

COMPARATIVE EVALUATION OF FEATURE CLASSIFICATION IN MINING REGIONS VIA MULTI-MODAL SENSOR DATA

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ABSTRACT. This report explores the possibilities of remote monitoring of mining areas by fusing sensor data from radar and optical satellite systems. The study is based on a feature-based machine learning method applied to the classification of an open-pit mine. A classification is performed using the Maximum Likelihood algorithm on a multiband dataset of structural, radiometric, and spectral information. This dataset is formed by the multispectral bands of Sentinel-2 and the polarimetric SAR parameters (Entropy, Anisotropy, and Alpha angle) derived from Sentinel-1 data. The spectral characteristics and polarimetric parameters are used as fused input features, with the latter providing additional information on scattering mechanisms and the structural characteristics of the investigated objects. In the processing of the radar signal, emphasis is placed on physical scattering from artificial targets within the mine, whereas the optical data relies on spectral resolution to identify different land cover types. The results of the comparative analysis indicate that the polarimetric characteristics of Sentinel-1 provide more stable information for determining object geometry. On the other hand, the Sentinel-2 classification delivers a more detailed class separation but remains highly dependent on the meteorological conditions characteristic of the study period, which in this case is early spring. The study confirms the necessity of applying a combined approach for monthly monitoring of mining territories with rugged terrain.

Key words: pixel-based classification, multi-sensor data fusion, dual-polarimetric SAR, multispectral imagery, open pit mining areas.

СРАВНИТЕЛНА ОЦЕНКА ПРИ КЛАСИФИКАЦИЯТА НА ОБЕКТИ В МИННИ РАЙОНИ ЧРЕЗ ИЗПОЛЗВАНЕ НА ДАННИ ОТ РАЗЛИЧНИ ТИПОВЕ СЕНЗОРИ

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РЕЗЮМЕ. В настоящия доклад се разглеждат възможностите за дистанционен мониторинг на минни райони чрез обединяване на данни от сензори на радарни и оптични спътникови системи. Изследването е базирано на метод за машинно обучение, основан на признаци, при класификацията на открит рудник. Прилага се класификация въз основа на алгоритъма Maximum Likelihood върху многоканален набор от структурна, радиометрична и спектрална информация. Той се формира от мултиспектралните канали на Sentinel-2 и поляриметричните SAR параметри (Entropy, Anisotropy и Alpha angle), получени от данните на Sentinel-1. Спектралните характеристики и поляриметричните параметри се използват като обединени входни признаци, като последните предоставят допълнителна информация за механизмите на разсейване и структурните характеристики на изследваните обекти. При обработката на радарния сигнал акцентът се поставя върху физическото разсейване от изкуствени структури в рудника, докато при оптичните данни се разчита на спектралната разделителна способност за определяне на различните типове земно покритие. Резултатите от сравнителния анализ показват, че поляриметричните характеристики на Sentinel-1 предоставят по-стабилна информация за определяне на геометрията на обектите. От друга страна, класификацията на Sentinel-2 осигурява по-подробно разграничаване на класовете, но остава силно зависима от метеорологичните условия, характерни за периода на изследването, който в случая е началото на пролетта. Изследването потвърждава необходимостта от прилагането на комбиниран подход при ежемесечен мониторинг на минни територии с пресечен релеф.

Ключови думи: пикселно-базирана класификация, обединяване на данни от различни сензори, двойно поляризиран SAR, мултиспектрални изображения, минни райони.

Introduction

Monitoring areas with intensive industrial activity, such as open-pit mines, is of critical importance for safety and environmental management. Environmental changes are dynamic and complex, requiring precise mapping and assessment methods. Ensuring reliable methods for year-round remote observation of these sites is partially limited by meteorological conditions (cloud cover) and complex terrain geometry.

Remote sensing via satellite platforms offers a cost-effective solution for operational monitoring of such facilities, as discussed by Joshi et al. (2016) and Tavares et al. (2019).

The traditional use of optical sensors, such as those on the Sentinel-2 satellite, represents a primary tool in Earth observation remote sensing due to the rich spectral information they provide. However, in many regions, their effectiveness is limited by frequent cloud cover and atmospheric disturbances. Synthetic Aperture Radar (SAR) data, such as from the Sentinel-1 satellite, can be applied as an alternative and complement, providing information on the structural and physical characteristics of the Earth's surface regardless of

atmospheric conditions. Scientific research and analysis show that integrating optical and radar data leads to a significant increase in classification accuracy compared to using a single data source alone (Joshi et al., 2016).

