Mapping of iron and steelwork by-products using close range hyperspectral imaging:
A case study in Thuringia, Germany

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Abstract
This paper presents the first use of close range terrestrial hyperspectral imaging to explore by-products from the iron and steel industry at a dump site cross section, using established mapping approaches in geological remote sensing. Laboratory reflectance measurements, X-Ray diffraction and chemical analysis provided a benchmark for the imaging results. In addition, terrestrial laser scanning was applied to create a high resolution 3D model of the studied section, for hyperspectral image and classification integration. Results demonstrate the applicability of spectral methods for remote discrimination and mapping of materials from iron and steel production which are of potential economic interest. This will aid the appraisal of resource distribution for urban mining and material recycling.

Keywords: Iron and steelwork materials, dump sites, reflectance spectroscopy, hyperspectral imaging, terrestrial laser scanning.

Introduction
The importance of raw materials and their availability for industry and the economy is an ongoing issue that has been debated by scientists, engineers, economists and policy makers at many levels of society. Furthermore, raw materials become increasingly difficult to acquire, prices fluctuate, and the availability of resources may change through time [Klinglmair and Fellner, 2010; Kaiser et al., 2012; Drobe and Killiches, 2014]. These issues concern a wide variety of primary materials, leading to increasing demand and supply shortages [Graedel, 2010; Huy et al., 2012; Kaiser et al., 2012]. To reduce imports and unpredictability associated with the global market, international and national initiatives have been launched to exploit new resource deposits, with special focus on identifying pre-existing anthropogenic metal stocks and recycling strategies for those materials [Faulstich, 2010; Graedel, 2010; Kaiser et al., 2012; Krook and Baas,
These stocks include former dump sites of secondary products and residue from metallurgical smelting processes, such as slags, sludge and ashes from the iron and steel industry, and which can bear economically important quantities of metals and other materials [Faulstich, 2010; Jandewerth et al., 2013].

The deposition and distribution of industrial by-products in dump sites is different to those of naturally-occurring rocks and minerals and cannot be compared to natural depositional environments, such as those studied in outcrop geology (e.g. [Enge et al., 2010]). By-products from iron and steel production are heterogeneous in their composition, caused by different slag formers, raw materials and production methods. As slags and other by-products from blast furnaces and steelworks are results of various smelting processes with different operational conditions and subsequent alteration with time, they can be termed “industrial” or “anthropogenic” rocks. As such, they exhibit similarities to magmatic or igneous rocks, though with differences in their mineralogical and chemical composition [Drissen, 2004]. Apart from the by-products themselves, the treatment and deposition technologies also changed over time as a result of technological progress [Jandewerth et al., 2013].

The current disposal of iron and steelwork by-products is realised systematically and following legal regulations. However, in many cases the historic treatment and deposition of such materials on dump sites is not well-documented or known, resulting in uncertain distributions of materials, especially from areas representing older production phases of a dump site. For that reason, historical maps and archives must be studied, and knowledge from local experts is important in order to detect areas relating to material layers of specific interest [Jandewerth et al., 2013]. In addition, field appraisal and mapping may be difficult, as layers tend to be similar in visual appearance but can be different in terms of mineralogical and chemical properties, or vice versa. Steelwork dump sites may also contain refractories, construction waste, excavated soil or other materials that are not by-products and which make the overall material composition even more heterogeneous.

Due to the above difficulties associated with dump site characterisation, new approaches are being explored to analyse both historical and current dump sites, spoil heaps and discarded secondary industrial products. These aim at identifying and mapping layers of economic interest against a background of economically unimportant materials, in order to benefit raw material recovery and reduce analysis costs for potential reuse or recycling of industrial by-products [Faulstich, 2010; Jandewerth et al., 2013].

