

Machine learning-assisted hyperspectral targeting of orogenic and placer gold deposits at Wadi Umm Eish El-Zarqa, Egypt

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Abstract

Purpose. This study develops a reproducible, precision-first framework for targeting gold mineralization in arid environments, addressing both bedrock and placer deposits at the Wadi Umm Eish El-Zarqa area in Egypt, the first such investigation in this region.

Methods. The methodology combines machine learning applied to hyperspectral EnMAP data and spatial geomorphometric analysis of ALOS-PALSAR DEM. Random Forest and Support Vector Machine with Radial Basis Function models were trained on pixel spectra from three known gold mining sites. A spectral probability tolerance of 0.05 was implemented to expand the training dataset. Drainage networks were extracted from DEM data to link upstream bedrock sources to potential downstream placer deposits. ASTER-derived alteration maps were generated for comparative assessment.

Findings. Ground-truth validation of the delineated mineralization targets showed SVM-RBF achieved slightly higher overall accuracy (91.8 vs 89.9%), RF delivered perfect precision in identifying mineralized targets, and crucially delineated 37% more high-confidence (> 80% probability) potentially mineralized targets than SVM-RBF. Drainage analysis identified 3rd to 5th-order streams as optimal zones for placer deposition. Fieldwork confirmed active artisanal excavations, with stream sediments reportedly yielding 25-30 grams per truckload (~85 tons).

Originality. This study addresses a clear gap in hyperspectral investigations for mineral exploration in the Eastern Desert of Egypt. It is the first study to integrate machine learning with EnMAP hyperspectral data to target placer gold deposits in this region, establishing a precision-focused exploration approach.

Practical implications. The framework provides a transferable methodology for mineral exploration in analogous arid terrains worldwide, reducing financial risk and enabling efficient allocation of follow-up resources.

Keywords: *EnMAP hyperspectral data; machine learning; random forest; support vector machine; placer gold; Umm Eish El-Zarqa*

1. Introduction

Advancements in satellite technology have made remote sensing an increasingly powerful tool for various scientific applications, with multispectral data being extensively used for geological applications, including lithological discrimination [1]-[3], geological structures [4], [5], and mineral resources mapping [6]-[10]. These datasets typically comprise a limited number of spectral bands, particularly in the Short-Wave Infra-Red (SWIR) region of the spectrum. For instance, Landsat8/9 and Sentinel-2 satellites provide only two SWIR bands, whereas the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) satellite provides six bands in the same SWIR spectral range. Given that most minerals exhibit distinct spectral signatures and absorption features in the SWIR region, satellites with higher spectral resolution, such as ASTER, are better suited for mineral investigations. Concurrently, ASTER data have been mostly the

preferred multispectral dataset for mineral mapping [11]-[13]. To address the limitations of the limited spectral bands in multispectral satellite imagery, these data are often integrated with geophysical and geochemical data to enhance the reliability of lithological and mineralization mapping [14]-[17].

In contrast, hyperspectral data represent the latest advancement in optical Earth observation, providing continuous spectral bands over the imaging range across the Visible and Near Infrared (VNIR) and SWIR regions of the spectrum. With tens to hundreds of narrow contiguous spectral bands, hyperspectral imagery offers superior capabilities for mineral exploration compared to multispectral data. A notable example is the Environmental Mapping and Analysis Program (EnMAP) satellite, which delivers 242 bands across the 420 to 2450 nanometer (nm) wavelength range. This high spectral resolution enables the capture of detailed spectral information and warrants precise mineral mapping [18]-[21].

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While remote sensing can't directly detect gold in host rocks, it is exceptionally effective at identifying and delineating the hydrothermal alteration zones that are diagnostic hosts for gold mineralization. Key alteration types include propylitic, argillic, phyllic, and potassic zones; each characterized by specific indicator minerals known as the alteration minerals. Propylitic alteration is marked by the carbonates, epidote, and chlorite; argillaceous alteration by clay minerals (e.g., kaolinite, smectite, illite, cordierite, and montmorillonite $\pm$ sericite); phyllic alteration by mica minerals, mainly sericite and less biotite $\pm$ quartz; and potassic alteration by K-feldspar and quartz [22]–[24]. Hyperspectral data, such as EnMAP, excel at mapping these indicator alteration minerals due to their contiguous spectral sampling. This advantage of hyperspectral data not only enables the mapping of various minerals with high accuracy but also allows the detection and separation of minerals in mixed-pixel spectra [18], [20].

Another important remote sensing dataset that can play a vital role in mineralization mapping is the Digital Elevation Model (DEM), which can further support mineralization mapping by identifying potential placer gold deposits in stream sediments. DEM is a digital representation of the Earth's land surface topography, commonly represented as a raster image with pixel values indicating ground elevation. Spatial analyses of DEM data can pinpoint accumulation zones where gold-bearing sediments are likely to settle after being washed out from their sources in juxtaposing upstream mineralized localities. The washed-out, mineralization-laden sediments can settle at the stream's meanders and confluences, where the rate of sediment transport is at its lowest. A similar approach has been successfully applied to investigate possible sources of black sand deposits [25] and heavy metals in mangrove ecosystems [26] along Egypt's Red Sea coast.

In the Egyptian-Nubian Shield region (the mountainous terrain along the Red Sea in the Eastern Desert of Egypt), numerous studies have mapped gold-related alteration zones using remote sensing data [27]–[31]. However, hyperspectral studies remain limited, as most research in this region has relied primarily on multispectral data. Pioneering work by Ghoneim et al. [20] employed EnMAP hyperspectral data to map mineralization in the Kab Amiri area of the Central Eastern Desert of Egypt. They adopted advanced processing techniques, including the wavelength of minimum absorption, band absorption depths, and 2D scatter plots, to map the abundance of key alteration minerals and to decipher mineral abundances in mixed-pixel spectra. Similarly, Shebl et al. [32] used EnMAP to map lithological and hydrothermal alteration in Neoproterozoic rocks in the southeastern desert of Egypt.

The current research study is a continuation of bridging the gap and addresses two critical objectives:

- the application of machine learning to hyperspectral data for gold targeting in Egypt;
- the integrated mapping of both bedrock (orogenic) and stream sediment (placer) gold deposits- the latter being addressed for the first time in this context.

This study also introduces a reproducible approach that addresses mapping issues arising from a limited number of training samples without requiring substantial computational resources.

2. Materials and methods

2.1. Study area and geological setting

Umm Eish El-Zarqa study area (Fig. 1) lies within Egypt's premier mining district, known as the Golden Triangle. This area was selected for investigation due to its proximity to three established mining districts: Semna, Atalla, and El Sid (Fig. 1b).

