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Synergizing remote sensing, support vector machine, and aeromagnetic data for precise lithological and mineral potential mapping: a case study from Egypt

Hatem M. El-Desoky^a, Ahmed M. Abdel-Rahman^a, Hamada El-Awny^a, Wael Fahmy^a, Reda Abdu Yousef El-Qassas^b, Kamal Abdelrahman^c, Hassan Alzahrani^c, Peter Andr   ^d, Yahia Z. Amer^e and Ahmed M. Eldosouky^f

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ABSTRACT

Precise lithological mapping is not only a strong key for exploring new mineralized areas but also could help in achieving the optimal exploitation of mineralized regions. In the present case, cause lithological mapping may provide advice not only to the distribution of possible placer deposit occurrences within the study region but also to small-scale blocks of gold-bearing rocks that are not specifically described in prior geological maps. Therefore, we effectively mapped the exposed rock units in the Hamash region of the Eastern Desert of Egypt by using Support Vector Machine (SVM) to Sentinel 2 data through executing machine learning algorithms (MLAs). This goal involves extensive fieldwork, petrographical examinations, and image processing remote sensing techniques to accurately reveal the exposed lithologies distribution besides the potential relic areas. Moreover, the results disclosed several occurrences of the gold-bearing rocks (e.g. alkali feldspar granites) within the study area besides highlighting the distribution of placer deposits that are mainly concentrated around the old mining workings. The lithological overall allocation accuracy (93.8%) was assessed through a confusion matrix, ground truth rock samples, and previous geological maps. Additionally, the airborne magnetic data were processed and interpreted to detect the main lineament structures controlling the favorable locations with high potential for gold mineralization and associated minerals. Also, the Center for Exploration Targeting (CET) porphyry map depicts the significant gold mineralization zones, which are regarded as targets for follow-up and ground studies. The current contribution greatly encourages further investigations for brownfields as their results could at least enhance a considered area of economic placer deposits, if not highlighting non-exploited lithological blocks.

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1. Introduction

The lack of optimal exploitation of old mines or well-known mineralized spots mostly results in the immense squandering of several mineral resources, other than environmental problems. In Egypt, several gold-bearing areas have not been perfectly exploited and severely invaded by random mining. Thorough lithological mapping of the prospective rocks serves as a foundation for more effective exploitation of these mineralized occurrences (Cardoso-Fernandes et al. 2020; Grunsky, Mueller, and Corrigan 2014; Shebl, Abdellatif, Elkhateeb, et al. 2021). Ensuring high resolution itemized distribution of the rock units may lead to revealing new possible sources or at least guarantee remaining resources exploitation. Accurate lithological mapping could be achieved by using various remote sensing datasets through specifying spectral signatures of the exposed rock units within a study

area. Subjectivity in lithological mapping is drastically reduced with the introduction of Machine Learning Algorithms (MLAs), and the resulting lithological units are intended to be objectively distributed. Consequently, implementing MLAs in geological mapping for brownfields may reveal new mineralized zones. Thus, accurate lithological allocation is still the main pillar that could help identify mineralized rocks in brownfield and green field exploration projects.

Several MLAs are recently utilized in mineral prospectively modeling and executing systematic lithological identification (Grunsky 2010; Guart  n and Emery 2021; Kuhn, Cracknell, and Reading 2018; McKay and Harris 2015; Rodriguez-Galiano et al. 2015; Xiang et al. 2020). For instance, support vector machines (Bentahar and Raji 2021; Cardoso-Fernandes et al. 2020; Karimzadeh and Tangestani

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2021; Othman and Gloaguen 2014, 2017; Otukey and Blaschke 2010; Pal and Mather 2005; Shebl and Csámer 2021b, 2021b; Shebl, Kusky, and Csámer 2022), neural networks (Haykin 2010; Latifovic, Pouliot, and Campbell 2018; Lee et al. 2012; Zhang et al. 2018), and random forests (Harris and Grunsky 2015; He et al. 2015; Othman and Gloaguen 2017; Rodriguez-Galiano et al. 2015) are considered efficient MLAs and extensively used in various applications besides lithological allocation. SVM is a prominent supervised machine learning algorithm based on statistical learning, widely used for binary and multi-class classification tasks, as a non-parametric classifier (Cortes and Vapnik 1995; De Boissieu et al. 2018; Mountrakis, Im, and Ogole 2011; Pal and Mather 2005). The goal is to minimize structural risk by identifying an optimal hyperplane in the feature space that maximizes the margin between different class samples. SVM is utilized for lithologic classification by selecting and testing pixels, training the classifier using a kernel function, and mapping input data into a higher-dimensional space to create a hyperplane to separate different classes (Chen et al. 2023; Harris and Grunsky 2015; Othman and Gloaguen 2014). Lithological mapping can be efficiently and accurately achieved using remote sensing and machine learning algorithms, enhancing accuracy and comprehensiveness, providing up-to-date information on anthropogenic changes, and handling large data amounts (Kanevski, Timonin, and Pozdnukhov 2009).

As input for these classifiers, several datasets could be implemented including both spaceborne and airborne sensors. With respect to the designations of Sentinel 2 Multispectral Instrument (MSI), reasonable performance could be achieved (Phiri et al. 2020) that makes Sentinel 2 an efficient and potential dataset for several geological applications (Ge et al. 2018; Karimzadeh and Tangestani 2022; Serbouti, Raji, and Hakdaoui 2022; Shebl and Csámer 2021a, 2021b; Van der Meer, van der Werff, and van Ruitenbeek 2014).

The magnetic method is a commonly used geophysical technique in mineral exploration. Rocks with different magnetic characteristics cause variations in the earth's magnetic field, which the magnetic method can detect. The existence of this contrast is used to detect mineral deposits, geological rock, and related geological structures. These variations can give indications about the concentration and location of mineral deposits, providing a noninvasive tool for identifying sites for mining potentiality (Eldosouky et al. 2021). One of the primary markers for prospective mineralized zones, particularly orogenic gold resources, is structural control. Magnetic survey maps could be utilized to outline structures, subsurface geology, and identify potential areas of mineralization, including iron, gold, and other valuable minerals (Abu-Donia, El-Qassas, and Mohamed 2023; Abuelnaga et al. 2019; Assran, El

Qassas, and Yousef 2019; Bencharef et al. 2022; Ekwok et al. 2023; El-Qassas et al. 2021; Eldosouky et al. 2020, 2021; Elkhateeb et al. 2021). The airborne magnetic survey provides a cost-effective and efficient tool for covering large regions, making it an essential tool for mineral investigation (Abdelrahman et al. 2023; Aboelkhair, Ibraheem, and El-Magd 2021; El-Qassas, Abu-Donia, and Omar 2023; Kharbush, Eldosouky, and Amer 2022). Furthermore, the high-resolution data of magnetic surveys can be used to guide future exploratory activities.

This contribution's primary goal is the integration of airborne magnetic data with remote sensing data for precise lithological mapping and detection of mineralized zones. In order to map the exposed rock units in the study area and identify certain gold-bearing occurrences and possible placer deposits, the current paper integrated comprehensive field and petrographical investigations with the widely advised SVM. Moreover, the analysis of airborne magnetic data to determine spatial changes in the magnetic characteristics of the Hamash region. In addition to detecting structural features and determining their influence on the existence of gold and associated mineralization.

2. Study area and geological setting

The Hamash concession region is situated in a rough, hilly area, South Eastern Desert in the Egyptian shield, between the Red Sea and the Nile Valley. The Hamash area lies 60 kilometers south of Idfu on the Idfu-Marsa Alam Road and covers about 78 km² between latitude: 24° 40' 30"N- 24°43'N, and longitude: 34° 02' 30" E-34° 12' E (Figure 1). They are intruded by volcanic rocks of various compositions, which may reach hundreds of meters in thickness and exhibit varying degrees of metamorphism throughout the flow sequence. Some intermediate intrusion that has been changed into diorite-granodiorite complexes as well as granitic rocks, dispersed in the country rocks. On the basis of the obtained present geological maps, field observations, petrography, remote sensing and previous works (Gharib et al. 2021; Hilmy and Osman 1989; Said 2010; Sakran et al. 2009); the rocks that exposed in the Hamash area are represented by metavolcanics, metasediments, late-to post-orogenic granites (diorite, granodiorites and alkali feldspar granites) and trachyte plugs (Figure 1).

The northeastern portion of the examined region is structurally affected by a major fold and faulting. There are NW-SE trending zones of intense shear. Thrust, strike-slip, and normal faults also cut through the area. Two significant right-lateral strike-slip faults moving WNW collide with a slight change in the strike to form a massive releasing bend and pull-apart basin measuring about 8 km long and 10 km wide. There are multiple normal faults in this

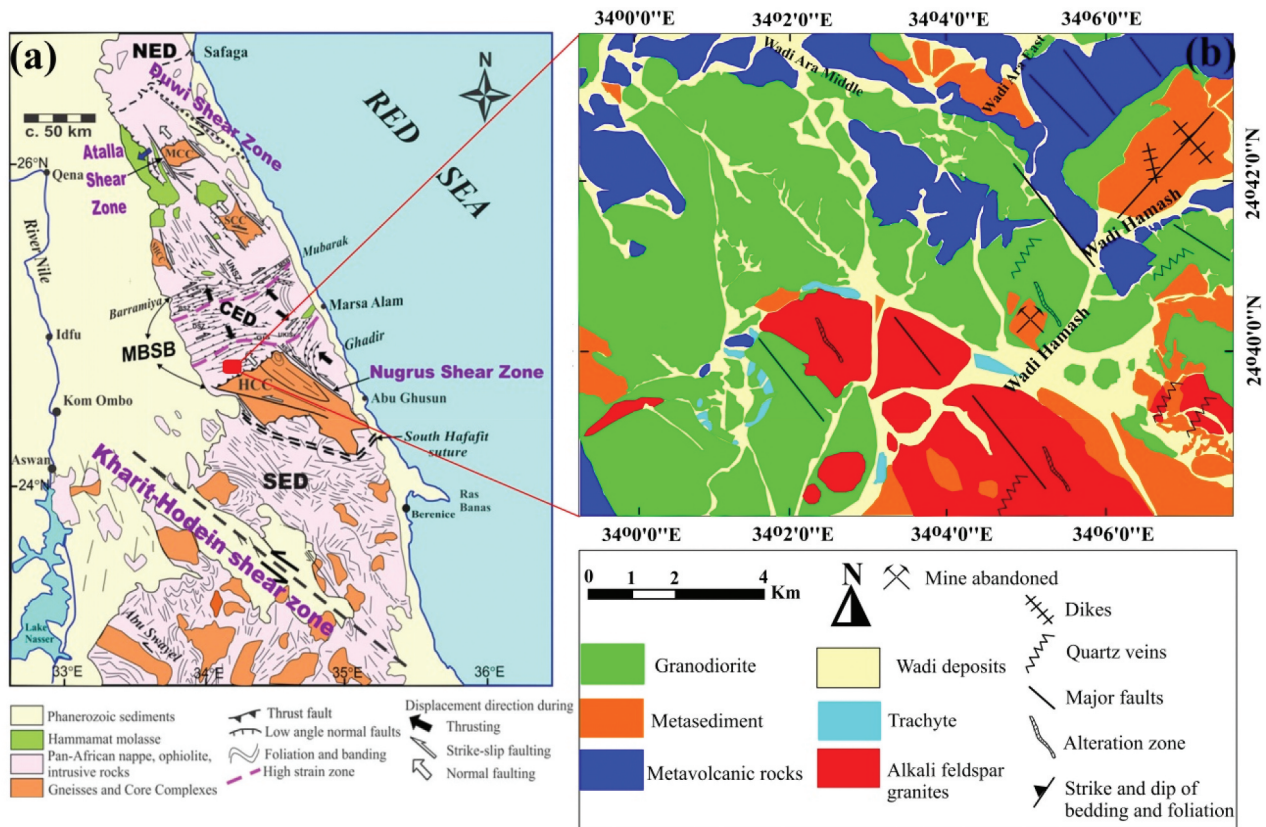


Figure 1. (a) Major structures in the central Eastern Desert (CED) including the studied area; abbreviation: SED; South Eastern Desert, CED; Central Eastern Desert, NED; Northern Eastern Desert, NSZ, Nugrus shear zone, UNSZ, Um nar shear zone, HCC; hafafit core complex, SCC; Sibai core Complex; MCC; meatiq core Complex; MBSB, mubarak-barramiya shear belt. This map is compiled from Greiling et al. (1994), Fritz et al. (1996), De Wall, Greiling, and Sadek (2001) and (M. A. Abd El-Wahed 2014). (b) Geologic map of Hamash area modified after Moustafa and Akaad (1962) and Selim (2019).

