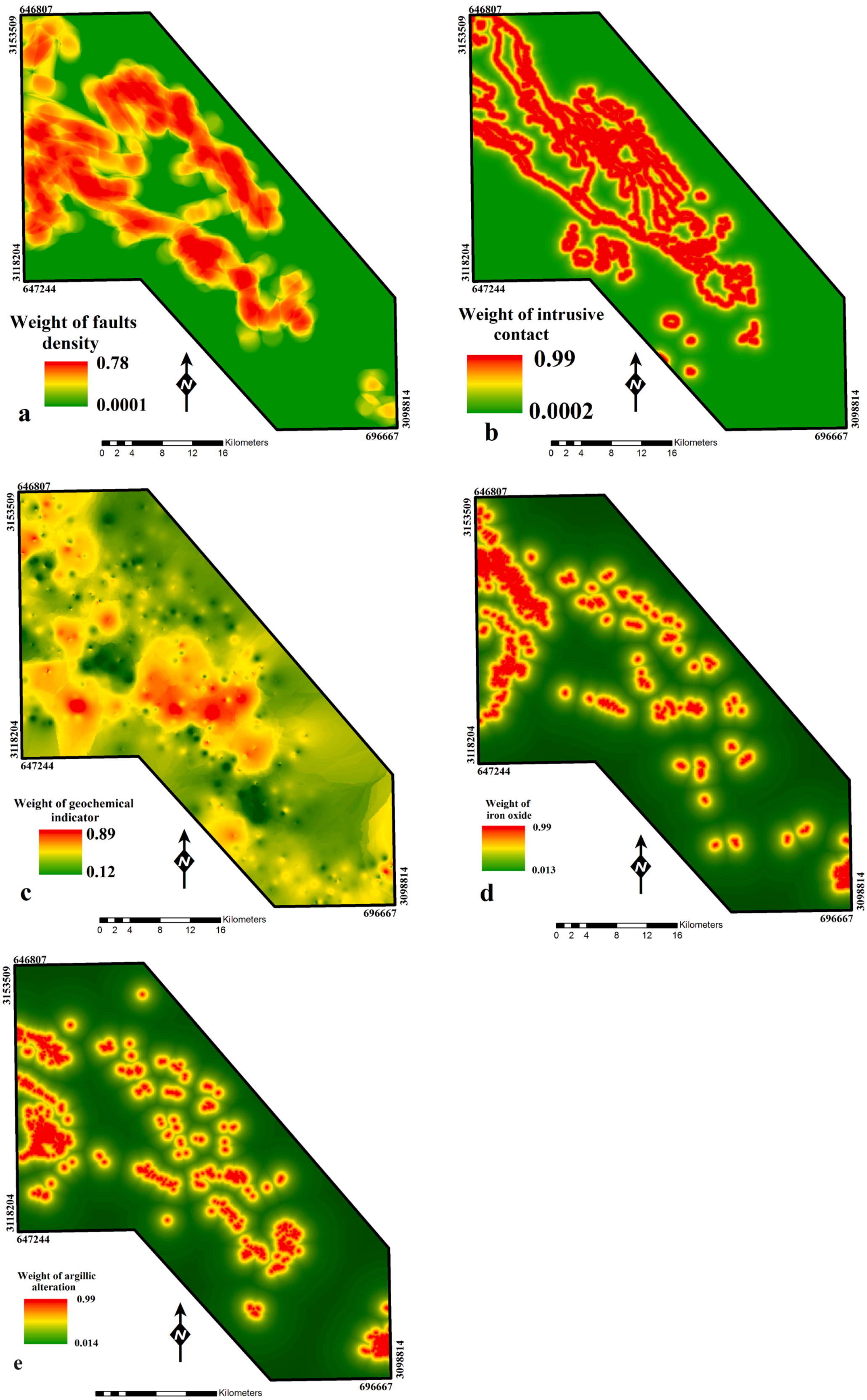

Fig. 2. Fuzzified (weighted) layer of (a) fault density, (b) intrusive contacts, (c) geochemical indicators, (d) iron oxide, and (e) argillic alteration.

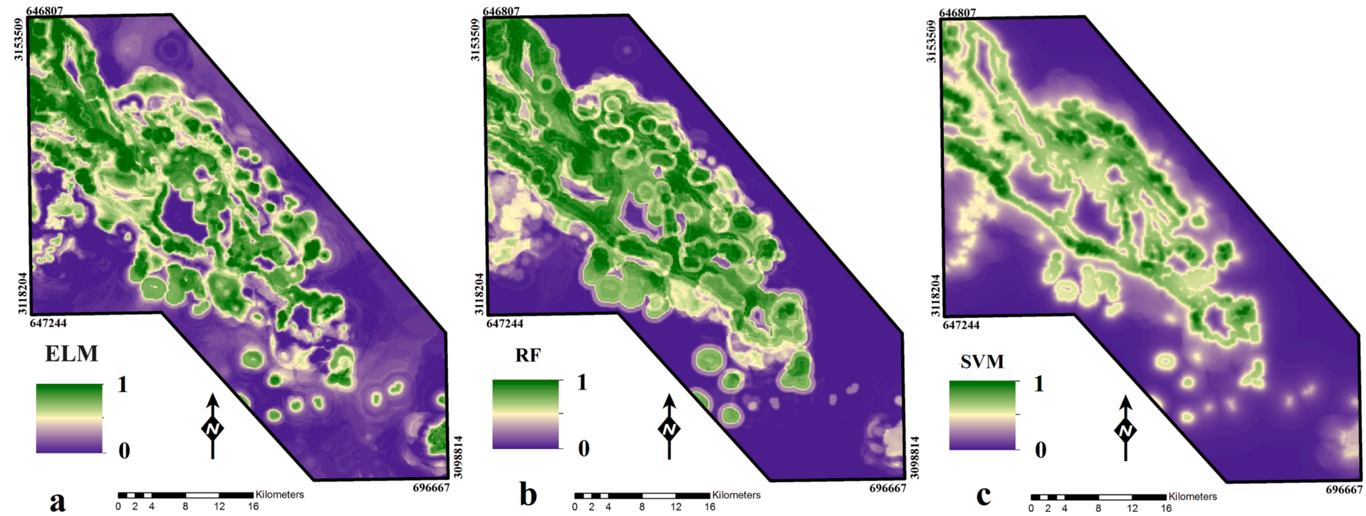

Fig. 3. Prospectivity models generated using extreme learning (a), random forest (b), and support vector machine (c).

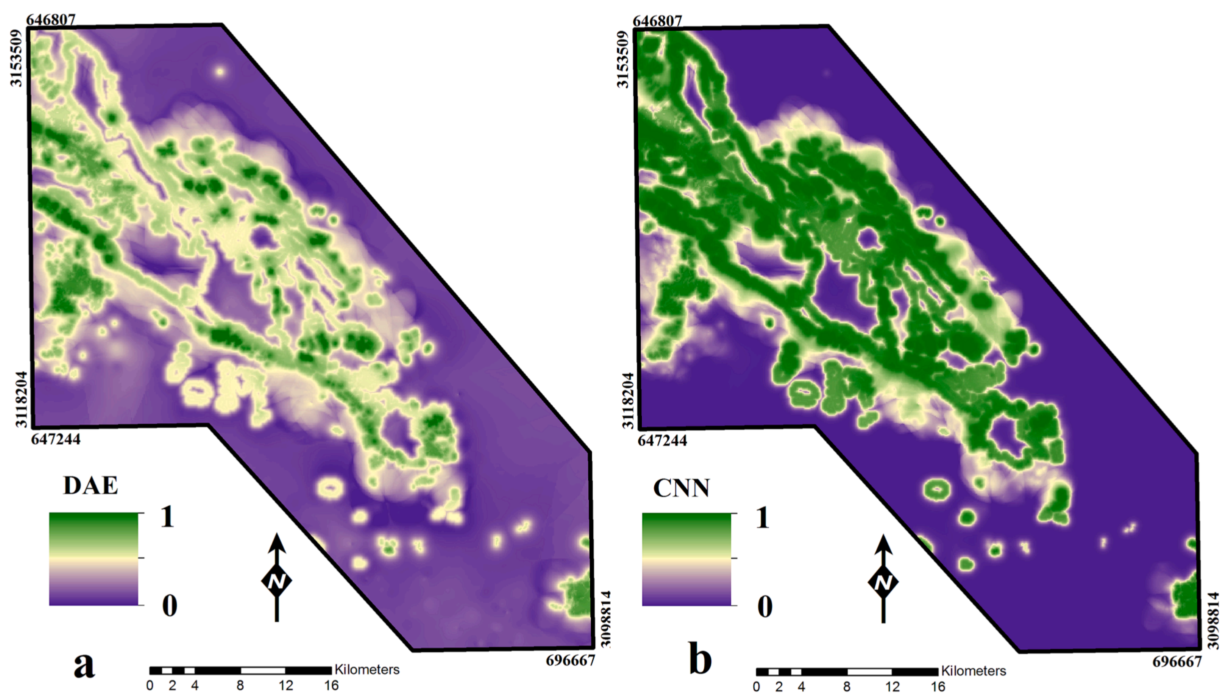

Fig. 4. Prospectivity models generated using deep auto encoder (a) and convolution neural network (b).

of decision criteria take the form of weights representing incompletely known information to model uncertainty (e.g., Yoshimura et al., 2009; Liu, 2013). Yousefi and Carranza (2015b) applied this function for mineral exploration targeting. They stated that the geometric average is the statistically correct average of heterogeneous sources, i.e., different mineral exploration evidence layers, with geometrical support. This integration method doesn't apply training samples is not an artificial intelligence technique, and is not subject to the advantages and disadvantages of supervised machine learning techniques described above. For the present study, there are five (n = 5) evidence layers (Fig. 2). Fig. 6 shows the geometric average prospectivity model generated by integrating the fuzzified evidence data.