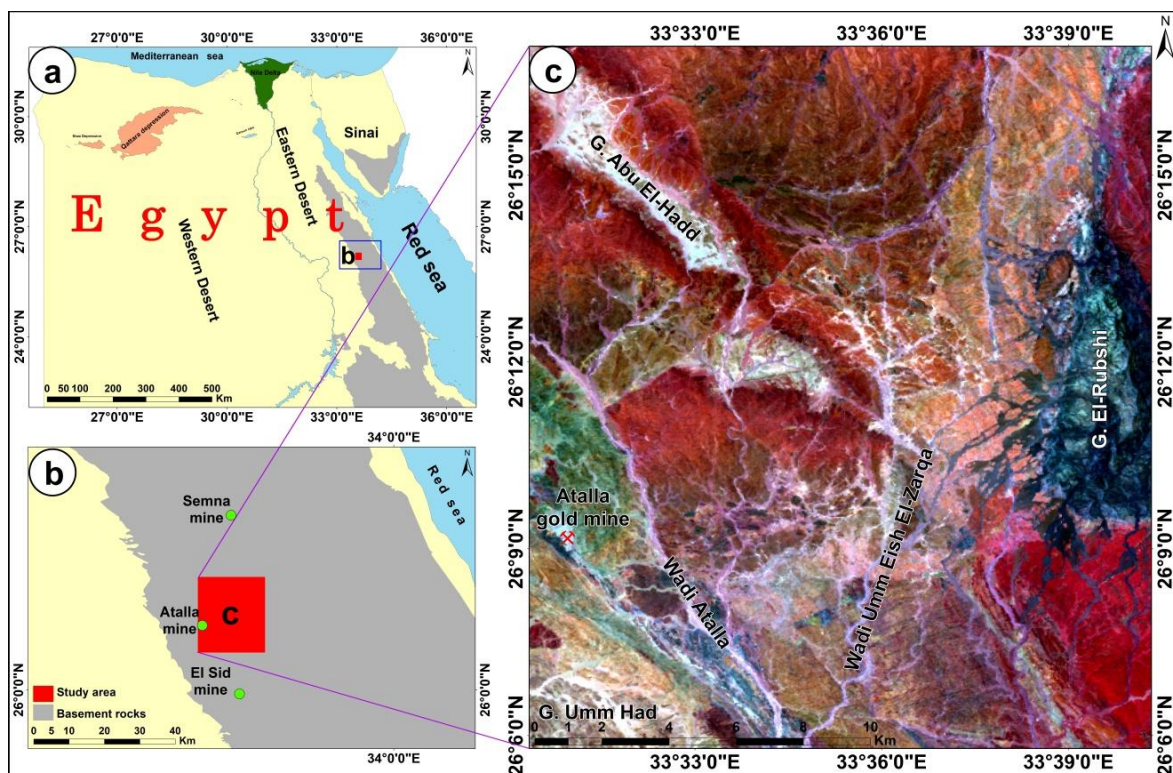


Figure 1. Location map of the Wadi Umm Eish El-Zarqa area

The strategic location, adjacent to major mining centers and major shear zones such as the Atalla and Duwi shear belts, positions the Umm Eish El-Zarqa area as a highly promising region hosting economic mineral deposits. Further motivation for this study is provided by evidence of intense, recent placer mining activity within the area's stream sediments, as observed in high-resolution Google Earth imagery (Fig. 2). This ongoing extraction strongly suggests that the surrounding highland terrains, which represent the logical source for these placer deposits, also hold high potential for lode gold mineralization. Finally, the lack of hyperspectral remote sensing investigations for mapping gold mineralization in bedrock outcrops and stream sediments across the entire Egyptian territory, including the study area, is another primary driver.

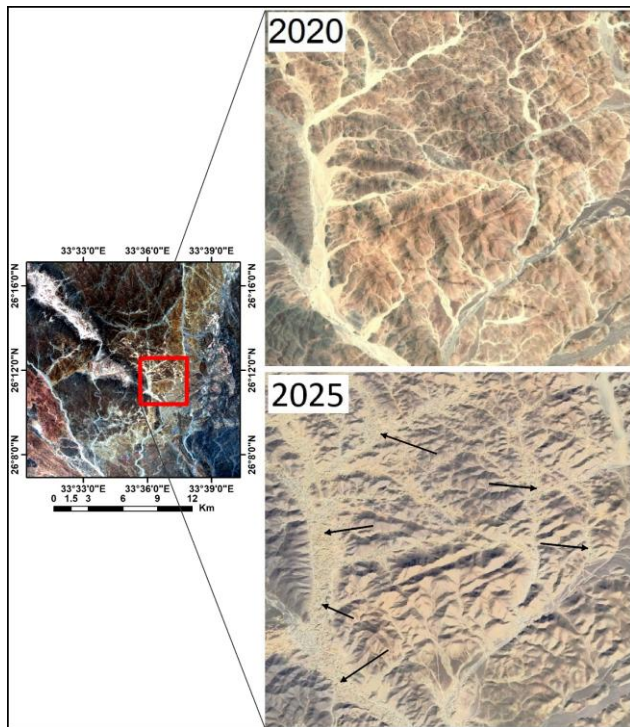


Figure 2. High-resolution Google Earth images showing intense excavations (black arrows) in the placer deposits at Wadi Umm Eish El-Zarqa

Geologically, the study area is composed mainly of metavolcanic rocks ranging in composition from felsic through intermediate to mafic (Fig. 3).

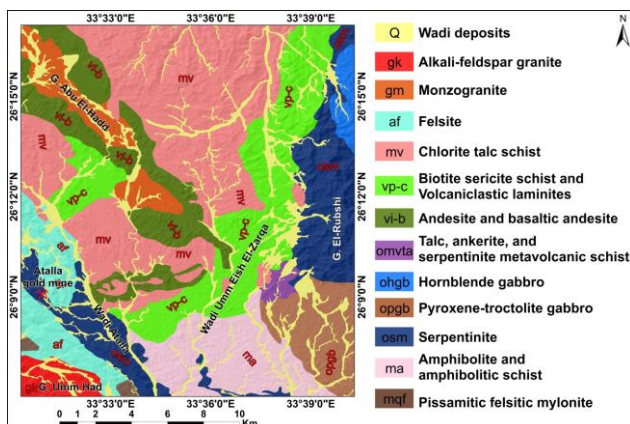


Figure 3. Geologic map of Wadi Umm Eish El-Zarqa area, modified after EGSM [33]

They are intruded by granitic rocks at localities such as Gabal Kab Amiri and Gabal Abu Qarahish. Elsewhere, they are thrust over dismembered ophiolitic rock units, notably serpentinites in the Gabal El-Rubshi area [33]. Furthermore, the area is also bounded by two mega shear zones -Duwi and Atalla shear zones- which are regional-scale structures [34] affecting almost the entire Central Eastern Desert of Egypt.

2.2. Data and data sources

The current study continues to utilize mainly remotely sensed data, including EnMAP hyperspectral data, ASTER multispectral data, and ALOS PALSAR DEM data, to map potential localities for gold mineralization in both the mountainous rocky reliefs and the detrital stream deposits at Wadi Umm Eish El-Zarqa, CED, Egypt.

EnMAP hyperspectral data is the backbone of the current study owing to its high efficiency in mineral mapping, with hundreds of spectral bands essential for mineral discrimination and differentiation. Two scenes of EnMAP L2A (surface reflectance) data (©DLR [2024] All rights reserved) encompassing the study area were acquired from the EOWEB Geoportal on June 10th, 2024, with 242 spectral bands within the range from 420 to 2450 nm. On the other hand, two ASTER scenes covering the study area acquired on October 20th, 2006, were obtained from NASA's Earth Data website (<https://search.earthdata.nasa.gov>). The adopted ASTER data are of level 1T and contain 14 spectral bands. Nine bands captured in the VNIR and SWIR regions were utilized to map the alteration zones in the current study. Finally, the ALOS PALSAR 12.5m DEM data utilized in the current study were obtained from NASA's Alaska Satellite Facility website (<https://search.asf.alaska.edu>).

2.3. Methodology

The methodological framework of the study (Fig. 4) illustrates various processing techniques applied to remotely sensed satellite data to delineate potential gold mineralization localities in the selected study area. EnMAP hyperspectral data were processed using advanced Machine Learning (ML) techniques, such as SVM and RF, leveraging the rich spectral information to achieve our study's objective. Moreover, ASTER multispectral data were processed using conventional mapping techniques, such as spectral indices, to enable comparison with the results from EnMAP hyperspectral data. Furthermore, the drainage network was extracted from the ALOS PALSAR DEM and draped over the mapped mineralization localities to highlight potential stream locations for placer gold deposits that migrated from upstream bedrock outcrop sources. Field observations further validated the mapped mineralization localities. Also, the locations of the known gold mines and mineralization occurrences were plotted on the results for more validation.

Two of the most widely accepted ML algorithms were adopted in this study: Support Vector Machine (SVM) and the Random Forest (RF) models to map the potential mineralization sites at Wadi Umm Eish El-Zarqa area, utilizing the EnMAP hyperspectral data and reference spectral signatures from the known mining sites within and near the studied area.

SVM is a powerful supervised learning technique commonly used for classification and regression tasks [3]. When coupled with the Radial Basis Function (RBF) kernel, SVM becomes particularly effective for handling non-linear tasks on high-dimensional data, such as hyperspectral satellite imagery.