As a non-contact means of identifying material types and distributions, remote sensing methods are well-established for ore prospecting, exploration of natural deposits, mineral mapping and detection of hydrocarbons [van der Meer et al., 2012]. Hyperspectral remote sensing refers to the recording of several hundreds of spectral bands across wide parts of the electromagnetic spectrum in the visible (VIS), near (NIR) and short wave infrared (SWIR) (typically 350-2500 nm) [van der Meer et al., 2012]. Most minerals show diagnostic absorption features in the SWIR caused by vibrational processes, or at VIS and NIR wavelengths due to electronic processes in the mineral lattice [Hunt, 1980]. These processes result in specific spectral signatures that can be used for identification and mapping purposes [Hunt, 1977; Clark et al., 1990a; van der Meer et al, 2012]. Relevant to the current study, anthropogenically influenced landscapes and materials have also been
studied using hyperspectral methods, including tailings and post-mining landscapes, acid mine drainage phenomena and accidents involving toxic industrial waste [Swayze et al., 2000; Kemper and Sommer, 2002; Gläßer et al., 2011; Zabcic et al., 2014]. Until now, most hyperspectral remote sensing has been conducted using airborne and spaceborne imagery. However, a recent trend is the application of hyperspectral imaging at close range, with field-portable equipment, which is increasingly used in outcrop geology [Kurz et al., 2012, 2013] and mining [Murphy and Monteiro, 2013]. Despite the growing diversity of hyperspectral applications, only a small number of studies have previously been carried out to characterise materials from the iron and steel industry [Picón et al., 2009; Gutiérrez et al., 2010; Rodriguez et al., 2010]. The contribution of this paper is therefore the assessment of a non-contact and high-resolution method for assessing the spectral properties and mapping the distribution of material found in an older part of a steelwork site in Thuringia, Germany. In addition, the use of terrestrial hyperspectral imaging to thematically map the spatial distribution of potentially reusable materials at such dump sites is a novel application and can be seen as a first feasibility study that is timely in terms of society’s drive to manage resource use. While a comprehensive knowledge base of the spectral properties of rocks and minerals exists in established spectral libraries (e.g. USGS or ASTER [Clark et al., 2007; Baldridge et al., 2009]), only limited information concerning the spectral characteristics of iron and steelwork (by-)products has previously been reported. Consequently, the paper incorporates analysis of such material using spectrometer reflectance measurements, supported by conventional laboratory methods (X-ray diffraction, XRD; and chemical analysis), to gain a further impression of the spectral responses and to build a spectral library of the different materials found at the study site. In addition, integration of 3D terrestrial laser scanning (lidar) data combined with conventional digital imagery is used as a spatial framework for the hyperspectral data, allowing novel fusion products for processing and validating spectral results.

Materials and methods

Study site and sampling strategy

The chosen study site represents a dump site of an iron and steel plant, today an electric steel work, at Unterwellenborn, Thuringia, Germany. This site has been used for iron and steel production since 1872 [Jandewerth et al., 2013]. During this time, technological progress has led to changes in production technologies and associated variations in by-products deposited at the dump site. Today, parts of the dump site have been recultivated and are covered by vegetation, while other areas are still used as disposal sites from current production. In this study, we focused on an area of the dump site where an access road had been cut, exposing a cross section through earlier disposed material. The cross section (Fig. 1) shows a wide variety of different layers from past production phases, and has dimensions of approximately 45 m in the horizontal direction and 2 m to 8 m in the vertical direction. Near the centre of the exposed section, a distinctive trough-like structure is visible, most likely related to infill from eroded material near the trough’s margin.
Fieldwork was carried out in June 2013. Retro-reflective markers were placed on the exposed cross section, so that areas of interest for spectral measurement and laboratory analysis could be identified. After the spectral measurements were completed, physical samples for laboratory analysis were collected directly beneath the reflective targets. Only very limited reference information was available about the material deposited at this site. Consequently, sampling was conducted based on visible layers, and differences in texture and colour, in order to represent the material heterogeneity as well as possible. In addition to the sampling points, six piles of secondary products were placed at the foot of the exposure (Figs. 1 and 2). These artificial piles represented materials of known economic interest and typical by-products found throughout the greater dump site, but which were not visibly identified on the studied section during fieldwork, and which were not present simultaneously in other exposures on the site. Placing the piles artificially allowed the spectral properties of materials of known economic interest to be studied in situ and in comparison to other typical material found on the dump site. The piles contained the following materials: mill scale from current steel production, which is already being reused; red converter sludge from past production procedures; scrap metal; electric arc furnace (EAF) slag from current production (one pile with coarse fraction, ~10-15 cm diameter, and one with less coarse fraction, ~5-10 cm diameter); one pile of ladle furnace (LF) slag from current production.
Mineralogical and chemical analysis
Mineralogical and chemical analysis was carried out on selected samples, to better characterise the materials at the study site. Because visual inspection of the exposed area was not necessarily representative of the actual material content distribution, such methods were required in order to assess the composition of the various by-products and to create a basis for interpretation and validation of the spectral measurements. Mineralogical characterisation of the samples was realised by XRD analysis using a PANalytical X’Pert PRO powder diffractometer and Cu Kα radiation. Minerals were identified utilising a Powder Diffraction File (PDF-1) from the International Centre for Diffraction Data (Swarthmore/USA, 2002, http://www.icdd.com/). Information on the element composition was provided by using inductively coupled plasma optical emission spectrometry (ICP-OES, apparatus by SPECTRO [ISO 11885, 2009]).