The development of polarimetric SAR analysis has further expanded the potential of radar data for characterising the physical properties and scattering behaviour of surface targets. Cloude and Pottier (1996a, 1996b, 1997) introduced entropy- and anisotropy-based polarimetric classification concepts, demonstrating the potential of these parameters as informative features for the interpretation and classification of polarimetric SAR imagery. The Cloude–Pottier framework provides physically interpretable parameters, including entropy (H), anisotropy (A), and the alpha angle (α), which describe the randomness and relative contribution of scattering mechanisms and the dominant scattering behaviour of observed targets. These parameters can therefore provide complementary structural information to the spectral information obtained from optical sensors.

Although the original Cloude–Pottier framework was developed for fully polarimetric SAR data, its principles can also be adapted for dual-polarisation observations. In this study, this approach is applied to Sentinel-1 dual-pol SLC data through

eigenvalue analysis of the C2 covariance matrix, which allows for the derivation of physically interpretable polarimetric features despite the reduced polarimetric information available from the sensor.

Mining sites, including open-pit mines, tailing ponds, and processing plants, represent complex industrial systems with high technological loads and significant potential risk to personnel safety and the environment. This requires continuous monitoring and safety assessment (Kostadinova and Vladkova, 2025). Effective monitoring of such sites is essential for the timely identification of changes, risk assessment, and support of safety management processes. Satellite remote sensing methods provide an opportunity for regular, objective, and comprehensive spatial monitoring of mining territories and their infrastructure.

Reliable monthly monitoring of mining territories cannot be effectively achieved using only one type of satellite data—optical or radar—but requires an integrated approach that combines the advantages of both sensor types. It is therefore expected that incorporating polarimetric features derived from Sentinel-1, particularly Entropy (H), Anisotropy (A), and Alpha angle (α), as additional input features to Sentinel-2 multispectral data will improve the discrimination and classification of land cover classes within open-pit mining environments.

Data and methods

“Ada Tepe” is an open-pit mine for the extraction of gold-bearing ore. Located 3 km south of the town of Krumovgrad (Fig. 1), it is the first modern, newly developed mine in the country in the past 40 years.

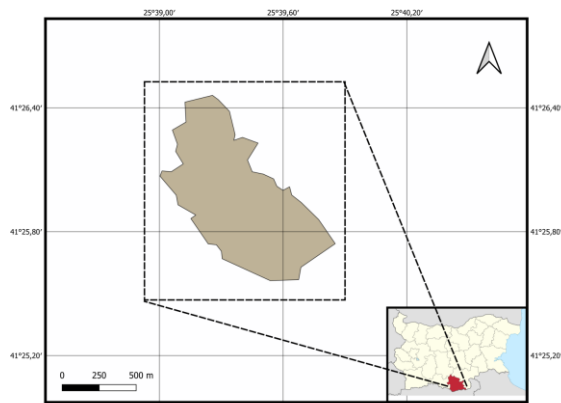


Fig. 1. A map showing the location of the “Ada Tepe” open pit mine

Ore mining and processing operations began in August 2019. The site utilises open-pit mining technology for gold-bearing ores and processing into a gold-silver concentrate through mechanical excavation, drilling and blasting, extraction, crushing, grinding, and flotation (DPM Ada Tepe, n.d.). After 8 years of operation, mining production ended in mid-2026. For the mine, which was constructed entirely within the “Natura 2000” protected area, active land reclamation is planned for 2028, followed by a mandatory 10-year environmental monitoring period. The entire process—from mine construction and operation to subsequent land reclamation and future site development—can be tracked over time using satellite remote sensing methods.

Data Sources

For the purposes of the study, satellite data from the period prior to the start of ore extraction and processing were used. The Single Look Complex (SLC) radar data from Sentinel-1, operating in dual-polarisation mode (VV and VH), are from February 2019. The multispectral data from Sentinel-2 are from March 2019, with the spectral bands offering the highest informative value for land cover determination selected for processing. These include the visible, the near-infrared (NIR), and the short-wave infrared (SWIR) bands. These data provide detailed spectral separation of natural and anthropogenic features on the Earth's surface.