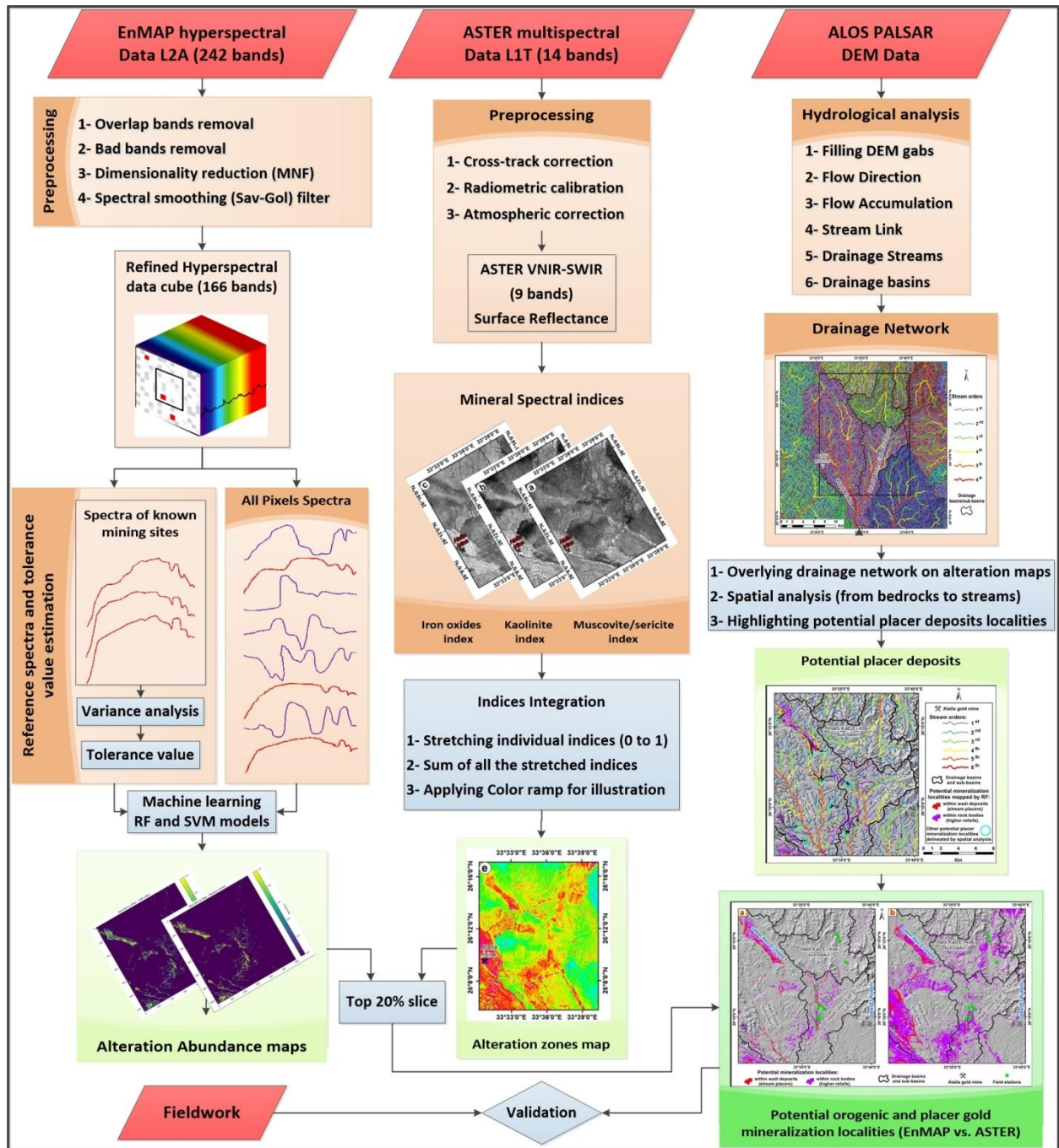


Figure 4. The methodological framework of the study

The RBF kernel transforms the complex input data into a higher-dimensional space, allowing the SVM algorithm to define non-linear decision boundaries, leading to higher classification accuracy. Thus, an SVM with an RBF kernel was adopted in the current study to delineate potential mineralization prospects based on the similarity or proximity in likelihood to a given spectral signature from well-known mining districts.

On the other hand, the RF technique is a bagging ensemble machine learning technique. It is highly effective for non-linear classification tasks, known for its robustness and ability to handle high-dimensional data. It works by constructing multiple decision trees from bootstrapped samples of the training data during training. Each decision tree acts as a separate sub-model, allowed to overfit its respective bootstrap sample to capture as much information as possible.

This overfitting of individual trees is mitigated by averaging their predictions, reducing overall model variance and preventing overfitting in the final model prediction. RF is particularly efficient in handling mixed pixels in hyperspectral data, where a single pixel may contain multiple minerals. It has been applied effectively to map complex mineral assemblages in mining areas [35], [36].

The adopted techniques can effectively map different minerals, even those with nearly similar or overlapping spectral signatures, by building intricate relationships among spectral bands, especially when trained on hyperspectral data. They can successfully discriminate minerals with subtle differences in their spectral signatures (i.e., spectrally-similar minerals), making them reliable for large-scale mineral exploration projects [37], [38].

2.3.1. Dimensionality reduction

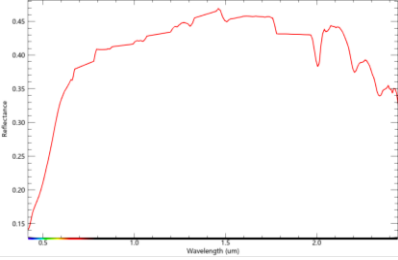
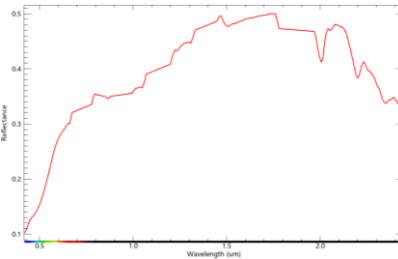
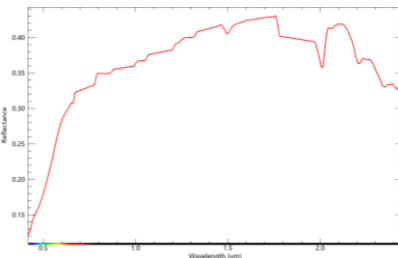
The obtained L2A hyperspectral EnMAP data are atmospherically corrected surface reflectance products generated by the EnMAP Land atmospheric correction processor. The dataset comprised the full VNIR and SWIR spectral range (420 to 2450 nm). Although the original product comprises 242 spectral bands, a significant portion contains bad bands, overlap bands between the VNIR and SWIR sensors, and redundant information or noise. A total of 76 bad (no data) and overlapping bands were excluded using the EnMAP toolbox in QGIS software, resulting in 166 informative spectral bands retained for analysis. Despite this initial cleanup, the data still exhibited high spectral redundancy and residual noise, which can obscure subtle information critical for the current investigation. To address this, a two-step Minimum Noise Fraction (MNF) transformation was applied to mitigate the spectral redundancy, segregate noise, and reduce data dimensionality [39]. The first step (forward MNF) decorrelates and rescales the data using an estimated noise covariance matrix (implemented in the MNF tool in ENVI), which computes the covariance of the differences between each pixel and its spatial neighbors to model the noise statistics. The resulting MNF components are ordered by decreasing signal-to-noise ratio (SNR), where the eigenvalues correspond directly to the SNR of each component. To determine the optimal number of MNF components to retain, the eigenvalues of the MNF components were examined, revealing a significant decrease in SNR after the 19th component. Furthermore, visual inspection of the MNF components confirmed that the first 19 components exhibit coherent spatial patterns that correlate with geological features. In contrast, the subsequent components display random salt-and-pepper noise. Based on this combined quantitative (eigenvalues) and qualitative (visual inspection), the first 19 MNF components were retained as informative, noise-reducing features. The second step involved an Inverse MNF transform, which was applied to project the 19 selected, noise-filtered components back into the original spectral domain. This process effectively acts as a spectral noise filter, reconstructing the 166 spectral bands while reducing the noise associated with the adopted higher-order components. The result was a refined, dimensionality-reduced EnMAP dataset with 166 bands, significantly improved, with minimized noise and redundancy. Subsequently, to further enhance the spectral smoothness and reduce high-frequency sensor noise, a Savitzky-Golay (SavGol) filter was applied [40]. A window size of 3 channels (3×3) and a second-order polynomial were selected to preserve critical spectral absorption feature shapes and widths, which are essential for mineral identification. This final step produced smoothed, improved pixel spectra that are optimal for subsequent spectral analysis and mineral mapping.