3.2. Majority voting

Majority voting is an ensemble machine learning technique combining several model predictions (e.g., Lam and Suen, 1997; Sun and Li, 2008; Usman et al., 2016). It is used to improve predictive performance by exploiting the benefits from an ensemble of models rather than relying on any single model from the ensemble. In the case of classification using hard voting, the predictions for each class label are summed, and the class label with the majority vote is returned as output so that the predictions are the majority vote of contributing models. In mineral exploration, targeting using different prospectivity modelling methods is the purpose of this paper. A voting ensemble can be applied when two or more prospectivity models perform a predictive modelling task. For instance, Fig. 7 shows an example using three classified prospectivity models. According to the majority voting approach, for a given cell of a study area, if two models predict the cell as a second class of prospectivity and one model predicts the cell as first class, the cell is assigned a second class of prospectivity in the ensemble model (Fig. 7). For the classification of the generated prospectivity methods to be used

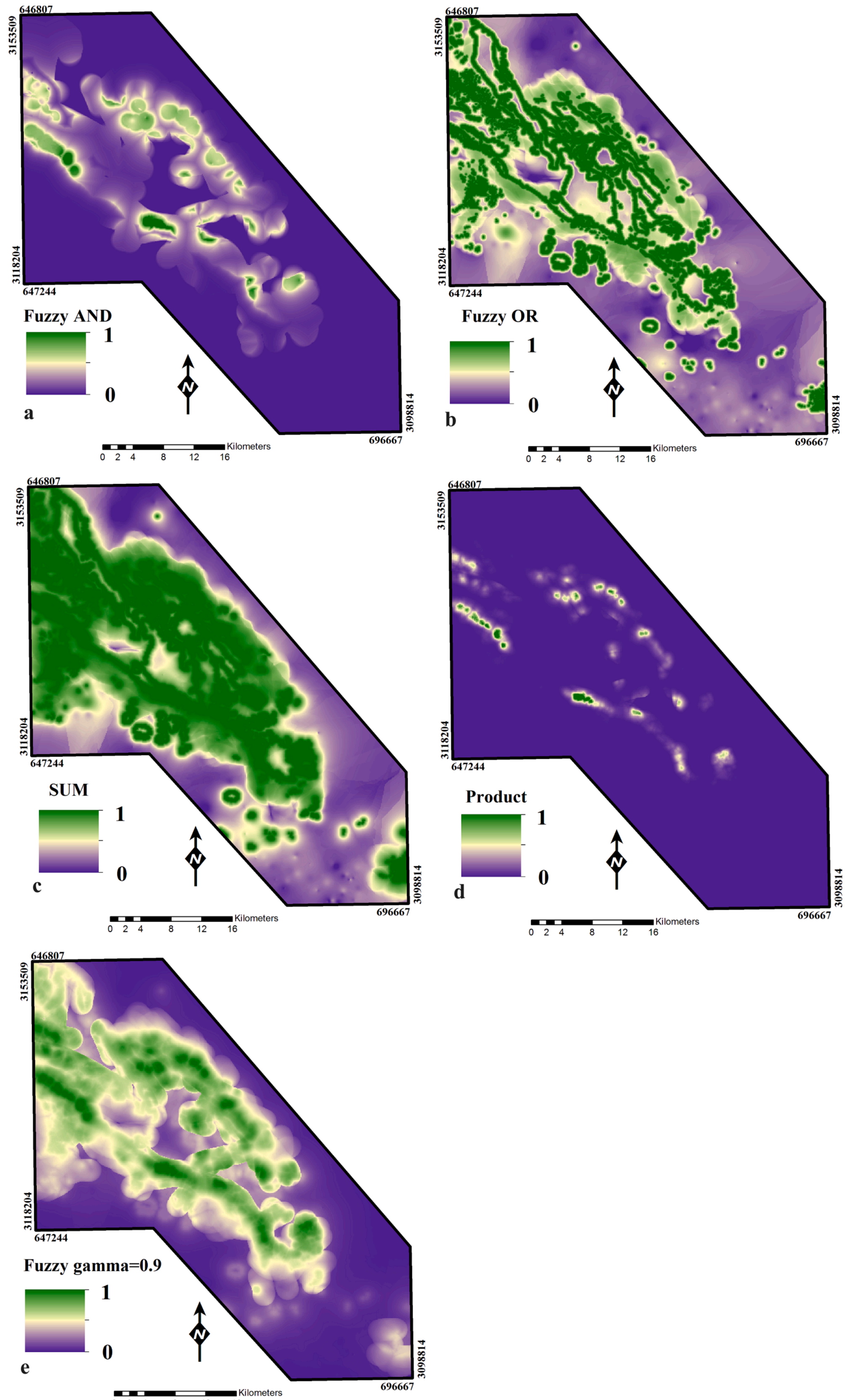

Fig. 5. Prospectivity models generated using fuzzy “AND” (a), “OR” (b), Sum (c), Product (d), and Gamma (e) operators.

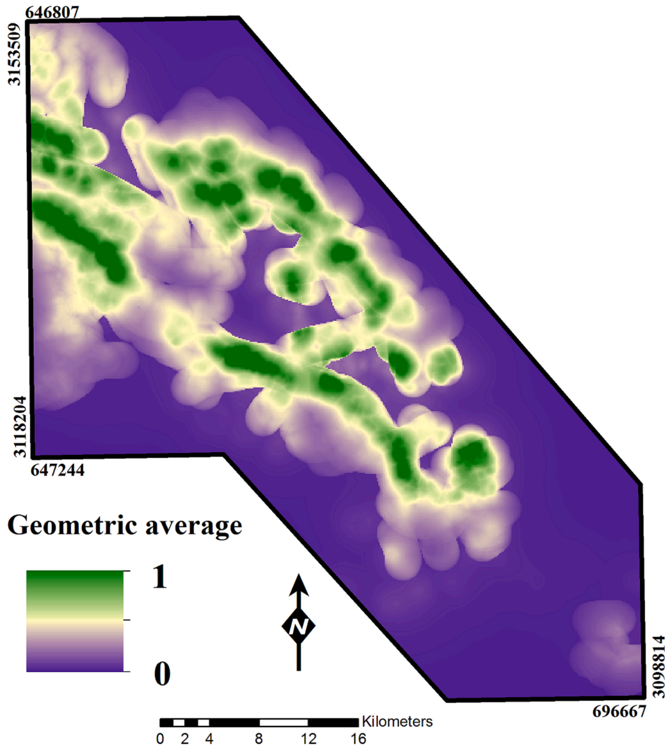

Fig. 6. The geometric average prospectivity model.

for majority voting (Fig. 8), we applied the geometrical interval method (Frye, 2007) in that the prospectivity value falls between natural breaks, equal interval, and quantiles approaches. Many classification methods can be used for majority voting. However, all models must be categorized into the same number of classes. Fig. 9 illustrates the application of the majority voting ensemble technique for the study area of this paper, which was generated using the classified maps in Fig. 8. While majority voting reduces the prediction variability of the models in the ensemble, the combined model cannot outperform all individual predictive models. For example, if most predictive models perform poorly and only a few perform well, the combined model will also perform poorly. Therefore, in the following sections, we explain how prediction results of various models can together outperform all individual predictive models, and how majority voting helps delineate a boundary for delimiting exploration targets.

3.3. Confidence index to measure uncertainty

In studies with various prospectivity models, we expect variation in the prospectivity values of a given cell of a study area as well. Some examples use the mean (*M*) and standard deviation (*Std*) statistical moments over rows of cells, but on individual modelling techniques/maps, to model uncertainty of mineral prospectivity and other geoscience models (Pakyuz-Charrier et al., 2018; Daviran et al., 2022; Huang et al., 2022; Lindsay et al., 2022; Wang and Zuo, 2022). Yousefi and Gholami (2010) describe Monte Carlo simulation and the effectiveness of using *M* and *Std* when risk analysis is carried out on a set of uncertain variables. Bonham-Carter (1994), proposed a ratio of contrast (*C*) to *Std* and named it studentized contrast (*Stud C*). This incorporates the variation of *C* as a form of uncertainty and was initially applied to weights-of-evidence prospectivity mapping procedures. *C* is a parameter calculated for classes of exploration data to quantify the degree of association between deposit locations and the classes (Bonham-Carter, 1994; Carranza, 2008). Furthermore, the coefficient of variation (*CV*) is the ratio of *Std* and *M* to model precision and experimental repeatability. The ratio is used to moderate the amount of variation in uncertain

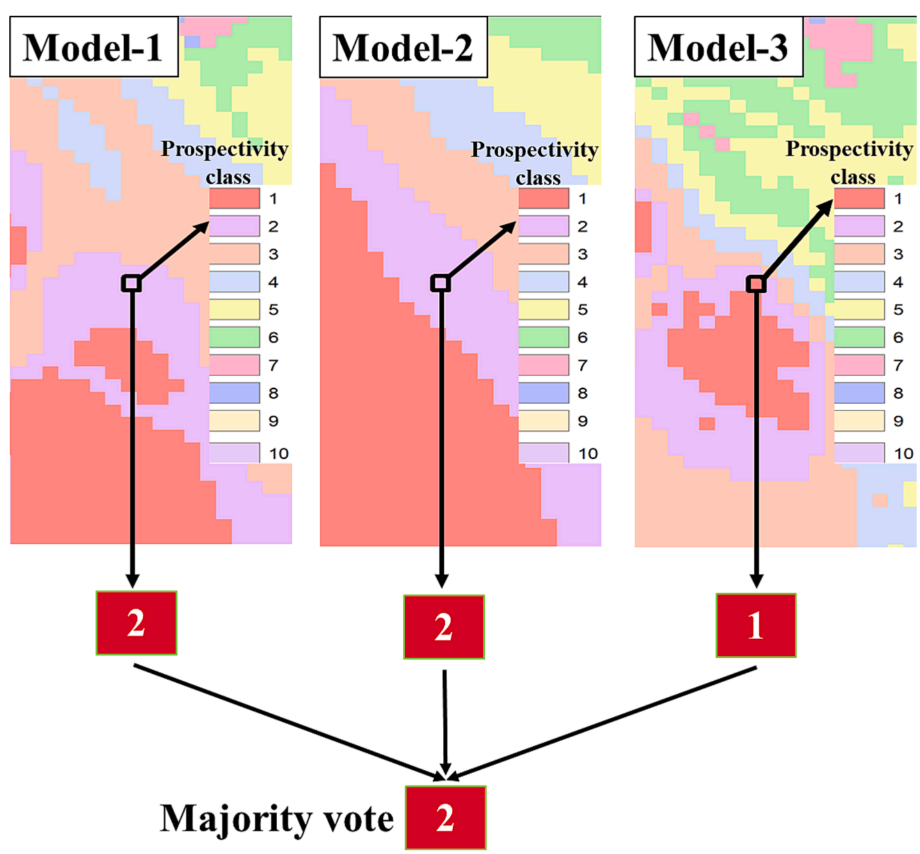

Fig. 7. Majority voting procedure for a given cell of an area using three prospectivity models.

