S34I Project: Secure and Sustainable Supply of Raw Materials for EU Industry

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Abstract: The Secure and Sustainable Supply of Raw Materials for EU Industry – S34I project is researching and innovating new data-driven methods to analyze Earth Observation (EO) data, supporting systematic mineral exploration and continuous monitoring of extraction, closure, and post-closure activities to increase European autonomy regarding raw materials (RM) resources, and to use EO not only for the management of technical and environmental issues for a green transition but also to support public awareness, mining's social acceptance, and better legislation. S34I uses data from satellites, airborne, unmanned aerial vehicles, ground-based sensors, underwater hyperspectral imaging and conventional in-situ techniques/methods and fieldwork. The S34I project is supporting the technical experiments and pilot validations/demonstrations for the six pilot use cases and at different phases of the mining life-cycle to address the challenges of the topic: Onshore exploration (Aramo in Spain); Shallow water exploration (Ria de Vigo in Spain); Extraction (Gummern in Austria); and Closure/post-closure (Lausitz in Germany, Aijala and Outokumpu in Finland). The S34I project involves 19 partners from 12 European countries. The project started in January 2023 and ends in June 2025.

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1 INTRODUCTION

Sustainable mining practices, i.e., the minimization of environmental damage, social responsibility, reduction of ecological footprints, rehabilitating mined land, managing waste effectively, and conserving biodiversity, are a very hot topic and have been a concern for many years (Laurence, 2011; Chen et al., 2024).

The Critical Raw Materials Act (CRMA), proposed by the European Commission, seeks to address the challenges faced by the European Union (EU) in securing a stable and sustainable supply of critical raw materials (European Commission, 2023). Its primary goal is to reduce the EU's reliance on external sources for these materials while ensuring their availability to support strategic sectors, including those vital for decarbonization and advancing green technologies (Hool et al., 2024). The Act sets several benchmarks by 2030 along the strategic raw materials value chain and for the diversification of the EU supplies: (i) at least 10% of the EU's annual consumption for extraction; (ii) at least 40% of the EU's annual consumption for processing; and (iii) at least 25% of the EU's annual consumption for recycling no more than 65% of the EU's annual consumption from a single third country.

Satellite data is crucial in sustainable mining practices by offering tools and insights to minimize environmental impact, optimize operations, and ensure compliance with sustainability standards (Farahnakian et al., 2024; Li et al., 2023; Persello et al., 2022).

Regarding the applications of satellite data in sustainable mining, using these data and image-processing techniques reduces the environmental impact by identifying high-potential areas remotely (Rajan Girija & Mayappan, 2019). Remote sensing has the ability to help exploration companies explore much larger and often more remote and inaccessible areas whilst at the same time focusing time and costs on identifying specific target areas for further testing (Pour et al., 2019; Beiranvand Pour et al., 2018). This will lead to more efficient timelines for discovery. Mineral mapping can analyze mine waste (tailings) for recoverable resources, turning waste into reusable materials and reducing the need for fresh extraction (Gulicovski et al., 2024; Rodríguez-Hernández et al., 2019; Zoran et al., 2009).

The recent advances in Artificial Intelligence (AI) algorithms and Earth Observation (EO) free data are aspects that broadly support several Sustainable Development Goals and promote sustainable mining (Chen et al., 2024; Persello et al., 2022).

The S34I project has explored new data-driven methods to analyze EO data for systematic mineral exploration, continuous extraction monitoring, closure and post-closure activities, increasing European autonomy regarding raw materials (Farahnakian et al., 2024; Carvalho et al., 2025). The consortium is composed of 19 partners from 12 countries (11 from the EU, plus Norway) (see Figure 1). The partners are 50% from academia and national research centres and 50% from private companies/industries. The project started in January of 2023 and will end in June 2025.

Figure 1: S34I project partners.