2.3.2. Reference training data preparation

The reference data used to train the ML models were spectral profiles (spectral signatures) acquired from the exact locations of known mining localities within the study area (Atalla mine) and outside the area (Semna and El-Sid gold mines). The spectral curves and the coordinates of acquisition are illustrated in Table 1.

After acquiring these spectral profiles, we compared them with the USGS spectral library to ensure they were relevant to alteration minerals commonly found at mining sites.

Table 1. The coordinates and spectral profiles were used as a reference to train the ML models

Mining site	Coordinates	Spectral profile (EnMAP)
Atalla gold mine	26°9'20.24"N 33°30'50.29"E	
Semna gold mine	26°26'31.90"N 33°35'23.51"E	
El-Sid Gold mine	25°59'12.26"N 33°36'42.65"E	

The USGS spectra were first resampled to match the EnMAP bands, and the comparison was then conducted using the Spectral Angle Mapper (SAM) to measure similarity. It is evident that these spectral curves taken from mining localities are mostly identified as mixed muscovite and goethite minerals owing to the diagnostic absorption features at 2200 and 2345 nm (for muscovite) and at around 500 nm (for goethite), which are known to be key index alteration minerals. Consequently, we confidently used these pixel spectra to train our models as reference spectra.

The hyperspectral data and the reference spectral signature derived from them were then converted to 2D arrays using the Python Jupyter Notebook web-based tool. Each row in the 2D array of hyperspectral data represents the reflectance values of a given pixel across all 166 bands. Similarly, the arrays of the reference spectra are built, with each row containing 166 values representing a single spectral signature.

Finally, before initiating the ML models, the data were randomly split into training and testing sets, with the testing set size set to 0.2. No scaling or standardization was performed on the data because the reference spectra were derived from the preprocessed EnMAP hyperspectral data itself, with the same number of values as the number of hyperspectral bands (166), thereby yielding more accurate results.

2.3.3. SVM and RF ML models and hyperparameter tuning

Numerous hyperparameters are known to influence the performance of ML models. In the current study, we adopted the RF and SVF-RBF models; each was tuned with specific hyperparameters to achieve the best possible results. Tuning or adjusting the hyperparameters is crucial for obtaining

higher accuracies. Initially, we conducted ablation experiments to assess the effects of various hyperparameters on the results. These experiments informed our choice of hyperparameters for the current research study. For the RF classifier, the number of estimators was set to 100. For the SVM classifier, the most important parameter was the choice of kernel; in this study, we chose the RBF kernel, which significantly outperformed the linear and sigmoid kernels. This high effectiveness of the RBF kernel can be attributed to its ability to handle non-linear classification tasks. Another important hyperparameter is the probability hyperparameter, which was enabled to capture the likelihood that a pixel spectrum matches the reference mineralization-related signature.

The primary challenge was the limited number of reference spectra, derived from only three known mining sites Atalla, Semna and El-Sid). To address this without computationally expensive synthetic data generation, we employed a spectral tolerance parameter to flexibly expand the effective training set. The tolerance value was calculated after accounting for differences among the three reference spectral signatures; slight differences were observed, with standard deviations ranging from 0.00439 to 0.0405. A tolerance value ($T = 0.05$) was adopted, slightly above the maximum observed standard deviation value, to define a bounded spectral space around the reference signatures. The reason for preferring to use a tolerance value rather than generating synthetic reference spectra is that the number of possible synthetic spectra, assuming a step interval of only 0.01, is 10166, excluding the original spectra; this number is computationally infeasible, and the process would require enormous computational resources. So, in our established pipeline, the model iterates over the entire hyperspectral data converted into a 2D array, allowing only a 0.05 tolerance between the pixel and the reference spectra. If a pixel meets this criterion, it is classified as potentially mineralized; otherwise, it is deemed non-mineralized. The degree of probability is a function of how closely the pixel spectrum matches the reference spectrum; the closer they are, the higher the likelihood of matching and, consequently, the greater the probability of mineralization. To ensure reproducibility, a constant random state argument was used during model initialization. Model performance was evaluated using both model-based internal metrics and a ground-truth assessment with a hold-out validation set, with accuracy, precision, recall, and F1 score as key metrics.

2.3.4. Extracting the drainage network

The drainage networks of the study area were extracted using the ALOS PALSAR DEM data. ALOS PALSAR data with 12.5 m resolution of the study area was processed through several consequent steps in the spatial analyst module within the ArcGIS software v. 10.8. These steps include (1) filling the DEM errors, (2) calculating the flow direction and flow accumulation layers, (3) extracting the drainage streams and their respective stream orders, (4) converting the streams into vector format for better representation and visualization, and (5) delineating the drainage basins and sub-basins. The drainage basins and network were then overlaid on the alteration maps derived from ML techniques, enabling the determination of the most likely localities for placer gold occurrences sourced from mother gold lodes in the upstream bedrock (Fig. 5).

Careful analysis of the drainage network and morphological features can help narrow down the search space for potential placer deposition sites.

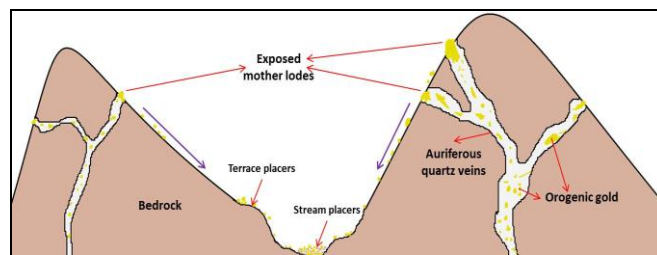


Figure 5. A sketch illustrating the formation of placer gold deposits from upstream bedrock sources, not to scale

Generally, placers tend to be deposited in areas where streamflow begins to decrease in transport velocity; this criterion excludes localities with steep slopes, which predominantly comprise first- and second-order streams where transport energy is expected to be at its maximum momentum. Consequently, streams of orders higher than the second are the most prospective for placer mineralization. Another important factor to consider is the morphological characteristics of the streams, including meandering, widening, and narrowing. Meandering stream localities connected to upstream source deposits are regarded as highly prospective targets for placer deposits. Similarly, localities with sudden widening after narrow stream necks are regarded as ideal sites for reducing transport velocity, thereby allowing placers to settle. Moreover, as stream order increases, the current tends to slow, and transport velocity gradually decreases to its lowest value. Thus, the last-order stream, being the least proximal to the sources and having received the most sediment deposition before it is reached, can be disregarded when searching for placers. This approach thus provides a robust scientific foundation for delineating the most prospective placer localities, significantly highlighting refined targets for subsequent exploration.

2.3.5. Mapping alteration zones from ASTER data for comparison

Since ASTER data is at level-1T, it was preprocessed through various procedures, including crosstalk correction, radiometric calibration and atmospheric correction. The crosstalk correction is primarily applied to the six SWIR bands to mitigate thermal leakage from sensors in bands 4 and 9 into the other SWIR bands. After applying the crosstalk correction, the ASTER VNIR and SWIR data were atmospherically corrected using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm in ENVI, yielding nine bands of pixel values representing surface reflectance. The 9 ASTER VNIR-SWIR bands data were then processed following the most commonly used spectral indices [6], [41] for mapping alteration minerals. These include sericite index, kaolinite index, and iron oxides index (Table 2).

ASTER data were used in the current study to further compare their results and accuracy with the EnMAP hyperspectral data. Such a comparison is intended to assess the performance of ENMAP hyperspectral data relative to the most widely accepted multispectral data (ASTER) for mineralization mapping.