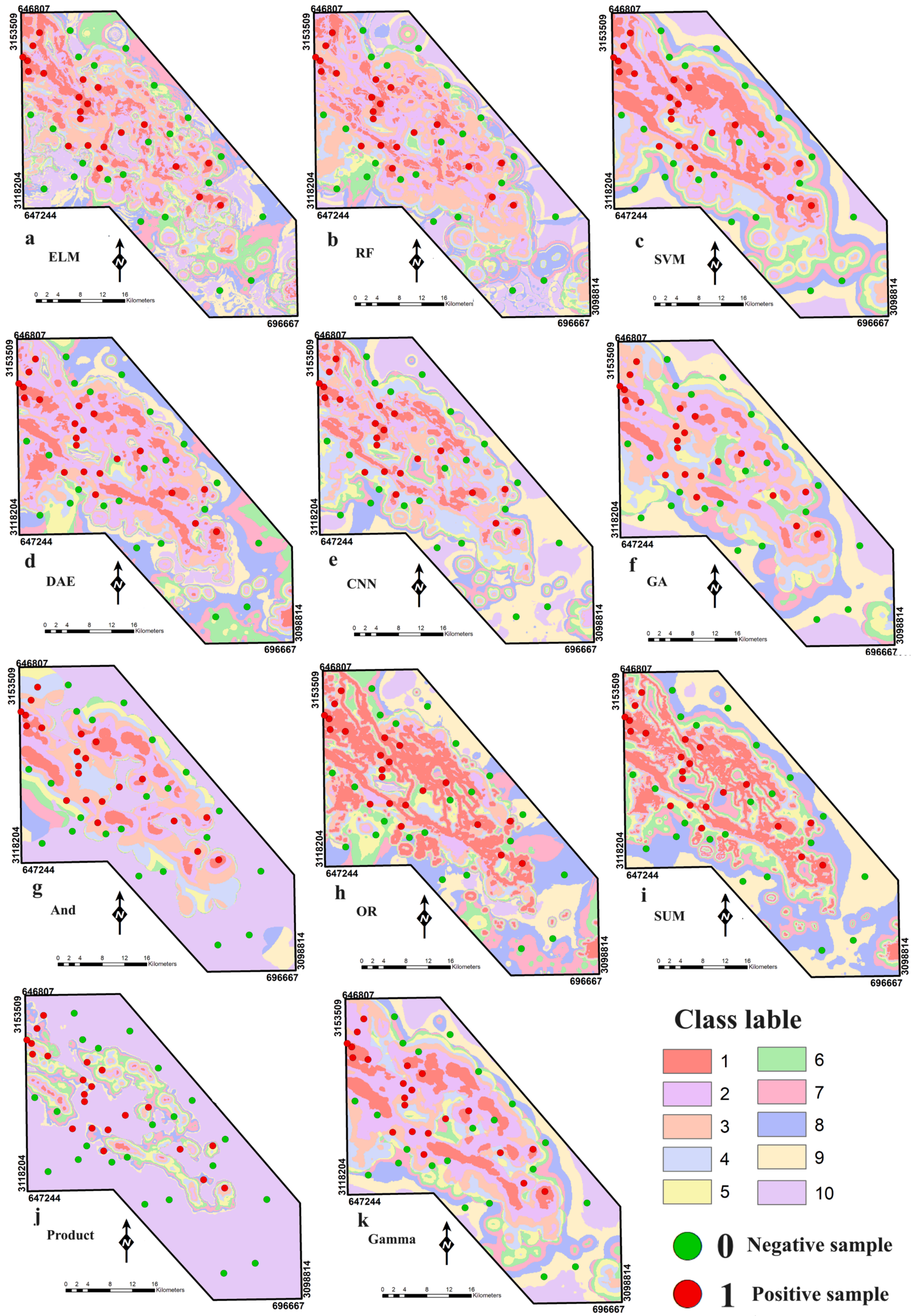

Fig. 8. Classified map of prospectivity models generated using extreme learning (a), random forest (b), support vector machine (c), deep auto encoder (d), convolution neural network (e), geometric average (f), “AND” (g), “OR” (h), Sum (i), Product (j), and fuzzy Gamma (k) operators. It should be noted for fuzzy operators, the geometric average function, and deep auto encoder models, training samples (negative and positive examples) have not been applied during the modelling processes. ELM: extreme learning machine, RF: random forest, SVM: support vector machine, DAE: deep autoencoder, CNN: convolution neural network, GA: geometric average, FA: fuzzy “AND”, FO: fuzzy “OR”, FS: fuzzy Sum, FP; fuzzy Product, FG: fuzzy Gamma.

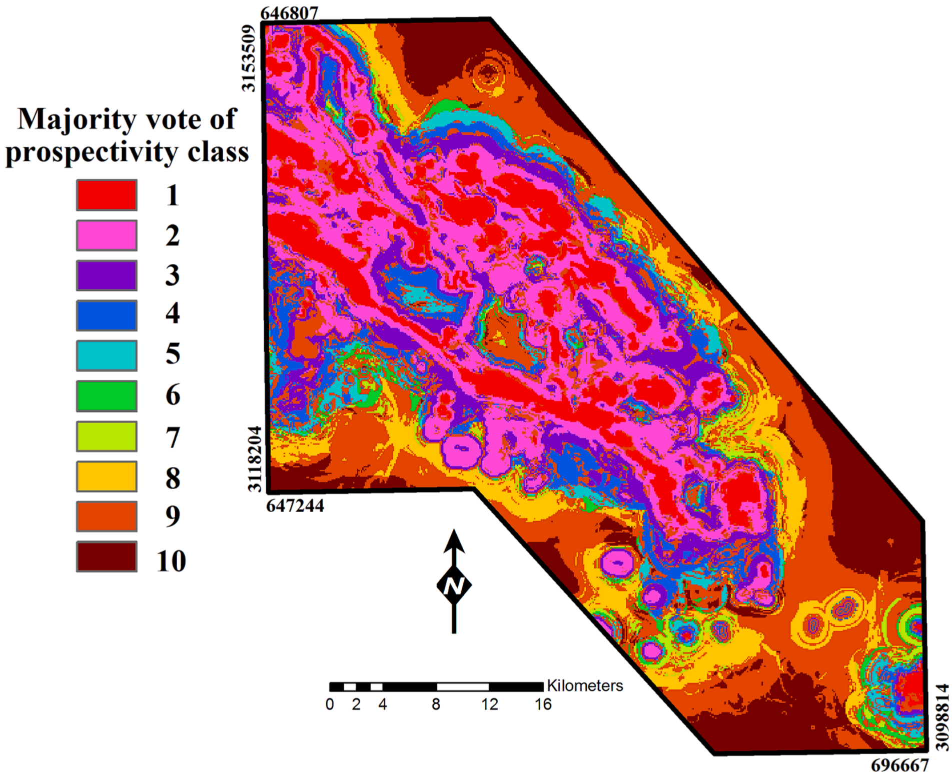

Fig. 9. A model of majority voting ensemble using 11 prospectivity models generated in this study.

variables. Here, following the discussion in this section, we invert *CV* and use a ratio of *M* prospectivity values obtained by a variety of prospectivity modelling methods and the *Std* of prospectivity values to find the 'confidence index', *CI*.

$$CI = \frac{M}{Std} \tag{1}$$

A single raster of *CI* supports the interpretation of the ensemble. Cells with higher *CI* values delineate more reliable targets in that such cells comprise high prospectivity values with less variation, and thus, greater confidence in finding relevant mineralization. For the dataset used in this study, maps of *M*, *Std*, and *CI*, are shown by Fig. 10a, 10b, and 11, respectively. The high *CI* values in Fig. 11 represent areas of greater prediction confidence and are selected for further exploration investment.

