Targeting local orogenic gold mineralisation zones using data-driven evidential belief functions: the Godarsorkh area, Central Iran

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ABSTRACT
Using GIS-based multi-criteria decision-making techniques, i.e. mineral prospectivity mapping (MPM), specific spatial problems can be solved by combining information from different sources. Orogenic gold mineralisation shows weak exploration signals on the surface that can challenge exploration geologists. This study investigates the ability of a MPM method called evidential belief functions (EBFs) to identify a local orogenic gold mineralisation in the Godarsorkh gold deposit, north of Sanandaj-Sirjan Zone (Central Iran). Several evidential layers such as geological, structural, geophysical, remote sensing, and geochemical data were generated by applying various processing methods. These layers are integrated to attain a MPM by applying the EBFs based on Dempster-Shafer’s rules. Precise selection of evidential layers and higher number of known mineral occurrences may lead to a higher degree of belief in the mineral prospectivity map. Accordingly, high probability values were correlated with the gold mineralisation in the study area, and three separate areas were identified as promising with N40E and N15W trends. It is concluded that the orogenic gold mineralisation occurred in shear zones, which is mainly controlled by tectonic structures. Consequently, analysing these structures can be considered as a key feature for identifying potential orogenic gold mineralisation zones in the study area.

1. Introduction
Integrating different data types such as geological, geochemical, geophysical, and remote sensing data has been one of the most efficient methods for creating mineral prospectivity maps in the past few decades (Carranza & Hale, 2003; Abedi et al., 2017; Yousefi & Nykänen, 2017; Khalifianti et al., 2019; Pahlavani et al., 2020; Sun et al., 2020; Parsa & Pour, 2021; Moradpour et al., 2022). The combination of different datasets can provide comprehensive information about the target mineralisation and understanding of the ore genesis (Abedi et al., 2017; Varekamp et al., 2010). Predictive mapping of mineralisation, also known as mineral prospectivity mapping (MPM), focuses on identifying areas with a high probability of finding undiscovered mineral occurrences based on known mineral deposits at various scales (Bonham-Carter & Bonham-Carter, 1994; Carranza, 2011; Carranza et al., 2009). Knowledge-driven, data-driven, and hybrid methods are considered as three major categories of MPM methods.

The knowledge-driven approach requires an expert who determines the weight of each layer which varies based on its relationship with the target mineralisation. This method is subjective but, however, has the advantage of being well-suited for greenfield areas with missing or scarce data and where few deposits are known (Harris et al., 2015; Lachaud et al., 2021; Yousefi & Kamkar Rouhani, 2010). Boolean logic (Carranza & Hale, 2009; Harris et al., 2001), index overlays (Carranza & Hale, 2009; Harris et al., 2001; Yousefi & Carranza, 2015), and fuzzy logic (Carranza & Hale, 2009; Yousefi & Nykänen, 2016; Abedi et al., 2017; Ma et al., 2020; Sekandari et al., 2020; MohammadMohammadpour et al., 2021) are examples of the knowledge-driven approach. The data-driven approach uses the spatial relationship between geospatial features and known mineral occurrences to estimate model parameters. In well-established mining areas where a large number of mineral occurrences is known, the model is ideally suited for quantifying the spatial association of evidential features with the model’s performance as well as its robustness (Lachaud et al., 2021; Yousefi & Kamkar Rouhani, 2010). Weights of evidence (Farahbakhsh et al., 2020; Harris et al., 2001; D Harris et al., 2003; Joly et al., 2012; Porwal et al., 2010; Z Zhang et al., 2016), logistic regression (D Harris et al., 2003; Porwal et al., 2010), neural networks (D Harris et al., 2003; Laben & Brower, 2000; Rodriguez-Galiano et al., 2015), support vector machine (Chen &
Wu, 2017; Ghezelbash et al., 2021; Zuo & Carranza, 2011), and random forest (Daviran et al., 2021; Harris et al., 2001; Lachaud et al., 2021; S Zhang et al., 2021) are examples of data-driven approaches. Hybrid algorithms take into account both mineral occurrence locations and expert comments when identifying possible mineralisation zones (Porwal et al., 2003, 2004, 2006; Yousefi & Carranza, 2015).

The Dempster-Shafer theory (Carranza & Hale, 2003; Dempster, 1967, 1968; Sheppard & Gustafson, 1976) provides the basis for evidential belief functions (EBFs) that can be used to identify the spatial association between the target mineralisation and the evidential layers (Dempster, 2008). This theory builds on the generalisation of lower and upper probabilities in Bayesian theory (Carranza & Hale, 2003; Dempster, 1967; Ford et al., 2016; Y Liu et al., 2014). According to Carranza et al. (2008), the upper probability represents plausibility, while the lower probability represents whether a certain amount of evidence supports a proposition (Ford et al., 2016; Y Liu et al., 2014). The EBF model uses Dempster’s combination rule to integrate evidential layers (Y Liu et al., 2014). The major benefit of employing EBFs is handing over the map of uncertainty for the final prospectivity model. This method has been mostly applied to map different mineralisation types on a regional scale and evidential layers have been combined to create mineral prospectivity maps (Abedi et al., 2017; Carranza & Hale, 2003; Carranza et al., 2005; Porwal et al., 2003). Using this method, four belief maps are independently derived: support, plausibility, disbelief and uncertainty (Carranza, 2008; Tangestani & Moore, 2002; Yousefi & Nykänen, 2017).

