# Hyperspectral sensing to boost mine waste characterization and water monitoring

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## Abstract

In this contribution, we explore the use of hyperspectral (HS) sensing, as a tool to monitor post-mining landscapes facing acid mine drainage (AMD). Emerging hyperspectral sensors can complement such monitoring by rapidly characterizing soil and water bodies at multiple scales. We propose a workflow to integrate hyperspectral visible to near-infrared (VNIR) data with mineralogical and geochemical data from a few specimens to precisely map the extent of acid mine drainage using machine learning algorithms. The resulting maps include the semi-quantified concentration of dissolved metals, physicochemical properties in water bodies, and associated AMD minerals sub-products in different post-mining scenarios.

**Keywords:** hyperspectral imaging, remote sensing, machine learning, unmanned aerial system, acid mine drainage, post-mining

## Introduction

Large quantities of mine wastes, such as waste dumps, slurry ponds, tailings and metallurgical wastes, are generated during the recovery of raw materials from primary mineral deposits (Hudson-edwards et al. 2011). Such facilities are quite heterogeneous compared with other industry sectors due to their quantity, mineralogical formation, and their properties. The composition changes depending on the type of mineral processing and the enrichment chain applied. Lottermoser (2010) defines Acid mine drainage (AMD) as a process whereby low pH mine water is formed from the oxidation of sulfide minerals. AMD can occur in these waste facilities and if superficially dumped, when iron sulfide in coal mines or sulfur in base metal mines, can undergo into oxidation conditions (Dold 2017). With the removal of ore from the ground exposure of sulfides to water and oxygen in air takes place; in turn, the oxidation processes of pyrite FeS2 associated with iron, coal, and sulfur deposits can produce an acidic environment (Lottermoser 2010).

As a result of these acidic and metal concentrated waters, the natural ecosystem and aquatic life can suffer. Mainly impacted areas are rivers, lakes, estuaries, and coastal waters. Its advancement can take years or decades and can continue spatially increasing for centuries (Lottermoser 2010). Hence, such environmental concern must be monitored carefully and, ideally remedied. Many efforts have been applied in order to monitor the spatial distribution of contamination by AMD, commonly involving systematic sampling and laboratory analysis of stream sediment followed by interpolation of the results in assembled distribution maps ((Ferrier 1999); (Kemper and Sommer 2002)) however, such approaches can be time-consuming, costly, and with limited spatial coverage.

Regular and multi-temporal monitoring is required for such complex and diverse adverse effects on Earth ecosystems. Active control can serve as an effective method for successful conservation or rehabilitation of natural systems. In this sense, remote sensing tools have been widely used in many environmental investigations since the technique enables the use of digital imaging sensors to reveal key information from a distance (typically from satellite or aircraft) (Christopherson et al. 2019). Thus, traditional monitoring studies based only on certain ground-sampling locations can be extended to large areas from derived aerial-image products. In general, optical spectral analysis refers to the measurement of matter-light interactions as a function of their energy. More specifically, this comprehends any radiation that is emitted, reflected or transmitted from the investigated target (Clark 1999). The development of new generations of sensors made it possible to examine processes on earth, beyond the visible spectrum of the human eye. Commonly, these devices can acquire data in different wavelength ranges (from the ultraviolet to the far-infrared spectrum of electromagnetic radiation) and have evolved from spectral over multispectral to hyperspectral sensors for different kinds of earth's surface investigations. Currently, hyperspectral sensors are employed in a wide range of spatial dimensions (scales) according to the platform used for data acquisition (e.g., satellite, airborne, up to lab-scale sensing for detailed-mineralogical analyses) (Figure 1). The emergent use of unmanned aerial systems (UAS), like multi-copters, and new-generation lightweight hyperspectral sensors have become a tool to collect data at a higher spatial resolution than some of their aircraft and satellite counterparts, resulting in greater precision (higher spatial resolution of a scene and enabling the investigation of up to a few centimeters sized pixels) (Booysen et al. 2020).