The main objective of this work is to present the project's main objectives and some preliminary results. The project tackles the entire mining life cycle (exploration, extraction, mine closure) by focusing on six distinct pilot sites. Each mining phase and pilot presents different challenges that were addressed using EO data and techniques. This work will summarize the S34I approach to address these challenges. First, all datasets used in S34I will be listed according to the mining phase. Then, an overview of the methods developed/adapted in the scope of S34I will be given. Preliminary results will be presented and discussed for selected methods. These methods and results will serve as a base to develop specific services to address the identified challenges.

2 DATA

S34I utilized data from Copernicus missions and Copernicus Contributing Missions (CCM) obtained from the European Space Agency and other satellite sensors, while additional platforms, which included airborne systems, unmanned aerial vehicles (UAVs), ground-based methods, in-situ techniques, and fieldwork, were employed for calibration, validation, or to complement the satellite data. The data used varied depending on the mining phase and pilot site:

- Exploration Phase - Onshore Pilot (Aramo Mine, Spain): Sentinel-1, Sentinel-2, Landsat-9, Hyperspectral Precursor of the Application Mission (PRISMA), Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR)-2, Constellation of Small Satellites for Mediterranean basin Observation (COSMO-SkyMed), airborne Light Detection and Ranging (LiDAR), hyperspectral data, and ground spectral libraries of rocks and soils.
- Exploration Phase - Shallow Waters Pilot (Rias Baixas, Spain): Sentinel-1, Sentinel-2, Landsat-9, WorldView-2/-3, EnMap, Underwater Hyperspectral Imaging (UHI), complementary spectral libraries, and pre-existing or newly acquired geological data.
- Extraction Phase (Gummern, Austria): Pléiades Neo tri-stereo, WorldView-2, Sentinel-1, Sentinel-2, COSMO-SkyMed, UAV data, and ground Global Navigation Satellite Systems (GNSS) stations.
- Closure and post-closure Phase (Lausitz and Outokumpu): Sentinel-2, PRISMA, WorldView-3, UAV data, and geochemical water data; and Sentinel-1, Sentinel-2, and COSMO-SkyMed data (Aijala).

It should be noted that the S34I consortium worked together with the holders of the rights for exploration in Aramo and for exploitation in Gummern.

3 METHODS

The data and methodology employed in the S34I project depend on the pilot case and the mining phase addressed. However, the principal outcomes of the S34I project focus on processing Copernicus and CCM data.

Several approaches were applied and developed, from traditional methods to new ensemble machine learning (ML) algorithms. Figure 2 presents the methods developed in the primary pilot area. The techniques have been developed in a specific location but later implemented in other pilot areas.

The methods were developed according to the type of EO data exploited (satellite and other data), as shown in Figure 3.

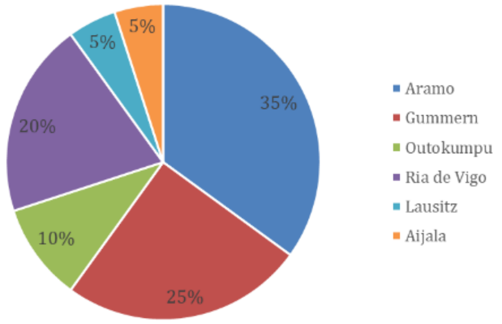

Figure 2: Developed methods according to the primary pilot area.

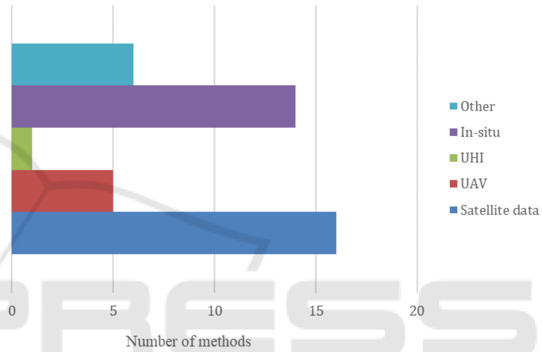

Figure 3: Developed methods according to the data.