Generally, orogenic gold deposits are found in metamorphic rocks in the mid- to shallow crust (5–15 km depth), at or above the brittle-ductile transition, where compressional settings facilitate the transfer of hot gold-bearing fluids from deeper levels (R Goldfarb et al., 2005; DI Groves et al., 1998; Phillips & Powell, 1993). Orogenic gold deposits are widespread throughout the world’s metamorphic belts. They are epigenetic and structurally controlled. This type of deposits provides weak exploration signals at the surface and individual data layers such as geology, geochemistry, geophysics, and remote sensing could not supply accurate information for mineral exploration. Therefore, the use of multivariate methods like the data-driven evidential belief functions (EBFs) for studying these deposits is highly applicable. The EBFs method was successfully used for the exploration of chromite and massive sulphide deposits, which are typically difficult to explore (Carranza & Sadeghi, 2010; Yaghoubpour & Hassanejad, 2006).

Notably, the NW–SE trending Sanandaj–Sirjan Zone (SSZ) in Iran is the most important geological setting for orogenic gold deposits. Among them, the most important orogenic deposits in this belt are Zartorosht (Omran et al., 2008), Muteh (Kouhestani et al., 2014), Meringhnaghshein (Asghari et al., 2018), Qolqoleh (Aliyari et al., 2009, 2007), Hamzehgharian (Maleki et al., 2021) and Kervan (Almasi et al., 2014). Moreover, few researches were conducted on the regional comparison in the SSZ for orogenic gold exploration (e.g. Aliyari et al., 2012; Khalifani et al., 2019; Sheikhrasmi et al., 2019). These studies used remote sensing, geochemical and geological evidential layers, and the knowledge-driven approaches for mineral prospectivity mapping (MPM) in Saqez prospecting zone of the SSZ. The Godarsorkh gold deposit placed in the northern part of SSZ (Figure 1a,b) was selected for this investigation. Gold mineralisation in the Godarsorkh is typically in the form of siliceous-haematite-carbonate gold and magnetite veins. A detailed mineral exploration study has not been documented for the Godarsorkh gold deposit, yet. In this study, the data-driven evidential belief functions (EBFs) method was used to investigate the ability of this method for identification of potential zones of gold mineralisation and generating a mineral prospectivity map for the Godarsorkh deposit. Therefore, the objectives of this study are: (i) to provide and generate evidential layers of geological, structural, geophysical, remote sensing for the study area by applying various processing methods; (ii) to integrate the evidential layers using EBFs method for identifying the prospective zones; and (iii) to analyse the capability of EBFs method for mineral prospectivity mapping (MPM). The EBFs method can be broadly applied to the frontier zones of the SSZ with similar geologic conditions for future MPM, and subsequent field campaign and drilling programmes.

2. Geographical and geological setting

The Godarsorkh gold deposit is located at 33°33’58” N, 50°31’06” E in the Isfahan province (175 km far from Isfahan city) and 20 km southwest of Muteh gold mine in Central Iran. It is placed in the northern part of SSZ (with 1500 km length and 150 km width, between the Zagros fold and thrust belt and the Urmieh-Dokhtar magmatic belt) and consisting of Palaeozoic-Mesozoic metamorphic assemblages, Mesozoic non-metamorphic deposits and Quaternary alluvium (Alavi, 1994; Azizi & Moinevaziri, 2009; Baharifar et al., 2004; Berberian & King, 1981; Mohajel et al., 2003; Sahandi & Soheili, 2005).

A variety of rock units are observed in the Godarsorkh area. The Devonian metasandstone-phylite unit involves sequences of mica-schist, quartzite, greenschist, felsic schist, carbonate shale, metar- mellite, and meta-volcanicslasts (Deqmsch in Figure 1b). Moreover, thin layers of phylite, gneiss schist, slate, and metamorphic sandstone in the metamorphosed greenschists facies are exposed. Various siliceous veins
that reach a thickness of 50 cm can also be observed in this unit. A low-grade foliation or slate cleavage along with quartz grains and phyllosilicate minerals is also obvious. The Devonian metatrichyte unit with alkaline and acidic volcanic rocks (Demtr) is the most altered unit which shows a small outcrop. The most important outcropped Permian units include marble (Prmb), marble with grey limestone interlayers (Prmd) overly on quartzite, altered marble limestones, and brown dolomites (Prmd), brown dolomite (Prd) composed of dolomite and dolomitic limestone, and laterite and limestone (Prlat). A red bauxite-laterite horizon up to 8 m thick is observed in the study area. The outcrops of Mesozoic units are very limited and only a non-metamorphosed Jurassic shale unit in the south and southwestern parts can be seen. This unit generally consists of thin layers of shale and sandstone and barren silicified veins. Quaternary sediments have accumulated in different parts of the study area including old terraces and young Quaternary sediments formed by parts of older units. The most important intrusive units are Jurassic diorite (Di) and rhyodacite (Ryd) which are mostly dyke-shaped along an NW-SE trend intruded stratigraphic units. These small intrusive dykes partially show cataclastic and shear textures due to dynamic processes which are intensely crushed and altered. The main mineralisation occurred within this altered part.