## Methods

### *Hyperspectral Imaging*

The main goal of hyperspectral remote sensing (also known as imaging spectrometry or imaging spectroscopy) is to measure quantitatively the components of the Earth System from calibrated (radiance, reflectance or emissivity) spectra acquired as images in many, narrow and contiguous spectral bands (van der Meer et al. 2012)). Collected data results in a three-dimensional data-cube composed of a set of pixels (represented as vectors), containing the measurement corresponding to a specific wavelength (Benediktsson and Ghamisi 2015). This provides the opportunity to query a plottable spectral signature for each spatial position on a surface. The accompanying amount of information results in much larger data sizes compared to polychromatic or multispectral imagery (Lorenz 2019). The vector size is equal to the number of bands or spectral channels. In opposition to multispectral data, which usually acquire up to tens of bands, hyperspectral data channels are able

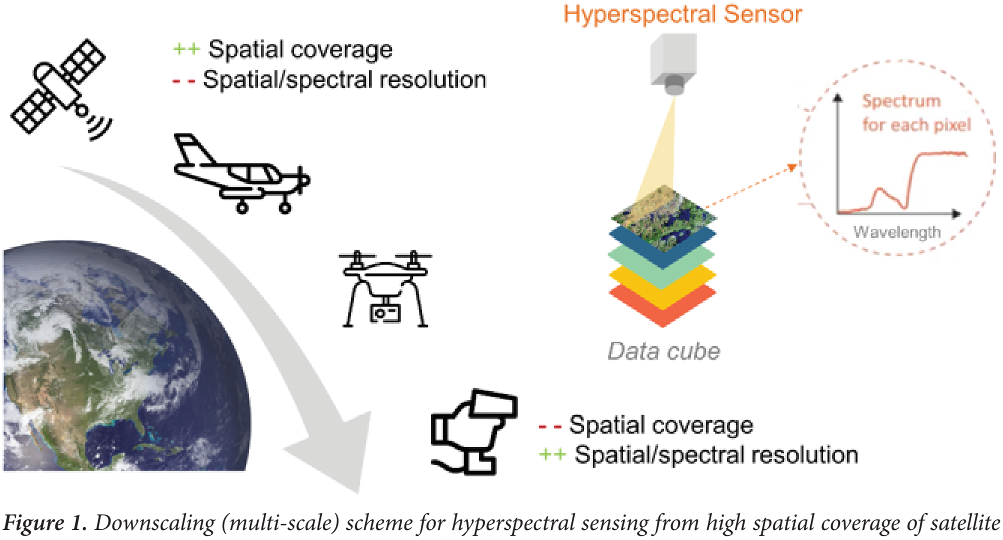


***Figure 1.*** *Downscaling (multi-scale) scheme for hyperspectral sensing from high spatial coverage of satellite based sensors to high spectral resolution of drone-borne/ terrestrial sensors and hyperspectral data cube scanning general concept (Modified from(Flores et al. 2022)).*