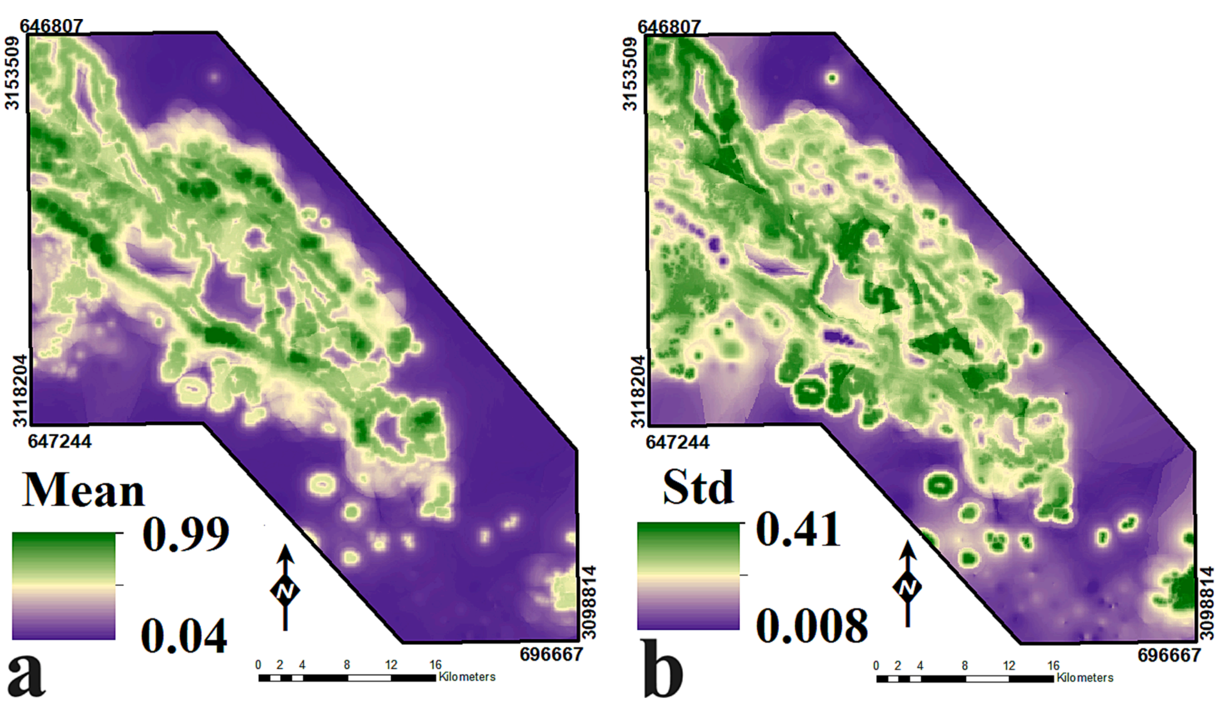

Fig. 10. Mean (a) and standard deviation (b) of the 11 prospectivity models generated in this study.

3.4. Extracting exploration targets from prospectivity models

While areas with high *CI* values can be delineated as exploration targets, delimiting targets is always a challenge as two questions arise: 1) what are the appropriate thresholds to discriminate the targets with different confidence levels? and 2) how is the target boundary delimited? To address the first question, we applied statistical techniques, including histogram, percentile, quantile, and box plot, to obtain the thresholds (Fig. 12a), similar to how the geochemical populations were classified (Bonham-Carter, 1994; Carranza, 2008). Thresholds can be explicitly extracted from the quantile box plot, which are the same obtained from the percentile-based classification. Therefore, we generated a classified *CI* prospectivity model (Fig. 12b) using the thresholds corresponding to the percentiles calculated in Fig. 12a. Subsequently, we returned the uppermost four classes of *CI* > percentile 90 as exploration targets (Fig. 12c). To delimit targets, we define a boundary condition using the outline of the first class of prospectivity obtained through a majority voting ensemble approach shown by Fig. 9. The final result is determining that about 10 % of the study area are exploration targets.

3.5. Information entropy analysis

Shannon or information entropy (Eq. (2) is a measure of uncertainty that quantifies the level of information revealed from datasets and models (Shannon and Weaver, 1949; Cover and Thomas, 2006) and in our case, prospectivity models.

$$E(X) = \sum P(x)*Log2P(x) \tag{2}$$

Based on Shannon's information theory, E(X) is entropy, a measure of uncertainty associated with variable X, and P(x) is the probability of outcome x of variable X. The higher the information entropy value, the more uncertain the variable. In addition to the *CI* that provides an extra dimension to the prospectivity assessment, we produce an entropy model (Fig. 13) for the 11 prospectivity models in this study to compare our approach with an established uncertainty quantification method.

CI (Fig. 11) and entropy (Fig. 13) mostly show lower uncertainty in the same locations. In the northwest corner, there is low entropy in the regions outlined by majority voting, but the *CI* shows these as more uncertain. The region just below this (the west of the study area) shows more extensive low uncertainty areas than *CI*, which agrees with the majority voting results more closely than entropy. Similar examples exist elsewhere and demonstrate that each measure shows slightly different things. Majority voting reveals regions of high prospectivity that are verified by most of the models, and *CI* recognizes regions of consistently high prospectivity with low uncertainty. Entropy may reveal additional targets in regions of low uncertainty, which are not as spatially consistent as those between *CI* and majority voting. The main difference is that *CI* generates exploration targets that are within the first class of majority voting, while entropy introduces some targets out of the

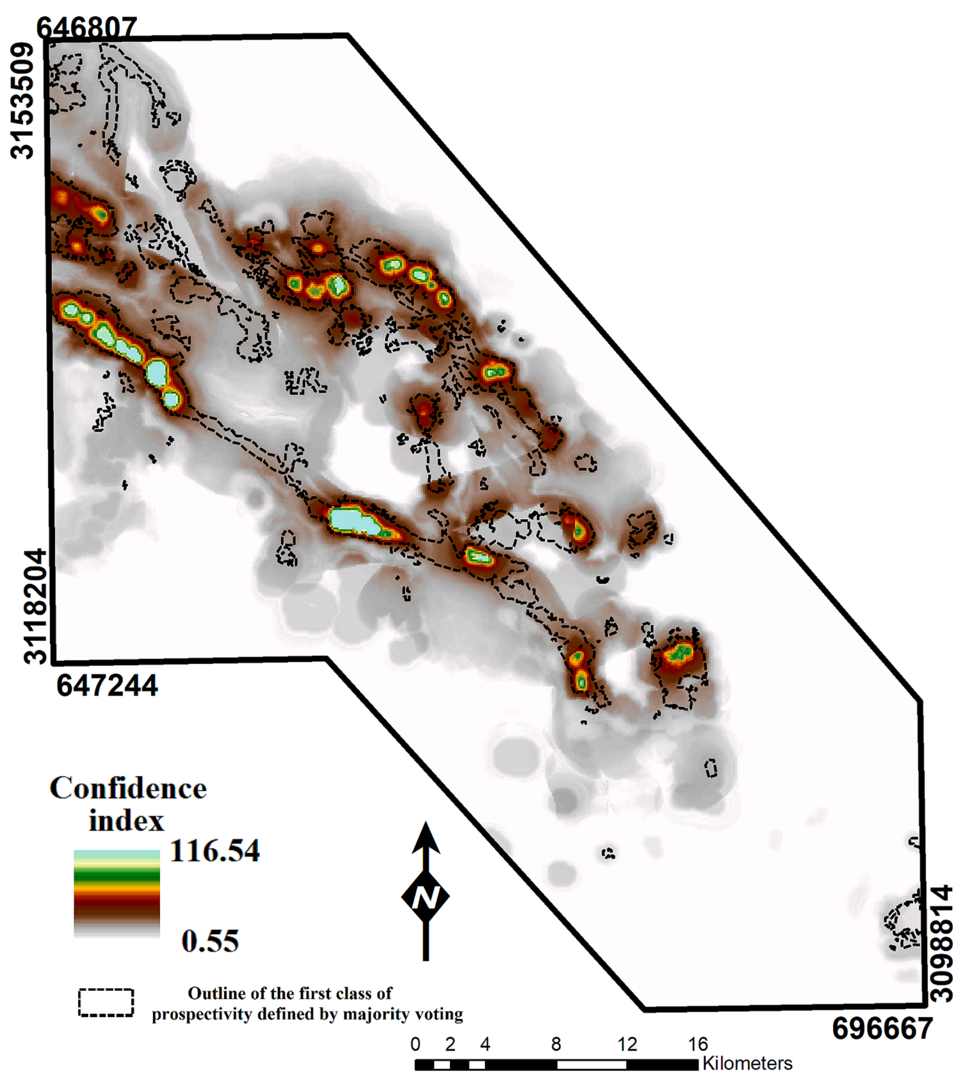

Fig. 11. *CI* model of the 11 prospectivity models generated in this study.