Non-imaging reflectance spectroscopy
To support the hyperspectral image analyses and classification, reflectance measurements were carried out using an Analytical Spectral Devices (ASD) FieldSpec® Pro FR spectrometer. This spectrometer covers a wider spectral range (350-2500 nm) than the HySpex SWIR-320m which was used for hyperspectral imaging, at a higher spectral resolution, and with sampling interval 1.4 to 2 nm, depending on the wavelength range [ASD, 2002]. Because it was not possible to reach all sampling points with adequate measurement orientation in the field, the reported spectrometer measurements are restricted to those carried out in a laboratory setting. Laboratory measurements were performed under controlled conditions in a spectroscopy chamber with black painted walls to prevent diffuse reflectance. An ASD Pro Lamp with a 50 W bulb served as light source. The incident angle of the illumination was 45°. The distance from the fibre optics to the sample surface was about 15 cm, resulting in a measurement diameter of ca. 6.6 cm. Fresh samples were used in order to avoid drying out and to prevent the formation of new minerals. In addition, no sample preparation was conducted to ensure the materials could be compared as closely as possible with the field situation. All reflectance measurements were made relative to a Spectralon® reflectance standard with an overall brightness of ~99 %. Preprocessing of the spectra included averaging and correction of splices caused by the three separate detectors within the spectrometer. Finally, all acquired spectra were compiled within a spectral library and analysed for reflectance intensities, the general shape and mineral absorption features, which were compared to reference mineral spectra from the USGS and ASTER spectral libraries [Clark et al., 2007; Baldridge et al., 2009] and further references. To support spectra analysis, continuum removal normalisation was applied to the spectra to highlight absorption features or introduce features that are hardly visible otherwise. The algorithm transforms a convex hull that covers local maxima in the spectrum to a reference baseline and thus normalises absorption features [Clark and Roush, 1984; Clark et al., 1990b; van der Meer, 2004].

Hyperspectral imaging: acquisition and image classification
Hyperspectral imaging was realised using a HySpex SWIR-320m hyperspectral scanner from Norsk Elektro Optikk [NEO, 2015]. This instrument covers the SWIR region (1300-2500 nm), which is suitable for geological and mineralogical remote sensing applications,
as most minerals show diagnostic absorption features in this wavelength range [Clark et al., 1990a; Clark, 1999; van der Meer et al., 2012]. The instrument has 320 spatial pixels in a line and 240 spectral bands, and a sampling interval of 5 nm [NEO, 2015]. For field measurements, the HySpex sensor was mounted on a tripod equipped with a rotation stage. Spectralon® reflectance panels with brightness levels of ~99% and ~50 % were placed on the exposed section for the later correction of the hyperspectral images.

Processing of the raw image data included the transformation to at-sensor radiances, bad pixel correction and correction to relative reflectance data using Spectralon® panels. A detailed description of the general preprocessing steps required for terrestrial hyperspectral images can be found in Kurz et al. [2013]. Savitzky-Golay filtering was applied to the hyperspectral images to reduce noise in the spectral signatures [Savitzky and Golay, 1964; Tsai and Philpot, 1998]. Subsequently, pixels unrelated to the material of interest (e.g. reference panels, retro-reflective targets, vegetation) were masked in the hyperspectral images and excluded from further analysis (Fig. 3).

Maximum noise fraction (MNF) transformation was applied to the hyperspectral imagery in order to decorrelate the data, segregate noise and reduce data dimensionality [Green et al., 1988; Boardman et al., 1994]. The resulting coherent MNF bands are considered to contain most of the variance within the HySpex data (first 10 to 15 bands). The analysis of MNF results and the combination of MNF bands as RGB colour composites has proven to be valuable for a first interpretation of the image content and end-member derivation in hyperspectral geological studies [Harris et al., 2005; Kurz et al., 2012; Kurz et al., 2013]. Thus, singular MNF bands and several band composites (one example of band composites is given in Fig. 3) were used for an initial analysis of the hyperspectral data in order to guide end-member selection for image classification in combination with supplementary laboratory spectrometer and mineralogical and chemical analysis.

![Figure 3 - False colour composite of MNF bands 1, 2 and 5. Black areas are masked.](image)

To map the spatial distribution of the different materials at the cross section, two established classification methods were used: Spectral Feature Fitting (SFF) and Spectral Angle Mapper (SAM) [van der Meer et al., 2012]. The SFF approach compares the absorption features found in the image pixel spectra to given reference spectra after continuum removal normalisation [Clark and Roush, 1984; Clark et al., 1990b; van der Meer, 2004]. Here, the Multi Range Spectral Feature Fitting method was used, which allows the user to manually and interactively select absorption features for different end-members [Pan et al., 2013]. To remove singular pixels in the results and improve the interpretability, post-classification methods were applied.
SAM determines the similarity between a given reference spectrum and an imaged spectrum by representing them as vectors in n-dimensional space and calculating the angle between each vector. A lower angle represents a higher degree of spectral similarity. This method was used as it takes the overall spectral shape into account and not only specific absorption features, and it is relatively tolerant to differences in reflectance intensity [Kruse et al., 1993].