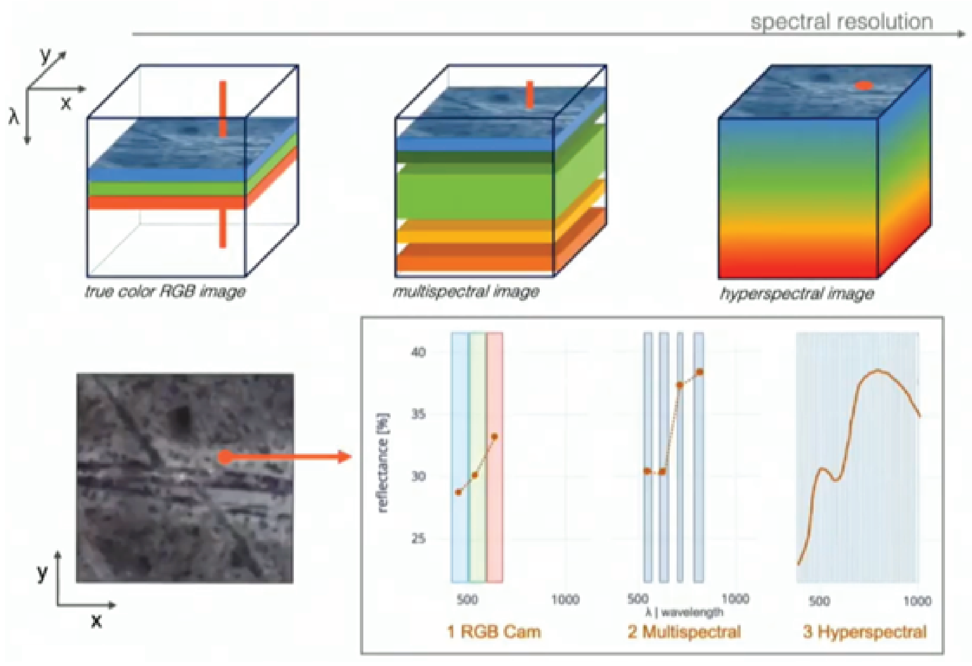


***Figure 2.*** *Schematic examples on different levels of dimensionality of spectral data with x, y, λ being x and y the spatial and λ the spectral (Modified from (Lorenz 2019))*

to collect several hundreds of contiguous bands along the spectral axis (van der Meer et al. 2012). Regardless the scale of acquisition, hyperspectral sensors bring higher spectral resolution, in comparison to multispectral sensors, offering higher accuracy to detect targets and characterize earth surface processes. In Figure 2, it is possible to distinguish the differences between a common Red Green Blue (RGB) composite, a multispectral dataset and the hyperspectral. The visualization format of any spectral dataset is similar, regardless the covered wavelength range, scanned specimen or area, and the spectral process underlying. A spectral imaging dataset is composed by three dimensions with at least one, even indistinct, value defining the measured signal intensity along at least two spatial and one spectral axis (Lorenz 2019).

A general workflow strategy is proposed in Figure 3. The methodology involves the integration of two main datasets and can be adapted to different scales of acquisition. The spectral data cube and state-of-the-art geochemical analyses over certain samples (ground validation/training data) are then fused using machine-learning techniques. In this article, two studies at different scales of acquisition are reviewed, in which different mapping algorithms have been applied to provide high-resolution maps of sediments, hand specimens, drill-cores and water bodies to quantify and monitor AMD extent.

## *Data Acquisition and Processing*

Acquisition parameters and set-up will vary according to used hyperspectral sensors, manufacturer, size dimensions and spectral range coverage. Particularly, the visible to shortwave infrared electromagnetic range has been widely used to monitor AMD mineralogy at mining surroundings since iron and also REE present strong and narrow absorption features in the visible to near infrared (VNIR). In any case, acquired hyperspectral images need a series of pre-processing steps in order to get worthwhile hyperspectral information out of the raw image. While laboratory scanning is usually only radiometric corrected (using dark and white calibration), aerial original data could