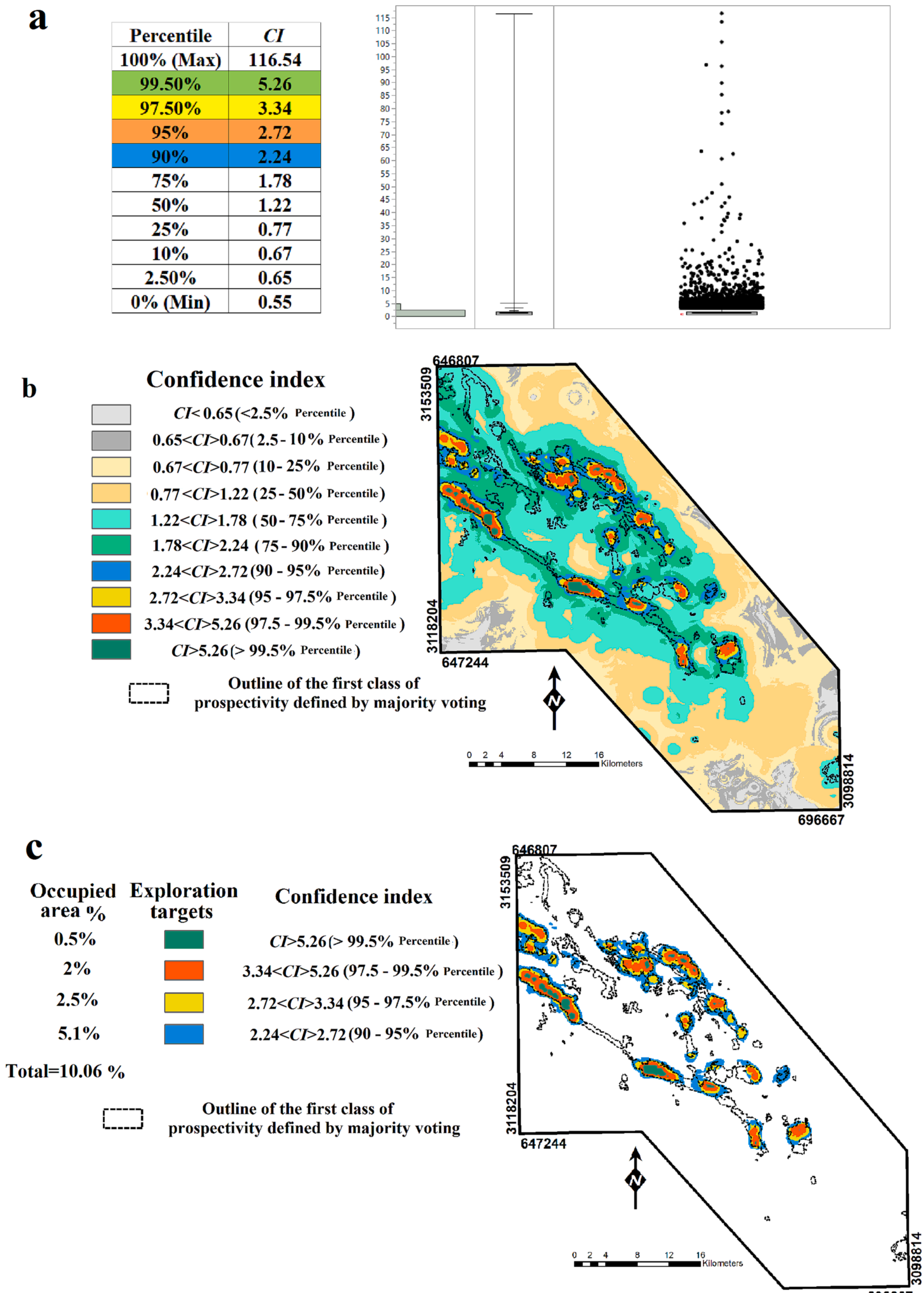

Fig. 12. (a) Statistical parameters and graphical tools including histogram, percentile, quantile, and box plot of the values in CI model, (b) a classified CI prospectvity model, and (c) delimited exploration targets using the boundary condition that outlines the first class of majority voting ensemble.

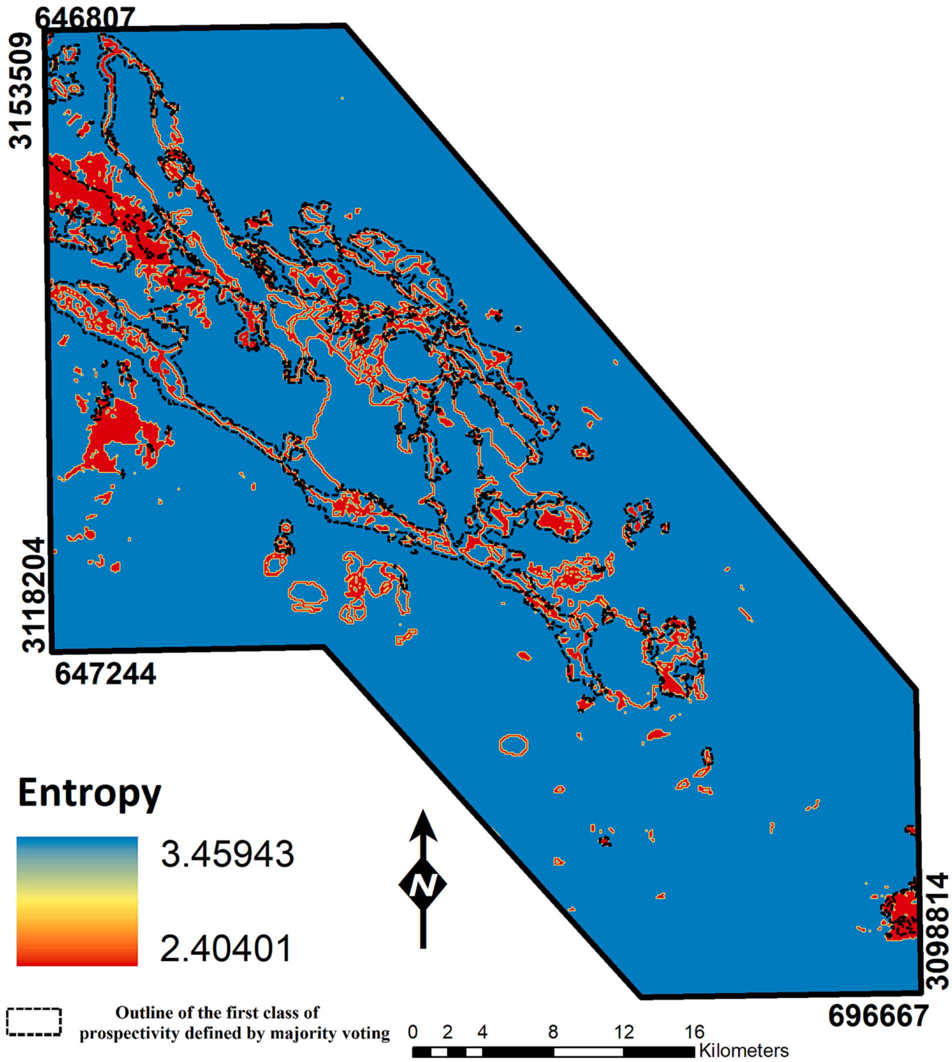

Fig. 13. Entropy model calculated from the 11 prospectivity models generated in this study.

first class of majority voting. Thus, in this context, we consider the pairing of majority voting and *CI* to offer lower risk.

3.6. Comparing and contrasting the models

There are a variety of tools developed for the evaluation of mineral prospectivity models, namely success-rate and prediction-rate curves (e.g., Fabbri and Chung, 2008; Agterberg and Bonham-Carter, 2005; Harris et al., 2015), prediction-area (P-A) plot (Yousefi and Carranza, 2015c), receiver operating characteristics (ROC) curves (Chauhan et al., 2010; Nykänen et al., 2015), normalized density (*Nd*; Mihalasky and Bonham-Carter, 2001; Yousefi and Carranza, 2015c), and posterior probability values sampled at training point locations (Nykänen and Salmirinne, 2007), which were reviewed by Yousefi et al. (2019). Associating the known mineral deposits with the modelled targets is a key aspect of all evaluation tools. Reducing the search space is one of the critical goals for any mineral exploration exercise. Thus, most of the evaluation tools consider the spatial extent occupied by exploration targets as the probability of finding undiscovered mineral deposits within smaller target areas is higher than that for larger areas (Bonham-Carter, 1994; Mihalasky and Bonham-Carter, 2001; Yousefi and Carranza, 2015c).

There is a general agreement that the uppermost classes of prospectivity values (e.g., Fig. 8), irrespective of the method, have higher priority for follow-up exploration programs. However, the main issue is that the application of different prospectivity modelling approaches on the same data set produces exploration targets that vary in terms of the number of targets introduced and their spatial patterns over the study area. Nonetheless, there are usually targets found in the uppermost classes of prospectivity that are predicted by most, if not all, prospectivity modelling methods. The targets located in the uppermost prospectivity classes are often areas where all or most of the exploration evidence features are simultaneously present and indicate high prospectivity with lower uncertainty. Low uncertainty in these areas results from consistently high prospectivity predictions from most of the methods utilised. Conversely, there are areas, mainly lowermost classes of prospectivity, that are recognised by most, if not all, of the prospectivity modelling methods as unfavourable areas. These areas are where there is no or less exploration evidence features and show low prospectivity with low uncertainty. Low uncertainty in these areas results from consistently low prospectivity predictions from most methods utilised. Thus, uncertainty is low, and agreement between methods is high in the lowermost and uppermost classes of prospectivity modelling approaches. Further, the lowermost classes of prospectivity values can be confidently excluded from further exploration programs.

In this study, the main challenge is selecting mineral exploration targets from ensemble prospectivity models to minimise the search space and maximise the number of potential undiscovered mineral deposits. Discrimination of exploration targets within the areas of high prospectivity is challenging. Prospectivity analyses are typically performed at a spatial scale appropriate for prediction (regional scale) but not detection via drilling (prospect scale) (McCuaig and Hronsky, 2000; Hronsky and Groves, 2008; McCuaig, Beresford and Hronsky, 2010). Thus, prospectivity analysis is an area-reduction exercise for a smaller-scale investigation that leads to ground sampling and drill planning but does not provide drill targets themselves. Ultimately, MPM aims to target undiscovered deposits and not to 'rediscover' those that have already been found. In this paper, we have followed Bonham-Carter, (1994), Mihalasky and Bonham-Carter, (2001), Yousefi and Carranza, (2015b), and Ghasemzadeh et al., (2022b), who explicitly describe and demonstrate that occupied area of exploration targets is an essential criterion for validation purposes and for generating layers of exploration criteria and associated weights (for some MPM methods). With this philosophy in mind, we calculated *Nd* (percentage of known predicted mineral deposits divided by the percentage of the study area occupied by the targets) for all of the 11 prospectivity models as well as the *CI* model generated in this study (Fig. 14).

The *CI* model is a combination of all the eleven prospectivity models generated in this study with the purpose of demonstrating how it can facilitate discrimination and selection of targets. The *CI* model, like all of the eleven models, was first classified using the same geometric interval method shown in Fig. 8. Then, the threshold corresponding to the 50 % percentile (in Fig. 12a) was used as a reference. For all models, *Nd* was calculated for the upper threshold classes (Fig. 14). The reason for this is that the uppermost and lowermost classes of prospectivity values represent areas with low uncertainty and, respectively, areas with high priority and where mineralization is less likely present. Consequently models that introduce more than 50 % of a study area as prospective should be excluded from the procedure of target generation (Bonham-Carter, 1994; Mihalasky and Bonham-Carter, 2001; Yousefi and Carranza, 2015b; Ghasemzadeh et al., 2022b). Subsequently, the prospectivity values corresponding to the 50 % percentile can be used as a threshold to discriminate high and low prospective areas. Comparing *Nd* values with the *CI* model (Fig. 14) demonstrates that discrimination of exploration targets and their selectivity are easier than that of other models. The *CI* model shows a larger number of mineral deposits within smaller areas. Discrimination of targets is straightforward when using the *CI* map (Fig. 11 and Fig. 12).