The study area is generally an antiform in shape with an axial plane striking WNW-ESE and a dip direction of NNE. The southern edge of this structure has folded and broken due to faults activity in some places. Small folds in macroscopic, mesoscopic and microscopic scales are obvious on the edges of this large anticline structure. The predominant trend of faults in the region is NE-SW. The average trend of these faults is N40E and N15W with an average slope of 60 to 75 towards NW and SE. There are also a few other faults striking NW-SEE in the study area that are less related to mineralisation. The faults are primarily categorised into normal or strike-slip faults. The thickness of the fault zone varies from 20 to 40 cm. The fragmentation and shear zones resulting from these faults plausibly have created a favourable condition for the ascension and deposition of gold-bearing fluids.

Mineralisation is mainly in the form of siliceous-hematite-carbonate gold and magnetite veins. These veins outcrop with a WNW-ESE trend and slope
towards NNE and SSW within the Prmb and Prmd units. These veins occurred in stretching fractures and were replaced long after the peak of metamorphism in the uplifting stage, controlled by tectonic structures. During the circulating of ore fluids in the channels of shear zones and normal faults located in the ductile-brittle or brittle zone in the upper section of the crust have entered the hydrothermal cycle due to mixing with meteoric water. Afterwards, mineralised siliceous veins have located along stretching fractures known as channels for the conduction and pathways of hydrothermal fluids. The veins often manifest as a vein-veinlet zone and sometimes reach a thickness of 11 m. Veins have a maximum thickness of about 2 m, whereas for veinlets it varies from 2 to 21 cm. In general, the restricted alterations are included silicific, haematite along with the mineralised portions, and limonite and goethite alterations in the margins of mineralised zones.

3. Materials and methods

In this study, geological maps of the region were analysed to reveal the fault, geological units and the location of gold mines and mineralisation. Geophysical data (magnetometry) were utilised to identify intrusive metallic masses. ASTER and Sentinel-2 remote sensing data were used to extract hydrothermal alteration zones. The data used in this analysis provided evidential layers for the EBFs method. Subsequently, the information layers were fused using the EBFs method. Four belief maps support, plausibility, disbelief, and uncertainty were calculated. As a result, potential maps were produced for the study area. Figure 2 shows decision tree flowchart for generating MPM.

3.1. Remote sensing data

Due to the predominance of the alterations related to the gold mineralisation in the study area, ASTER and Sentinel-2 satellite images were used to map the alteration zones (Table 1). For this research, a cloud-free ASTER Level 1 T data (accuracies terrain corrected registered at-sensor radiance) were acquired and used (Table 1). The data have spatial resolution of 15 m, 30 m and 90 m in the VNIR (3 bands), SWIR (6 bands), and TIR (5 bands) spectral subsets (Table 1). The SWIR bands are resampled to the VNIR spatial resolution (15 m). Using VNIR and SWIR bands of ASTER imagery, it is possible to identify hydrothermal alteration zones based on the minerals that are specific to each alteration type (Bolouki et al., 2020; Pour et al., 2021; Wambo et al., 2020). Sentinel-2 satellite are being used for global monitoring for land cover mapping (Ge et al.,

![Figure 2. Decision tree flowchart for generating MPM.](image-url)
The multispectral imagery of Sentinel-2 includes 13 spectral bands in the VNIR and SWIR ranges, and different spatial resolutions ranging from 10 to 60 m (Table 1). The VNIR bands of Sentinel-2 have great capabilities for mapping iron oxide/hydroxide minerals (haematite, goethite and jarosite; Sekandari et al., 2020). We map the alteration zones using the spectral angle mapper (SAM) technique (Kruse et al., 1993) available in the ENVI software package. The Spectral Angle Mapper (SAM) algorithm is a supervised approach, which has been widely utilised for remote sensing image. It is based on an ideal assumption that a single pixel of remote sensing image represents one certain ground cover material and can be uniquely assigned to only one ground cover class. SAM is an automated method for comparing image spectra to individual spectra or to a spectral library (Kruse et al., 1993). SAM assumes that the data have been reduced to apparent reflectance (true reflectance multiplied by some unknown gain factor, controlled by topography and shadows). The algorithm determines the similarity between two spectra by calculating the spectral angle between them, treating them as vectors in n-D space, where n is the number of bands. Pixel with minimum or zero spectral angles in comparison to the reference spectrum is assigned to the class defined by reference vector. However, when threshold for classification based on spectral angle is modified, the probability of incorrect object detection may increase. Because SAM uses only the direction of the spectra, not the length, SAM is insensitive to the unknown gain factor (topography and shadows; Girouard et al., 2004; Kruse et al., 1992). Accordingly, SAM has high capability to map endmember of specific alteration minerals or alteration zone in mountainous and rough topography regions (i.e. the location of Goldarsorkh gold deposit). The maps created using the SAM method are in greyscale, whose shadow intensity depends inversely on the correlation between end-member numbers and spectra related to each specific pixel (Gabr et al., 2010). A ponderation value between 0 (low resemblance) and 1 (high resemblance) is assigned to each pixel in the image.