extension zone, mostly running NW to NNW and N-S (Hilmy and Osman 1989; Said 2010; Sakran et al. 2009). Mineralogically, the Hamash area's gold-bearing veins are classified as gold quartz formations, which are accompanied with a copper deposit (Sabet and Bordonosov 1984). These veins are also rich in iron and copper minerals, including pyrite, chalcopryrite, and malachite, as well as disseminated gold. The gold-bearing quartz veins in the country rocks have a variety of changes (Saad et al. 2015).

3. Materials and methods

This study utilizes Sentinel-2 remote sensing data for lithological mapping and airborne geophysical data of the study area (Figure 2).

3.1. Remote sensing data

3.1.1. Remote sensing image processing

We used a cloud-free scene (L1C_T36RXN_A033008_20211017T083235_2021-10-17) that we obtained via Copernicus Open Access Hub in October 2021 for our present study. Data preprocessing including geometric, radiometric corrections were performed using QGIS and Sentinel Application Platform

(SNAP). All of the 20 m pixel-sized bands are resampled to 10 m using the cubic convolution method, and then they are re-projected using UTM (Universal Transverse Mercator projection) WGS84 zone 36 N to achieve our goal of better resolution mapping. Moreover, bands 1, 9, and 10 are excluded due to the large pixel size (60 m).

The data for the study was obtained from the U.S. Geological Survey and the European Space Agency using various satellites. The data was processed using the Environment for Visualizing Images (ENVI) software version 5.6; re projected to UTM WGS 84 zone 36N, and radiometrically corrected using the Sentinel Application Platform (SNAP). The data was also pre-processed using the Sentinel-2 toolbox, and ALOS PALSAR1 data underwent reprojection, radiometric calibration, and speckle reduction using SNAP.

3.1.2 Training sample preparation

The study area is covered by nine primary information classes. Sentinel-2 data is therefore used to define representative, evenly distributed nine groups (for training and testing samples) based on the geological map and visual interpretation of the photos. Table 2 provides a detailed description of the training and ground truth pixels, whereas Figure 2 displays their

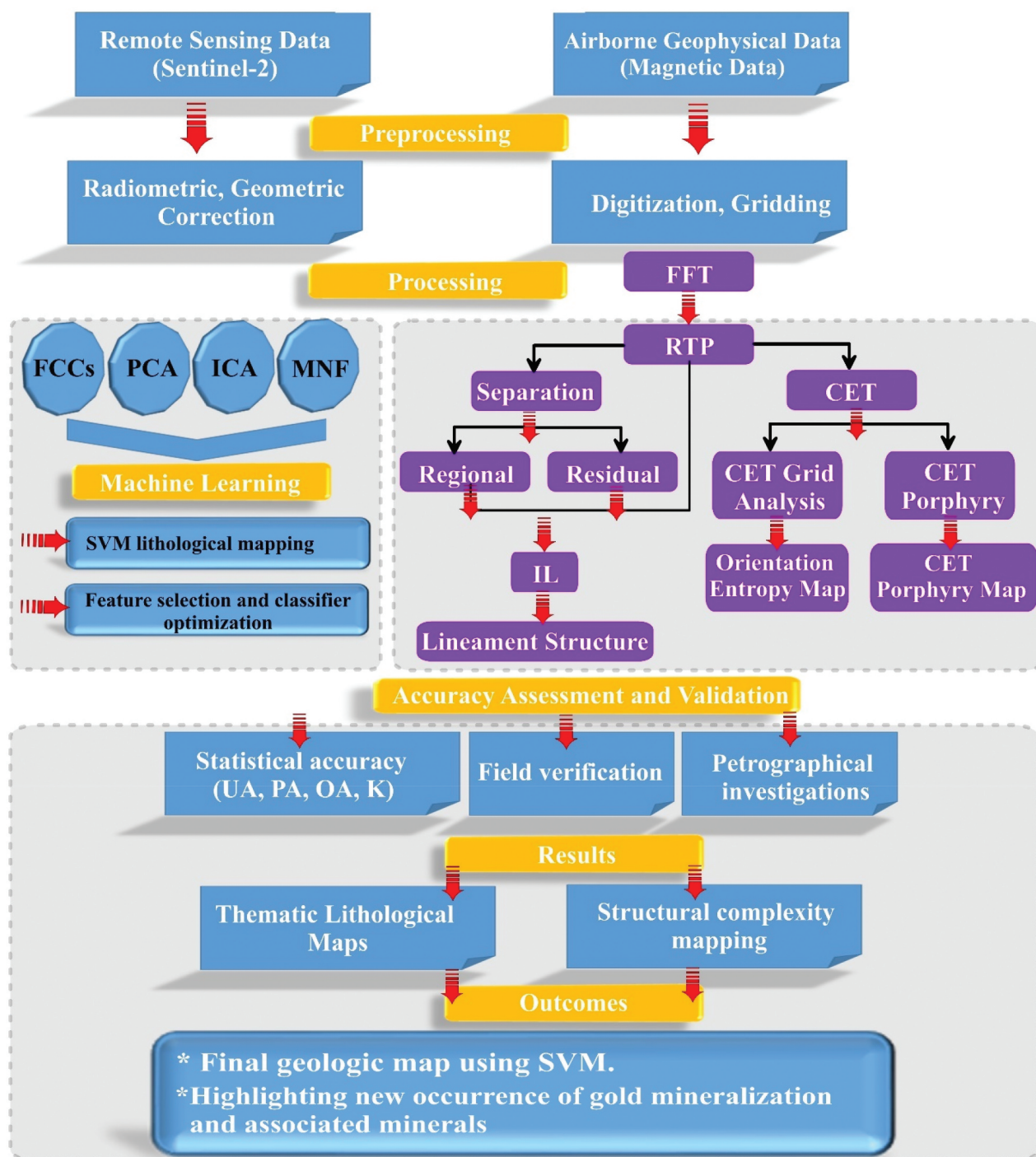


Figure 2. Flow chart showing sentinel-2 and magnetic data methodology.

Sentinel-2 spectral signatures. The classifiers are trained with prototype pixels to create theme maps for the classes, and the accuracy of these outputs is evaluated using ground truth samples.

Table 1 shows that Sentinel 2 data provides 13 wide-swath spectral channels encompassing areas in the visual near-infrared (VNIR), and short-wave infrared (SWIR), in addition to having a higher spatial resolution (up to 10 m). To achieve the desired target, diagnostic lithological identification should be fulfilled to purely elicit the classifier training data. Consequently, various image processing techniques

including false color composites (FCCs), principal component analysis (PCA), independent component analysis (ICA), and minimum noise fraction (MNF) are applied. FCC is a common band combination (Red, Green, and Blue) method that is utilized extensively in geological applications and typically provides a fair identification of the exposed lithologies (M. Abd El-Wahed et al. 2019; Shebl and Csámer 2021a). It should be emphasized that the optimal RGB combinations for the PCA, MNF, and ICA processes were meticulously chosen through intensive visual interpretation of the distribution of rock units. This selection

Table 1. Characteristics of Sentinel 2 data.

Band (b)	Central wavelength (μm)	Pixel size (m)
1	0.443	60
2	0.490	10
3	0.560	10
4	0.665	10
5	0.704	20
6	0.740	20
7	0.782	20
8	0.842	10
8a	0.865	20
9	0.945	60
10	1.375	60
11	1.610	20
12	2.190	20

process was informed by our comprehensive field data and precise field observation points for each rock unit. The selected band ranges depend mainly on the objects to be emphasized. Principal component analysis is a statistical image processing technique mostly used to minimize the data dimensionality and maximize the extracted amount of information by transforming the original bands to a new less correlated group of bands called principal components. The latter are considered a projection of the data onto the principle axes (eigenvectors) and mostly the first components have the considered data structure (Gholami, Moradzadeh, and Yousefi 2012; Hall and Llinas 1997).

Results of PCA are mostly useful in various geological interpretations (Abd El-Wahed et al. 2019; Bentahar and Raji 2021; Shebl and Csámer 2021b). Independent Component Analysis is another signal processing technique that could efficiently diminish higher-order statistical dependencies (Hyvärinen 1999). As the name suggests, ICA transforms mixed signals to independent components and thus considered a vigorous technique for remote sensing source separation especially when no considered available mixing information. Unlike PCA (based on Gaussian assumption and utilizing second-order statistics), ICA could discriminate the desired targets even in the smaller areas, as it employs non-Gaussian assumption and uses higher-order statistics (Chen and Zhang 1999; Gholami, Moradzadeh, and Yousefi 2012; Shebl, Abdellatif, Hissen, et al. 2021). Similar to PCA and ICA, minimum noise fraction is a dimensionality reduction technique where the original datasets are transformed into new optimum group depending on mathematical manipulation that in turn vary according to the applied algorithm (Gao et al. 2017). The resultant MNF components are arranged according to the image quality whatever the noise distribution within the bands.

Toward better lithological decisiveness and to relatively overcome the mixed-pixels indiscernible identification (mostly associated with multispectral datasets), dimensionality reduction methods including PCA, ICA, MNF are implemented (Hu et al. 2018; Pour et al. 2018; Sekandari et al. 2020;

Serbouti, Raji, and Hakdaoui 2022; Shebl and Csámer 2021a).