3.1 Exploration Phase

For the onshore pilot (Aramo, Spain), various analytical methods were employed, including RGB combinations, band ratios, Principal Component Analysis (PCA), K-means clustering, end-member extraction, minimum wavelength mapping, Spectral Angle Mapper (SAM), Self-Organizing Maps (SOM), and Artificial Neural Networks (ANNs). A novel ensemble AI method was developed by integrating Support Vector Machines (SVM), Random Forest (RF), and ANNs. Additionally, a specialized AI algorithm was designed for automated pre-processing of hyperspectral airborne data, requiring minimal ground truth input. This was aided by pre-existing geochemical datasets, which minimized the requirement for a large part of follow-up ground truthing.

In the shallow water exploration pilot (Rias Baixas, Spain), RGB combinations, band ratios, PCA, K-means clustering, spectral unmixing, and Object-Based Image Analysis (OBIA) enhanced feature detection and classification.

3.2 Extraction Phase

In the extraction pilot (Gummern, Austria), high-resolution Digital Elevation Models (DEMs) were generated, and UAV photogrammetry was effectively performed using Structure from Motion (SfM) for detailed surface modelling.

Interferometric Synthetic Aperture Radar (InSAR) and change detection techniques, including the Normalized Decorrelation Change Index (NDCI), were applied to Synthetic Aperture Radar (SAR) data for detailed surface analysis. Additionally, advanced AI models—Residual-in-Residual Dense Block (RRDB), Super-Resolution U-Net (SRUN), and Optical-Guided Super-Resolution Network (OGSRN)—were implemented to enhance the resolution and quality of SAR imagery.

A Low-cost GNSS Monitoring System (LGMS) using low-cost GNSS receivers to monitor displacements with high precision was implemented. The LGMS receives and stores GNSS observations continuously, which are later post-processed to estimate daily displacements of the monitoring locations.

3.3 Closure and Post-Closure Phase

For closed mines affected by Acid Mine Drainage (AMD) (Lausitz, Germany and Outokumpu, Finland), unsupervised learning methods such as SOM and K-means clustering were utilized for pattern recognition and data analysis. Supervised classification techniques were applied to improve predictive accuracy, including ANN, logistic regression, RF, and K-nearest Neighbors (KNN). Additionally, image enhancement and change detection techniques were implemented at the Aijala pilot (Finland).

4 RESULTS AND DISCUSSION

In this section, some preliminary results will be presented and discussed.

4.1 Exploration Phase

In the onshore pilot study, SOM was applied for data exploration to analyze geochemical sample points. A K-means clustering algorithm was also applied to the SOM output to categorize the data into distinct clusters. This combination allows for identifying meaningful groupings and enhances the interpretability of spatial and spectral patterns. Ultimately, it improves understanding of Cobalt (Co) distribution captured by PRISMA and LiDAR data (Figure 4).