In this study, the reference spectra of alteration minerals were selected from the USGS spectral library (version 7.0; Kokaly et al., 2017). Endmember spectra of kaolinite, alunite, haematite, jarosite, opal and chalcedony were selected and convolved to response functions of ASTER VNIR+SWIR and Sentinel-2 VNIR+SWIR bands, respectively (Figure 3a,b). Argillic alteration is typically dominated with kaolinite, alunite, illite and montmorillonite and shows Al-OH absorption features at 2.17 to 2.20 µm, which are corresponded with bands 5 and 6 of ASTER (Pour et al., 2021). In this analysis, we considered kaolinite and alunite as the indicators of argillic alteration and consequently this zone was mapped by implementing the SAM algorithm to ASTER VNIR+SWIR bands (Figure 4a). To characterise haematite and jarosite, the VNIR spectral bands contain the most important information due to electronic transitions of Fe$^{3+}$/Fe$^{2+}$ in the VNIR region from 0.45 to 1.2 µm; hence, the SAM algorithm was applied to Sentinel-2VNIR+SWIR bands. Figure 4b shows the surface distribution of iron oxide/
hydroxide minerals in the study area. Si-OH absorption features are mostly concentrated at 2.20 to 2.30 μm, which are coincident with bands 6 and 7 of ASTER (Pour et al., 2019). For mapping the silicification in the study area using ASTER data, the reference spectra of opal and chalcedony were used for running the SAM. As a result, spatial distribution of silicified zones was mapped (Figure 4c). Gold mineralisation mainly occurred in a shear zone of the study area and appears to be the primary factor controlling mineralisation; therefore, tectonic lineaments are also mapped by processing satellite images.
3.2. Geophysical data

Magnetic data as one of the popular exploration data types are used to identify subsurface properties of the Earth from the perspective of magnetic field anomalies (Nabighian et al., 2005; Shirazy et al., 2022, 2018). These anomalies originate from the magnetic properties of subsurface rock units (H Liu et al., 2017). A magnetic survey can outline differences in the amount of magnetic minerals (i.e. magnetite, pyrrhotite, and haematite) and associated rock types (the magnetic properties of rocks). As a result, a magnetic map is capable to pinpoint mineral deposits by detecting specific rock types and geological features (Eldosouky et al., 2021). At Godarsorkh, data acquisition lines were designed with the spacing of 200–400 m and the data points are 25 m far from each other on
each line (Figure 5a,b). The total number of data points is 1255 and the data were acquired using a proton reversal magnetometer. In this study, in addition to the total magnetic intensity, we applied various filters to this grid including Reduction to the pole (RTP; Figure 6a), analytic signal (Figure 6b), upward-downward continuation (Figure 6c), tilt angle (Figure 6d), and derivative-based filters (Figure 6e,f) to create more evidential layers.

The RTP map was created using the characteristics of the magnetic field on the acquisition date. By using the RTP map, magnetic anomalies can lose their dipolar nature and have an asymmetric shape changed to a symmetric one (Ansari & Alamdar, 2009; Nabighian et al., 2005). The total gradient (analytic signal) is
and second vertical derivatives, can detect surface anomalies in either space or frequency domains. These operators boost high-frequency noise and special frequency response is usually applied to control the noise (Nabighian et al., 2005). This conversion amplifies small wavelengths as opposed to long wavelengths (Blakely & Simpson, 1986).

The RTP map shows magnetic anomaly that indicates the highest enrichment among limestone, dolomite and calc-schist units. Considering that the magnetic property of these rock units is very low, the exposed enrichment must be separate from the rock unit. The presence of gold-bearing magnetite veins among these lithological units or geological structures associated with gold mineralisation might be considered as one of the most important reasons for the enrichment of magnetic anomaly maps. This indicates the direct connection of the enriched sections in the magnetic anomaly map with structurally controlled mineralised zones. In addition, the existence of known mineral indices also confirms the obtained results.

Induced polarisation (IP) is a complex phenomenon, and its anomalies appear because of minerals, rocks, or lithology acting as main capacitors. The IP method has proven to be very useful for mineral exploration in different subsurface settings in many places in the world (Taha et al., 2018; Yuval & Oldenburg, 1996), which is especially suitable to manifest zones with dispersed sulphide minerals (Abidi et al., 2012). Electrical resistivity is a physical property of rocks that is strictly affiliated with the pore fluid’s electrical resistivity and saturation content (Kiberu, 2002). Resistivity is characterised as a measure of the opposition to flow of charge in a material and the dielectric behaviour refers to a substance displaying a polarisation due to charge detachment in an electric current. In this study, induced polarisation-resistivity (IP-RS) data acquired along 17 profiles with a distance between 200 and 400 m using a dipole–dipole array measured to a depth of 250 m are used to validate the results. Two types of IP-RS models including inverse geoelectric sections along the profiles and the inverse model of chargeability and electrical resistance at depths of 50, 110, 150, 210 and 250 m have been studied. The dipole–dipole electrode array consists of the current (source) and potential (receiver) electrodes in this analysis.

