# VERY HIGH RESOLUTION LAND COVER EXTRACTION IN URBAN AREAS: VERY HIGH RESOLUTION URBAN LAND COVER EXTRACTION USING AIRBORNE HYPERSPECTRAL IMAGES

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**ABSTRACT:**

During last decade, needs for high resolution land cover data have been growing. Such knowledge is namely often required in environment monitoring studies. Thus, to answer these needs, national mapping or environment agencies, in many countries, have undertaken the production of such large scale national land cover database. Nevertheless, these databases provide a general classification and may not suit some specific (often new) applications requiring a semantic or geometric finer level of details. That is to say that, on one hand, additional land cover classes should sometimes be specified, whereas, on the other hand, some existing classes should be delineated at a finer level.

More particularly, in urban areas, knowledge concerning very high resolution land cover and especially material classification are necessary for several city modelling applications. Most of these applications are still experimental scientific ones in various fields such as micro-meteorology, hydrology, pollutants flow monitoring and ground perviousness monitoring. Thus, knowledge concerning the roofing materials or the different kinds of ground areas (pervious, vegetated, impervious…) are required. Airborne remote sensing techniques appear to be convenient for providing such information at a large scale since no existing map contains such information. However, remote sensing imagery of urban environments from airborne acquisitions namely still remains a major scientific issue, since on one hand, urban areas are characterized by a high variety of materials, and on the other hand, results provided by most of the traditional processing methods based on usual red-green-blue-near infrared multispectral images remain limited for such applications. A possible way to improve classification results is to enhance the imagery spectral resolution using superspectral or hyperspectral imagery.

Thus, the present experiments are part of a work aiming at designing a future superspectral camera system dedicated to high resolution urban land cover classification applications, and especially material mapping. The choice of optimal band sets will here be processed from a set of airborne hyperspectral data.

A data acquisition campaign named UMBRA has recently been carried out thanks to the French collaboration of IGN[1] and ONERA[2]. Data have been captured over two French cities chosen for their difference in building architecture, urbanization planning and their variety in urban material. Airborne images have been acquired simultaneously by multispectral and hyperspectral cameras with a ground sampling distance ranging from 0.12m for multispectral to 1.6m for hyperspectral in the SWIR channels. The images were radiometrically and geometrically calibrated and have a noticeable low signal-to-noise ratio.

The first urban land cover / material classification results obtained from this new reference data set will be presented in this paper.

## 1. NEEDS AND POTENTIAL APPLICATIONS INVOLVING VERY HIGH RESOLUTION URBAN LAND COVER

In urban areas, knowledge about very high resolution land cover and especially maps of the urban materials are required by several city modelling applications. Urban environment is indeed strongly influenced, in terms of ecology, energy and climate by the present materials. These materials can be either natural or artificial. Most of these applications are still experimental scientific ones such as micro-meteorology, hydrology, pollutants flow monitoring and ground perviousness monitoring. Several possible applications requiring very high resolution knowledge about urban land cover and materials are listed in (Heldens et al., 2011) and (Shafri et al., 2012).

[1] IGN is the French National Institute of Geographic and Forest Information
[2] ONERA is the French Aerospace Lab, that is to say the French aeronautics, space and defense research lab

### 1.1 Quantification of pollutant flows from roofs in urban rainwaters

Some roofing materials can generate pollutant elements. Thus, in the actual context of the EuropeanWater Framework Directive (2000/60 CE), whose aim is to obtain a good ecological state of aquatic environments, it seems necessary to reduce the production of pollutants at their sources. This implies to identify sources and to quantify emissions.
Several kinds of pollutions are generated by roofing materials. First, it has been proven that roof runoff water plays an important role in the high metallic concentration levels in urban rainwater since metallic elements are generated by corrosion of roof materials before being swept away by rainwater. Zinc-based materials are largely used in urban areas, especially for infrastructure, such as furniture or siding and roofing for buildings. Exposed to atmospheric conditions, these materials are progressively corroded. During a rain event, a part of the corrosion products formed at their surface will be released and washed off. In Paris, experiments have established that atmospheric corrosion of roofing materials could be a major source of zinc, cadmium, lead and copper during wet weather (Chebbo et al., 2001). Several researches on identification of metals from roofing materials have been carried out, showing that zinc emissions are mainly in the labile form (Heijerick et al., 2002), which is bioavailable and therefore harmful to aquatic organisms (both animals and plants). Copper roofs have also been identified as a possible source of pollution.
Last, some other kinds of roofing materials can help to release organic polluting elements (polycyclic aromatic compounds, organic carbon) due to a not visible bitumen layer (Lemp et al., 2004 ; Lemp et al., 2005).

Laboratory experiments have often already been done to model pollutant runoff rates for roofing materials (for instance, see (Robert-Sainte, 2009) for metallic elements). Knowledge about the different roof coverage areas is thus required to be able to extrapolate these results to whole drainage areas: a map of roofing materials is thus needed.