4. Discussion

The method described in this contribution balances the benefits and drawbacks of unsupervised and supervised machine learning methods and other data integration techniques by exploiting statistical methods to extract new information from prospectivity model ensembles. Unsupervised methods (Xiong et al., 2018; Zuo et al. 2019; Rahimi et al., 2021) reveal patterns among multiple exploration data, yet may not produce results consistent with known deposit locations and knowledge. Supervised machine learning approaches are usually consistent with known deposit locations and exploration knowledge as they use positive and negative training point sets to constrain spatial predictions (e.g., Abedi and Norouzi, 2012; Abedi et al., 2012; Zuo and Carranza, 2011; Carranza, and Laborte, 2016; Zhang et al., 2016; Sun et al., 2019; Xiong and Zuo, 2021). The geometric average integration approach (Yousefi and Carranza, 2015b) introduces exploration targets in a way that respects uncertainty in the input prospectivity values among an exploration dataset. Statistical integration benefits the positive aspects of statistics in target generation. Consequently, every weighting and integration method has inherent advantages and disadvantages in the context of MPM and EIS.

The uppermost classes of prospectivity values from each model in the ensemble represent areas of greater prospectivity and higher exploration priority. In contrast, the lowermost classes of prospectivity values resulting from each model in the ensemble portray areas where mineralization is less likely to be present and, thus, should be regarded as low priority. In this regard, given that the majority voting technique favours predictive ability by selecting the uppermost classes of prospectivity values, it utilizes the advantageous aspects of these approaches, while *CI* avoids their disadvantages by excluding areas showing low prospectivity values in the generated models. This is why there are parts of the first class of majority voting that are not robust enough to be in the 90th percentile (Fig. 12). Thus, the conjunction of majority voting with *CI* results in new and more reliable exploration targets that superimpose with other mineralization evidence as well. As discussed by Yousefi and Hronsky (2023), such methods have the potential to identify exploration targets that, one day, could yield the next generation of mineral deposits, including those deeper examples with weaker surface mineralization signals due to a previous reliance on surficial datasets.

In some cases, surficial datasets may contain subtle evidence of hidden mineralization such as faint or patchy hydrothermal alteration or locally anomalous geochemical pathfinder elements. Such expressions, even if very subtle, can guide exploration geologists to deeper mineralized sites. However, as stated by Yousefi and Hronsky (2023) future work should be designed to take the learnings from this study into areas that are poorly known and characterised. There are cases where critical data such as surface geochemical and remote sensing data are not available or in which these types of surficial datasets are not sufficient to represent concealed bedrock.

Whilst here we used only the first class from the majority voting

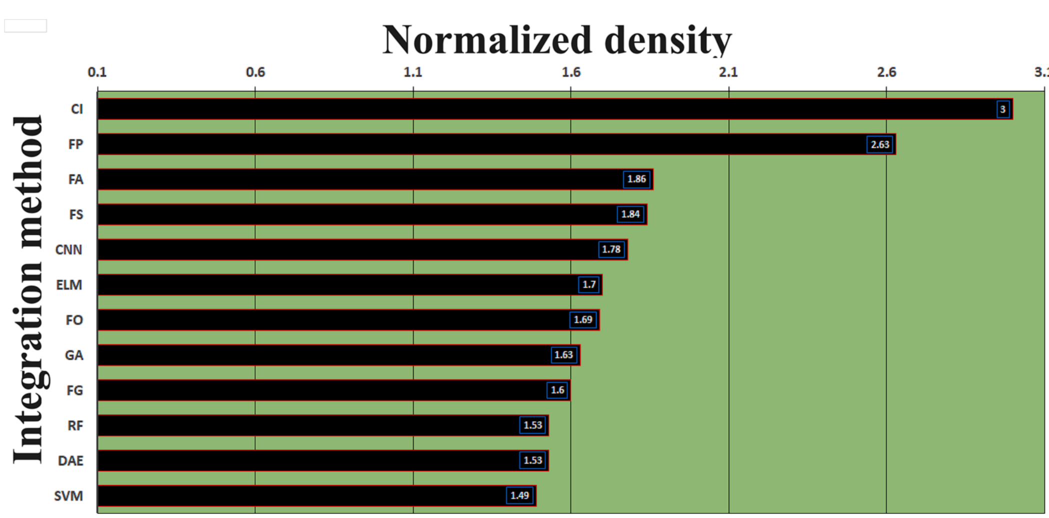

Fig. 14. Normalized density of the prospectivity models; ELM: extreme learning machine, RF: random forest, SVM: support vector machine, DAE: deep auto encoder, CNN: convolution neural network, GA: geometric average, FA: fuzzy "AND", FO: fuzzy "OR", FS: fuzzy Sum, FP; fuzzy Product, FG: fuzzy Gamma.

model (Fig. 9) as a condition to select exploration targets (Fig. 12c), it would be possible to use the second class of majority voting results to delimit targets of lower priority, depending on the exploration budget, targeted mineral deposit type, exploration evidence and risk tolerance after field checking of the delineated targets.

Exploration targeting models and target prioritisation are subject to a diverse set of uncertainties (e.g., Partington and Sale, 2004; McCuaig et al., 2007a, McCuaig, 2007b; Hronsky and Groves, 2008; Kreuzer et al., 2008, 2015; Kreuzer and Etheridge, 2010; Partington, 2010; Lindsay et al., 2012, 2014, 2016, 2022; Yousefi and Carranza, 2015a, Yousefi, 2017a). Hence, uncertainty analysis is an important and ongoing topic of research. For example, uncertainty associated with interpolation techniques (e.g., Yousefi, 2017b) is a concern that should be modulated as well. In all MPM methods, it is a common practice to rasterize layers of polygon, line, and point features, representing mineral deposits, to generate weighted predictor maps for integration purposes. Consequently, errors can arise when using a cell size inappropriate for data distribution (cell size too small), or the spatial extent of the mineralising signal (cell size too large) with subsequent uncertainty and ambiguity. While further work is needed to mitigate these types of error and uncertainties during the implementation of mineral exploration targeting approaches, the combination of prospectivity and uncertainty representations provokes a discussion on what data should be sampled and from where. It is noteworthy here that, as can be seen in Fig. 1 and Fig. 2, there is no evidence for the eastern part of our study area to be mineralised as this part of the study area is covered by post-mineral Quaternary units. The eastern area could be investigated using geophysical surveys, which may reveal hidden structures and the possible shallow bodies that may warrant follow-up drilling. In the present study, this small part has obtained the lower most weights close to 0 in all of the evidence layers in Fig. 2, and is classified as an unfavourable zone by all methods. Lack of visible exploration evidence and a lack of data from this small area do not affect results from the rest of the study area that have sufficient exploration features and data. However, in the case of gathering geophysical data and conducting prospectivity analysis, the estimation error and uncertainty associated with interpolation techniques must be considered for this small part of the study area.

In this study, we used a single indicator, Cu content, as the main indicator of Porphyry-Cu deposits, which was enforced by data availability (specifically, the lack of it). However, where available it is strongly recommended to use multi-element compositional data analysis to identify broader and robust geochemical signatures of mineral deposits that may be present in the study area.

There are limitations to using ROC for prospectivity model evaluation. The ROC prospectivity model evaluation process uses deposit sites and non-deposit sites. Recognized exploration targets that do not have points belonging to the deposit training sets therefore do not contribute to the ROC analysis. Ignoring the areas recognized as targets is in contradiction with the purpose of mineral exploration targeting and reducing the search space. Furthermore, collation of non-deposit sites, i.e., negative samples, is a well-known challenge (e.g., Rahimi et al., 2021) and is a source of uncertainty. The reason for this is that known deposit sites are proven locations, but non-deposit locations are not confirmed sites and their selection is based on analyst's decision even though some of these sites may be prospective, but have not been adequately verified to be barren of mineralization. There may be mineral deposits deeper than the drilling depth. In addition, selection and distribution of non-deposit sites are subject to the analysts judgment and bias, with no consensus on how the true non-deposit sites can be recognized and then selected. Thus, selection is essentially a subjective process and analysts may change their locations depending on prior experience, economic factors, or levels risk tolerance. The aforementioned issues are not just relevant for ROC method, but for every evaluation tool and any MPM approach that uses non-deposit locations to form negative training point sets.

Known deposit locations help to evaluate the prediction ability of prospectivity models in terms of finding the same deposit model type, or the same pattern that have been used in training the models. However, to find mineral deposits of the future, which may show features not yet recognised by exploration knowledge, or characterised by relevant data (Yousefi, 2022), we may be ignoring the discovered deposit locations for evaluation purposes.

5. Concluding remarks

- Majority voting utilises the intrinsic advantages of different mineral prospectivity modelling (MPM) methods by incorporating an ensemble of spatial prospectivity predictions informed by all MPM methods utilised.
- The confidence index minimises problems caused by the disadvantages of the different techniques allowing uncertainty to be mitigated to a certain degree.
- Using majority voting in combination with a confidence index and appropriate boundary conditions facilitates more objective and repeatable delineation and delimitation of exploration targets.
- Combining a framework as proposed in this study with an Exploration Information System (EIS) will serve to increase objectivity in the selection of exploration targets. More objective mineral exploration targeting is one of the important step changes required for the EIS to become a more effective exploration tool. Incorporation of mineral systems uncertainty assessment combined with model comparison offers a step-change needed for development of an effective EIS.
- Given that the purpose of an EIS is to generate a variety of prospectivity models to select exploration targets, we recommended the procedure of implementing majority voting and confidence index proposed in this paper be included in the EIS to boost its ability to utilize the positive aspects of a variety of prospectivity models, and minimise their negative aspects.