**Terrestrial laser scanning and hyperspectral image registration**

In order to build a geometric framework for the study site, to highlight hyperspectral classifications and to allow a clearer interpretation of the results, terrestrial laser scanning (lidar) was performed using a Riegl LMS Z420i [Riegl, 2014]. A calibrated Nikon D100 digital camera was mounted on top of the scanner, allowing captured RGB photographs to be registered with the laser data [e.g. Buckley et al., 2008]. Three scans were collected to ensure complete coverage of the exposed section. These were later registered and the raw point clouds segmented to only cover the area of interest. In addition, a coloured point cloud was produced by projecting each 3D point into the covering D100 imagery. Finally, a 3D triangulated mesh was produced, which was then textured using the D100 photography to give a high resolution photorealistic model of the dump site section (Fig. 1; [Buckley et al., 2008]). The raw hyperspectral images were registered to the lidar and digital photo data using the semi-automated workflow proposed by Sima et al. [2014]. This approach extracted and matched interest points in both the hyperspectral and registered RGB images, and 3D coordinates were obtained in the associated lidar mesh. Finally, space resection was used to solve for the unknown position and orientation of the hyperspectral image using the conjugate image and 3D coordinates as input [Buckley et al., 2013]. Subsequently, fusion products could be created as in Buckley et al. [2013].

**Results and discussion**

**Geochemical characterisation of samples corresponding to chosen target-materials**

Within the scope of the current study, 16 target materials (end-members) were selected based on field appraisal, supported by MNF band interpretation (Fig. 3) and results from the laboratory chemical, mineralogical and spectral analysis. These 16 end-members comprised four of the piled materials relating to known economic interest and typical by-products from current steel production, as well as a selection of 12 unknown materials found at the cross section and exhibiting varying mineralogy and geochemistry (e.g. iron content). The pile of scrap metal was not considered as target material within this study, due to the focus on iron and steelwork by-products. In addition, the two piles of EAF slag with different grain size were treated as one material class.

Table 1 gives an overview of the XRD results for the 16 corresponding samples, highlighting main (x) and minor (o) crystalline constituents identified by compilation with PDF-1 database, International Centre for Diffraction Data, Swarthmore/USA, 2002.

All analysed samples represent mixtures of several minerals, though calcium carbonates (calcite (CaCO₃), as well as vaterite (CaCO₃) in some cases) are present in most cases. Quartz (SiO₂), which is present in most of the samples in various concentrations, is not a typical mineral in by-products of iron and steel production, though commonly found due to the presence of natural sand, demolition waste or soil. The composition of sample 2 is dominated by dolomite ((Ca,Mg)CO₃), while samples 3, 7 and the red converter sludge (B) contain lower
levels of dolomite. Apatite (Ca$_5$(PO$_4$)$_3$(OH,F)) was found in sample 5, collected from the trough in the centre of the section. In contrast, sample 6, from the same area, is dominated by calcite, indicating that the composition within the trough is not homogenous.

**Table 1 - XRD mineralogical composition of the samples corresponding to chosen target materials**

| Mineral                  | Material |
|--------------------------|----------|
|                          | 1 2 3 4 5 6 7 8 9 10 11 12 A B C D |
| Anhydrite                | o        |
| Apatite                  | x        |
| Baryte                   | x        |
| Bredigite                | x        |
| Calcite (Vaterite)       | o x x x x x o x (x) o x (x) x o o |
| Dolomite                 | x x x o  |
| Feldspar                 | o x      |
| Goethite                 | o        |
| Gehlenite/- Akermanite    | x x x x o |
| Gypsum                   | o        |
| Halffhydrate             | o o o    |
| Hematite                 | o o x o o  |
| Iron (metallic)          | x x o x o |
| Jarosite                 | o        |
| Larnite                  | o x      |
| Magnetite/Jacobsite      | x x o x o |
| Mayenite                 | o        |
| Mica                     | o        |
| Periklase                | o        |
| Quartz                   | x o o o o o o x x x x x o o o |
| Wüstite                  | x o x o |
| X-ray amorphous          | a a a a a a a a a a a |
| γ- dicalcium silicate    | x        |
The typical slag mineral gehlenite/akermanite (Ca$_2$Al$_2$SiO$_7$/Ca$_2$MgSi$_2$O$_7$) was found in samples 1, 11 and 12 as well as in the EAF slag (material C) and LF slag (material D). Wüstite (FeO$_x$) is present in the mill scale (material A) and EAF slag. The iron oxides hematite (Fe$_2$O$_3$) and magnetite (Fe$_3$O$_4$) as well as jacobsite (MnFe$_2$O$_4$) are present in several samples and are the dominating mineral phases in the mill scale and red converter sludge. Jarosite (KFe$_3$(SO$_4$)$_2$(OH)$_6$) was detected only in sample 1, which exhibited an ochre yellow crust in situ. Notably, almost every sample contains X-Ray amorphous materials and low levels of metallic iron are present in selected samples.

Besides the mineralogical composition, chemical parameters like CaO, SiO$_2$ and MgO are typically used to characterise slags [Drissen, 2004]. As metals are of potential economic interest, this study will give focus on the iron and zinc contents (Tab. 2). In addition, H$_2$O contents are presented, since molecular water is known to affect spectral properties [Hunt et al., 1977]. However, it has to be considered that each layer at the cross section is not homogenous and that the chemical properties may vary to a certain degree within one layer.