3.2. Airborne magnetic data

The Western Geophysical Company of America's Aero-Service Division conducted an aerial survey of the study region (Aero-Service 1984). The high-sensitivity (0.01nT) aerial magnetometer Varian (V-85) was used to measure the overall magnetic intensity. The survey was carried out in NE-SW-oriented parallel flight lines spaced 1.5 km apart, with tie lines flown at 10 km intervals in a NW-SE direction at a nominal flight altitude of 120 meters above the ground (Aero-Service 1984). Fast Fourier transformation (FFT) was employed in this investigation to construct the residual and regional magnetic maps from Reduced to the North Pole (RTP) airborne magnetic data.

The potential field (PF) under observation encompasses both regional and residual anomalies. Regional anomalies display smooth, incremental gradients, expansive reach, extended wavelengths (low wavenumbers), and intensified amplitudes. These anomalies stem from the influence of deep-seated origins. Conversely, residual anomalies display sharp gradients, finite reach, abbreviated wavelengths (high wavenumbers), and diminished amplitudes, originating from shallow sources. The separation of magnetic anomalies into regional and residual sorts is a pivotal step in the interpretation process. During this phase, a specific filter is appointed based on a designated cutoff wavenumber, selectively enabling, or excluding anomalies with wavenumbers below or above this threshold. The low-pass filter facilitates the transmission of anomalies retaining lower wavenumbers than the cutoff, while the high-pass filter rejects these anomalies, allowing passage only to those with higher wavenumbers. This procedure is utilized to exhibit intrusions, basement complexes, and subsurface structures. Spector and Grant (1970) conducted spectral analysis through Fourier Transform on potential data for in-depth analysis.

For achieving precise unveiling of edges and lineaments, we employed a robust filter founded on the logistic function of the analytic signal (Pham et al. 2018). This method, known as the improved logistic (IL) (Eldosouky, Pham, and Henaish 2022; Pham et al. 2020), was utilized to harmonize the disparity in signals and is presented by:

$$IL = \frac{1}{1 + \exp[-p(R_{THG} - 1) + 1]} \quad (1)$$

where,

$$R_{\text{THG}} = \frac{\frac{\partial \text{THG}}{\partial z}}{\sqrt{\left(\frac{\partial \text{THG}}{\partial x}\right)^2 + \left(\frac{\partial \text{THG}}{\partial y}\right)^2}} \quad (2)$$

and p is between 2 and 5.

In this groundbreaking study, we used an innovative technique to geological analysis utilizing two distinct methodologies: Center for Exploration Targeting (CET) grid analysis and CET porphyry analysis. These techniques represent a notable improvement in the field of geosciences, delivering an exhaustive and detailed understanding of subsurface structures. The CET grid analysis approach employs a refined algorithm to meticulously analyze spatial variations in geological parameters, providing high-resolution understandings into the allocation of subsurface features (Assran, El Qassas, and Yousef 2019; Eldosouky, Abdelkareem, and Elkhateeb 2017, 2020; Holden et al. 2010; Kovess 1991). Jointly, the CET porphyry analysis technique focuses on the identification and characterization of porphyry-like-structures, employing a combination of cutting-edge data processing algorithms (Holden et al. 2012; Loy and Zelinsky 2003). The efficacy of the CET grid and porphyry analysis techniques has been validated through strict testing and application in multifarious geological environments (Assran, El Qassas, and Yousef 2019; Eldosouky et al. 2020).

4. Results

4.1. Remote sensing results (Features selection and classifier optimization)

The rock units are well-recognized by the integration of the findings of various approaches (FCC, PCA, ICA, and MNF), enabling suitable feature selection to be applied to predict the exposed rock units within the study area. As seen in Figures (3–5), each approach helps in the thorough identification of all the exposed rock units by differentiating between one or more rock kinds. Investigating their outputs highlights seven spectrally-separated classes including metavolcanics (Mvs), Metasediments (Ms), Alkali feldspar granite (Afg), Granodiorites (Gd), Trachyte (Tr), Wadi (Wd), and Placer (Pl) deposits. Table 2 displays the selection of field studies, applied image modification techniques, training, and testing data concerning the

preceding geological map following Moustafa and Akaad (1962). The percentages of training to testing data were kept as (75%–80% to 25%–20%) to fulfill efficient allocation as recommended by (Kumar et al. 2020; Shebl and Csámer 2021b). Because SVM could effectively create a decision boundary hyperplane that divided spectrally related classes, it was used in this work (Pal and Mather 2005; Scholkopf and Smola 2018). Moreover, it is widely recommended by several researchers (Bachri et al. 2019; Shebl and Csámer; 2021b) in lithological allocation. The present work utilized the Radial Basis Function (RBF) as the kernel, gave 0.1 and 100 as the misclassifications penalty parameters, and included Gamma in the kernel function. After several trials, these parameters were adjusted by consulting other earlier research conducted under comparable circumstances.

Utilizing the previously mentioned characteristic training samples, pixel-based lithological generalization was executed using SVM which allocates each pixel to a certain class. The resultant thematic map (Figure 6) has been evaluated statistically, spatially, and interpreted with previous geological maps (Moustafa and Akaad 1962; Selim 2019) through a visual comparison of the thematic classes distribution with their corresponding units. Reasonable matching was evident. Statistical accuracy assessment was fulfilled through User Accuracy (UA), Producer accuracy (PA), Overall Accuracy (OA), Kappa Coefficient (K), and error matrix (Table 3), using testing pixels that have never been seen by the classifier (Congalton 1991). The overall classification accuracy was 93.8% however some misclassifications were observed especially with trachyte plugs as shown by its lower producer accuracy. Moreover, a spatial assessment was achieved by comparing our results with a number of field stations and representative rock samples.

4.2. Field verification

Field verification for every exposed rock unit was carried out to evaluate and validate the allocation results. This analysis found that metavolcanics, the oldest of which dates back around 780–750 Ma, cover over 40% of the basement rock units that crop out in the study region (Ali et al. 2009). Coinciding with the resultant thematic map (Figure 6) metavolcanics are mostly located in the northern section, on the eastern flank of Wadi Umm Ara East and the northern flank of Wadi Umm Hagalig. These rocks have a well-developed preferred orientation, as well as micro-folding and faulting, near large strike slip faults. Hamash metavolcanics have a relatively wide composition range, however they comprise felsic (acidic) and mafic (basic) metavolcanics. They occur as alternated sheets and masses. Occasionally, their color is

Table 2. Characteristics of training and testing data.

Class	Training data		Testing data	
	Pixels	%	Pixels	%
Mvs	1280	0.784	351	21.53
Afg	1337	0.770	399	22.99
Gd	1889	0.758	601	24.14
Ms	919	0.768	277	23.17
Tr	527	0.758	175	24.93
Wd	1212	0.770	362	23.00
Placer	554	0.754	180	24.53

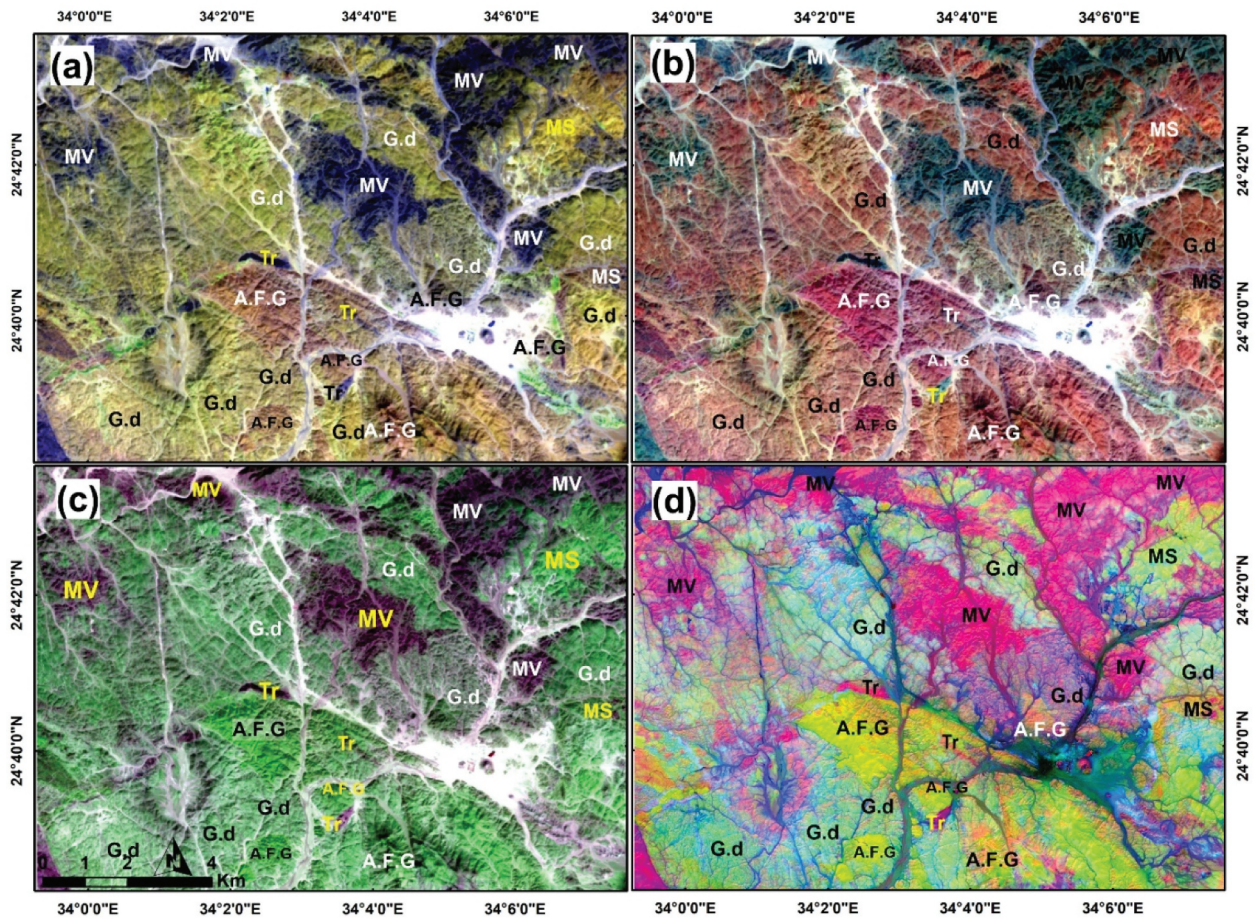


Figure 3. Lithological differentiation utilizing FCCs of (a) 12/11/2, (b) 12/6/2, (c) 4/12/7 and (d) PCs of 1/2/3 bands, in RGB respectively. Abbreviations; A.F.G = Alkali Feldspar Granites, G.D = Tonalite-Granodiorite, MV = Metavolcanics, Ms = Metasediments, tr = Trachyte plugs.

changing from deep blackish for the metabasalt and metaandesite to white grayish for the metatrachyte (interpreting the pixels classified as trachytic rocks within metavolcanics and confirming the reliability of the generalization process) and metarhyolite. They are fine to medium grained rocks, comprises the massive – high relief outcrops relative to the surrounded other rock units. Sometimes displaying porphyritic texture where plagioclase crystals are embedded in the microcrystalline groundmass (Figure 7 (a,b)).