The processing and analysis workflow was implemented using the SNAP and QGIS software products and involved strictly defined pre-processing steps for both optical and radar data. The primary processing was conducted in SNAP, while additional analyses and accuracy assessment were performed in QGIS. A key advantage for selecting the QGIS geographic information software is its rich ecosystem of plugins, which allow for expanding its functionality according to user needs—ranging from terrain analysis and remote sensing to modelling and automation (Slavova, 2025).

Methodological Framework

In data fusion classification, two approaches are applied:

- pre-classification fusion – combining features prior to classification;
- post-classification fusion – combining two separate classifications performed on satellite data obtained from different sensors.

In the first approach, classification within the workflow is performed on the combined information obtained from different sensor types. The resulting output is based on a single joint matrix of input features containing spectral and structural information simultaneously available for each sample. In the second approach, optical and SAR data are classified independently, and the resulting maps are combined using rules, statistical methods, logical operators, or by selecting the most probable class predicted by both models. To illustrate the physical interpretation of the considered parameters, fig. 2 (European Space Agency, n.d.) presents the H – α plane, which describes the primary scattering mechanisms—surface scattering, volume scattering, double-bounce scattering—as well as an assessment of the degree of randomness of the scattering process.

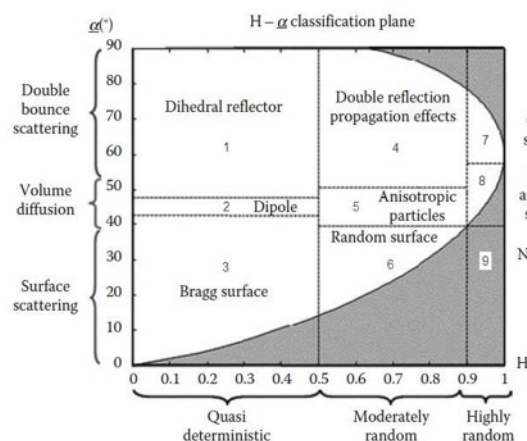


Fig. 2. H / Alpha plane (adapted from Cloude & Pottier, 1997/ESA)

The defined H - α plane (Fig. 2) enables quantitative analysis of POL-SAR images within the ranges $0 \leq H \leq 1$ and $0 \leq \alpha \leq 90^\circ$. In the two-dimensional H - α classification space, all possible random and deterministic scattering mechanisms can be represented. At $H = 0$, all values of $0 \leq \alpha \leq 90^\circ$ can be obtained, whereas at $H = 1$, only a single value of $\alpha = 60^\circ$ exists. This reflects the increasing inability to distinguish between different scattering mechanisms as entropy increases.

The two boundary curves, I and II, define the region in which partially polarised scattering mechanisms can be identified, intersecting at $H = 1$ and $\alpha = 60^\circ$. As shown by Cloude and Pottier (1997), all experimental results, regardless of the method used to measure the full polarimetric matrix (such as the Kenneough matrix or others), must fall within the admissible region (between curves I and II) of the H - α plane.

Due to the lack of full polarimetric coverage, an adapted Cloude–Pottier dual-polarisation decomposition is utilised. This approach is based on the eigenvalue analysis of the covariance matrix (C2) (Mascolo et al., 2021). Entropy (H) reflects the degree of randomness of the scattering process. A value of 0 indicates pure surface scattering, whereas a value of 1 indicates fully random scattering (characteristic of dense vegetation). Alpha angle is a parameter describing the dominant scattering mechanism type. Small angles ($\alpha \approx 0^\circ$) represent dominant surface scattering from a smooth terrain. Intermediate values ($\alpha \approx 45^\circ$) correspond to volume scattering from vegetation, while high values ($\alpha \approx 90^\circ$) indicate double-bounce scattering, typical of metallic mining structures and steep pit walls (Wang et al., 2024).

Data Processing and Experimental Results

Two independent supervised classifications were performed using the Maximum Likelihood Classifier algorithm: the first utilised solely the multispectral bands of Sentinel-2, while the second is based on the fusion of optical and radar data.

Preprocessing of the Sentinel-2 optical image was performed for subsequent fusion with Sentinel-1 data. Spatial resampling of the optical data was applied to bring the Sentinel-2 bands to a uniform spatial resolution. To optimise the computational process, a subset was performed, retaining only the spectral bands relevant for mapping the mine. Reprojection of the image into the UTM coordinate system was executed, ensuring the necessary geometric alignment with the radar data required for subsequent processing stages.