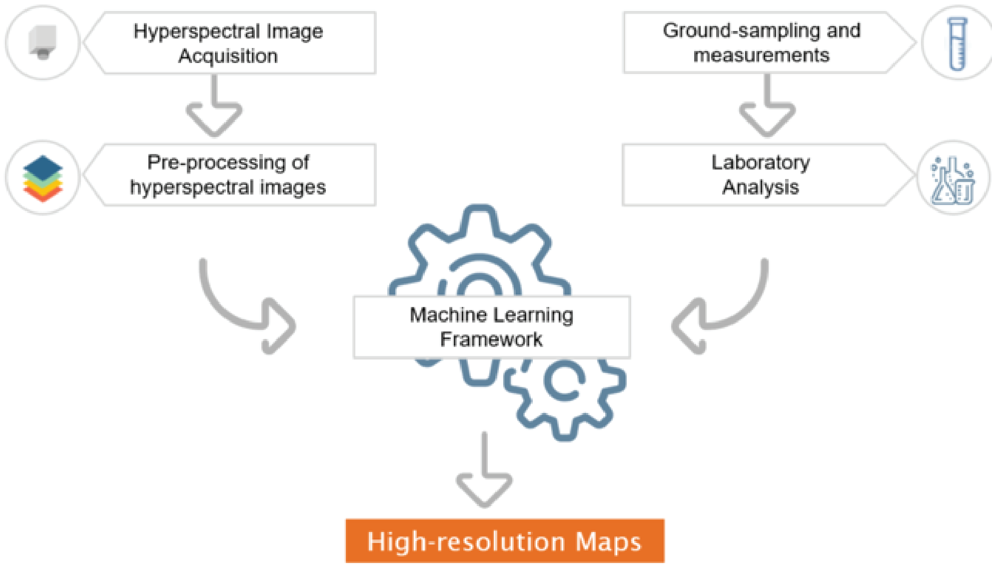


***Figure 3.*** *Proposed general workflow for integrated hyperspectral mapping.*

be affected by many other factors, such as constant movement of the platform and, the effect of the microrelief on illumination and viewing angle. The series of procedures developed by (Thiele et al. 2021) in the open source python-based *hylite* tool deals with the mentioned issues and has been used in some of the reviewed multi-scale studies.

### *Sampling strategy and analytics*

In general all hyperspectral surveys, should be accompanied by validation campaigns, in where point spectral measurements have to be done in discrete and strategic spots of the investigated area, as well as the incorporation of further geochemical/mineralogical datasets to support the spectral method. Sampling is tailored to the target to be mapped: surface water or drainage, sediment, drill-core or waste dump material. The representability of scene elements should be considered as well as the notable optical and morphological differences. Once specimens are collected, can be taken to the laboratory for specific analyses of geochemistry and mineralogy (rock, sediments) and elemental composition (water) which then are integrated into the mapping as training data-sets. Local samples, on-site spectral point measurements or reference spectral libraries (e.g., United States Geological Survey (USGS) Spectral Library) and analyses are the basis for the accuracy of hyperspectral studies, hence the importance of their correct collection, preservation and preparation up to analysis.

### *Machine learning as mapping tool*

Corrected hyperspectral image mosaic in radiance is subsequently processed using machine learning algorithms which pursues the integration of the performed validation analysis (e.g., geochemical, hydrogeochemical, mineralogical) with the HSI data of the target area or material. In order to improve the speed and accuracy of such data analysis, machine learning algorithms such classification and regression has been suggested in different scientific fields in the last decades (Acosta et al. 2019). Normally, the number of known observations is limited (i.e., training data), the goal of a classification system is to learn the characteristics of a set of predefined classes and assign a unique class label to each unknown data sample (Acosta et al. 2019). Machine learning techniques provides automatic approaches to discover underlying relations within both the HSI dataset and validation studies. For the proposed workflow, supervised classification and regression can be applied for mapping acidic environments (Flores et al. 2021).

## Results

In this section, we present two recent study cases in which the proposed mapping workflow have been applied in post-mining scenarios. The first have been used to monitor acidic environment surrounding mining legacies in the Iberian Pyrite Belt, Huelva, Spain (Flores et al. 2021), and the second study case is part of the European Union Horizon 2020 project TRIM4Post-mining (Benndorf et al. 2022) in which together with other near spectral sensors, hyperspectral imaging is used as tool for mine waste characterization along the life cycle (from operation area to waste dump) of coal mining operations Leipzig, Germany.

### *UAS scale*

Unmanned aerial system (UAS) or more commonly known as drones represent an emerging tool in environmental monitoring. In regard to AMD, (Jackisch et al. 2018) implemented HSI for high-resolution, multi-temporal mapping of proxy minerals for AMD in the Sokolov lignite region, Czech Rebublic. Most recently, mapping water bodies has been subject of hyperspectral research by (Flores et al. 2021) where the hydrogeochemical properties (pH, redox, Electro Conductivity and iron concentration) to assess the extent of AMD in Odiel and Tintillo waters (Figure 4A-B) have been mapped. In this study, several techniques have been combined to produce high resolution maps (Figure 4 C-D)), a machine learning approach using random forest regression (Figure 4D) was applied to fuse geochemical data using in-situ stations as training data at the field, with the hyperspectral dataset and mineralogical map over the river bed sediments for secondary iron minerals (e.g., goethite, jarosite, schwertmannite).