The majority of the metasediments occur in the northeastern region of Hamash area, which indicates a good agreement with the resulting geological map. These metasediments are foliated, folded (mesodimension folds and boudinage are mostly parallel to the foliation planes), and are extremely deformed. The metasediments in the examined district are likewise younger than the genuine metavolcanics, according to field observations (Figure 7(c)).

Late-to post-orogenic granites, this group represents the youngest granitic rocks in the studied district, distributed in the study area especially at the central, and southern part. Therefore, the investigated granites called younger granite or alkali feldspar granite depending essentially on the field relationship and

mineralogical composition. They are characterized by several quartz veins, and xenoliths of old rocks (Figure 7(d)). The granitic rocks in the study area can be classified into diorite, granodiorites and alkali feldspar granites.

Diorite intrusive suite is widely distributed with granodiorite. These medium- to coarse-grained rocks are dark green to greenish gray in color and usually occur as massive intrusions with spheroidal weathering and contain xenoliths of metavolcanic rocks (Figure 7(e)). Field investigations into the distribution of granodiorite rocks in the central and southern regions of the study area highlighted the thematic geological map's dependability. These rocks are medium- to coarse-grained grayish rocks with a predominance of xenoliths and alignment of mafic minerals in the form of gneissose texture. They are highly jointed and cross-cut by the alkali feldspar granite and invaded by dikes (Figure 7(f)). Similarly, the allocated alkali feldspar granites have been verified through several ground control points that revealed an outstanding matching especially at the central and southern parts of the investigated area. These rocks are composed of high masses of the so-called Hamash granite, which have spheroidal weathered masses and

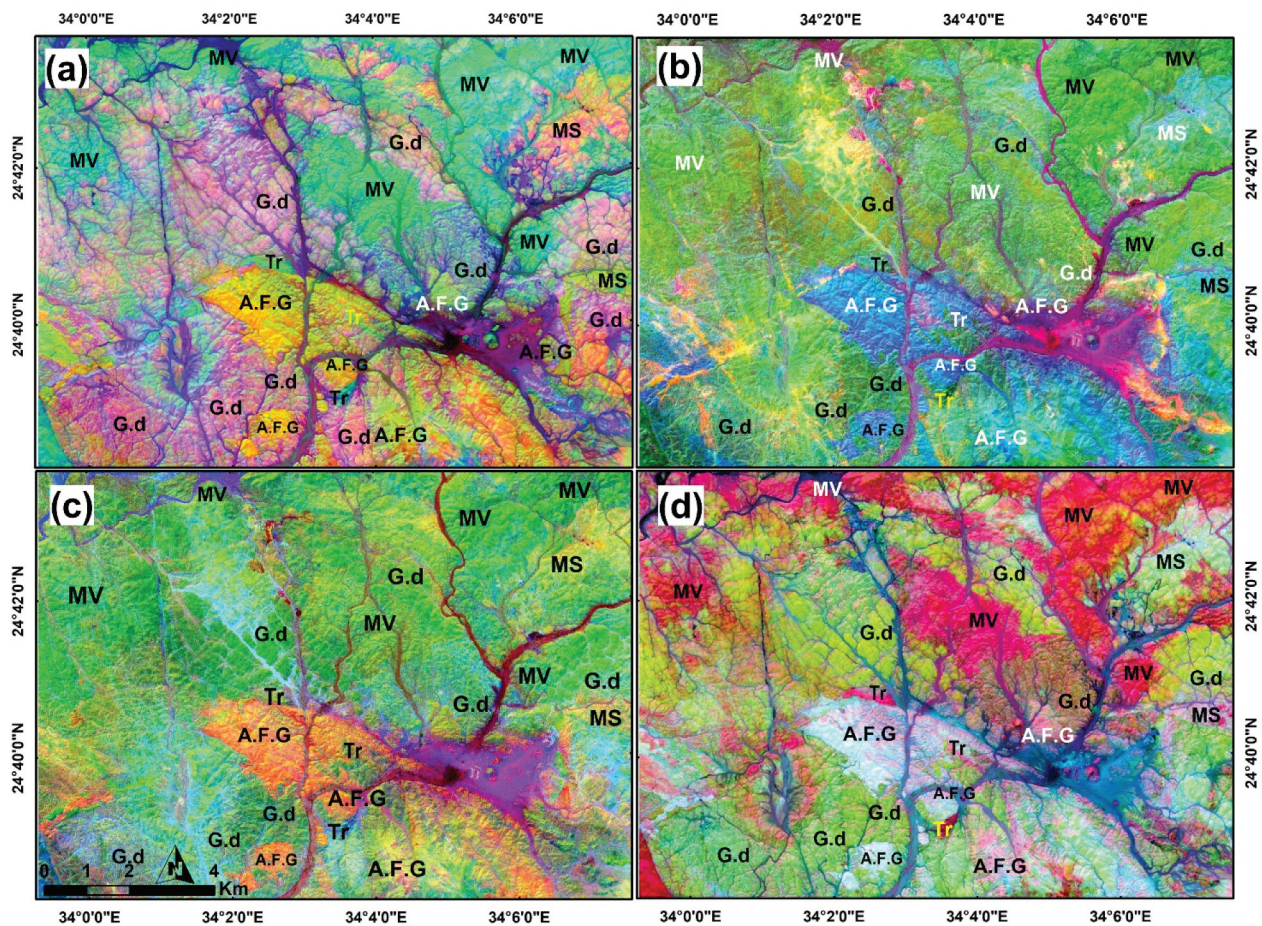


Figure 4. Lithological differentiation utilizing (a) 2/1/3 PCs, (b) 2/3/4 ICs, (c) 4/3/5 ICs and (d) PC1/PC2/IC4, in RGB respectively.

strong contacts cut across the island arc metavolcanic rocks. Numerous basic and acidic dikes have also invaded these rocks. The investigation AFG are medium to coarse-grained, pink to light red in color, sometimes they are light pink to grayish pink, equigranular, often exhibits exfoliation, poor in xenoliths, and have significant jointing systems, as well as it stands up as separated masses with different size and shapes. Moreover, it has a sharp contact with the other surrounding country rocks (Figure 7(g)). Gold-bearing placer deposits are frequently concentrated near alkali feldspar granite locations (Figure 7(h)). The alkali feldspar granite was affected by high tectonic processes, which contributed to the huge widespread of hydrothermal alteration zones, and mineralized veins bearing gold ore (Figure 7(i,j)). Several smoky quartz veins cut through these rocks, with thicknesses ranging from 10 cm to 4 m (Figure 7(k)). These field observations are mostly coincided with the detected pixels of placer deposits and AFG supplementing the desired aim of the usefulness of detailed lithological mapping in resolving new gold bearing spots in imperfectly exploited mineralized areas.

Trachyte plugs are common in the middle and southern part of the study area. They show reasonable

coincidence with the thematic map at the entrance to Wadi Hamash from the south. They appear as plugs with a creamy white tint and a high relief about 479 m (above sea level). These rocks are considered the youngest volcanic phase. They are mostly trachytic, with some showing a porphyritic texture. These rocks form massive masses at Gabal Sufra (the highest peak in the local environs), to the south of the study area, where they intrude the so-called Shaitian granite (highly sheared granite). Because there is no direct field relationship between these trachyte plugs (Figure 7(i)) and the previously documented mafic and felsic dikes, it is difficult to determine their age.

4.3. Petrographical investigations

We conducted a thorough petrographic description of the lithological units, ordered chronologically according to the field geologic context, from the oldest to the youngest, as metavolcanics, Late-to post-orogenic, and younger volcanics, to better support the categorized geological map.

The main types of metavolcanic rocks range in composition from rhyolite, andesite, to basalt. The metarhyolites are fine-grained with occasionally feldspar and quartz phenocrysts exhibiting

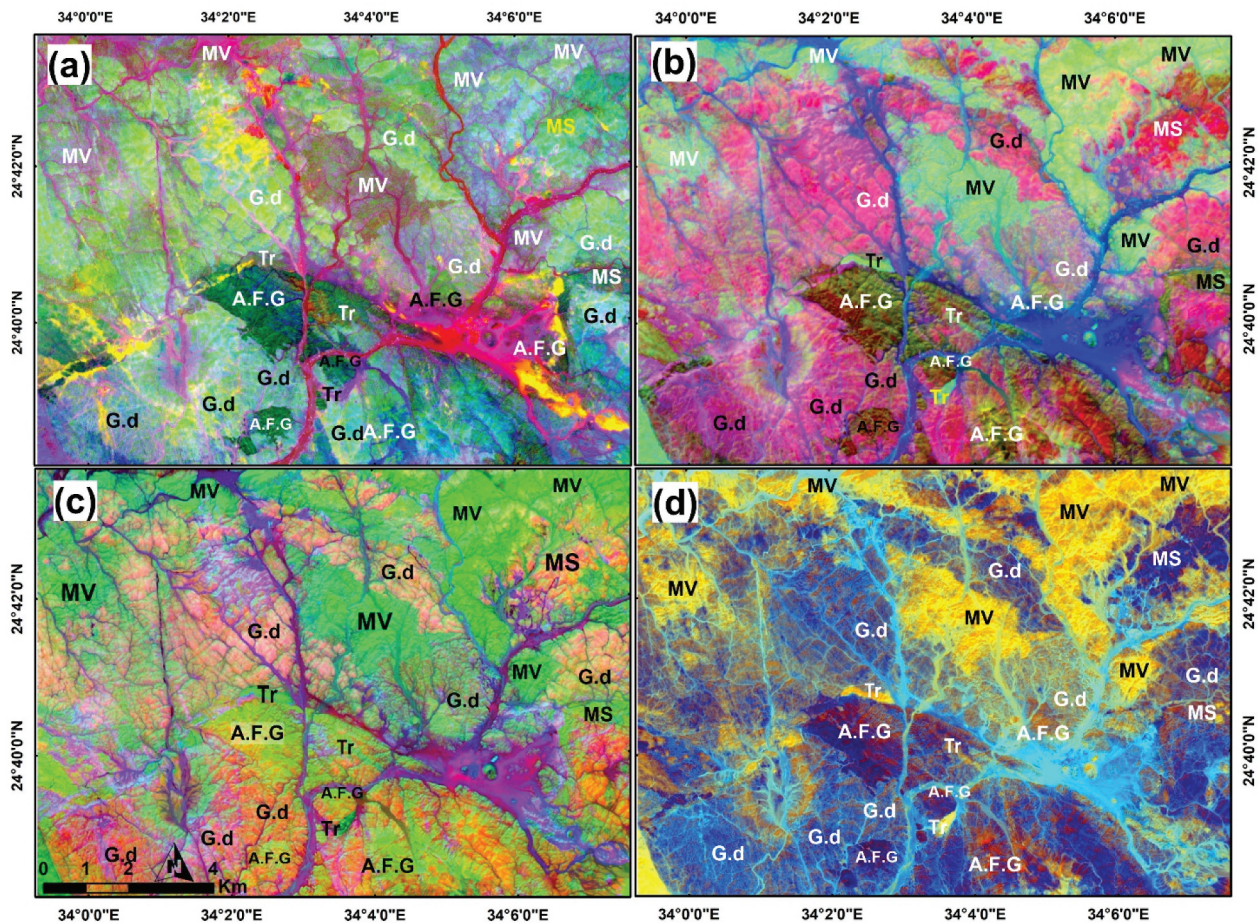


Figure 5. Lithological differentiation utilizing (a) MNF of 2/3/4 bands, (b) MNF of 3/1/2 bands, (c) IC1/PC1/IC2 and (d) MNF1/PC2/PC1, in RGB respectively.