CRediT authorship contribution statement

Mahyar Yousefi: Conceptualization, Methodology, Investigation, Formal analysis, Project administration, Writing – original draft, Writing – review & editing. **Mark D. Lindsay:** Investigation, Methodology, Formal analysis, Writing – review & editing. **Oliver Kreuzer:** Investigation, Writing – review & editing.

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.

Data availability

The authors do not have permission to share data.

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References

Abedi, M., Mostafavi Kashani, S.B., Gholam-Hossain Norouzi, G.H., Yousefi, M., 2017. A deposit scale mineral prospectivity analysis: A comparison of various knowledge-driven approaches for porphyry copper targeting in Seridune, Iran. J. Afr. Earth Sci. 128, 127–146.

Abedi, M., Norouzi, G.H., 2012. Integration of various geophysical data with geological and geochemical data to determine additional drilling for copper exploration. J. Appl. Geophys. 83, 35–45.

Abedi, M., Norouzi, G.H., Bahroudi, A., 2012. Support vector machine for multi-classification of mineral prospectivity areas. Comput. Geosci. 46, 272–283.

Agha Seyyed Mirzabozorg, S.A., Abedi, M., 2023. Recognition of mineralization-related anomaly patterns through an autoencoder neural network for mineral exploration targeting. Appl. Geochem. 158, 105807.

Agterberg, F.P., Bonham-Carter, G.F., 2005. Measuring performance of mineral-potential maps. Natural Resourc. Res. 14, 1–17.

Alavi, M., 1980. Tectonostratigraphic evolution of the Zagrosides of Iran. Geology 8, 144–149.

Almasi, A., Yousefi, M., Carranza, E.J.M., 2017. Prospectivity analysis of orogenic gold deposits in Saqez-Sardasht Goldfield, Zagros Orogen, Iran. Ore Geol. Rev. 91, 1066–1080.

An, P., Moon, W.M., Rencz, A., 1991. Application of fuzzy set theory for integration of geological, geophysical and remote sensing data. Can. J. Explor. Geophys. 27, 1–11.

Bahri, E., Alimoradi, A., Yousefi, M., 2023. Investigating the performance of continuous weighting functions in the integration of exploration data for mineral potential modeling using artificial neural networks, geometric average and fuzzy gamma operators. Internat. J. Mining Geo-Eng. 57, 405–412.

Berberian, F., Muir, I.D., Pankhurst, R.J., Berberian, M., 1982. Late Cretaceousand Early Miocene Andean-type plutonic activity in northern Makran and central Iran. J. Geol. Soc. Lond. 139, 605–614.

Bonham-Carter, G.F., 1994. Geographic Information Systems for Geoscientists: Modelling with GIS. Pergamon, Oxford.

Burkin, J.N., Lindsay, M.D., Occhipinti, S.A., Holden, E.J., 2019. Incorporating conceptual and interpretation uncertainty to mineral prospectivity modelling. Geosci. Front. 10, 1383–1396.

Carranza, E.J.M., 2008. Geochemical Anomaly and Mineral Prospectivity Mapping in GIS. Handbook of Exploration and Environmental Geochemistry, Vol. 11. Elsevier, Amsterdam.

Carranza, E.J.M., Laborte, A.G., 2016. Data-driven predictive modeling of mineral prospectivity using random forests: a case study in Catanduanes Island (Philippines). Nat. Resour. Res. 25, 35–50.

Chauhan, S., Sharma, M., Arora, M.K., Gupta, N.K., 2010. Landslide susceptibility zonation through ratings derived from artificial neural network. Int. J. Appl. Earth Obs. Geoinf. 12, 340–350.

Cover, T.M., Thomas, J.A., 2006. Elements of Information Theory – 2nd Ed., Wiley-Interscience, ISBN 978-0-471-24195-9.

Daviran, M., Parsa, M., Maghsoudi, A., Ghezelbash, R., 2022. Quantifying uncertainties linked to the diversity of mathematical frameworks in knowledge-driven mineral prospectivity mapping. Nat. Resour. Res. 31, 2271–2287. https://doi.org/10.1007/s11053-022-10089-w.

Fabbri, A.G., Chung, C.F., 2008. On blind tests and spatial prediction models. Nat. Resour. Res. 17, 107–118.

Frye, C., 2007. About the Geometrical Interval classification method. ArcGIS Blog Retriveved 21.12.2022 from https://www.esri.com/arcgis-blog/products/product/mapping/about-the-geometrical-interval-classification-method.

Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Mihalasky, M.J., 2019. Stream sediment geochemical data analysis for district-scale mineral exploration targeting: Measuring the performance of the spatial U-statistic and C-A fractal modeling. Ore Geol. Rev. 113, 103115.

Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Mihalasky, M.J., 2022a. Recognition and incorporation of mineralization-efficient fault systems to produce a strengthened anisotropic geochemical singularity. J. Geochem. Explor. 235, 106967.

Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Mihalasky, M.J., 2022b. Information value-based geochemical anomaly modeling: A statistical index to generate enhanced geochemical signatures for mineral exploration targeting. Appl. Geochem. 136, 105177.

Ghasemzadeh, S., Maghsoudi, A., Yousefi, M., Kreuzer, O.P., 2023. Spatially weighted singularity mapping in conjunction with random forest algorithm for mineral prospectivity modelling. Internat. J. Min. Geo-Eng. 57, 455–460.

Hagemann, S.G., Lisitsin, V.A., Huston, D.L., 2016a. Mineral system analysis: Quo vadis. Ore Geol. Rev. 76, 504–522.

Hagemann, S.G., Angerer, T., Duuring, P., Rosière, C.A., Figueiredo, E., Silva, R.C., Lobato, L., Hebsler, A.S., Walde, D.H.G., 2016b. BIF-hosted iron mineral system: a review. Ore Geol. Rev. 76, 317–359.

Harris, J.R., Grunsky, E., Behnia, P., Corrigan, D., 2015. Data-and knowledge-driven mineral prospectivity maps for Canada's North. Ore Geol. Rev. 71, 788–803.

Hronsky, J.M.A., Groves, D.I., 2008. Science of targeting: definition, strategies, targeting and performance measurement. Aust. J. Earth Sci. 55, 3–12.

Huang, D., Zuo, R., Wang, J., 2022. Geochemical anomaly identification and uncertainty quantification using a Bayesian convolutional neural network model. Appl. Geochem. 146, 105450.

Kreuzer, O.P., Etheridge, M.A., Guj, P., McMahon, M.E., Holden, D.J., 2008. Linking mineral deposit models to quantitative risk analysis and decision-making in exploration. Econ. Geol. 103, 829–850.

Kreuzer, O.P., Etheridge, M.A., 2010. Risk and uncertainty in mineral exploration: implications for valuing mineral exploration properties. AIG News 100, 20–28.

Kreuzer, O.P., Miller, A.V., Peters, K.J., Payne, C., Wildman, C., Partington, G.A., Puccioni, E., McMahon, M.E., Etheridge, M.A., 2015. Comparing prospectivity modelling results and past exploration data: A case study of porphyry Cu–Au mineral systems in the Macquarie Arc, Lachlan Fold Belt, New South Wales. Ore Geol. Rev. 71, 516–544.

Kreuzer, O.P., Yousefi, M., Nykänen, V., 2020. Introduction to the special issue on spatial modelling and analysis of ore forming processes in mineral exploration targeting. Ore Geol. Rev. 119, 103391.

Lam, L., Suen, C.Y., 1997. Application of majority voting to pattern recognition: An analysis of its behavior and performance. IEEE Trans. Syst. Man Cybernet. Part A, Syst. Humans Publ. IEEE Syst. Man Cybernet. Soc. 27 (5), 553–568.

Lindsay, M.D., Aillères, L., Jessell, M.W., De Kemp, E.A., Betts, P.G., 2012. Locating and quantifying geological uncertainty in three-dimensional models: analysis of the Gippsland Basin, south eastern Australia. Tectonophysics 546–547 (3), 10–27.

Lindsay, M., Aitken, A., Ford, A., Dentith, M., Hollis, J., Tyler, I., 2016. Reducing subjectivity in multi-commodity mineral prospectivity analyses: Modelling the west Kimberley. Australia. Ore Geol. Rev. 76, 395–413. https://doi.org/10.1016/j.oregeorev.2015.03.022.

Lindsay, M.D., Betts, P.G., Ailleres, L., 2014. Data fusion and porphyry copper prospectivity models, southeastern Arizona. Ore Geol. Rev. 61, 120–140. https://doi.org/10.1016/j.oregeorev.2014.02.001.

Lindsay, M.D., Occhipinti, S., Laflamme, C., Aitken, A., Ramos, L., 2020. Mapping undercover: Integrated geoscientific interpretation and 3D modelling of a Proterozoic basin. Solid Earth 11, 1053–1077. https://doi.org/10.5194/se-11- 1053-2020.

Lindsay, M.D., Piechocka, A.M., Jessell, M.W., Scalzo, R., Giraud, J., Pirot, G., Cripps, E., 2022. Assessing the impact of conceptual mineral systems uncertainty on prospectivity predictions. Geosci. Front. 13, 101435.

Liu, P., 2013. Some geometric aggregation operators based on interval intuitionistic uncertain linguistic variables and their application to group decision making. App. Math. Model. 37, 2430–2444.

Mao, X., Ren, J., Liu, Z., Chen, J., Tang, L., Deng, H., Bayless, R.C., Yang, B., Wang, M., Liu, C., 2019. Three-dimensional prospectivity modeling of the Jiaojia-type gold deposit, Jiaodong Peninsula, Eastern China: A case study of the Dayingezhuang deposit. J. Geochem. Explor. https://doi.org/10.1016/j.gexplo.2019.04.002.