Six regions of interest (ROIs) were defined for the mining complex and its surrounding territory: Forest, Urban Land, Agriculture Land, Open Pit Mine, Water, and Barren Land. Following the application of the Maximum Likelihood Classifier, a classified index image of the mine and its surrounding area was generated (Fig. 3).

To execute the second classification, data from Sentinel-1 and Sentinel-2 were integrated via data fusion. Six land cover classes were established within the mining complex and its surrounding area. The Maximum Likelihood Classifier algorithm was applied, following methodologies also utilised in similar classification studies by other authors (Sim et al., 2013; Kumar et al., 2017).

For the purpose of this classification, the parameters Entropy (H), Anisotropy (A), and Alpha angle (α), derived via the Cloude–Pottier dual-pol decomposition of Sentinel-1 SLC

data, were used as input features in the pre-classification fusion process.

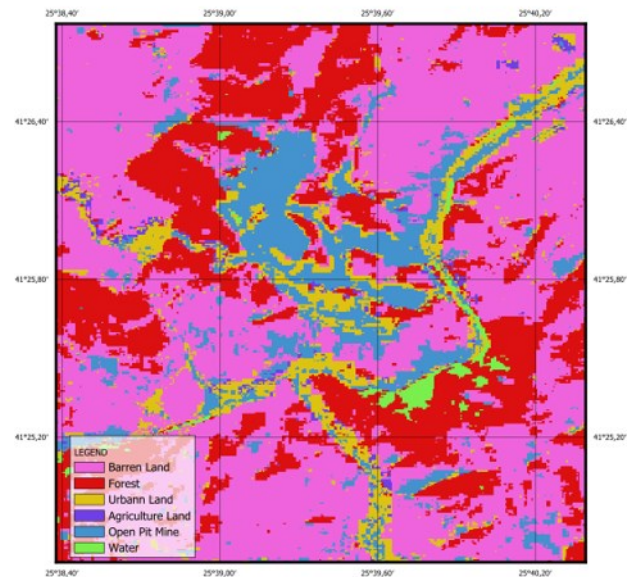


Fig. 3. A classified land cover index image derived from Sentinel - 2 data

In the data processing graph presented in fig. 4, H and α were not used for direct classification within the H - α space, but rather as additional bands within the Maximum Likelihood Classifier alongside the Sentinel-2 optical bands.

The Sentinel-1 data provide partial polarimetric information from which a set of informative features was defined for subsequent classification by calculating σ_{VV}^0 , σ_{VH}^0 , the VV/VH ratio, GLCM texture features, and the polarimetric attributes H , A , and α derived from the Cloude–Pottier dual-pol decomposition.

This partial polarimetric information includes $H/A/\alpha$ derived from the decomposition of the C2 covariance matrix, where C2 represents reduced polarimetry containing only VV, VH, and their mutual coherence.

Although Sentinel-1 SLC data do not provide the complete structural information available from full-pol SAR satellites, the extracted parameters contain sufficient physically interpretable features for effective classification when performing multi-sensor fusion.

A flowchart of the second classification process is presented in fig. 4.