Table 2. ASTER spectral indices of alteration minerals (after Ninomiya [6]; Kalinowski and Oliver [41])

Alteration mineral	ASTER spectral index
Sericite / muscovite	$(b5 + b7) / b6$
Kaolinite	$(b4 / b5) \cdot (b8 / b6)$
Iron oxides	$b2 / b1$

The obtained mineral index maps were then integrated by summing them to produce a cumulative alteration abundance map, following the technique introduced by Ali et al. [17]. Before summing all mineral index maps, we first stretched each index to the range 0-1 to ensure equal contribution of the three indices to the final cumulative alteration map. This technique is highly effective at combining multiple alteration index layers into a cumulative alteration decision layer, as it identifies localities anomalous for alteration minerals across all implemented layers. This technique is equivalent to overlaying the mineral index layers with equal weights in a GIS model, but with faster and easier implementation.

3. Results and discussion

3.1. RF mineralization map

The mineralization potential map obtained from the Random Forest model (Fig. 6) indicates that the study area is highly prospective for mineralization.

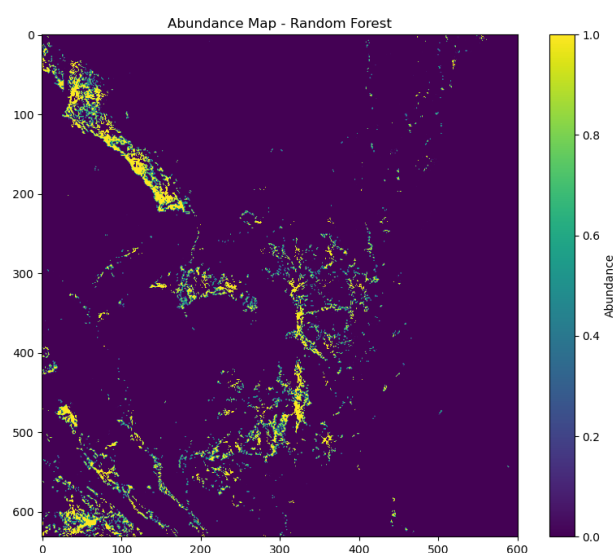


Figure 6. Alteration abundance map created using the RF technique based on similarity to the provided reference training spectra

The RF algorithm captured various sporadic localities with spectral signatures (within the allowable tolerance of 0.05) similar to those of the reference spectra (muscovite and goethite) collected from known mining districts within and near the study area. The RF mineralization potential map delineated some highly mineralized localities (yellowish), especially in the central and western parts of the study area. In contrast, the eastern parts were found to be almost barren. The highlighted localities in the central parts are associated with metavolcanic rocks, mainly biotite-sericite schists. Also, the detrital wadi deposits in this central part of the study area show high potential for mineralization. A high-resolution Google Earth image showed intense artisanal excavations at the wadi deposits in the central part of the study area (Fig. 2), lending high credibility and reliability to the results obtained. In the northwestern part of the study area, the Gabal Abu El-Hadd granite and its adjacent wadi deposits are also highly prospective for mineralization. Moreover, the southwestern corner of the study area, which is occupied by part of Gabal Umm Had, is also highly prospective for mineralization. This specific part is composed mainly of various rock units having

acidic affinity, including granites, pisolitic gneiss, and felsites. Finally, a few additional patches were delineated in the northeastern part of the biotite-sericite schist belt. Other sporadic localities with lower potential for mineralization (bluish-cyan colors) were also mapped across the study area.

3.2. SVM-RBF mineralization map

The mineralization potentiality map obtained from the SVM-RBF classifier (Fig. 7) shows that the highly potential localities for mineralization (yellowish colors) are mostly in the same localities depicted by the RF classifier.

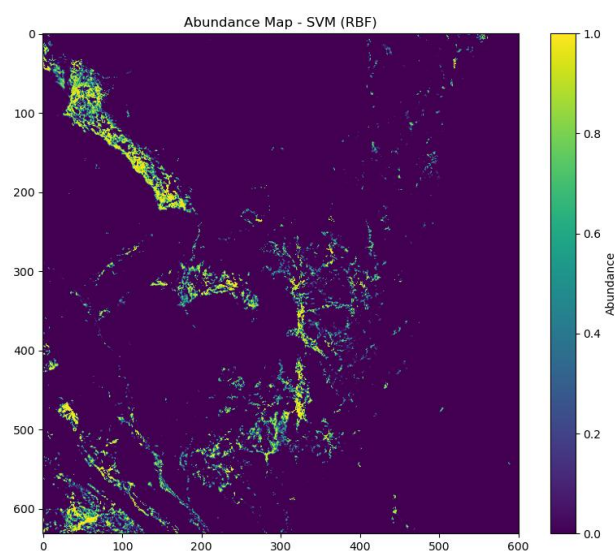


Figure 7. Alteration abundance map created using the SVM technique with RBF kernel based on similarity to the provided reference training spectra

The only difference is the vastness of distribution of these “high potential mineralization” localities, which is obviously higher in the RF map than that in the SVM-RBF one; this is further demonstrated by quantitative analysis (Fig. 8). On the other hand, the SVM classifier defined larger spatial distribution of the lower potential localities (bluish cyan color) than that were identified by the RF classifier.

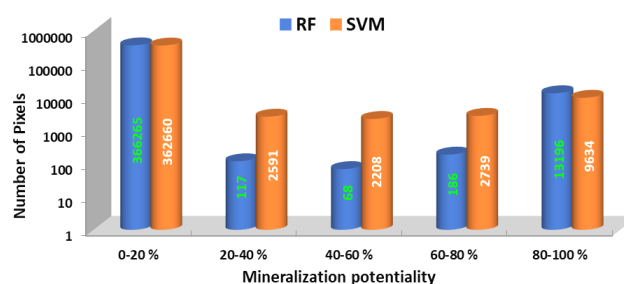


Figure 8. Mineralization abundance and the corresponding number of pixels from each model

All in all, both the RF and SVM-RBF classifiers highlighted nearly the same localities in the central, northwestern and southwestern parts of the study area as having high potential for mineralization, corroborating each other and reinforcing confidence in the identified localities for gold mineralization potential.

Quantitative analysis of both the results (Fig. 8) shows that RF delineated 366265 pixels with 0-20% mineralization potential, 117 pixels with 20-40% mineralization potential, 68 pixels with 40-60% mineralization potential, 186 pixels

with 60-80% mineralization potential, and 13196 pixels with > 80% mineralization potential. On the other hand, SVM-RBF delineated 362660 pixels with 0-20% mineralization potential, 2591 pixels with 20-40% mineralization potential, 2208 pixels with 40-60% mineralization potential, 2739 pixels with 60-80% mineralization potential, and 9634 pixels with > 80% mineralization potential.

3.3. Evaluation and accuracy assessment

3.3.1. Model-based evaluation

The model-based evaluation using K-fold cross-validation with 5 folds yielded overly optimistic estimates for both implemented models, as illustrated by the performance metrics of accuracy, precision, recall, and F1 score (Table 3).

Table 3. Model-based evaluation metrics of the performance of the adopted classifiers

Metrics	ML classifier	
	RF	SVM-RBF
Accuracy	0.9993	0.9895
Precision	0.9951	0.8491
Recall	0.9852	0.8591
F1 score	0.9902	0.8541

The high metric scores obtained for the two models are attributed to the reference spectral signature used for training and prediction being taken directly from the hyperspectral EnMAP data, with no scaling or standardization applied. The metrics showed that the RF classifier outperforms the SVM-RBF classifier. Both models achieved very high accuracy values of 99.9 and 98.9% for RF and SVM, respectively; however, these values can be misleading, as they reflect the proportion of true positives and true negatives relative to the total number of training and testing data. Consequently, other metrics, including precision, recall, and F1-score metrics (Table 3), are more reliable for comparing the model-based performance evaluation of the two models. Precision is the proportion of true positives among true positives and false positives, providing insight into the model's positive predictive value. In the current study, the RF model achieved 99.51% precision, whereas the SVM-RBF model achieved 84.91%. In terms of recall, it is defined as the true positive rate, i.e., true positives divided by the sum of true positives and false positives. Again, the RF model achieved a near-perfect recall of 98.52%, compared to 85.91% for SVM-RBF. Similarly, the F1-score - which is the harmonic mean of both the precision and recall metrics - was 99.02 and 85.41% for RF and SVM-RBF, respectively. The perfection noted in the model-based performance evaluation, especially the RF model metrics, raises doubts of overfitting and suggests the need for a more reliable ground-truthing-based evaluation.