porphyritic and spherulitic textures (Figure 8(a)). The meta-andesite is composed of plagioclase, hornblende and little pyroxene as large porphyries embedded in fine-grained groundmass of plagioclase laths, pyroxene, amphiboles, and opaque minerals (Figure 8(b)). Although metatrachyandesite is a meta-andesite rock, it has a directed texture due to the preferred orientation of grains caused by magmatic flows (Figure 8(c)). The basaltic rocks are composed of plagioclase, pyroxene, amphiboles, and relics of olivine as essential minerals (Figure 8(d)). Sericite, chlorite, quartz, epidote, and carbonate minerals occur as secondary minerals with opaque minerals as accessories. Metabasalt rocks include two varieties: metadoleritic basalts and metatrachybasalts. Metadoleritic basalts (metadiabasic basalts) are medium-grained, dark-gray basic rock consists essentially of labradorite, augite and ore minerals. These rocks exhibit doleritic, subophitic and diabasic textures (Figure 8(e)). Metatrachybasalts are fine- to medium-grained in equigranular rocks that are green in color. These rocks show a trachytic texture (Figure 8(f)). Metasediments rocks are medium- to coarse-grained and composed of quartz, plagioclase, sericite, biotite, chlorite, and carbonate. These rocks characterized by schistose, cataclastic textures as

well as mylonitized quartz (Qtz) with clear augen structure (Figure 8(g)).

Diorites are composed of plagioclase and quartz as essential minerals with biotite and hornblende as mafic minerals. Secondary epidote, chlorite, calcite, kaolinite, sericite as well as accessory opaques are observed (Figure 8(h)). Two types of granitic rocks have been recorded in this area. The first type is alkali feldspar granite, which is composed of potash feldspars, quartz, and plagioclase as essential minerals. These rocks exhibit well-developed granophyric and graphic textures and occasionally a granular texture. Graphic intergrowth of quartz within the perthitic orthoclase is commonly observed (Figure 8(i,j)). The second type is granodiorite consisting mainly of plagioclase and quartz with secondary sericite, epidote, kaolinite, chlorite, and characterized by graphic and granular textures (Figure 8(k)).

Trachyte Plugs are composed mainly of fine-grained, euhedral to subhedral phenocrysts of both sodic plagioclase and sanidine (Figure 8(i)). Mafic minerals (ferromagnesian) are occasionally represented. Alkali feldspars are configured as sodic plagioclase and sanidine displaying a subparallel alignment direction (trachytic texture).

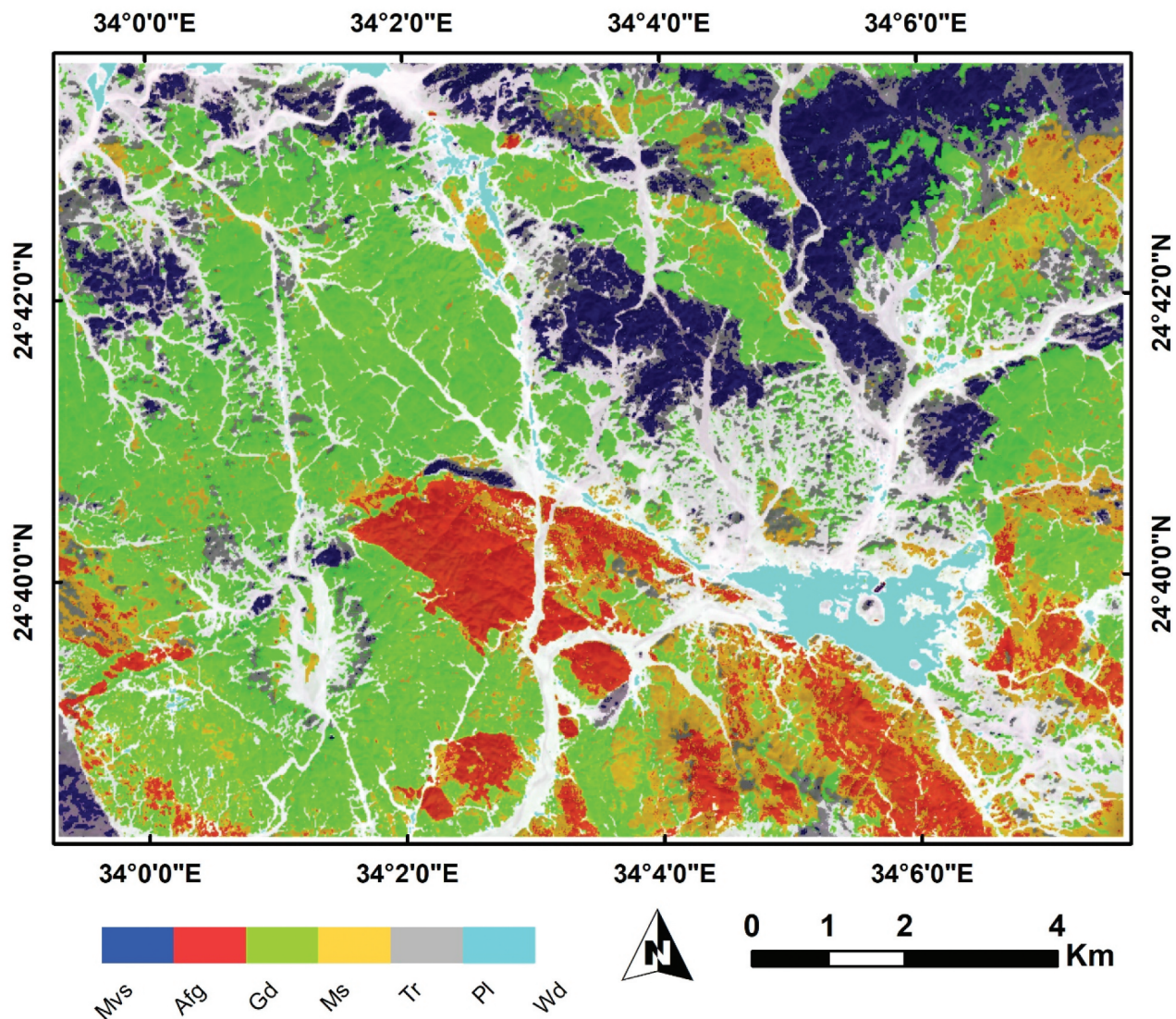


Figure 6. Lithological map of the study area created using SVM.

Table 3. Error matrix, Producer accuracy (PA), user accuracy (UA), overall accuracy (OA), and kappa coefficient (K) of SVM classification results.

S2	MVs	Gd	Ms	Tr	Pl	Wd	AFG	Tot	PA (%)	UA (%)
MVs	351	0	0	99	0	0	0	450	100	78
Gd	0	596	0	0	0	0	0	596	99.17	100
Ms	0	5	271	0	0	0	10	286	97.83	94.76
Tr	0	0	0	77	0	0	0	77	41.4	100
Pl	0	0	0	0	165	0	0	165	91.67	100
Wd	0	0	0	10	15	362	0	387	100	93.54
AFG	0	0	6	0	0	0	389	395	97.49	98.48
Tot	351	601	277	186	180	362	399	2356	OA = 93.84	K = 0.92

4.4. Airborne magnetic results

The RTP map has been modified to a datum (42500 nT) to aid and facilitate the interpretation. The RTP map (Figure 9(a)) shows various magnetic anomalies with different amplitudes, frequencies, and shapes. It displays magnetic values varying from -633 nT to 590 nT. This range reflects the composition of magnetic anomalies, depths, and dissected faults. Three magnetic zones may be distinguished based on the features of magnetic

anomalies as follows: a relatively high magnetic zone (Z1), a moderate magnetic zone (Z2), and a relatively low magnetic zone (Z3), as shown in Figure 9(a). Z1 is characterized by the wide range of magnetic amplitude from 24 nT to 590 nT and the vast distribution at the central, eastern, south-eastern, southern, southwestern, northwestern, and northern parts (Figure 9(a)). These anomalies have NW-SE, NNW-SSE, and NNE-SSW trends. The magnetic amplitude of Z1 suggests that it is