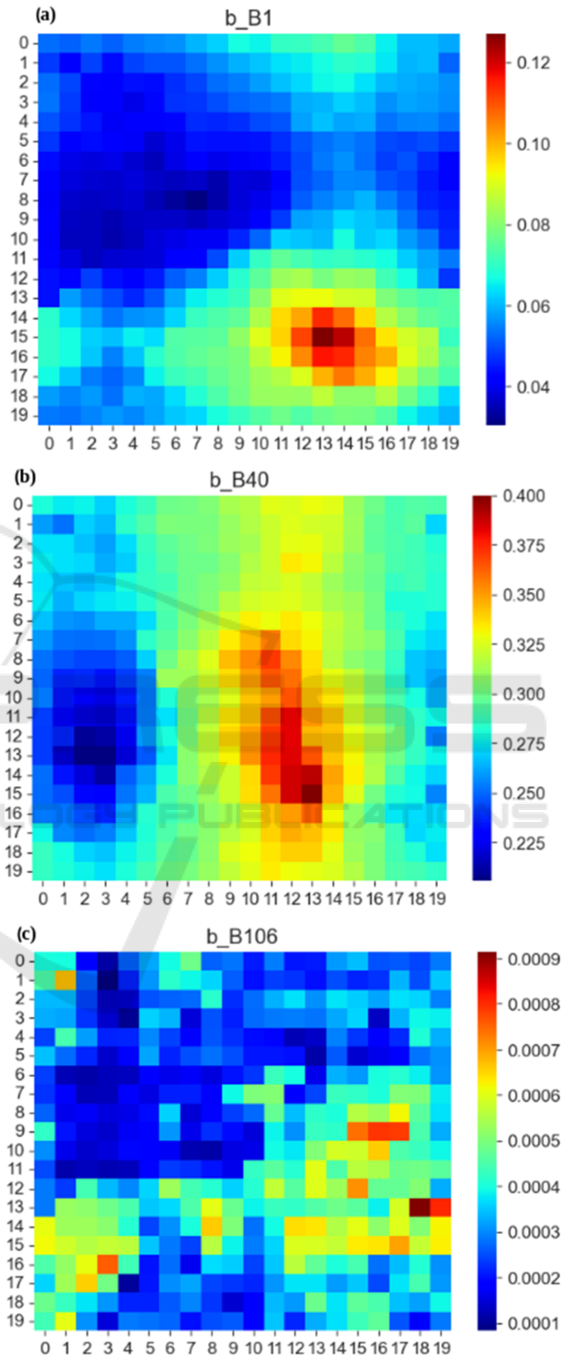

Figure 4: SOM results from geochemical sample points of PRISMA: (a-c) Example variable SOMs related to the band information (band 1, 40 and 106).

A new ensemble AI method was developed by integrating SVM, RF, and ANN to exploit different satellite-based datasets. Emphasis was given to Copernicus data (Sentinel-2), Landsat-9 and PRISMA, combining multispectral and hyperspectral images. This classifier ensemble method employed a Soft Voting strategy. The ensemble classifier shows variable performance with different input data. PRISMA data allows for better class separability, but the model tends to overfit, indicating the need for better regularisation (Figure 5).

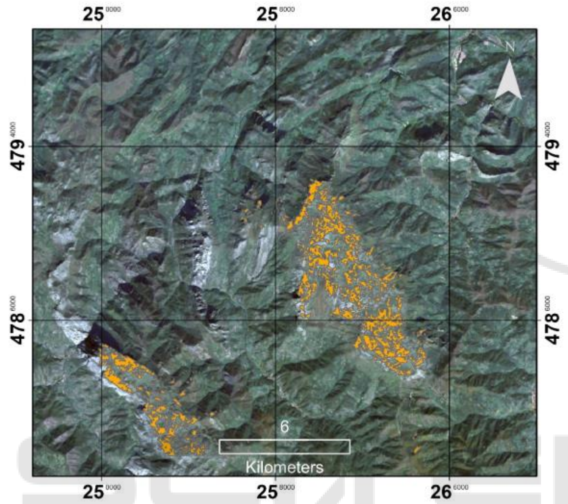

Figure 5: Examples of prediction map of hydrothermal alteration area (coloured pixels) generated from PRISMA dataset on the onshore exploration phase.

A spectral library was created, including 311 samples of outcropping rocks, 371 samples of soils, and 208 samples from the old mine in Aramo. The mineralogical associations corresponding to the outcropping rocks and soils in the Aramo Plateau, their spectral signatures in the SWIR region and their relationship with the contents of Co and other elements (Nickel (Ni) and Copper (Cu)) were determined. Although no clear spectral signature for Co was identified, the study successfully defined nine distinct spectral signatures from the 11 mineralogical associations. This could be mainly attributed to the fact that the deposit is mainly enriched in Cu, but with associated Cu and Ni. Additionally, statistical correlations between mineralogical associations and geochemical data revealed that specific associations showed a higher probability of containing elevated Co, Ni, and Cu levels.