### Table 2 - Selected chemical properties of the samples collected at the cross section and piled materials (1-12 = Unknown materials, A = Mill scale, B = Red converter sludge, C = EAF slag, D = LF slag; wt% = Weight percent).

| Parameter | Material | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  |
|-----------|----------|----|----|----|----|----|----|----|----|
| H$_2$O    | wt%      | 8.64 | 16.30 | 8.62 | 12.50 | 14.00 | 12.90 | 8.02 | 7.94 |
| Fe        | wt%      | 13.30 | 1.42 | 16.12 | 1.21 | 6.32 | 8.91 | 8.81 | 22.70 |
| Zn        | wt%      | 0.12 | 1.86 | 1.77 | 1.59 | 3.19 | 4.13 | 1.99 | 1.25 |
| H$_2$O    | wt%      | 3.29 | 5.71 | 3.30 | 11.20 | 2.03 | 7.20 | 0.21 | 5.20 |
| Fe        | wt%      | 2.91 | 1.58 | 3.33 | 0.47 | 62.59 | 37.63 | 35.63 | 8.40 |
| Zn        | wt%      | 0.09 | 0.03 | 0.41 | 0.02 | 0.02 | 3.16 | 0.02 | 0.02 |

The total iron content encompasses metallic iron as well as ferric or ferrous iron and ranges from < 1 wt% (sample 12) to more than 60 wt% in the mill scale, with 35-40 wt% in the red converter sludge and the EAF slag. Although the artificial piles showed the highest overall iron contents, several layers and materials (1, 3 and 8) sampled on the exposed face also showed contents between 10 wt% and 25 wt%. Besides iron, zinc is present in widely contrasting concentrations that show no direct correlation to the iron content. The highest zinc concentrations can be found in samples 5 (~3.2 wt%) and 6 (~4.1 wt%), both collected in the trough-structure. The red converter sludge also contains high amounts of zinc (material B, ~3.2 wt%). The water content is strongly varying, indicating amounts of molecular water within the samples between < 1 wt% (material C, EAF slag) up to around 16 wt% (sample 2).
Spectral characterisation of iron and steelwork by-products

Following geochemical analysis, the samples were characterised by reflectance measurements in the wavelength range 350-2500 nm. Although it is outside the scope of the current study to provide a complete assessment of the spectral properties, some basic observations can be made (Fig. 4).

The majority of the laboratory spectra show absorption features at 1400 and 1940 nm which are typical for molecular water within the samples [Hunt, 1977; Clark et al., 1990a]. In general, the samples with higher H$_2$O contents (e.g. samples 2, 4, 5, 6, 12; Fig. 4; Tab. 2) show stronger absorptions compared to the samples with lower H$_2$O contents (e.g. samples 7, 8, 11; Fig. 4; Tab. 2). The mill scale (H$_2$O content 2%), EAF slag (H$_2$O 0.2%) and the red converter sludge (H$_2$O 7%) only show weak absorption features at 1400 and 1940 nm due to relatively low water content or since the features may be masked by iron oxide absorptions (Fig. 4D). However, it has to be taken into account that despite differing amounts of molecular water the samples are affected by varying moisture and grain size or texture effects. Several samples (e.g. 10, 11, 12; Fig. 4A and B) and the LF slag (Fig. 4D) show distinctive absorption features near 2240 nm. Absorption features in the wavelength region between 2200 and 2300 nm are typical for minerals bearing hydroxyl groups (Al-OH, Fe-OH, Mg-OH) [Hunt, 1977; Clark et al., 1990a; van der Meer et al., 2012]. However, no hydroxyl-bearing mineral phases are indicated by the equivalent XRD results (Tab. 1), making the reason for these absorption features unclear and suggest hydroxyl to be part of the X-ray amorphous material. Sample 9 shows an absorption feature at 2210 nm (Fig. 4B), again indicating the presence of hydroxyl-bearing minerals [Clark et al., 1990a]. In this case mica is indicated by the XRD results (Tab. 1). Several samples (e.g. 4, 7, 11, 12; Fig. 4A and 4B) show weak absorption features at around 2330-2350 nm which may indicate the presence of calcite [Hunt, 1977; Clark et al., 1990a; van der Meer, 1995], which has been confirmed by the XRD results (Tab. 1). However, even in samples, where calcite was expected to be a dominant mineral phase, the distinctive absorption feature associated with calcite at 2330-2340 nm was weaker than foreseen (sample 4, Fig. 4B) or in some cases not determinable at all (sample 6, Fig. 4C). In contrast, the spectrum of sample 9 shows a distinctive feature at 2340 nm, even though calcite is only a minor constituent. Since the presence of amorphous materials could be detected for several samples and Mg-OH is a potential component thereof as well as a possible cause for absorptions near 2350 nm [Doublier et al., 2010], the precise cause for the observed features at 2330-2350 nm could not be completely solved within this case study. Although the geochemical analysis of sample 2 indicated dolomite, no clear absorption feature difference to the dolomite-free samples was recognised (Fig. 4A). Apatite is present in sample 5 (Tab. 1; Fig. 4C) but could not be spectrally detected since pure apatite does not show distinctive absorption features [Hunt et al., 1972]. Even though the XRD results suggest that sample 1 contains only minor amounts of jarosite the corresponding spectrum (Fig. 4A) seems to be dominated by that mineral, showing typical absorptions at 430, 2210 and 2260 nm [Hunt et al., 1971b; Clark et al., 2007]. The LF slag as well as the EAF slag spectra (Fig. 4D) show absorptions near 960, 1120, 1270 and 1330 nm that could not clearly be related to any of the mineral spectra in the reference spectral libraries [Clark et al., 2007; Baldridge et al., 2009]. These features tend to disappear in the spectra of dried material and are presumably caused by vibrational processes of the liquid water molecule as features at similar positions have been described in the literature [Hunt, 1980].
Figure 4 - Laboratory spectra of unprepared samples acquired with the ASD FieldSpec® Pro FR, with sample number and total iron content corresponding to Table 2. A: spectra of cross section materials with unique global shapes or absorption features, B and C: spectra of cross section materials that show similar spectral shapes and absorption features, D: spectra of piled iron and steelwork by-products.