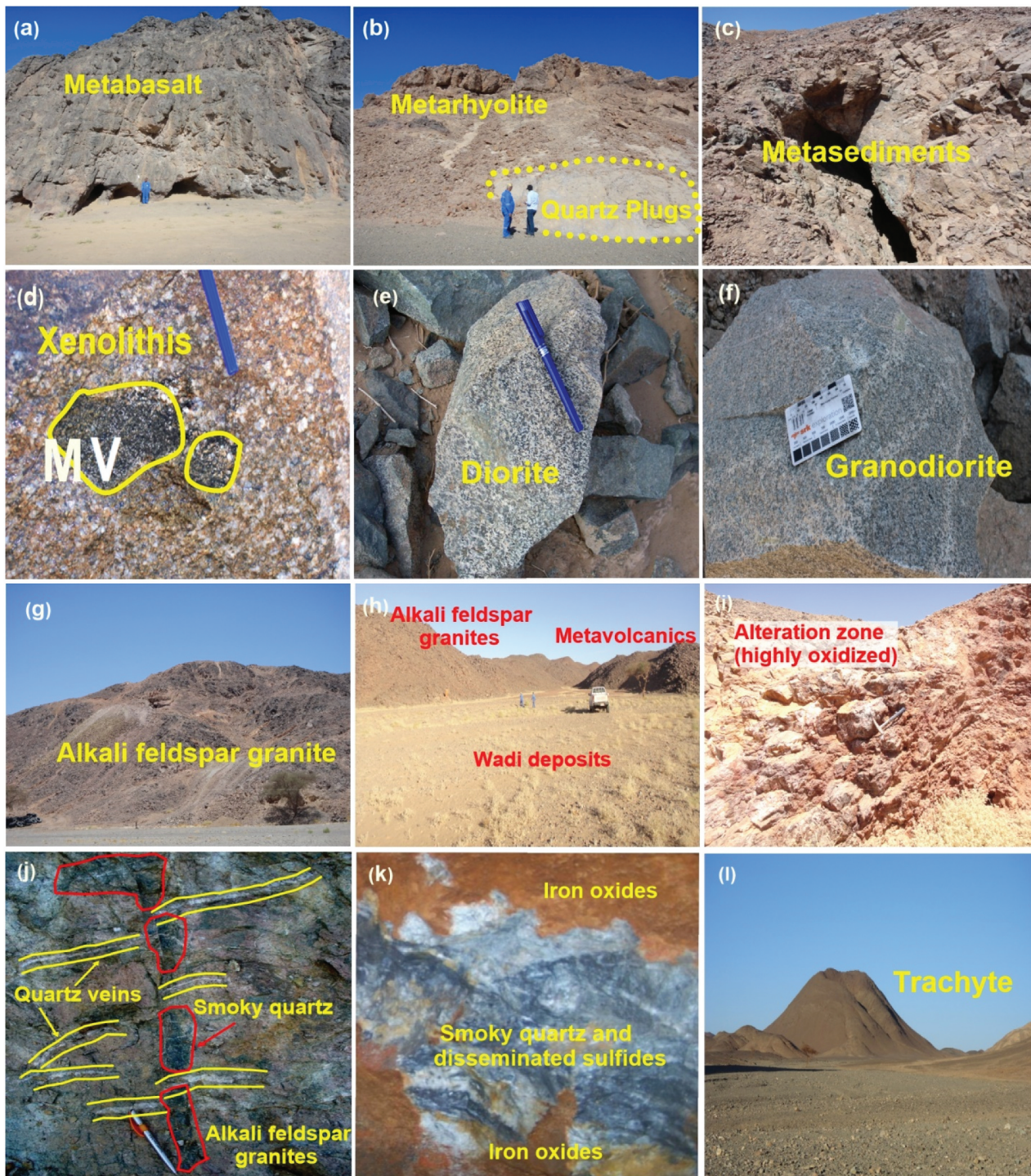


Figure 7. Field verification of the classified rock units highlighting: (a) Deep blackish color of metabasalt, and (b) metarhyolites invaded by quartz plugs accentuating the intraclass variability detected within metavolcanics. (c) Well-developed deformed metasediments. (d) Rounded xenoliths of metavolcanics (MV) enclosed within granites. (e) Medium- to coarse-grained diorite. (f) Greyish color and medium grained granodiorite. (g) Highly fractured alkali feldspar granites. (h) Wadi deposits and placers between alkali feldspar granites and metavolcanics. (i) Alteration zone (highly mineralized veins). (j) Mineralized quartz veins cutting alkali feldspar granites. (k) Sulfides disseminated with smoky quartz veins. (l) Low hills of trachyte plugs.

probably attributed to subsurface serpentinite rocks that have outcrops around the Hamash area. The high frequencies in Z1 may indicate that magnetic anomalies may have shallow or near-surface depths. However, the low frequencies in Z1 reflect that these anomalies are slightly deeper (Figure 9(a)). Z2 has magnetic amplitudes of -78 nT to 24 nT

and is spread over the entire Hamash area. The magnetic amplitude of Z3 (-78 nT to -663 nT) and frequencies may suggest that causative sources in this zone have an acidic composition and different depths (Figure 9(a)).

The high-pass (residual) map displays that the area includes high and low magnetic anomalies with

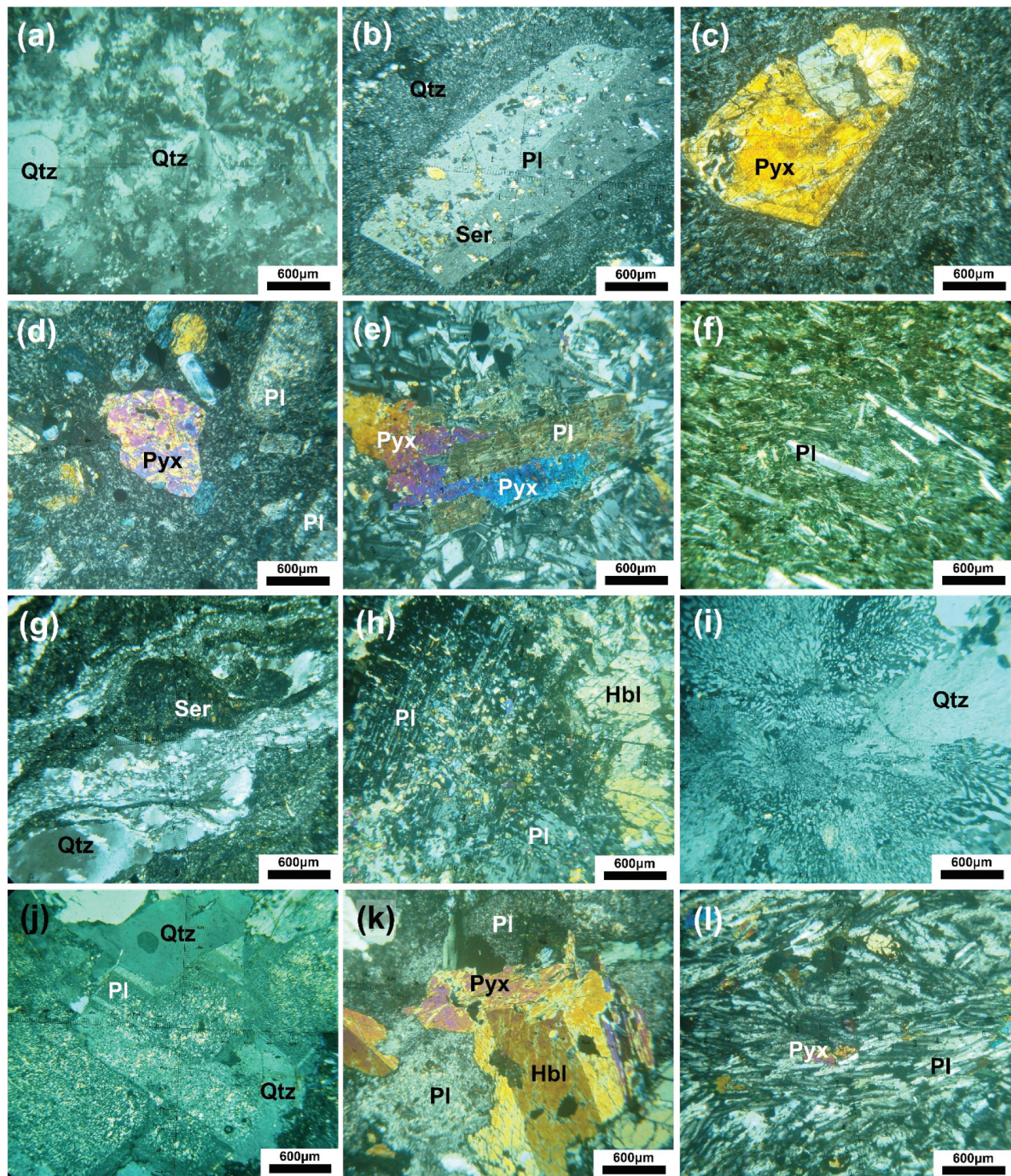


Figure 8. Microscopic photographs showing; (a) Spherulitic and porphyritic texture in metarhyolite. (b) altered plagioclase (pl) showing porphyritic texture in meta-andesite. (c) phenocryst of orthopyroxene (pyx) enclosed in fine groundmass of metatrachyandesite. (d) and (e) subophitic and diabasic texture in metabasalts and metadoleritic basalts. (f) directive texture of plagioclase (pl) crystals in metatrachybasalts. (g) cataclastic and mylonitic texture of quartz (qtz) in metasediments rocks. (h) coarse grains of plagioclase (pl) and hornblende (hbl) in dioritic rocks. (i) graphic and granophyric textures in alkali feldspar granites. (j) highly altered of plagioclase (pl) crystals in alkali feldspar granites. (k) coarse grains of plagioclase (pl) and pyroxene (pyx) crystals altered to hornblende (hbl) in granodiorite. (l) well developed form of trachytic texture in trachyte plugs rocks.

various amplitudes and frequencies. They are trending in the NW-SE, NNW-SSE, and NNE-SSW directions (Figure 9(b)). The low-pass (regional) map exhibits the same features (high and low magnetic anomalies), which coincide well with their locations on the RTP and high-pass magnetic maps (Figure 9(c)). These

demonstrate that these magnetic anomalies have shallow depths and deep roots (Figure 9(a-c)). Furthermore, numerous faults in various directions dissected these anomalies (Figure 9(c)).

Most sites of gold mineralization and associated minerals are related to high and low magnetic anomalies

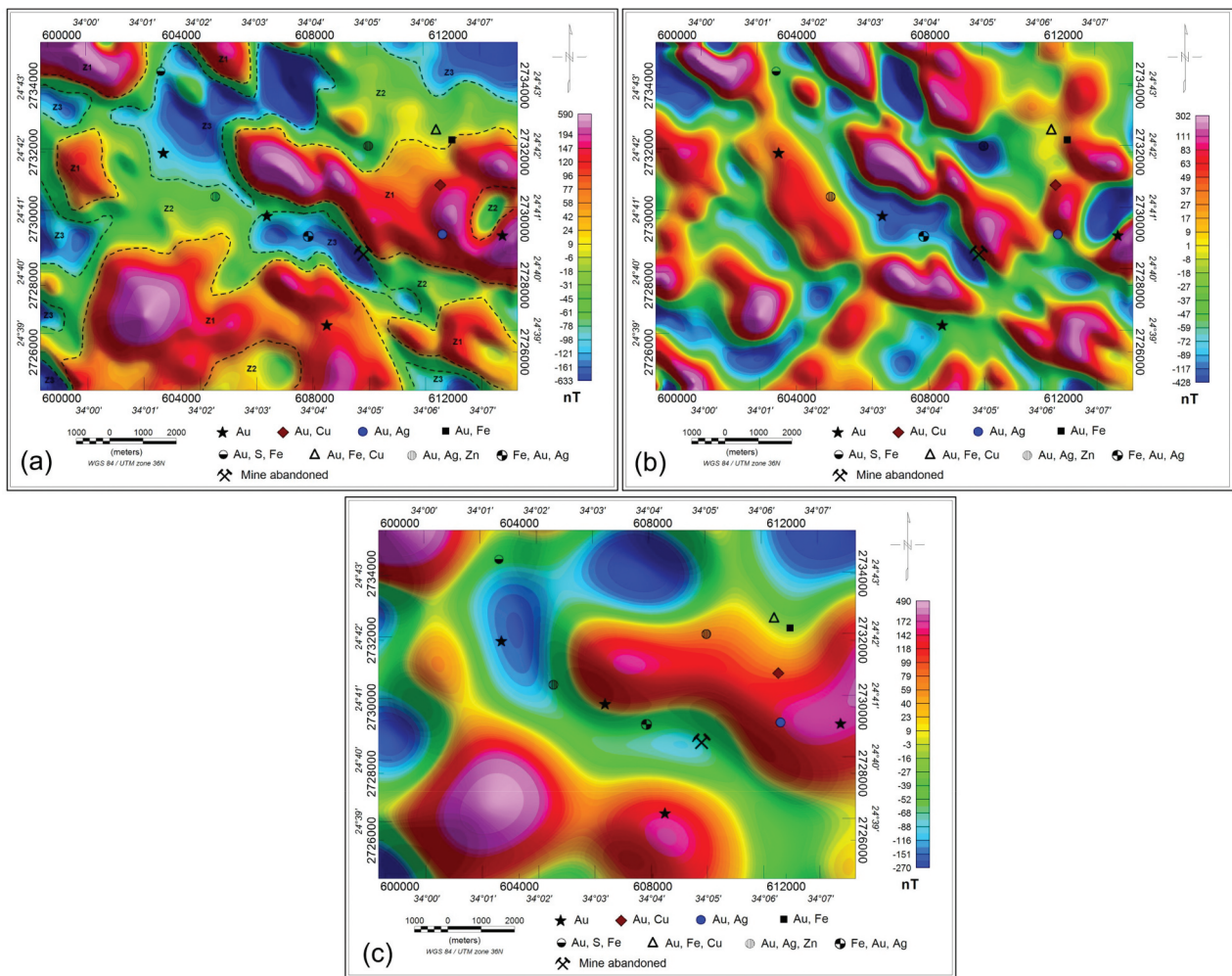


Figure 9. Airborne magnetic maps: (a) reduced to the north magnetic Pole (RTP after Aero-service 1984), (b) high-pass (residual), and (c) low-pass (regional).

in the eastern, central, and northern parts of the Hamash area, respectively (Figure 9(a–c)). This may suggest that the rock composition plays an essential role in the occurrence of gold mineralization. The IL method is applied to the datasets, including RTP, residual, and regional within the Hamash area (Figure 10(a–c)). The resultant lineaments, derived from the application of the IL (Figure 11), experience statistical analysis using rose diagrams (Figure 12). It is noteworthy that the predominant trend observed is the NW–SE direction, with minor traces of the NE–SW direction noticeable in the IL of RTP (Figures 11 and Figure 12(a)). In the IL of the residual component, the NW–SE, WNW–ESE, E–W, and ENE–WSW directions exercise the most effect (Figures 11 and Figure 12(b)). In the IL of the regional one, the NW–SE, E–W, WNW–ESE, and NNW–SSE directions are predominant (Figures 11 and Figure 12(c)).