3.3.2. Field-based (ground-truth) evaluation

The performance of the two implemented models was objectively assessed through intensive fieldwork and investigation of high-resolution imagery of active mining localities, providing a comprehensive basis for ground-truthing. This allowed precise determination of mineralized and non-mineralized localities, which could be used as a reference for assessment. A validation set of 790 pixels was used to evaluate the classification performance of the adopted models rigorously; forty-nine localities (312 pixels) were assigned "Mineralized", and sixty-two localities (478 pixels) were considered non-mineralized (Barren) (Fig. 9).

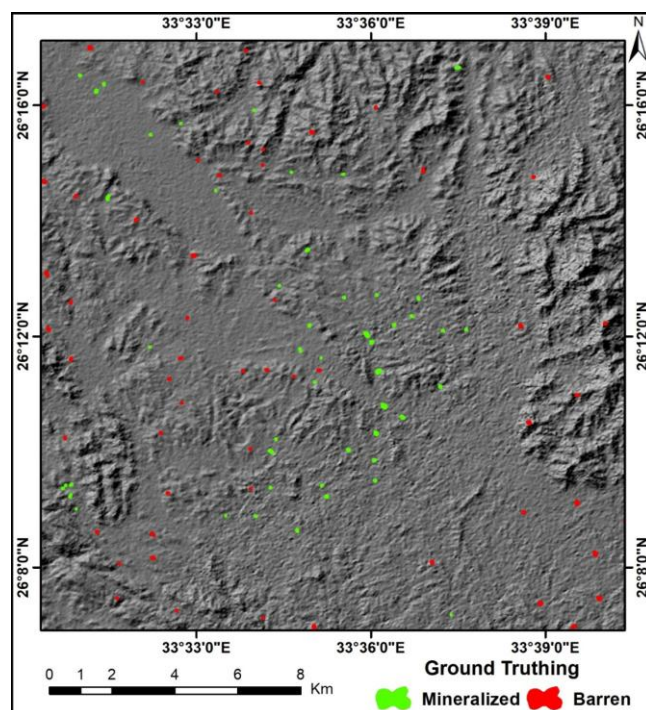


Figure 9. Mineralized and barren ground-truthing regions of interest overlain on a darkened shaded-relief image of the study area.

The analysis, based on the confusion matrices (Table 4), showed that the SVM-RBF classifier attained a slightly higher Overall Accuracy (OA) of 91.8%. It excelled in precision (user's accuracy), particularly for the "Mineralized" class, where 99.2% (249/251) of its positive predictions were correct, indicating high reliability when it flags an area as "Mineralized". However, its recall (producer's accuracy) for the same class was 79.8% (249/312), meaning it failed to detect approximately 20% of the true "mineralized" ground-truthed pixels.

Table 4. Ground-truthing-based evaluation metrics of the adopted classifiers

Metric	Class	SVM-RBF	RF
Overall Accuracy		91.8%	89.9%
		(725/790)	(710/790)
Kappa coefficient		0.8218	0.7782
Precision (user's accuracy)	Mineralized	99.2% (249/251)	100% (232/232)
	Barren	88.3% (476/539)	85.7% (478/558)
Recall (producer's accuracy)	Mineralized	79.8% (249/312)	74.4% (232/312)
	Barren	99.6% (476/478)	100% (478/478)
F1-score	Mineralized	88.4%	85.3%
	Barren	93.6%	92.3%

In contrast, the RF model achieved a slightly lower OA of 89.9%; it exhibited dual perfection (100%) in the recall of the "Barren" class and the precision of the "Mineralized" class. A compromise balanced such perfection on the precision of the "Mineralized" class: the model missed 80 true mineralized pixels (25.6%), resulting in a recall of (74.4%). This pattern suggests the RF model adopted a highly conservative threshold for predicting the "Mineralized" class, minimizing the false positives at the expense of increased false negatives.

In the real world of mineral exploration, where the cost of false positives is measured in wasted capital and operational expenditure, the primary objective is to maximize the reliability of the predicted targets. In this context, precision (the probability that a predicted target is truly mineralized) is the most critical evaluation metric for decision making. Our ground-truth validation reveals that the RF model achieves perfect precision, correctly mapping all “Mineralized”-labeled targets. This means that every pixel it identifies as “Mineralized” represents a true target with no false alarms. While this conservative approach reduces the overall recall (resulting in potential missing of some true mineralization targets), it ensures that all the resources allocated for follow-up investigations -such as drilling with its associated high cost- are deployed with maximum confidence. Therefore, when prioritizing the mitigation of financial risk over exhaustive target detection, the RF model provides the most reliable and actionable mineralized localities for consideration.

Critically, despite its lower OA, the RF model demonstrates superior exploration potential by delineating 13196 pixels with a high-confidence (> 80%) probability of mineralization occurrence (Fig. 8) -over 37% more than the SVM model (9634 pixels). This larger high-confidence prospect portfolio, combined with absolute predictive reliability (precision), makes the RF model decisively more actionable; we therefore use its output for further integration with other datasets.

3.4. Drainage pattern and potential placer mineralization localities

The drainage map of the study area (Fig. 10) exhibits a dendritic pattern drainage system. It also presents the mineralization-potential localities extracted using the RF technique, with the highest mineralization-potential slice (80-100%) overlying the hill-shade image of the study area. This slice was extracted from the RF result using the rule classifier tool in ENVI, with a 80% probability threshold.

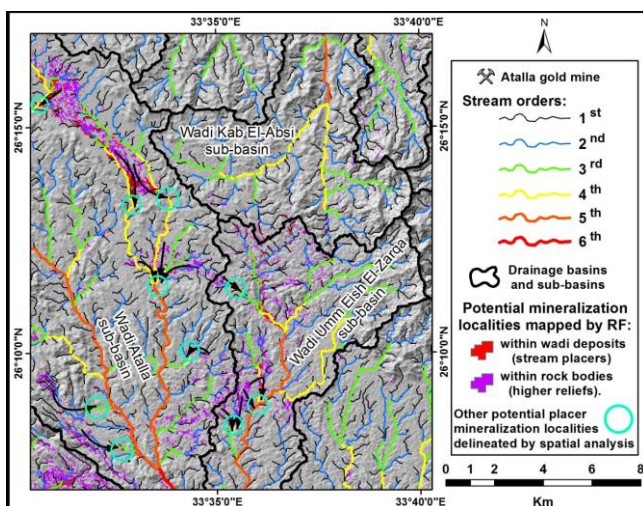


Figure 10. Drainage basins/sub-basins and streams network, and the delineated potential alteration zones localities from EnMAP data overlay on the hill-shade image of the study area

The potential mineralization localities are categorized into two groups based on their geomorphological context: those in higher-elevation bedrock terrains (magenta) and those within wadi stream sediments (red). In addition to the

RF-derived localities, several other potential placer mineralization sites were identified (highlighted by cyan circles). These were delineated based on their proximity to other mapped mineralization localities in the rocky terrain (sources) connected to these potential deposition localities by lower-order streams. Meaning that, if one of these highlighted localities is of 4th stream order, then it should be connected to near potential sources with 1st to 3rd stream orders.

As a general rule, these localities represent depositional areas for leached mineralization from potentially high-topography rocky terrains. Black arrows indicate the possible migration directions from the mapped sources to the delineated potential areas. It can be found that the most preferred localities for placer mineralization occurrence are mainly linked to potential sources with streams having order rankings from the 3rd to the 5th orders within Wadi Umm Eish El-Zarqa and Wadi Atalla sub-basins (Fig. 10). This sounds logical because the 1st and 2nd order streams are mostly located on higher elevation levels within the rock exposures themselves rather than within the mainstreams. Conversely, the single 6th-order stream area is too distal from the mapped bedrock sources, suggesting that the mineralized material may have been diluted or dispersed over the longer transport distance.