### 3.3. Geochemical data

Lithogeochemical samples were taken along four profiles with 42 samples in the study area. The profiles were designed along the haematite-carbonate-siliceous vein and veinlet outcrops to determine the concentration values of gold and associated elements.
According to the selected samples, the gold concentration in most of the samples is over 1 ppm. The maximum value is around 19 ppm with an average of 5 ppm. Based on the Pearson correlation coefficient calculated between gold and other elements, gold and arsenic are closely related concentration values which both show a weak correlation with Ca, Fe and Ba (Table 2). Among the samples taken from the study area, 19 samples are considered as anomalous. Hence, we used the collected geochemical data due to abnormal distribution in the study area only to validate the results.

3.4. Evidential belief functions

Evidential belief function is a mathematical model with a statistical duration of two variables based on evaluating evidence and determining its reliability (Carranza, 2008; Carranza & Hale, 2009; Dempster, 1967, 1968). This method is usually used for the knowledge-driven modelling of potential mineralisation zones. Furthermore, the modified type of this method can be used for data-driven modelling, used in this study to determine potential areas. The knowledge-driven method is suitable for mineral potential modelling in areas where little or no exploration work has been done. However, the data-driven modelling method is useful for areas where the exploration work is mediocre or good and there are several known indices of the type sought.

The difference between the EBF and other methods is the possibility of including uncertainty in the data. Uncertainty can be considered as the interval between belief and plausibility. For each control point used to evaluate a specific point, four values in the range [0,1] can be determined. The EBFs include the degree of
Table 2. A summary of the abundance of basic elements in the study area.

| Element | Unit | DL* | Method | Mean   | Median | Mode  | Range | Minimum | Maximum |
|---------|------|-----|--------|--------|--------|-------|-------|---------|---------|
| Au      | ppb  | 5   | Fire assy | 4639.4 | 3742.0 | 1116.0 | 17679.0 | 11160.0 | 18795.0 |
| Ag      | ppm  | 0.1 | ME-02   | 0.5    | 0.4    | 0.3    | 2.4    | 0.2     | 2.6     |
| Al      | ppm  | 100 | ME-02   | 19313.1| 5235.5 | 591.0  | 87676.0| 591.0   | 88267.0 |
| As      | ppm  | 0.5 | ME-02   | 46.6   | 33.9   | 100.0  | 97.1   | 2.9     | 100.0   |
| Ba      | ppm  | 5   | ME-02   | 88.0   | 64.0   | 17.0   | 426.0  | 16.0    | 442.0   |
| Ca      | ppm  | 5   | ME-02   | 68294.9| 81476.5| 100000.0| 98769.0| 12310.0 | 100000.0|
| Cu      | ppm  | 1   | ME-02   | 34.2   | 9.8    | 6.0    | 519.0  | 1.0     | 5200.0  |
| Fe      | ppm  | 5   | ME-02   | 60205.8| 77593.5| 100000.0| 96630.0| 33700.0 | 100000.0|
| Mg      | ppm  | 100 | ME-02   | 9825.1 | 6193.5 | 20000.0| 19807.0| 193.0   | 20000.0 |
| Mn      | ppm  | 5   | ME      | 545.0  | 469.3  | 217.0  | 1886.0 | 17.0    | 1903.0  |
| Mo      | ppm  | 0.5 | ME      | 3.3    | 1.3    | 1.0    | 39.2   | 0.8     | 40.0    |
| Pb      | ppm  | 1   | ME-02   | 58.1   | 29.5   | 7.0    | 425.0  | 5.0     | 430.0   |
| S       | ppm  | 50  | ME-02   | 487.6  | 146.0  | 69.0   | 7483.0 | 50.0    | 7533.0  |
| Zn      | ppm  | 0.5 | ME-02   | 68.2   | 57.0   | 36.0   | 512.0  | 8.0     | 520.0   |

*Detection limit.

disbelief (Dis), degree of uncertainty (Unc), degree of plausibility (Pls), and degree of belief (Bel); Pls and Bel indicate upper and lower probabilities that evidence bolsters a proposition (Carranza & Hale, 2009; Carranza et al., 2008; Dempster, 1967). Thus, Bel may be less than or equal to Pls. Pls-Bel is equal to Unc and represents doubt (or ignorance) of the belief in the proposition based on a piece of given evidence. If Unc = 0, then Pls = Bel. Dis is the belief that the proposition is false based on given evidence; it is equal to 1-Unc-Bel or 1-Pls. Thus, Unc + Bel + Dis = 1. However, if Bel = 0, then Dis = 0 for the reason if there is no definite value for Bel, so no definite value for Dis can be calculated, and only the complete Unc is present, which is equal to 1 (Carranza, 2011; Carranza et al., 2008, 2005). In the probability approach, if Unc = 0, then Bel + Dis = 1. According to the combination rule, Unc, Bel, and Dis are the EBFs used to integrate evidence.