Within the ASD spectra, absorption features of iron or other metal ions can be found in the VIS and NIR. Features at 490 and 680 nm in the EAF slag spectrum (Fig. 4D; also sample 11, Fig. 4B) are similar to those occurring in goethite, indicating the presence of ferric iron [Clark et al., 2007]. Further absorption features are visible at around 420, 500 and 560 nm in the spectra of samples 5 and 6 (Fig. 4C), near 520 and 630 nm (LF slag, Fig. 4D; sample 10, Fig. 4A) and at 720 nm (e.g. sample 4, Fig. 4B). The general decrease of reflectance from around 700 nm towards the shorter wavelengths, observed in nearly all samples, is typical for materials containing even minor amounts of iron [Hunt et al., 1971a]. Further absorption features are visible between 800 and 1200 nm in several samples (e.g. samples 5, 6, 7, 8, 11, Fig. 4B and 4C). The piled red converter sludge, also found in several areas across the greater dump site, exhibits a peak at around 750 nm (Fig. 4D). The mill scale (Fig. 4D), however, shows a broad absorption feature at 530 nm, followed by a small feature at 640 nm and a shoulder near 700 nm, which are only weak indicators for the presence of hematite which is determined by the XRD results [Hunt et al., 1971; Clark et al., 2007]. Magnetite, which is also present in the mill scale, is spectrally featureless, opaque and therefore explains the low reflectance of this material and other magnetite-bearing samples (e.g. red converter sludge and samples 3 and 5, [Hunt et al., 1971a]). In summary, samples with high amounts
of hematite and magnetite/jacobsite also show the highest total iron concentrations and are associated with very low degrees of reflectance and the absence of distinctive absorption features in the SWIR region. As the typical slag minerals gehlenite, akermanite and wüstite do not bear hydroxyl, carbonate or molecular water, no distinctive absorption features are present in these spectra. In addition, the influence of amorphous materials, present in the majority of the presented samples (Tab. 1), has to be taken into account.

A comparison of ASD laboratory spectra and HySpex pixel spectra is given in Figure 5. Several materials (e.g. samples 1 and 12, Fig. 5A) show absorption features in the SWIR in the laboratory spectra which are also clearly visible in the corresponding HySpex spectra in the field, suggesting the applicability of laboratory spectra as reference for feature-based mapping approaches, such as SFF. However, the limited spectral range of the HySpex sensor utilised does not allow absorption features in the VIS and NIR to be considered. As the HySpex images were acquired under field conditions, atmospheric, topographic, illumination and shadow effects have an impact on the image spectral signatures. In addition, in situ moisture, grain size and texture effects have to be considered as physico-chemical factors are known to affect reflectance properties [Hunt, 1980]. Thus, the comparability of ASD and HySpex spectra of dump materials with no or only weak absorption features in the SWIR, combined with low reflectance is limited in this case study, indicating limited transferability of laboratory to field results for certain materials (e.g. samples B and C, Fig. 5B).

Consequently, the ASD laboratory spectra that show distinctive spectral characteristics were used for the SFF approach, and image-derived spectra were used for the SAM classification. As a large part of the materials is similar in terms of the overall spectral shape, finely graduated maximum angles, ranging between 0.025 and 0.125 (increments of 0.025), were selected for the individual end-members to spectrally separate the different cross section materials.