3.5. Comparison against alteration zones from ASTER data

The alteration mineral indices of sericite, kaolinite, and ferri-iron oxides were obtained from ASTER data and presented in Figures 11a, b and c, respectively. The targeted potential abundance areas for each alteration index mineral are marked by the bright (white color) pixels in these figures. It is found that the spatial distribution of these three indicator minerals shows a strong correlation, as they are preferentially associated with felsic rock units, including granites, felsites, and schists.

Given that hydrothermal alteration zones are typically defined by the coexistence of multiple alteration minerals, a cumulative map (Fig. 11d and e) was generated to represent the co-occurrence of the obtained three indices (Fig. 11d and e). Figure 11d shows the combined result in grayscale, where white pixels indicate the highest probability of the simultaneous presence of all three minerals. Figure 11e presents the same data using a cyan-magenta color ramp for enhanced visualization, with magenta highlighting localities of maximum spatial coincidence among the three index alteration minerals, which represent the most promising localities for mineralization.

The alteration zones identified from ASTER data exhibit a larger spatial extent than those derived from EnMAP data. The highlighted localities are associated with the metavolcanic rocks, especially the biotite-sericite-schists, extending from the northeastern to the central and south-central parts of the study area. Additional high-potential localities correlate with granitic and felsitic rocks in the Gabal Abu El-Hadd area in the northwestern part of the investigated area, and at Gabal Umm Had and Wadi Atalla in the southwestern part of the investigated area.

A direct comparison between the highest-probability mineralization maps obtained from EnMAP (Fig. 12a) and ASTER (Fig. 12b) reveals significant differences. The illustrated results in both figures are the highest-mineralization probability slices, used to represent prospectivity localities with potential greater than 80%.

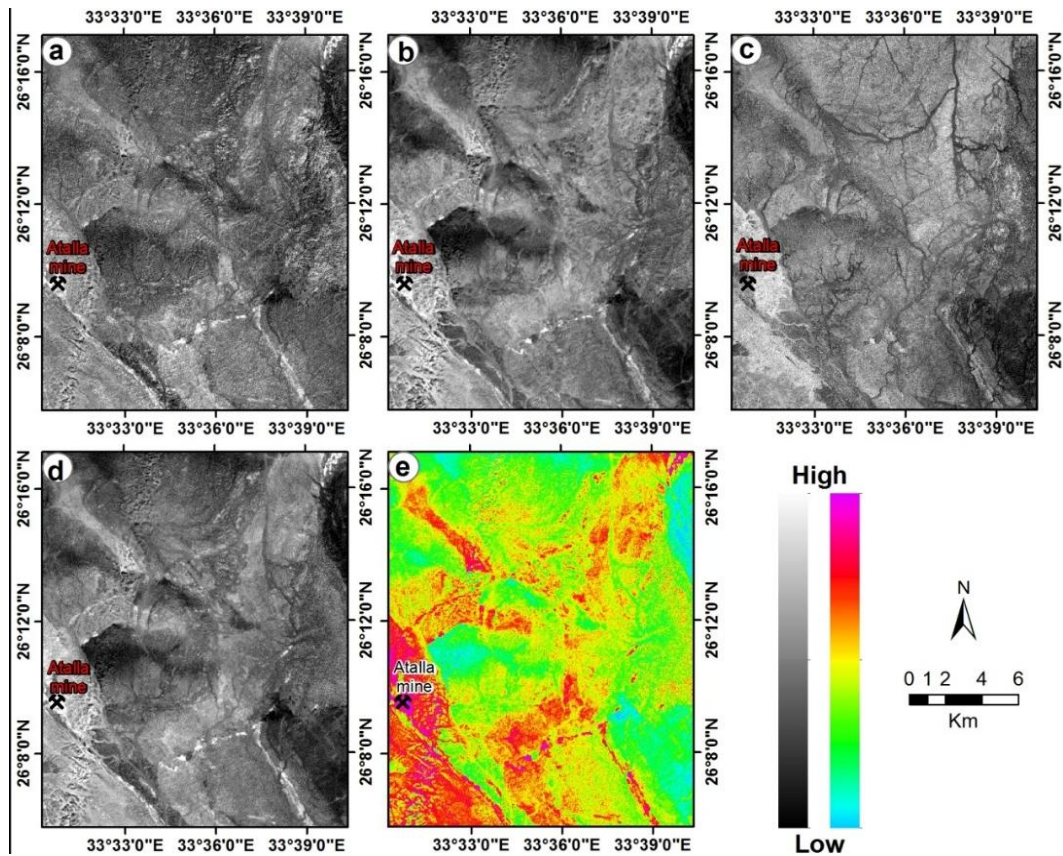


Figure 11. Alteration index maps obtained from ASTER data: (a) sericite index; (b) kaolinite index; (c) ferric iron oxides index; (d) the cumulative alteration map in grey scale; (e) the cumulative alteration map in cyan-magenta color ramp

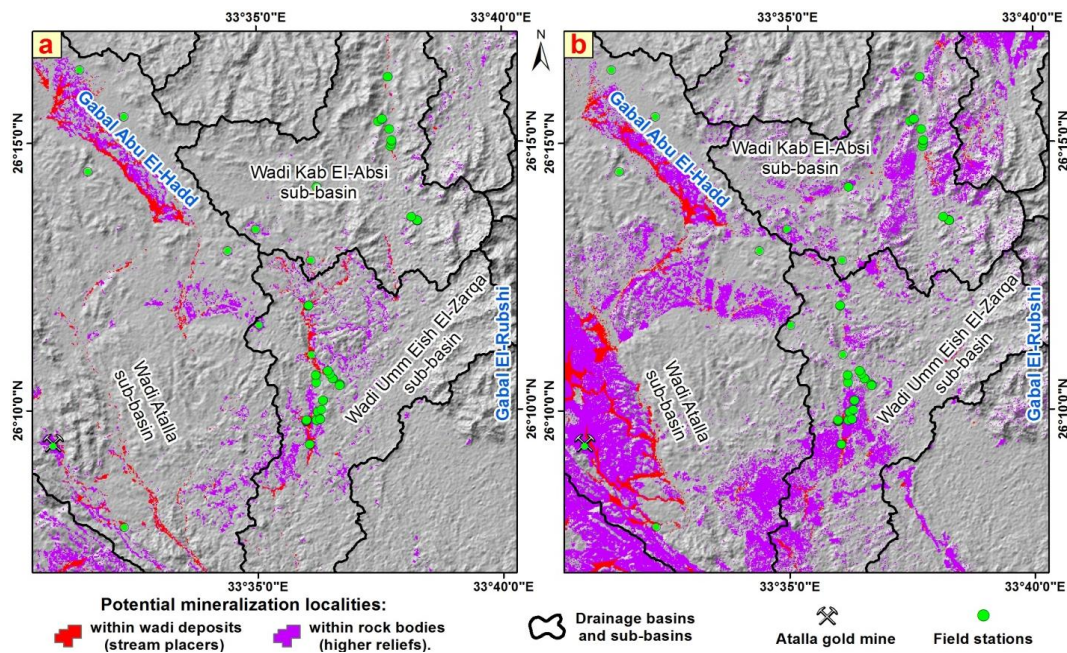


Figure 12. Potential mineralization localities obtained from (a) EnMAP hyperspectral data, and (b) ASTER multispectral data

While ASTER-derived results cover a broader area, the EnMAP-derived map is more spatially constrained, highlighting smaller, more concise targets. Notably, EnMAP successfully identified a potential placer mineralization (red) near the center of Wadi Umm Eish El-Zarqa sub-basin, which ASTER did not detect. Conversely, ASTER data delineated almost the entire Wadi Kab El-Absi sub-basin as highly prospective for mineralization. In contrast, EnMAP delineated only sporadic localities (a few pixels) within this sub-basin.

In summary, both datasets successfully identified nearly the same prospective localities. However, the EnMAP results suggest a narrower, more specific spatial distribution of mineralization, likely due to its superior spectral resolution, which enables more precise discrimination of mineralization. The evident discrepancies between the two results were further investigated by fieldwork.

3.6. Validation of results

The results of this study were validated through a multi-faceted approach, encompassing direct field verification, comparison against known mineralization sites, and analysis of high-resolution satellite imagery.