Dempster equations are used to obtain the value of data-driven functions, and the values of Bel, Dis, Unc, and Pls are calculated using these equations (Carranza et al., 2005):

\[
\text{Bel}_{cij} = \frac{W_{cij \cdot D}}{\sum_{j=1}^{n} W_{cij \cdot D}}
\]

\[(1)\]

\[
W_{cij \cdot D} = \frac{N(c_{ij}) - N(c_{ij} \cap D)}{N(c_{ij})}
\]

\[(2)\]

\[
\text{Dis}_{cij} = \frac{W_{cij \cdot D}}{\sum_{j=1}^{n} W_{cij \cdot D}}
\]

\[(3)\]

\[
W_{cij \cdot D} = \frac{N(c_{ij}) - N(c_{ij} \cap D)}{N(c_{ij}) - N(c_{ij} \cap \neg D)}
\]

\[(4)\]

\[
\text{Unc}_{cij} = 1 - \text{Bel}_{cij} - \text{Dis}_{cij}
\]

\[(5)\]

Using the equations, for the case study area T, there is a total number of pixels N(T) and a number of pixels N(D) for training mineral occurrences or deposits D. In this study, data layers including geological map (1:5000), faults, alterations and geophysical layers were used as evidential maps and high-grade geochemical samples were applied as deposit locations. According to the evidential map Xi (i = 1, 2, ..., n), every evidential class Cij (j = 1, 2, ..., m) has N(Cij) pixels. By overlaying the binary map of D on each evidential map, we were able to determine the number of Cij pixels that overlapped D (i.e. N(Cij ∩ D)) and the number of Cij pixels that did not overlap D (i.e. N(Cij) - N(Cij ∩ D)) (Abedi et al., 2017; Carranza & Hale, 2003; Carranza et al., 2005). After estimating and calculating the estimation functions, these values were stored for each Xi evidential layer and then the EBF maps (Dis, Bel, Pls and Unc) were generated for each evidence.

Geoscientists use EBFs for integrating exploration data layers and also modelling for identifying prospective areas (Carranza & Hale, 2003; Carranza et al., 2008; Abedi et al., 2017; MohammadMohammadpour et al., 2021). Despite the lack of evidence, spatial data representation using uncertainty models is considered superior to other methods. Different operators can be used to combine evidence models using two or more models. The EBFs model (An et al., 1994; Carranza et al., 2008) was used to map prospective zones by combining exploration data through the ‘OR’ or ‘AND’ operator (An et al., 1994). Practically, it may be suitable to use various factors to generate prospectivity maps (see, Figure 2). In this research, the likelihood of mineralisation is high in areas in which recrystallised dolomite and iron oxide alteration are present. However, there may be recrystallised dolomite rocks in segments of the regions where exhibit no alteration, decreasing the possibility of mineralisation in these areas. Since data layers are controlled at the pixel level, the AND operator would be appropriate for this combination. Due to the nature of mineralisation detection factors and how they interact with each other, it is preferable to utilise
the appropriate operator at each step of the model integration process rather than using one operator for all layers such as OR or AND (Carranza et al., 2008). In this research, the operator AND is employed for combining alteration and geological layers and OR is used to combine faults and geophysical data. The final map is generated using the operator AND.

4. Results

4.1. Evidential layers

The evidential layers used for mapping gold prospective areas include lithological units, alteration zones, distance to faults and geophysical layers. The geochemical layer and samples showing a high gold concentration value were used as deposit locations. The geological evidential layers were generated using the 1:5000 geological map of the study area by considering altered dolomite, marble and intrusive bodies. The estimation function was calculated for each data layer (Tables 3, 4 and 5). To classify each evidential layer into four classes, we used the statistical characteristics of the mean value ($\bar{X}$) and the standard deviation ($\sigma$) of six disparate geophysical datasets (d; Table 6). Known deposits show a good correlation with units Pr$^m$ and Pr$^d$ into which iron oxide veins occurred (Figure 7a). The evidential layer of alterations includes the alteration zones related to gold mineralisation including argillc, silification and iron oxides. Mineral deposits often correspond to the areas where argillc and iron oxide-bearing minerals are observed (Figure 7b).