The CET grid analysis method is specifically applied to the RTP data. Figure 13(a) visually illustrates the lineaments delineated through CET grid analysis, signifying mutable intersection zones capable of hosting mineralization and demarcating edges and boundaries

between different rock types. A statistical analysis of these CET lineaments is shown in Figure 13(b). The delineated CET lineaments are then employed to generate a density map (Figure 14(a)). Remarkably, known mineralization locations in the Hamash region are correlated with three paramount junction trends: NW–SE, NNW–SSE, and NE–SW directions (Figures 13(a–b) and Figure 14(a)).

The CET porphyry analysis method is applied to map porphyry-like structures (Figure 14(b)). The CET porphyry map (Figure 14(b)) explains that circular features and recognized mineralization sites are controlled by NW–SE, NE–SW, and N–S directions. Upon comparative investigation with known mineralization spots, the results obtained from both CET grid and porphyry analysis techniques underline the potential presence of mineralized zones within the Hamash region, warranting additional in-depth ground investigations.

Our findings reveal the ability of these approaches to enhance the precision and efficiency of geological mapping, sharp detection of lineaments and subsurface exploration, with implications for resource

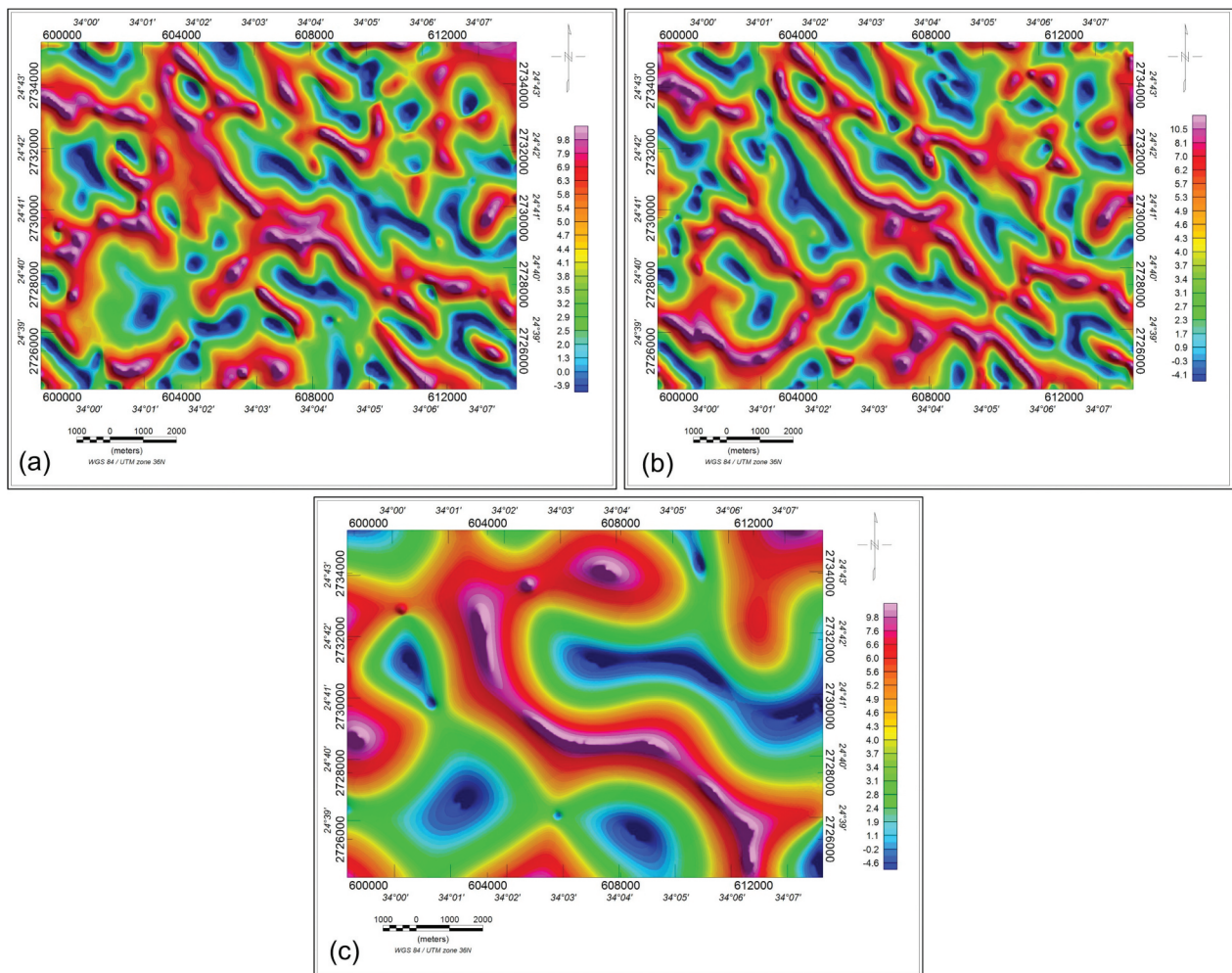


Figure 10. Improved logistic (IL) filter of airborne magnetic maps: (a) RTP, (b) high-pass (residual), and (c) low-pass (regional).

assessment and geological investigation. This research contributes to the evolving landscape of geoscientific procedures and establishes a foundation for forthcoming refinements in the delineation of structures and geological mapping.

5. Discussion

Lithologically, granodiorites and metavolcanics were the prevailing rock units within the study area, granodiorites are mostly classified correctly as shown by their UA and PA in Table 3. Contrarily, allocation inaccuracy was observed with metavolcanics, however, they are clearly discriminated in the constructed reference maps (for example FCCs). These misclassifications are attributed to intra-class spectral variability or mixed pixels due to the wide composition of the exposed metavolcanics (metarhyolite, metaandesite, metabasalt and metatrachyte are recorded during field investigations). This could be meticulously observed (even by the naked eye for example in the 12/11/2 FCC) when comparing the rim of the rock unit to its central part. This tonal variability

may be also imputed to the differential effect of water at the marginal parts and through the wadis crossing the rock unit which is reflected by marginal fading compared to strong central representation highlighting the tonal contrast. Consequently, the classifier committed an error (22%) and occasionally classified metavolcanics as trachyte due to its closer spectral reflectance or sometimes a real representation of trachyte within metavolcanics. Metasediments are well-classified and mostly located in the eastern and central regions of the research area, according to geological maps and field investigations. Similarly, the classifier, to a great extent, correctly allocated the wadi and placer deposits however some erroneous is observed among the two classes, and it is acceptable because the detected placers are originally located within wadi deposits.

Well-classified alkali feldspar granite (AFG) is found in the southern and central regions of the research area in the form of noticeable blocks. AFG is given special consideration since it is one of the rocks in the research region that is thought to contain gold. Analyzing distribution of the resultant AFG

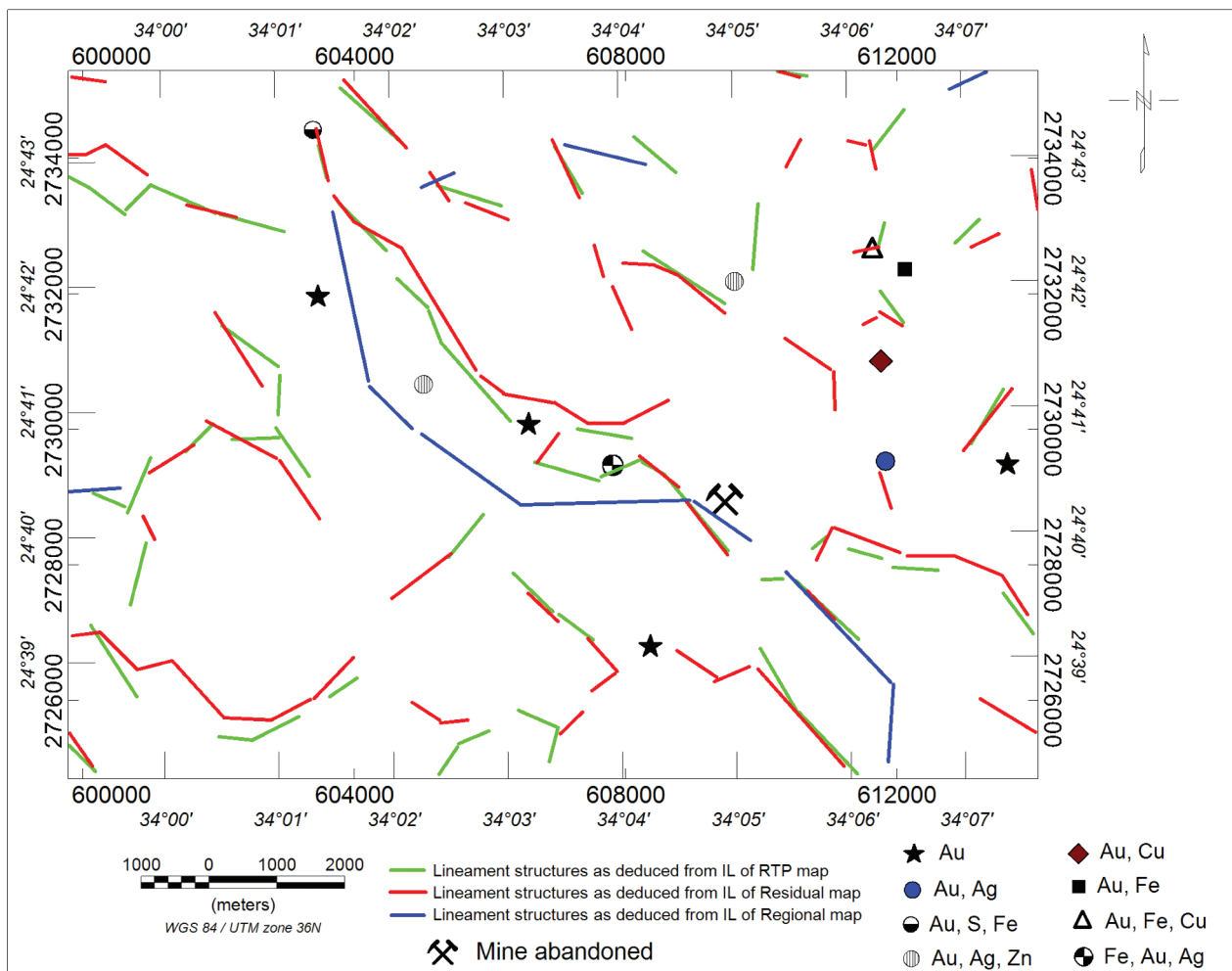


Figure 11. Lineament structures as deduced from improved logistic (IL) filter (Figure 9(a–c)).