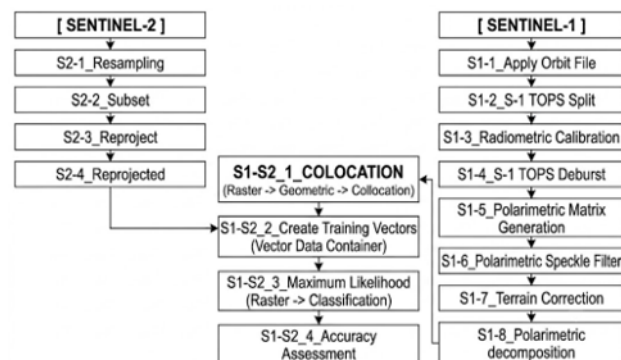


Fig. 4. Data fusion of radar data as additional variables to the optical data

Preprocessing of the Sentinel-1 SLC radar data is carried out to convert the complex radar signal values into indicators of terrain structure, extract polarimetric information, and apply geometric corrections. The processing is executed in several sequential stages, including covariance matrix extraction (C2), filtering and decomposition, and geocoding with terrain correction. The extraction of the covariance matrix (C2) involves applying precise satellite orbit files to the product (Apply Orbit File), thermal noise removal (S-1 Thermal Noise Removal), signal calibration to complex values (Calibration), followed by merging into a single image by removing inter-burst boundaries (S-1 TOPS Deburst). In the subsequent stage, polarimetric speckle filtering (Speckle Filtering) and polarimetric decomposition (Polarimetric H-A-Alpha Decomposition) are performed. To mitigate radar-specific speckle noise, a specialised filter (Refined Lee) is applied, which allows, for example, the preservation of sharp quarry contours. This is followed by Cloude–Pottier decomposition, through which the physical scattering parameters of the radar signal are computed—Entropy (H), Anisotropy (A), and Alpha angle (α). The third stage of radar data preprocessing involves geocoding and terrain correction (Terrain Correction). Utilising a Digital Elevation Model, geometric distortions—such as those occurring on steep mine slopes—are corrected, and the radar data are reprojected into the UTM coordinate system. The next step in the data processing of the second classification process presented in fig. 4. consists of performing supervised classification on the fused data from both satellite images, using the predefined training regions of interest (ROIs) from the first classification. For the classification, the Maximum Likelihood statistical algorithm was applied, which jointly analyses both the spectral channels of the optical image and the radar polarimetric features. This statistical algorithm was selected for its ability to account not only for the mean reflectance values of the pixels, but also for the variances and correlations between individual spectral channels (Lillesand et al., 2015). As a final result, a thematic map of the mine site and its surrounding area is generated (Fig. 5).

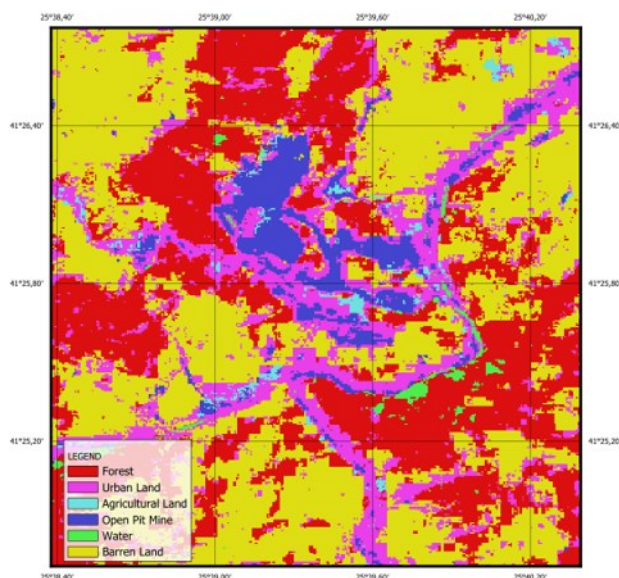


Fig. 5. A classified index image of land cover derived from an integrated set of optical and SAR data

In addition to the two aforementioned classifications, a polarimetric unsupervised classification (Cloude–Pottier Dual Pol) was performed for the Ada Tepe mine area using Sentinel-1 SLC data (Fig. 6).

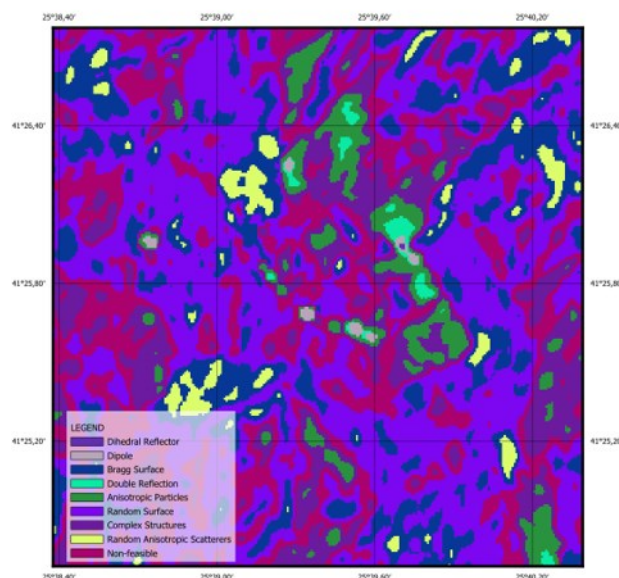


Fig. 6. Polarimetric land cover classification in the Ada Tepe mine area derived from Sentinel-1 data

Despite the overall low model accuracy, the polarimetric classification of Sentinel-1 data illustrates a high discriminative capability in identifying features with distinct physical properties in the Ada Tepe mine area. Water bodies are classified with high precision due to strong surface scattering and low entropy of the radar signal, as previously described by Cloude and Pottier (1997). A similar conclusion can be drawn from analysing the spatial distribution of classes across the two approaches, as presented in Table 1. While all other feature classes are redistributed among different object categories relative to their percentage proportions in the provided table, water areas maintain identical values and are identified with equal reliability by both approaches.