![Figure 5 - Comparison of selected ASD FieldSpec® Pro FR laboratory (350-2500 nm) and corresponding HySpex field spectra (1300-2500 nm) after continuum removal normalisation. A: Spectra of samples 1 and 12 with well-fitting distinctive absorption features in the SWIR (marked by dashed lines), B: Spectra of samples B (red converter sludge) and C (EAF slag) with no distinctive absorption features in the SWIR. Arrows indicate absorption features in the VIS and NIR. The wavelength regions near 1400 and 1900 nm are affected by noise due to atmospheric water vapour absorptions and were masked in the HySpex data.](image-url)
Image classification

SFF results for selected absorption feature classes, used reference sample spectra and the chosen wavelength ranges are displayed in Figure 6. Using this approach, the layer corresponding to quartz-rich sample 9 could be detected using the absorption feature at 2210 nm (Fig. 6, class 1). This corresponds to a reddish layer visible in the field. Based on the distinctive absorption feature at 2260 nm, areas of jarosite-bearing materials could be mapped in good agreement to field findings (Fig. 6, class 2). Jarosite was therefore the only mineral that could be directly mapped using diagnostic absorption features within this case study. Using sample spectrum 3 (Fig. 4C) as reference, a horizontal layer to the right of the trough-structure in the centre of the cross section could be mapped (Fig. 6, class 3). Further materials with absorption features near 2240 nm could be mapped (Fig. 6, class 4). However, even though the samples 10, 11 and 12 are different in terms of mineralogy and chemical composition and show slight variations in the position and shape of the absorption feature near 2240 nm, very similar results were achieved using the corresponding spectra for the SFF classification. Thus, these features cannot be seen as diagnostic or unique to satisfactorily differentiate the materials within this case study. Consequently, the SFF results from sample spectra 10, 11 and 12 were grouped to one class. The pile of LF slag (material D) could be successfully mapped using the corresponding laboratory reference spectrum (Fig. 6, class 5). However, the results show mapped areas at the cross section that are also highlighted using the reference spectra of samples 10, 11 and 12 (grouped as class 4), indicating the high spectral similarity of these materials in the HySpex data. Material within the trough-structure could be detected using the spectrum of sample 5 (Fig. 4C) as reference (Fig. 6, class 6). Even though this spectrum shows only weak absorption features, it matched several pixels in the HySpex image that correspond to the sampling location. As the absorption features near 2340 nm were weak in the laboratory spectra, corresponding materials could not be mapped in the HySpex image using this feature alone. Instead, based on sample 4 (Fig. 4B), which shows a feature with minima at 2240 and 2340 nm, materials with similar spectral properties on the right-hand side of the exposure could be highlighted (Fig. 6, class 7).

In general, the materials mapped using SFF are of lower iron content (~0-20 wt%) compared to the samples that could not be mapped using this approach.

Figure 6 - Spectral Feature Fitting results, used reference samples and wavelength ranges. The classes 10, 11 and 12 are grouped due to high similarity (class 4). Class 5 (reference spectra of sample D - LF slag) partially overlays class 4.
A SAM classification based on spectra extracted directly from the hyperspectral imagery allowed a more comprehensive mapping of the material heterogeneity of the exposed cross section, even allowing the separation of those layers characterised by higher iron content, lower reflectance and no or only weak distinctive spectral features (Fig. 7A). The classification shows a good separation of the piled materials from the background materials, and a variety of layers to the left of the trough-structure, which is in good agreement with field findings. The material within the trough and the scree beneath, as well as near-horizontal layers to the right of the trough could all be distinguished. The piled materials at the left foot of the cross section can be seen as a benchmark for the classification results as they are supposed to occur only at the piles. In addition, the trough materials are assumed to be found only within this structure. Thus, misclassifications are clearly recognisable concerning the classes A (mill scale), B (red converter sludge), D (LF slag) and class 6 (trough material).

As the ASD spectrometer results indicated that several materials showed only minor spectral differences in the SWIR region, but more distinctive variances in the VIS/NIR, an additional workflow was developed to integrate the RGB bands from the lidar-mounted Nikon D100 imagery into the HySpex data cube. A new three-channel (RGB) image was defined, with identical number of columns and rows as the acquired hyperspectral image (1600 x 320). Using the registered orientation and position data of the hyperspectral image, and the coloured point cloud created from the raw lidar and D100 data, each pixel of the new image was projected into the point cloud using the reverse collinearity equation [Buckley et al., 2013]. The nearest 3D point to the projected ray defined the RGB value for that pixel of the new image. Finally, the three-channel RGB-image was integrated into the hyperspectral data cube, allocating a wavelength to each channel. The channel centers of the Nikon D100 were assumed to be 470 nm (blue), 525 nm (green) and 600 nm (red).