McCuaig, T.C., Kreuzer, O.P., Brown, W.M., 2007a. Fooling ourselves — dealing with model uncertainty in a mineral systems approach to exploration. Mineral Exploration and Research—Digging Deeper. Proceedings of 9th Biennial SGA Meeting, Dublin, pp. 1435–1438.

McCuaig, T.C., Hronsky, J.M.A., 2000. The current status and future of the interface between the exploration industry and economic geology research. In: Hagemann, S. G., Brown, P. (Eds.), Gold in 2000: Society of Economic Geologists Reviews in Economic Geology, pp. 553–559.

McCuaig, T.C., Beresford, S., Hronsky, J., 2010. Translating the mineral systems approach into an effective exploration targeting system. Ore Geol. Rev. 38, 128–138.

McCuaig, T.C., Kreuzer, O.P., Brown, W.M., Porwal, A.K., Etheridge, M.A., 2007b. Fooling ourselves— dealing with model uncertainty. Oral Presentation, Mineral Exploration and Research—Digging Deeper. Proceedings of 9th Biennial SGA Meeting, Dublin 2007.

Mihalasky, M.J., Bonham-Carter, G.F., 2001. Lithodiversity and its spatial association with metallic mineral sites, Great Basin of Nevada. Nat. Resour. Res. 10, 209–226.

Mostafaei, K., Kianpour, M., Yousefi, M., 2024. Delineation of Gold Exploration Targets based on Prospectivity Models through an Optimization Algorithm. J. Mining Environ. 15, 597–611.

Nykänen, V., 2008. Radial basis functional link nets used as a prospectivity mapping tool for orogenic gold deposits within the Central Lapland Greenstone Belt, Northern Fennoscandian Shield. Nat. Resour. Res. 17, 29–48.

Nykänen, V., Groves, D.I., Ojala, V.J., Eilu, P., Gardoll, S.J., 2008. Reconnaissance scale conceptual fuzzy-logic prospectivity modeling for iron oxide copper—Gold deposits in the northern Fennoscandian Shield, Finland. Aust. J. Earth Sci. 55, 25–38.

Nykänen, V., Lahti, I., Niiranen, T., Korhonen, K., 2015. Receiver operating characteristics (ROC) as validation tool for prospectivity models – a magmatic Ni–Cu case study from the Central Lapland Greenstone Belt, Northern Finland. Ore Geol. Rev. 71, 853–860.

Nykänen, V., Salmirinne, H., 2007. Prospectivity analysis of gold using regional geophysical and geochemical data from the Central Lapland Greenstone Belt, Finland. Geol. Survey Finland 44, 251–269.

Pakyuz-Charrier, E., Lindsay, M.D., Ogarko, V., Giraud, J., Jessell, M., 2018. Monte Carlo simulation for uncertainty estimation on structural data in implicit 3-D geological modeling, a guide for disturbance distribution selection and parameterization. Solid Earth 9, 385–402.

Pan, G.C., Harris, D.P., 2000. Information synthesis for mineral exploration. Oxford University Press Inc, New York.

Partington, G.A., 2010. Developing models using GIS to assess geological and economic risk: an example from VMS copper gold mineral exploration in Oman. Ore Geol. Rev. 38, 197–207.

Partington, G.A., Sale, M.J., 2004. Prospectivity Mapping Using GIS With Publicly Available Earth Science Data – A New Targeting Tool Being Successfully Used for Exploration in New Zealand. Australian Institute of Mining and Metallurgy, Pacrim 2004 Congress Volume, Adelaide, pp. 239–250.

Prado, E.M.G., de Souza Filho, C.R., Carranza, E.J.M., Motta, J.G., 2020. Modeling of Cu-Au prospectivity in the Carajas mineral province (Brazil) through machine learning: dealing with imbalanced training data. Ore Geol. Rev. 124, 103611.

Quigley, M.C., Bennetts, L.G., Durance, P., Kuhnert, P.M., Lindsay, M.D., Pembleton, K. G., et al., 2019. The provision and utility of earth science to decision-makers:

synthesis and key findings. Environ Syst Decis 39, 349–367. https://doi.org/10.1007/s10669-019-09737-z.

Rahimi, H., Abedi, M., Yousefi, M., Bahroudi, A., Elyasi, G.R., 2021. Supervised mineral exploration targeting and the challenges with the selection of deposit and non-deposit sites thereof. Appl. Geochem. 104940 https://doi.org/10.1016/j.apgeochem.2021.104940.

Shannon, C.E., Weaver, W., 1949. The Mathematical Theory of Communication, Univ of Illinois Press. ISBN, 0-252-72548-4.

Sillitoe, R.H., 2010. Porphyry copper systems. Econ. Geol. 105, 3–41.

Sun, T., Chen, F., Zhong, L., Liu, W., Wang, Y., 2019. GIS-based mineral prospectivity mapping using machine learning methods: a case study from Tongling ore district, eastern China. Ore Geol. Rev. 109, 26–49.

Sun, J., Li, H., 2008. Listed companies' financial distress prediction based onweighted majority voting combination of multiple classifiers. Expert SystemsWith Applications 35, 818–827.

Usman, M., Shafique, Z., Ayub, S., Malik, K., 2016. Urdu text classification using majority voting. Int. J. Adv. Comput. Sci. Appl. 7, 265–273.

Wang, J., Zuo, R., 2022. Model averaging for identification of geochemical anomalies linked to mineralization. Ore Geol. Rev. 146, 104955.

Wellmann, F.J., Horowitz, F.G., Schill, E., Regenauer-Lieb, K., 2010. Towards incorporating uncertainty of structural data in 3D geological inversion. Tectonophysics 490, 141–151.

Xiong, Y., Zuo, R., 2021. A positive and unlabeled learning algorithm for mineral prospectivity mapping. Comput. Geosci. 147, 104667.

Xiong, Y., Zuo, R., Carranza, E.J.M., 2018. Mapping mineral prospectivity through big data analytics and a deep learning algorithm. Ore Geol. Rev. 102, 811–817.

Yoshimura, J., Tanaka, Y., Togashi, T., Iwata, S., Tainaka, K.I., 2009. Mathematical equivalence of geometric mean fitness with probabilistic optimization under environmental uncertainty. Ecol. Model. 220, 2611–2617.

Yousefi, M., 2017a. Recognition of an enhanced multi-element geochemical signature of porphyry copper deposits for vectoring into mineralized zones and delimiting exploration targets in Jiroft area, SE Iran. Ore Geol. Rev. 83, 200–214.

Yousefi, M., 2017b. Analysis of Zoning Pattern of Geochemical Indicators for Targeting of Porphyry-Cu Mineralization: A Pixel-Based Mapping Approach. Nat. Resour. Res. https://doi.org/10.1007/s11053-017-9334-7.

Yousefi, M., Carranza, E.J.M., 2015a. Fuzzification of continuous-value spatial evidence for mineral prospectivity mapping. Comput. Geosci. 74, 97–109.

Yousefi, M., Carranza, E.J.M., 2015b. Geometric average of spatial evidence data layers: A GIS-based multi-criteria decision-making approach to mineral prospectivity mapping. Comput. Geosci. 83, 72–79.

Yousefi, M., Carranza, E.J.M., 2015c. Prediction-area (P-A) plot and C-A fractal analysis to classify and evaluate evidential maps for mineral prospectivity modeling. Comput. Geosci. 79, 69–81.

Yousefi, M., Nykänen, V., 2016. Data-driven logistic-based weighting of geochemical and geological evidence layers in mineral prospectivity mapping. J. Geochem. Explor. 164, 94–106.

Yousefi, M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., 2019. Exploration information systems-a proposal for the future use of GIS in mineral exploration targeting. Ore Geol. Rev. 111, 103005.

Yousefi, M., Nykänen, V., 2017. Introduction to the special issue: GIS-based mineral potential targeting. J. Afr. Earth Sc. 12, 1–4.

Yousefi, M., Carranza, E.J.M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., Mihalasky, M.J., 2021. Data analysis methods for prospectivity modelling as applied to mineral exploration targeting: State-of-the-Art and Outlook. J. Geochem. Explor. 229, 106839.

Yousefi, M., Gholami, R., 2010. Risk management and decision making in economic systems, first ed. Jahad Daneshgahi press, Amirkabir University of Technology (in Persian).

Yousefi, M., Yousefi, S., Kamkar Rouhani, A.G., 2023a. Recognition coefficient of spatial geological features, an approach to facilitate criteria weighting for mineral exploration targeting. Internat. J. Mining Geo-Eng. 57, 365–372. https://doi.org/10.22059/IJMGE.2023.355380.595037.

Yousefi, M., Barak, S., Salimi, A., Yousefi, S., 2023b. Should geochemical indicators be integrated to produce enhanced signatures of mineral deposits? A discussion with regard to exploration scale. J. Min. Environ. 14, 1011–1018. https://doi.org/10.22044/jme.2023.13160.2398.

Yousefi, M., Hronsky, J.M.A., 2023. Translation of the function of hydrothermal mineralization-related focused fluid flux into a mappable exploration criterion for mineral exploration targeting. Appl. Geochem. 149, 105561 https://doi.org/10.22059/IJMGE.2023.355380.595037.

Yousefi, M., 2022. Challenges with exploration targeting of blind mineral deposits. Geological Survey of Finland, Open File Research Report, Mineral Prospectivity and Exploration Targeting - MinProXT 2022 Webinar, Freiberg, Germany.

Zhang, Z., Zuo, R., Xiong, Y., 2016. A comparative study of fuzzy weights of evidence and random forests for mapping mineral prospectivity for skarn-type Fe deposits in the southwestern Fujian metallogenic belt. China. Sci. China Earth Sci. 59, 556–572.

Zuo, R., Carranza, E.J.M., 2011. Support vector machine: a tool for mapping mineral prospectivity. Comput. Geosci. 37, 1967–1975.

Zuo, R., Wang, Z., 2020. Effects of random negative training samples on mineral prospectivity mapping. Nat. Resour. Res. https://doi.org/10.1007/s11053-020-09668-6.