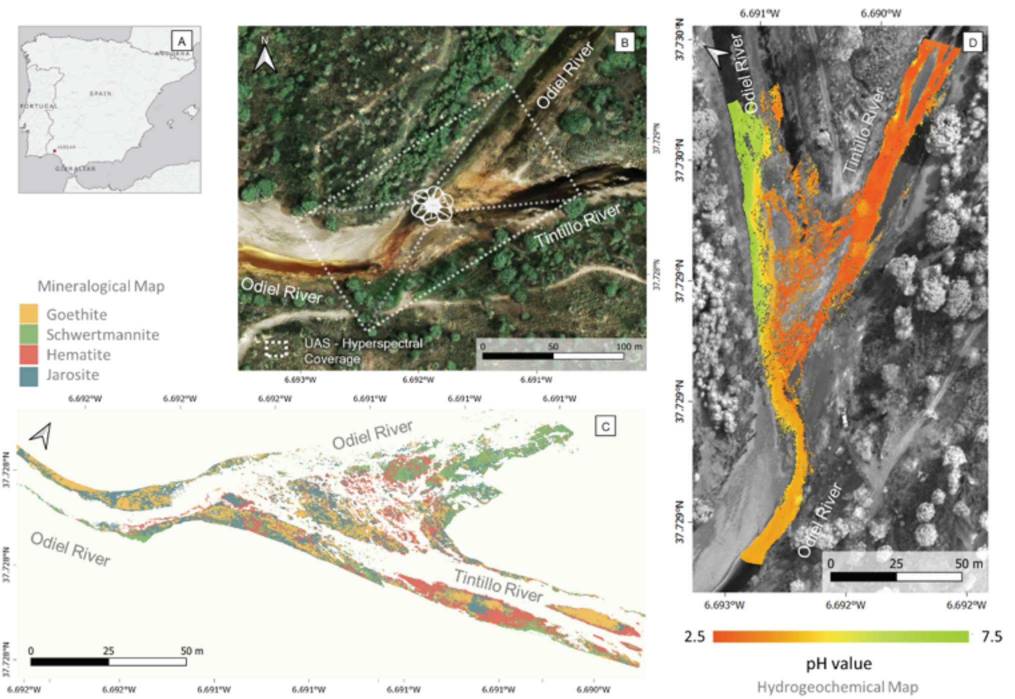


*Figure 4. UAS-Hyperspectral environmental monitoring. (a) Location of the investigated area in the Odiel River (Huelva, Spain), (b) spatial coverage of hyperspectral survey (c) mineral classification map using Spectral Angle Mapper over river sediments (d) Hydrogeochemical map using regression over river flow path (Modified from (Flores et al. 2021))*