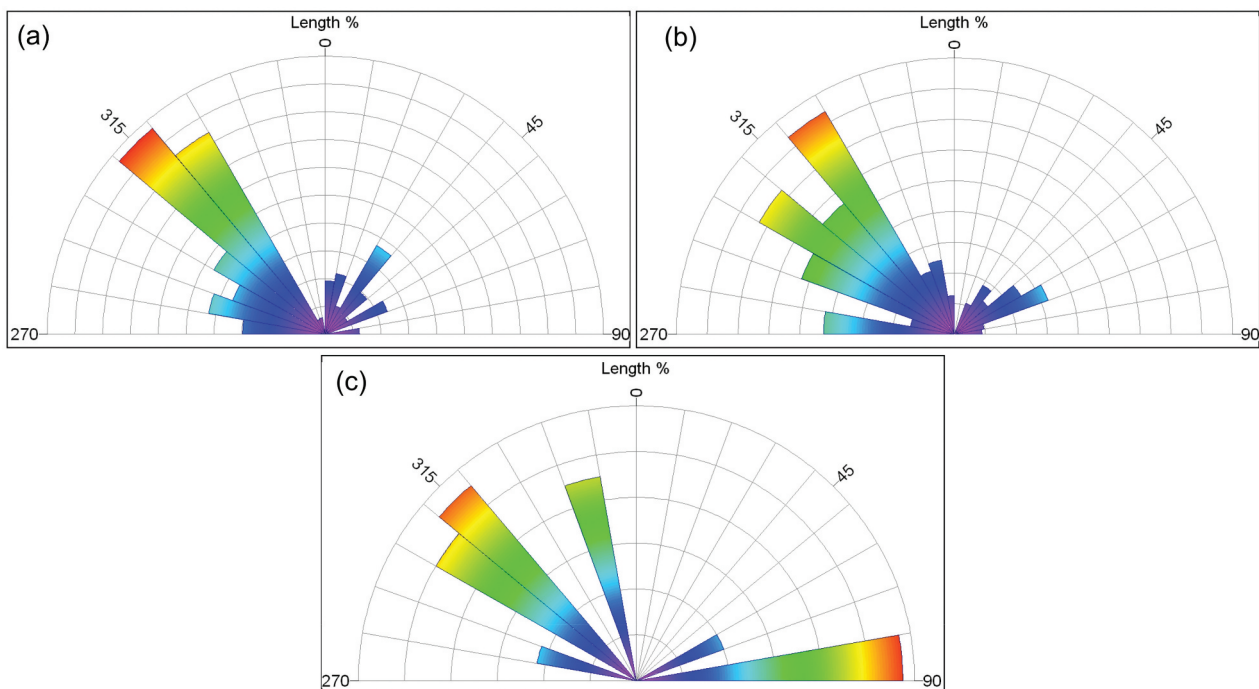


Figure 12. Rose diagrams of the main lineaments structures that deduced from IL (Figure 10): (a) RTP, (b) high-pass (residual), and (c) low-pass (regional).

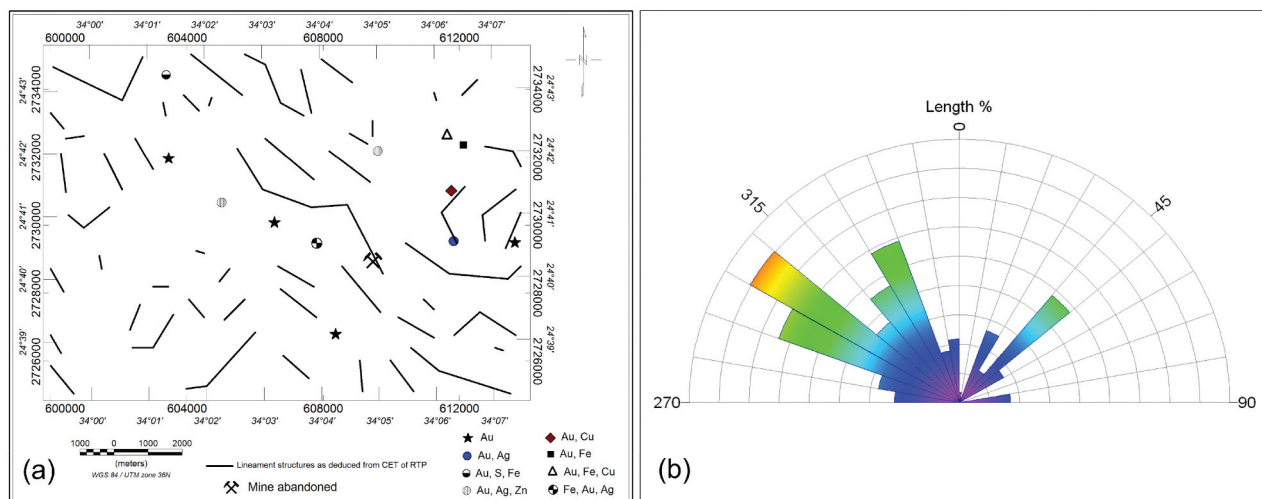


Figure 13. (a) CET lineaments structures, and (b) rose diagram of CET.

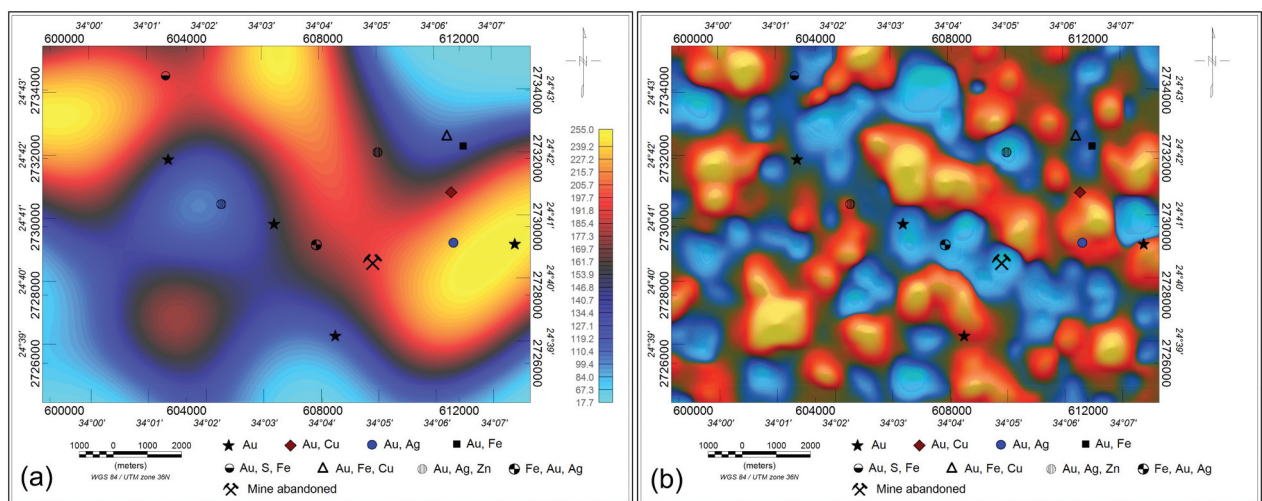


Figure 14. (a) Orientation entropy (OE) from CET grid analysis, and (b) CET porphyry map.

pixels (Figure 6) revealed some detailed new (that is not wholly represented in the previous geological maps) occurrences at the southern part of the investigated area. Because they have the same composition and are located inside the same tectonic framework as the gold-bearing blocks within the research region, these red pixels (Figure 6) are assumed to be gold-bearing. In addition to fieldwork and petrographical studies that mostly validated the resulting theme map, our hypothesis in this study is corroborated by earlier gold potentiality mapping investigations across the study region.

According to Data Integration, a significant coincidence between the resultant lithological map and the structural anomalies detected by the magnetic analysis has been noticed. For example, the detected pixels of AFG and placer deposits highlighted in the current research have mostly coincided with medium-to-high favorable mineralized zones suggested by the current magnetic investigations and a recent study that integrated aeromagnetic, airborne gamma-ray

spectrometric data and remote sensing in delineating potential mineralized zones (Aboelkhair, Ibraheem, and El-Magd 2021). Thus, the latter, in turn, accentuated our concept about the role of detailed geological mapping in monitoring minor distributions of gold-bearing rocks and placer deposits to achieve the optimal exploitation of the known mineralized areas or detailed incipient exploration of the other regions. Additionally, all the areas suggested to be favorable mineralized zones (mainly AFG and placer pixels) using the lithological mapping were confirmed as potential zones through magnetic analysis.

6. Conclusions

The current research accentuated the role of detailed (10 m) lithological mapping (using SVM) in highlighting gold-bearing blocks that need further potential exploitation. Our findings have been validated through field investigations and petrographic

analysis. The airborne magnetic maps have been utilized for the structural implications and confirmed the lithological findings; the current research concludes, the following;

- (1) SVM and Sentinel 2 provide an efficient lithological allocation that could be extremely useful in fundamentally targeting gold-bearing host blocks. The current classification results combined geological field observations, and petrography investigation revealed that the studied Hamash district is composed mainly of metavolcanics (mostly rhyolite, andesite, and basalt), metasediments, Late-to post-orogenic granites (alkali feldspar granites and granodiorite-diorite), and younger volcanics (Trachyte).
- (2) Within the gold-bearing current case study, some occurrences of gold-bearing AFG and placer deposits are highlighted and recommended for further economic exploitation.
- (3) The airborne magnetic maps characterized three magnetic zones (low, moderate, and relatively high). The IL and CET techniques were applied to the airborne magnetic data to outline the lineament structures in the Hamash area. These techniques showed that structural trends such as NW-SE, NNW-SSE, and NE-SW influenced the area.
- (4) The CET porphyry map showed circular features that may represent suitable locations for occurrences of gold mineralization and associated minerals.
- (5) Through the multiscale integration of Remote sensing images, SVM, airborne magnetic maps, geological field observations, and petrography investigation, we recommend conducting detailed geochemical and geophysical studies, especially on the place's circular features of CET porphyry maps.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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