The location of the proven Atalla gold mine served as a key reference point for validation. The adopted approaches applied to both EnMAP and ASTER data proved successful in identifying the Atalla gold mine in the southwestern part of the study area (Fig. 12) as a potential mineralization locality, confirming the fundamental accuracy of both methodologies.

Fieldwork was conducted to ground-truth the existence of alteration indicators in the mapped potential mineralization within bedrocks and (Fig. 13a-c) and stream sediment localities by both approaches. This investigation confirmed the superior precision of EnMAP-derived results, with the RF results offering additional precision and delineating target areas without the overestimation observed in the ASTER output.



Figure 13. Field verification of the mapped prospective targets: (a) quartz veins within the metavolcanic rocks at Wadi Kab El-Absi; (b), (c) excavations in quartz veins within metavolcanics at Wadi Umm Eish El-Zarqa; (d), (e) excavation machines at different places in the main stream of Wadi Umm Eish El-Zarqa; (f) panorama view showing piles of stream sediments in the middle of the study area; (g) – (i) Google Earth images showing excavations at different parts of the study area

Crucially, the placer mineralization localities mapped by EnMAP were validated by the presence of active excavations and artisanal operations (Fig. 13d – i). These excavations are carried out using loaders and mechanical shakers (Fig. 13d, e) – observed mainly in the main stream of Wadi Umm Eish El-Zarqa- to process the sediments, with the concentrated material receiving further treatment for gold extraction.

An interview with the artisan miners in the mainstream of Wadi Umm Eish El-Zarqa sub-basin provided quantitative insight into the productivity of these placers. The artisans reported extracting about 25-30 grams of gold per truckload (~85 tons) of processed stream sediments, confirming the economic viability of these deposits. The artisans also reported that this amount is highly profitable due to minimal operational costs, as extraction requires no blasting or other complex, costly operations associated with regular open-pit or underground hard-rock mining.

The delineated high-potential localities were further investigated using high-resolution Google Earth imagery to identify signs of excavation activity. This analysis revealed extensive artisanal mining, particularly within stream deposits in the central Wadi Umm Eish El-Zarqa sub-basin, and near the Atalla gold mine site in the Wadi Atalla sub-basin (Fig. 13g – i). Conversely, no excavation marks were observed within Wadi Kab El-Absi sub-basins. This absence of activity supports the EnMAP results. It suggests that the broader anomalous zone mapped by ASTER in this area is a false positive, further underscoring the superiority of the hyperspectral data.

4. Conclusions

The study developed an integrated framework from remote sensing, machine learning, and fieldwork-based evaluation and validation for gold exploration, yielding the following key conclusions:

Hyperspectral EnMAP data demonstrated clear superiority over ASTER for mapping the gold-related alterations, with its enhanced spectral resolution enabling precise identification of key indicator minerals. Specifically, muscovite (diagnostic absorption features at 2200 and 2345 nm) and goethite (absorption at 500 nm), identified from EnMAP pixel spectra at known mining sites, served as reliable alteration indicators for training Random Forest (RF) and Support Vector Machine with Radial Basis Function kernel (SVM-RBF) models. To address the limited number of reference spectra, a spectral probability tolerance was implemented to expand the training dataset and enhance model robustness.

Ground-truth validation is very important for model evaluation and can define the model's utility. Although the SVM-RBF technique achieved a slightly higher OA, the RF model achieved perfect precision in mapping mineralized targets, resulting in zero false positives. It also delivered a larger high-confidence target portfolio with the highest mineralization probability. Such a trade-off highlights RF as the superior choice for risk-averse exploration, where minimizing false alarms is critical, while SVM-RBF may be preferable for maximizing overall detection rates.

Spatial analysis of ALOS PALSAR DEM data by extracting drainage patterns and investigating morphological features effectively linked sources of mineralization in upstream bedrock areas to downstream localities, highlighting potential placer deposits. Highlighting intermediate stream-orders as the most prospective for placer occurrence.

A robust gold mineralization potential map was produced, delineating prospective bedrock and stream-sediment targets, with fieldwork and high-resolution Google Earth imagery confirming active artisanal mining and positive stream-sediment assays that corroborate their economic potential.

Despite the adopted validation approach, it is important to acknowledge that the study is constrained by a limited number of reference mining sites available for model calibration, and independent geochemical validation was not per-

formed for all predicted targets. Consequently, intense follow-up geochemical investigations are highly recommended.

Overall, the study presents a complete, cost-effective, and reproducible exploration framework that integrates hyperspectral data, machine learning, and geomorphometric analysis, providing a powerful basis for targeting bedrock and placer gold deposits with reduced exploration risk in similar arid and semi-arid terrains worldwide.

Author contributions

Conceptualization: SMG, CW; Data curation: SMG, HFA; Formal analysis: SMG, HFA, MF, IY; Funding acquisition: SMG, CW; Investigation: SMG, CW, IY, MF; Methodology: SMG, CW, HFA, MF; Project administration: SMG, CW; Resources: CW, SMG, HFA; Software: SMG, CW, HFA, MF, IY; Supervision: CW; Validation: SMG, HFA, MF; Visualization: SMG, CW, HFA, MF; Writing – original draft: SMG, CW, MF; Writing – review & editing: SMG, CW, HFA, MF, IY. All authors have read and agreed to the published version of the manuscript.

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Conflicts of interests

The authors declare no conflict of interest.

Data availability statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

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Машинне навчання та гіперспектральні дані для прогнозування орогенних і розсіпних золоторудних об'єктів у ваді Умм-Ейш-ель-Зарка, Єгипет

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Мета. Розроблення відтворюваної методики з пріоритетом високої точності для прогнозування золоторудного зруденіння в аридных умовах, що охоплює як корінні, так і розсіпні родовища в районі ваді Умм-Ейш-ель-Зарка в Єгипті. Це перше дослідження такого типу для зазначеного регіону.

Методика. Методика поєднує машинне навчання на основі гіперспектральних даних EnMAP із просторовим геоморфометричним аналізом цифрової моделі рельєфу ALOS-PALSAR. Моделі випадкового лісу та методу опорних векторів із радіально-базисною функцією були навчені на спектральних характеристиках пікселів із трьох відомих ділянок видобування золота. Для розширення навчальної вибірки застосовано допустиме спектральне відхилення 0.05. На основі цифрової моделі рельєфу виділено дренажну мережу для встановлення зв'язку між розташованими вище за течією корінними джерелами золота та потенційними зонами формування розсіпів нижче за течією. Для порівняльного аналізу побудовано карти зон гідротермальних змін за даними ASTER.

Результати. Наземна верифікація виділених перспективних ділянок показала, що модель SVM-RBF забезпечила дещо вищу загальну точність порівняно з RF – 91.8 проти 89.9%. Водночас модель RF продемонструвала максимальну точність позитивного прогнозування під час ідентифікації мінералізованих ділянок і, що особливо важливо, виділила на 37% більше потенційно мінералізованих об'єктів із високою достовірністю прогнозу понад 80%, ніж SVM-RBF. Аналіз дренажної мережі визначив водотоки третього-п'ятого порядків як найбільш сприятливі зони для накопичення розсіпного золота. Польові дослідження підтвердили наявність діючих кустарних виробок. За наявними даними, із руслових відкладів отримують 25-30 г золота з однієї вантажної партії масою близько 85 т.

Наукова новизна. Дослідження усуває наявну прогалину в застосуванні гіперспектральних методів для пошуку корисних копалин у Східній пустелі Єгипту. Уперше для цього регіону машинне навчання інтегровано з гіперспектральними даними EnMAP для прогнозування розсіпних родовищ золота, що дало змогу сформулювати орієнтований на високу точність підхід до геологорозвідувальних робіт.

Практична значимість. Запропонована методика може бути використана для пошуків корисних копалин в аналогічних аридных районах світу. Її застосування сприяє зниженню фінансових ризиків і раціональному спрямуванню ресурсів на подальші польові та геологорозвідувальні дослідження.

Ключові слова: гіперспектральні дані EnMAP; машинне навчання; випадковий ліс; метод опорних векторів; розсіпне золото; Умм-Ейш-ель-Зарка

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