A method was also developed for pre-processing airborne hyperspectral data. This involves converting digital counts from hyperspectral sensors into radiance values through several key steps. Geometric correction ensures that image pixels correspond to their correct geographic locations, while atmospheric correction mitigates the effects of the atmosphere, such as absorption and scattering, on the measured radiance. Additionally, spectral calibration ensures precise wavelength alignment to match known spectral features. A semi-automated workflow was implemented for the large-scale interpretation of hyperspectral data, integrating satellite, airborne platforms and UAVs, combined with ground spectroradiometer measurements to automate extracting meaningful features for geological interpretation.

A methodology for utilizing EO data from airborne and/or UAVs to develop predictive mineral maps for the Aramo plateau during the exploration mining phase was also developed.

Regarding the shallow waters pilot, a methodology was developed for identifying placer deposits using an OBIA and high-resolution satellite data. This analysis revealed distinct signatures for each material within the spectral resolution of the WorldView-3 satellite data, leading to the creation of a new band ratio for prospective deposit categorization (VNIR1-VNIR4 band ratio to identify Ilmenite) and one for determining the geological background from vegetation (VNIR6-VNIR8). Three different ML approaches are developed and compared with each other: a single-level model using the SVM algorithm, a multi-level model using the KNN algorithm, and a dynamic classification developed with a decision tree model. The outcome of implementing these methods is the production of maps illustrating the distribution of placer deposits within the coastal area of Vigo, which can be seen in Figure 6.

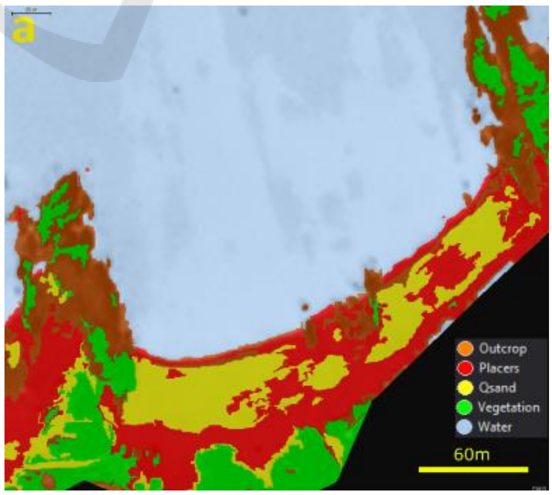

Figure 6: Examples of prediction map generated using Single-level OBIA on the WorldView-3 dataset on the shallow waters pilot.

We also applied an innovative UHI for shallow water exploration to identify potential areas for the occurrence of CRMs. UHI data was acquired with field work and refers to three different sea zones in Ria de Vigo, along with seabed samples from the same areas. The methodology centres on the Mixture Tuned Matched Filtering (MTMF) algorithm to map seabed targets by matching known spectral signatures with UHI data. It also identified sediments with spectral signatures consistent with placer deposits found on Ria de Vigo beaches.

Finally, we integrate traditional geological methodologies with EO techniques for delineating CRM prospective areas for placer deposits.

4.2 Extraction Phase

The experimental results include images at a global scale, as collected in the Sentinel-1 and -2 datasets. All models' performance was evaluated using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index Measure). The Sentinel-2 enhanced model (OGSRN) performs less than the Dense Residual-in-Residual Dense Block (RRDB) model, based on Sentinel-1 only. Overall, it demonstrated how deep learning models can improve the resolution of SAR data, showing an increase of 18% for the PSNR score and about 2% for the SSIM score compared to the corresponding baseline bicubic scores.

The Multigrid InSAR technique provides accurate measurements, with millimetre accuracy, of the ground deformations along the satellite radar line-of-sight (LOS) direction. Combining multi-band and multi-orbit SAR data, the obtained LOS displacement measurements can be profitably exploited to compute three-dimensional (3D) ground movement (Figure 7). Deformation is due to soil compaction, so the material added to the waste dump naturally keeps compacting.

The implementation of LGMSs at Gummern Mine includes two stable reference points (F1 and F3) placed on the stable ground and three observation points (ST1, ST2, and ST3), realized with metal poles, mounted in concrete pillars (Figure 8).