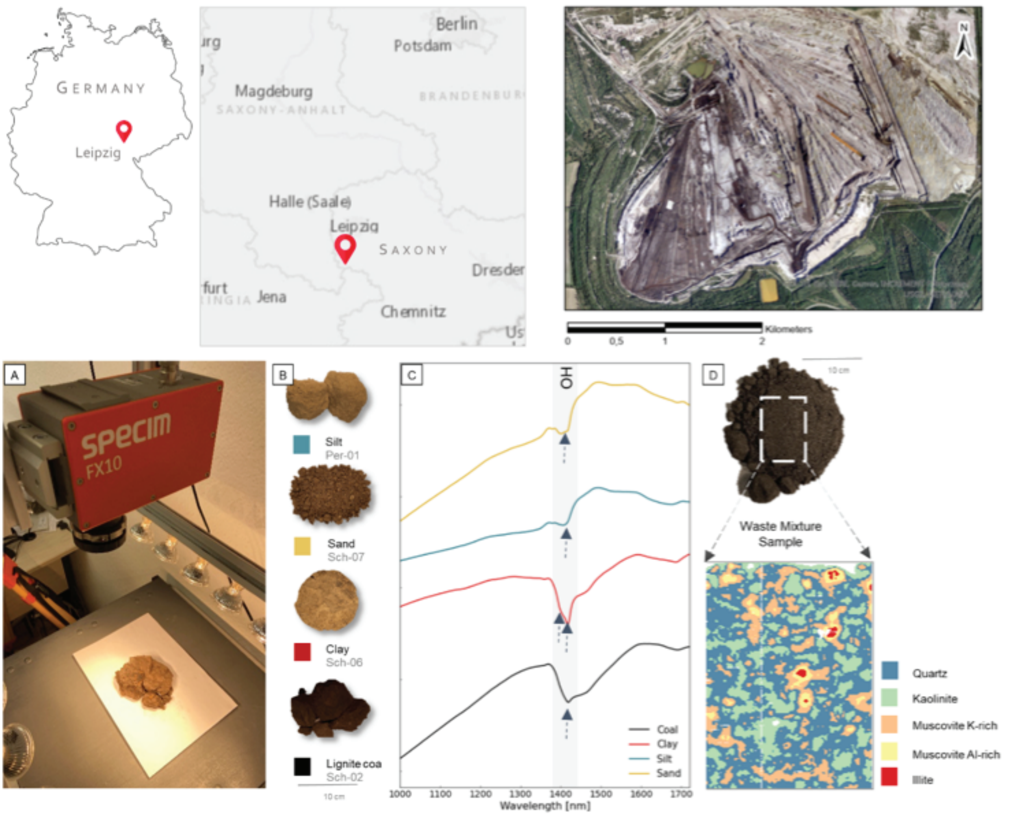


*Figure 5. Spectral mapping using supervised classification for waste samples in Schleenhain and Peres dump areas for the TRIM4Post-Mining EU Project (Leipzig, Germany). (a) Sensor assembly at TU Bergakademie Freiberg, Department of Mine Surveying and Geodesy, Germany, (b) identified main lithologies (hand samples), (c) spectral profile of the main lithological groups in the mine (blue arrows shows different absorptions features for each group at 1400 nm) and (d) waste mixture sample and supervised classification map.*

### *Laboratory scale*

The TRIM4Post-Mining project (Benndorf et al. 2022) demonstrated the versatility and cross-scale application of hyperspectral sensors. In this project, a processing chain is being developed to analyze samples from a lignite dump. The goal is to obtain a high-resolution characterization of the mine materials throughout the life cycle of the mine and to detect both potentially acid-forming and buffering minerals. Figure 5 shows the laboratory setup for hyperspectral data acquisition (Figure 5A), the major lithologies for the case study (Figure 5B), followed by spectral interpretation and mapping recognition in one of the pit waste samples (Figure 5D) showing the major mineral facies discovered. Data acquisition was performed using the hyperspectral sensors of the project partner (TU Bergakademie Freiberg). Data processing, pre-processing, spectral analysis and predictive mapping are performed at the Research Center of Post-Mining in Germany. The detailed mineralogical information collected in this step is critical for subsequent geochemical modelling incorporating other data sets. This will allow mine operators to better plan reclamation activities and manage acidic wastewater generated in tailings ponds, on the efforts of finding the best post-mining scneario.

## Conclusions

With the high demand for raw materials comes the waste generation and the perpetual tasks associated with efficient post-mining management and risk supervision. In this sense, accurate and constant monitoring on terrain or vegetation cover of spoil banks is often required for two different reasons in post-mining management: (i) to monitor and prevent adverse effect of hazards; and (ii) to assess restoration success. Hyperspectral data brings several advantages as a complement to traditional environmental monitoring studies. The development towards lighter and smaller sensors, allows easier incorporation of hyperspectral technology into different stages of mine waste management. It could be used, rather during active mining to identify potential lithologies hosting minerals prone to AMD and forecast adverse effects, or in post-mining scenarios to target affected areas and continuous monitor restored areas. While laboratory HSI analysis, allows fast scanning for mineralogy identification of AMD drivers at different stages of the mine life cycle, UAS mapping compared to traditional ground surveying represent a reduction in the time employed on acquiring data. It allows reaching locations that may be difficult to access, under protected status or that involve personal security risks for terrestrial-sampling. Regardless the scale, hyperspectral sensors allow repeatability and recurrent data-acquisition. Therefore, multi-temporal analysis are feasible and may allow constant monitoring of sensible ecosystems.

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