Table 3. Values of Bel, Dis, Unc and Pls for lithological units.

| Lithological unit | Ncij | Ncij / D | Wcij D | Bel | Dis | Unc | Pls |
|-------------------|------|---------|--------|-----|-----|-----|-----|
| Qt m              | 596  | 0       | 0      | 0   | 0   | 1   | 0   |
| Qal               | 1027 | 0       | 0      | 0   | 0   | 1   | 0   |
| Di                | 216  | 0       | 0      | 0   | 0   | 1   | 0   |
| De mtr            | 1229 | 0       | 0      | 0   | 0   | 1   | 0   |
| De cmsch          | 964  | 0       | 0      | 0   | 0   | 1   | 0   |
| J shr             | 3493 | 0       | 0      | 0   | 0   | 1   | 0   |
| De qmsch          | 7220 | 0       | 0      | 0   | 0   | 1   | 0   |
| Mag Vein          | 5    | 0       | 0      | 0   | 0   | 1   | 0   |
| Pr mb             | 8998 | 10      | 8.459  | 0.564 | 0.249 | 0.185 | 0.814 |
| Ry d              | 146  | 0       | 0      | 0   | 0   | 1   | 0   |
| Qc                | 16,393 | 0       | 0      | 0   | 0   | 1   | 0   |
| Pr md             | 23,469 | 6      | 1.062  | 0.070 | 0.650 | 0.278 | 0.721 |
| Fe-ox Vein        | 7    | 0       | 0      | 0   | 0   | 1   | 0   |
| Pr lat            | 145  | 16,393 | 0      | 0   | 0   | 1   | 0   |
| Pr d              | 3612 | 4      | 5.455  | 0.364 | 0.100 | 0.535 | 0.464 |
| Qt l              | 5331 | 0       | 0      | 0   | 0   | 1   | 0   |
| Qt sh             | 683  | 0       | 0      | 0   | 0   | 1   | 0   |
| De csch           | 60   | 0       | 0      | 0   | 0   | 1   | 0   |
| Qf sh             | 3886 | 0       | 0      | 0   | 0   | 1   | 0   |

Table 4. Values of Bel, Dis, Unc and Pls for different alteration types.

| Alteration     | Bel   | Dis   | Unc   | Pls   |
|----------------|-------|-------|-------|-------|
| Kaolinite      | 0.002172 | 0.168995 | 0.828833 | 0.831005 |
| Quartz         | 0.0216314 | 0.0201448 | 0.782237 | 0.798552 |
| Limonite       | 0.024602 | 0.201351 | 0.774047 | 0.798649 |
| Jarosite       | 0.787702 | 0.191588 | 0.02071 | 0.808412 |
| Haematite      | 0.03219 | 0.201227 | 0.766583 | 0.798773 |
| Alunite        | 0.41424 | 0.195915 | 0.389845 | 0.804085 |

Table 5. Values of Bel, Dis, Unc and Pls for six classes of distance from faults.

| Distance (m) | Bel  | Dis  | Unc  | Pls  |
|--------------|------|------|------|------|
| 0–10         | 0.042771 | 0.199907 | 0.757322 | 0.242678 |
| 10–20        | 0.286309 | 0.200109 | 0.513582 | 0.486418 |
| 20–30        | 0.207683 | 0.199904 | 0.592413 | 0.407587 |
| 30–40        | 0.371495 | 0.200093 | 0.428412 | 0.571588 |
| 40–50        | 0.091742 | 0.199988 | 0.70827 | 0.29173 |
| 50–c         | 0.0     | 0.0   | 1.0   | 0.0   |

Table 6. Values of Bel, Dis, Unc and Pls for RTP, upward 20 m, analytic signal, tilt angle, first horizontal derivative along x-axis and first horizontal derivative along y-axis layers.

| Class | Value d | N_cij | N_D | Ncij / D | Wcij D | Bel | Dis | Unc | Pls |
|-------|---------|-------|-----|----------|--------|-----|-----|-----|-----|
| 1     | $d \leq X$ | 936,753 | 19 | 1 | 0.272 | 0.029 | 0.249 | 0.720 | 0.279 |
| 2     | $X < X < 1$ | 224,737 | 19 | 4 | 6.295 | 0.681 | 0.250 | 0.668 | 0.931 |
| 3     | $X < 2$ | 1492,46 | 19 | 13 | 2.003 | 0.216 | 0.250 | 0.533 | 0.467 |
| 4     | $X < 25$ | 4,219,887 | 19 | 13 | 0.672 | 0.072 | 0.249 | 0.677 | 0.323 |
Based on field observations, the mineralisation occurs at fewer than 50 m from the faults (Figure 7c). The geophysical evidential layers were prepared by correcting and normalising raw magnetic data and applying various filters. Known deposits are well-correlated with the areas showing a moderate to high total magnetic intensity (Figure 7d). For each evidential layer, the value of the EBF was obtained by the Dempster laws in different ratios (Bel, Dis, Unc, Pls) and integrating them.

4.2. Prospectivity map

We used known gold occurrences in the data-driven EBFs to map prospective regions. Following the integration of evidential layers, four maps were created.
An advantage of using EBFs is the concurrent make of four outputs. By comparing these maps, better results can be obtained (Figure 8). The benefits of EBFs include the calculation of belief also disbelief and uncertainty for each evidence with respect to the supposition that a location is prospective for orogenic gold mineralisation. As a result, the EBFs were calculated with reference to known orogenic gold occurrences; therefore, the calculated Bel, Dis and Unc values can be interpreted in terms of the probability of finding orogenic gold in every location. Mineralisation predictions are made from the final map of integrated Bel values. Details concerning the application of data-driven EBFs to map prospective mineralisation areas can be found in Carranza and Hale (2003) and Carranza et al. (2005).