Based on the one-year testing period, it can be stated that LGMS performed well and detected slow movement with sub-centimetre accuracy. The results indicated that horizontal and vertical displacements of 10 and 20 mm occurred in ST1, while larger displacements were noticed in ST2, which moved 25 mm horizontally and 40 mm vertically.

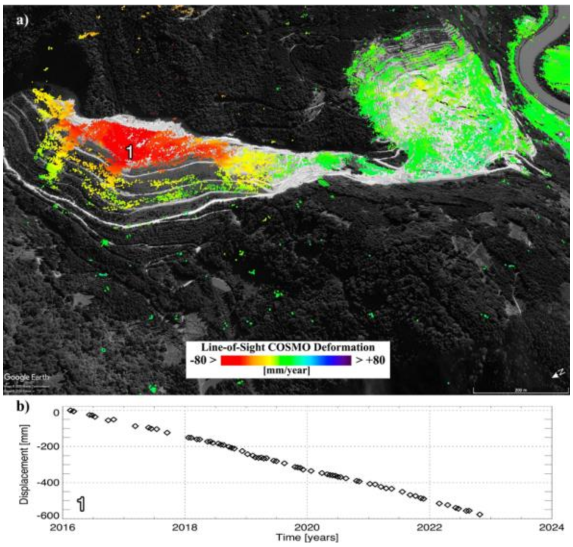

Figure 7: Gummern ground deformation map (a) and time series obtained from COSMO-SkyMed (b).

Figure 8: Locations of measuring stations.

An innovative methodology was also developed based on satellite images to continuously monitor the life and evolution of mining waste deposits. Initially, land surveying is conducted to establish ground control points (GCPs). Following this, UAV flights are undertaken to produce high-resolution DEMs. The data acquisition process involves SfM processing. The next stage involves acquiring new satellite image datasets for specific epochs. For each epoch, a different DEM and orthophoto are obtained. Comparative analysis of successive DEMs allows calculating geometric or volumetric changes in the waste dumps over time. The Pléiades Neo tri-stereo dataset was the first satellite imagery used in the study, captured in October 2023, approximately one month after the UAV flight. These images already showed notable changes in the waste dump. To compare the UAV-derived high-resolution DEM (HR DEM) with the Pléiades Neo-derived DEM, the UAV HR DEM was resampled to match the resolution of the Pléiades Neo DEM (30 cm). WorldView-2 images, taken in April 2024, six months after the Pléiades Neo tri-stereo images, provided an opportunity to study changes over a longer period. Figure 9 illustrates altitude differences between the DEM from WorldView-2 (12. 4. 2024) and the DEM from Pléiades Neo (1. 10. 2023). The volume changes in the areas where waste dumping occurred are summarized, with a total discharge volume of 101,872 m³.

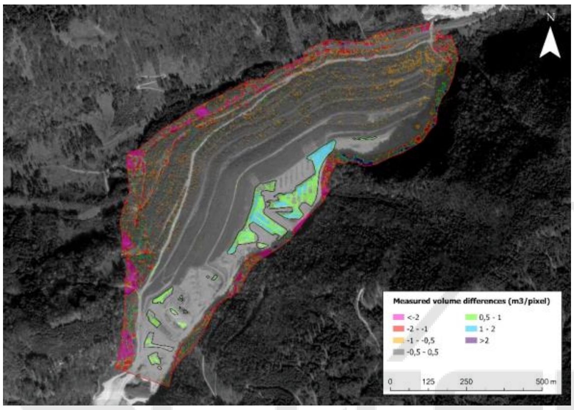

Figure 9: Volumes of waste dumps between 12. 4. 2024 (DEM from Pléiades NEO) and 1. 10. 2023 (DEM from WorldView 2).

4.3 Closure and Post-Closure Phase

Several ML algorithms were adapted to enhance pixel classification of AMD from Sentinel 2 imagery (Lausitz and Outokumpu) and also using space- and airborne- multispectral and hyperspectral imagery. SOM was also utilized to visualize and cluster high-dimensional data to interpret complex spatial data for AMD mapping. The study also evaluates the potential of spaceborne hyperspectral imagery for AMD mapping.