![Figure 7 - SAM classification using image-derived end-members based on (A) the original HySpex image, and (B) the HySpex image with additional RGB bands from the lidar and Nikon D100 data fusion.](image-url)
Based on the fusion of the Nikon D100 RGB bands into the hyperspectral image, a second SAM classification was carried out (Fig. 7B). Considering the RGB bands in the classification led to an improvement of the result compared to the classification based on the SWIR region alone (Fig. 7A). Although more pixels are unclassified, the result is in higher agreement with the field findings, as the unclassified pixels are located in shadowed areas or represent layers that were not represented by end-members. Furthermore, a better separation of the LF slag from the background materials was achieved, as well as a reduction in falsely classified pixels for the red converter sludge and mill scale classes, and the material classes found in the trough. In summary, materials that show spectra with distinctive absorption features (e.g. samples 1 and 9) were found to be mapped in better agreement to field appraisal using SFF than with SAM. In contrast, materials that barely show diagnostic absorption features but differ in variations of the overall spectral shape might be detected in a more sufficient way using the SAM approach, suggesting that a combination of both classification methods is favorable to map all target materials at the cross section.

Besides mapping the spatial distribution of a variety of materials with different chemical properties at the cross section, the mapped classes (Fig. 7B) were grouped and colour-coded according to the iron and zinc contents of the corresponding laboratory samples (Tab. 2) to highlight areas at the cross section of potential economic interest (Figs. 8 and 9).

![Figure 8 - Grouped classes and associated iron contents of the corresponding samples.](image)

Group I (Fig. 8) represents materials with the lowest iron contents (0 - <5 wt%). These materials dominate the left and right parts of the cross section, while the material within the trough-structure, the scree material beneath and several layers to the left of the trough are mainly represented by group II (5 -10 wt% total iron). Materials with iron contents between 10 to 25 wt% were combined in group III and occur to the left of the trough-structure as well as parts of the near-horizontal layer to the right. Group IV and V represent materials with the highest iron contents, encompassing the pile of mill scale (Group V), which is already being reused in the steel production process. The second highest iron content was found in the placed pile of red converter sludge, which is found in large quantities throughout the dump site. The two piles of EAF slag (35 wt% total iron) are also highlighted.

Similarly, mapped classes with comparable zinc contents in the corresponding samples were combined to give a visual impression of areas with contrasting contents of this metal (Fig. 9).
The results show that layers with high iron content do not necessarily show high zinc content, which is in general agreement with the chemical analysis. The highest zinc concentrations can be found in the trough and the scree beneath, as well as a layer to the left of the trough and in the red converter sludge. As this approach is not based on statistical modelling, and although individual layers may contain higher or lower metal contents, the areas indicated by these thematic maps suggest a first screening to identify the most promising parts of the exposed area with respect to the general goal of identifying material that is economically viable for recycling.

For visualisation of the results, singular MNF bands or bands composites, classification results and colour-coded combined classes can be integrated into the lidar model as new texture layers, as in Buckley et al. [2013]. Figure 10 gives an example of the data integration and shows a visualisation of the lidar model with integrated RGB photographs, a MNF band composite (Fig. 3) and the SAM classification image with grouped classes based on the iron contents (Fig. 8) of the associated samples. The linkage between high-resolution geometrical information generated with the laser scanner and the hyperspectral image analysis is beneficial for 3D visualisation as well as benefitting the interpretation of the material distribution at the cross section. As edges and boundaries of certain layers are not identifiable in two-dimensional images, they are more easily recognisable in the 3D model. Furthermore, the overlay and blending of several information layers can be used for validation purposes.

Figure 9 - Grouped classes and associated zinc contents of the corresponding samples.

Figure 10 - Lidar model of the cross section textured with high resolution true-colour photos, MNF results and colour-coded classes based on corresponding sample iron contents.
Conclusion and outlook
This research showed that close range terrestrial hyperspectral mapping is a suitable non-invasive tool that can be used to detect and distinguish historical and current industrial by-products from iron and steel production under field conditions. Application to a dump site case study indicated that the spatial distribution of several by-products associated with different metal contents could be successfully mapped. This has the potential to improve the assessment of existing raw material stocks for potential recycling or reuse, as using hyperspectral imaging aided the separation of layers of contrasting metal content. The SFF approach worked well to detect several materials with distinctive absorption features, but was not sufficient to separate all layers of interest as especially the materials with high amounts of iron or iron oxide content show very low reflectance and few distinctive features in the SWIR region. Therefore, classification approaches have to be applied that take the overall spectral shape into account. In this study, the SAM classifier performed well and the best results could be produced using end-members derived from the image. However, more sophisticated classification approaches and end-member definitions should be applied to optimise mapping results.
Because the SWIR did not cover all spectral features of interest, full range hyperspectral scanning would be beneficial, as absorption features caused by electronic processes were observed in the VIS and NIR, improving the final classifications and increasing the potential of mapping metal related material properties. Although such instrumentation was not available in the current study, an effective alternative was realised by integrating the RGB bands from a standard digital camera mounted on a lidar scanner into the co-registered hyperspectral data cube. The results of this paper can be seen as a pilot study for the use of hyperspectral mapping methods for resource assessment and demonstrate the potential to apply this method to different anthropogenic deposits and applications worldwide.

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