Table 1. Spatial class distribution for both approaches

Class name	Sentinel 2		
	Pixel count	Percentage(%)	Area(m ²)
Forest	1375527	31,70%	137552700
Urban Land	678924	15,60%	67892400
Agricultural Land	64692	1,50%	6469200
Open Pit Mine	183464	4,20%	18346400
Water	12413	0,30%	1241300
Barren Land	2025586	46,70%	202558600
Class name	Sentinel 1+Sentinel 2		
	Pixel count	Percentage(%)	Area(m ²)
Forest	956587	25,60%	95658700
Urban Land	41748	9,70%	4174800
Agricultural Land	78492	1,80%	7849200
Open Pit Mine	430388	9,90%	43038800
Water	13751	0,30%	1375100
Barren Land	2289425	52,70%	228942500

The metallic buildings and industrial facilities of the processing plant (represented in yellow in fig. 6) stand out distinctly due to the double-bounce scattering mechanism. This

mechanism is highly characteristic of man-made structures and metallic corner reflectors, which generate stable and unique classification features in the radar image, even when overall classification of the surrounding terrain is challenging (Cloude & Pottier, 1997). Table 1 also shows a percentage increase in mapped Open Pit Mine areas (from 4.2% to 9.9%) and Barren Land (from 46.7% to 52.7%), accompanied by a reduction in areas classified as Forest and Urban Land. This indicates a more detailed discrimination of complex mining territories and contributes to more reliable mapping; however, for certain feature classes, there remains a need to optimise classification features or the classification model used.

Analyses and comparison

The overall accuracy assessment results derived from Sentinel-2 data show an Overall Accuracy (OA) of 82.5% (95% CI: 70.6%–90.2%) and a Kappa coefficient of 0.78 (95% CI: 0.6612–0.9052), indicating high accuracy and good agreement between the classification and reference data.

The accuracy assessment obtained from the joint processing of active and passive sensor data (Sentinel-1 + Sentinel-2) demonstrates an increase in overall accuracy to 87.7% (95% CI: 76.8%–93.9%) and a Kappa coefficient of 0.85 (95% CI: 0.7428–0.9535). This represents a 5.2% accuracy improvement, confirming the enhanced effectiveness of combining Sentinel-1 and Sentinel-2 data compared to utilising optical imagery alone.

The obtained results align with the conclusions reported by Clerici et al. (2017), who achieved an accuracy of 88.75% for land cover mapping in Colombia using a similar data fusion approach of Sentinel-1 and Sentinel-2 imagery. Furthermore, Hu et al. (2021) reported that during the classification of agricultural and industrial areas, using Sentinel-1 satellite data alone yielded an accuracy of approximately 60%, whereas applying data fusion with Sentinel-2 satellite data increased this performance metric to over 95%.

This demonstrates that phase information, along with conventional magnitude data, can be used to study scattering mechanisms and resolve ambiguities regarding the source of scattering from vegetation and soil components of the target area. Polarimetric classifiers can utilise polarimetric contrast classification, scattering mechanism classification, or more conventional approaches (such as Maximum Likelihood Classification), where phase information provides additional channels to the classifier (Boerner et al., 1998).

Conclusion

The results obtained from applying supervised classification to the fused data from both approaches, as well as unsupervised classification based on Sentinel-1 data, provide complementary spectral and structural information, thereby enhancing the quality of thematic classification in mining areas. By integrating polarimetric features - such as Entropy (H), Anisotropy (A), and Alpha angle (α) - along with spectral and textural characteristics, the Overall Accuracy increased from 82.5% to 87.7%, and the Kappa coefficient rose from 0.78 to 0.85, confirming the efficacy of the multi-sensor data fusion approach. The supplementary polarimetric classification of Sentinel-1 imagery demonstrated a strong ability to discriminate features with distinct scattering

mechanisms, such as water bodies and industrial facilities, offering a viable means to complement the information derived from multispectral imagery. The proposed data processing approach can be applied to operational monitoring of open-pit mines, tracking land cover changes, and supporting reclamation and management activities in mining territories. This research can be expanded by using time series of Sentinel-1 and Sentinel-2 data, alongside the implementation of advanced machine learning algorithms and the evaluation of additional polarimetric parameters to further enhance classification accuracy.

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