We also proposed ML algorithms, including RF, KNN, Logistic Regression (LR), and MLP. They are used to perform a pixel-based classification of the images into AMD or non-AMD classes, as well as to assess the severity of AMD by quantitative mapping of AMD constituents, such as iron concentration and pH values. The prediction map for three lakes in the Outokumpu area is shown in Figure 10. The visualization indicates that the RF model accurately classified the pixels, as the lakes were primarily contaminated by AMD rather than coastal areas.

Additionally, the SOM method was also used to visualize and cluster high-dimensional data, simplifying the understanding and interpretation of complex spatial data for AMD mapping. The output of the SOM method is grid data, such as heatmaps or U-matrix plots, which provide insights into the clustering and organization of the data within the grid. The main objective was the identification of AMD-affected areas. These experiments were conducted in three lakes located in Outokumpu, Finland.

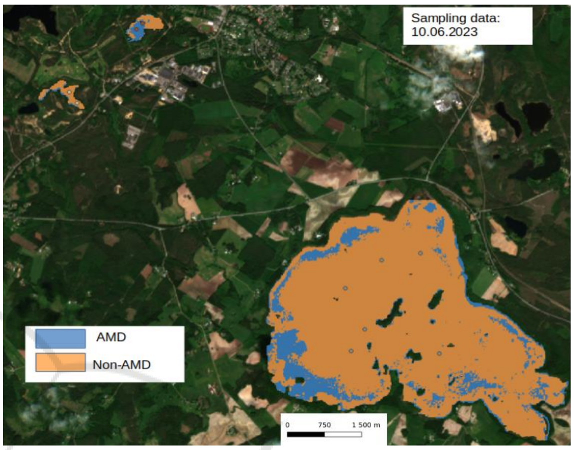

Figure 10: Prediction map of the best model (RF) for three study lakes and their water samples in Outokumpu.

Finally, we perform cross-sensor analysis over water bodies to harmonize Worldview-3 and UAV multispectral datasets to Sentinel-2. Given the free availability of Sentinel-2 data and the typically high costs of high-resolution commercial EO datasets, we propose a methodology where MLP is trained using Sentinel-2 data over a large area in conjunction with extensive geochemical monitoring data and the established dependencies are applied to commercial high-resolution datasets for targeted identification of AMD in specific areas. This approach enables a cost-efficient combination of free-of-charge and commercial EO datasets for AMD mapping.

Despite the cessation of mining activities, a sudden ground collapse in February 2017 near the Aijala refinery highlighted ongoing environmental risks, demonstrating the need to monitor post-closure mining sites continuously. SAR image coherence measures how similar two radar images of the same area are, taken at different times. For the temporal decorrelation analysis, we proposed calculating a new index, the Normalized Decorrelation Change Index (NDCI), presented in Figure 11. The method's effectiveness was validated by comparing results with

Sentinel 2A images and relevant background information about the Aijala site.

Figure 11: NDCI depicting ongoing high disturbances in the Aijala post-closure site between 2015-2017.

5 CONCLUSIONS

In this work, we present the preliminary results of the S34I HORIZON project. At the moment, the methods are being validated and verified in the pilots and also with the end-users.

Based on the methods developed under the scope of S34I, we prototyped EO-based services that cater to the specific needs of mining stakeholders. These services aim to address three key areas:

1. RM Deposits Mapping: This involves using EO data to identify and map potential mineral deposits, both on land and in shallow waters.
2. Early Warnings: The focus here is on developing EO-based systems that can provide early warnings of potential hazards at mining sites, such as ground instability.
3. Environmental Monitoring: This encompasses the use of EO data to monitor the environmental impact of mining activities, such as the detection of AMD.

In the future, these services will be available for the stakeholders and end-users.

The result of this project will be an important step forward in monitoring all phases of the mining cycle using EO data, contributing to more sustainable mining practices.

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