4.3. Validation

Validation points were selected at random locations where geochemical samples show a high concentration value and were not used in the mapping process. They show a relatively good correlation with the prospectivity map of the target mineralisation. The samples were mostly collected from the east and centre of the research area and the average correlation of the potential map with validation data can be due to the non-uniform distribution of samples in the area. According to the results of geophysical surveys and the general trend of faults, this area can be considered as a potential region for economic gold mineralisation. Based on the IP-RS results, two rechargeable anomalies were recorded, possibly caused by sulphide mineralisation. These zones in the northwestern section of the research area are semicircular with increasing electrical resistance in schist units and border of carbonate units and show high electrical resistivity in carbonate units in the southeastern section. Most of the rechargeable anomalies are associated with positive magnetic anomalies. Considering the gold mineralisation along with magnetite, these anomalies can be exploratory important (Figure 9). Field studies of anomalous parts show argillitic alterations and iron oxides along with metamorphic carbonate units and the boundary of schist units. The gold concentration in altered samples is higher than 1 ppm (Figure 10).

5. Discussion

The Dempster–Shafer theory of evidential belief has been usually used for the knowledge-driven modelling of potential mineralisation zones (Carranza & Hale, 2003; Chung & Fabbri, 1993). Using the equations presented before, when suffiecient information about the area and several mineral indices are known in the area (Carranza et al., 2008), the data-driven approach can estimate degrees of disbelief, belief, and uncertainty. Not only do the equations consider the spatial relationship between an evidential data layer and the target mineralisation, but also the relationship between the subsets of an evidential layer.

The Godarsorkh area, with a total area of approximately 14 km², is divided into 77,504 cells, in which 19 gold mineral indices with a grade higher than one ppm were identified. Data-driven methods for GIS-based mineral potential mapping invariably represent these indices as points (or unit pixels; Agterberg et al., 1990; An et al., 1994; Bonham-Carter et al., 1988; Porwal et al., 2003). Argillic, iron oxide and silicified zones were detected with the aid of ASTER and Sentinel-2 satellite data. The alteration zones are mainly located on marble with grey limestone interlayers located on quartzite, mica-schist, calc-schist, altered marble limestones and dolomite units, and are considered as the main host rocks of gold mineralisation in the study area. Fault structures control gold deposits in shear zones (RJ Goldfarb et al., 2001; D Groves et al., 2005; DI Groves et al., 1998). These structures at Godarsorkh consist of a set of normal and strike-slip faults that often extend in a NE-SW and SE-NW direction, and the mineralisation occurred at a short distance from these faults. In the altered parts, siliceous veins along with iron oxides are observed in the same trend as fault structures, which seem to be the main host of gold mineralisation.

Magnetic anomalies have shown the mineralisation shape and position below the surface due to the association of gold with magnetite veins. Magnetic anomalies show their highest enrichment in metamorphosed units with little magnetism, and it seems that the main enrichment factor is the presence of magnetite with ore veins. The IP-RS studies showed the highest resistance in dolomitic units and the highest chargeability in altered calc-schist units. Notably, these results are significantly consistent with the mineralisation study, so that mineralisation with iron oxide alterations, silicification, and less argilitization in the form of narrow veins can be seen inside the metamorphic and altered units. The MPM shows three mineralised zones in the Godarsorkh area. According to this map, the western zone is significantly compared with other parts of the study area. The data-driven estimation function method is one of the multivariate methods that can help in deciding on the exploratory future of a mineral range. The use of this method at Godarsorkh shows promising results which can be useful for exploration geologists in future studies. Moreover, because of the non-uniform distribution of mineralisation indices in this area, it is possible that some potential areas were excluded from the study which can be considered as the main weaknesses of this method.

6. Conclusions

Gold deposits related to shear zones are among those deposits that are often formed by tectonic tensions and
do not show substantial mineralisation signals such as extensive alterations, geochemical dispersion and significant mineralisation evidence, and different factors should be reviewed simultaneously to identify and explore these deposits. Using prospectivity maps and considering several factors in identifying these deposits, exploration geologists will be able to efficiently map high potential mineralisation areas and specify drilling sites.

This study used EBFs to identify a local orogenic gold mineralisation in the Godaesorkh gold deposit. – Using geological, structural, alteration, and geophysical evidential layers, two independent maps of Bel and Pls could suitably localise the three most favourable sections of gold mineralisation. The Unc maps suggest that a great portion of the study area shows low potential for Au mineralisation and, therefore, can

Figure 9. Profile map No. 12 is the result of the collection of EPRS data, based on which a high overlap between magnetic anomaly, IP-RS and geological units can be seen. Based on this profile, metamorphic calc schist units have the highest chargeability and limestone and dolomite units have the highest resistance.
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Disclosure statement

No potential conflict of interest was reported by the authors.

Data Availability Statement

Raw data were generated at Iran Minerals Production and Supply Company (IMPASCO) data supporting the findings of this study are available from the corresponding author Mehdi Maleki on request.

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