Previous works aiming at extracting maps of roofing material out of airborne imagery exist. (Le Bris et al., 2009) performed supervised classification of red-green-blue-near infra-red aerial ortho-images. Non roof areas were masked using building objects of a topographic database. (Lemp et al., 2004 ; Lemp et al., 2005) used hyperspectral HyMap data in association with Lidar measurements. Slope information derived from such 3D data was shown to be useful to help the discrimination between some roofing material classes. More recently, (Chisense et al., 2012) obtained good results using HyMap data: 11 features were first extracted (using projection pursuit and LDA) and supervised classification was then performed.

### 1.2 Monitoring of asbestos-cement roofs

Another possible application in the field of urban materials concerns the monitoring of asbestos-cement roofing materials (Heldens et al., 2011 ; Bassani et al., 2007 ; Marino et al., 2000). Asbestos-cement based materials can indeed be dangerous for human health, especially when they are deteriorated. Therefore, it is important to be at least able to evaluate the amount of buildings covered by asbestos-cement roofing sheets. Evaluating their deterioration status is also a useful issue. A method to achieve this using hyperspectral images has been proposed in (Bassani et al., 2007): it focuses on special spectral bands identified from spectrum analysis.

### 1.3 Electro-magnetic wave propagation models used to define the best location for telecommunication infrastructure

Such possible application is mentioned by (Carrileiro et al,. 2001). (Carrileiro et al,. 2001) indeed aimed at obtaining material maps in order to enrich 3D building models used as input data of electro-magnetic waves propagation simulators used to define the best location for telecommunication infrastructures (that is to say antennas).

### 1.4 Determination of road type and monitoring of road condition

Other applications in the field of urban materials concern road materials. At least, maps of road types (cobblestone, asphalt …) can be useful for some applications. A more important and complex application focuses on the monitoring of road condition: such information indeed offers great interest for authorities in charge of the planning of road network renovation projects. Extracting this knowledge out of aerial data could be a way to avoid expensive and long field investigation (Herold et al., 2004b).
Two examples of methods aiming at determining road condition from aerial hyperspectral data are presented in (Herold et al., 2004b) and (Mohammadi, 2012). These works focus on special spectral bands identified from spectrum analysis.

### 1.5 Monitoring of ground perviousness

Two kinds of applications requiring knowledge about ground perviousness exist.
On one hand, it has been shown that the continuous development of impervious areas (especially in the periphery of cities), such as wide parking areas in commercial districts, plays an important role in the aggravation of flooding events, both in terms of magnitude and speed. Thus, having tools making it possible to monitor the extension of impervious areas and to check their appliance to new legislations would really be useful.
On the other hand, perviousness maps are required by ("micro") hydrological models (Heldens, 2011). For instance, (Kermadi et al., 2010) extracted a land cover classification out of multispectral images with a very high spatial resolution such as BDOrtho or QuickBird and then integrated this data in hydrological models. This example is not a "micro" hydrological one and land cover classes do not correspond to specific materials. Other studies aiming at mapping ground perviousness in urban areas used unmixing approaches applied to lower spatial resolution hyperspectral data (Roessner et al., 2001; Demarchi et al., 2012).

### 1.6 Weather models

Very fine knowledge concerning urban land cover (in terms of materials, perviousness and vegetation) are required by “micro” weather (wind, temperature, …) model simulators (Heldens et al., 2011 ; Heldens et al., 2010).

## 2. VERY HIGH RESOLUTION URBAN LAND COVER: WHICH NOMENCLATURE AND EXTRACTION PROCESS?

### 2.1 Urban land cover nomenclatures

Several urban land cover nomenclatures have been proposed in literature. Most of them are related to the specific applications aimed at in the different papers and have therefore more or less detailed material classes as in (Cavalli et al., 2008).
Some of them include different levels of details, as (Heiden et al., 2007) or (Franke et al., 2009).
The most exhaustive ones focused on urban materials and have been presented in (Heiden et al., 2007) and (Herold et al., 2004a).

### 2.2 Extracting very high resolution urban land cover

Very high resolution urban land cover is required to provide knowledge about the roofing materials and the different kinds of ground areas,. Such information can be a map of urban material (i.e. a classification) as for instance in (Lemp et al., 2005) or statistics giving the proportion of the different materials in some cells (cf unmixing approaches) as in (Demarchi et al., 2012 ; Franke et al., 2009 ; Roessner et al., 2001).
Since no existing map contains such information, airborne remote sensing techniques often appear to be convenient for obtaining such a map at a large scale. However, remote sensing of urban environments from airborne acquisitions namely still remains a major scientific issue, since on one hand, urban areas are characterized by a high variety of materials which can appear very on images, and on the other hand, results provided by most of the traditional processing methods based on usual red-green-blue-near infrared multispectral images remain limited for such applications. A possible way to improve classification results is to enhance the imagery spectral resolution using superspectral or hyperspectral imagery.

### 2.3 Toward a superspectral camera dedicated to urban materials application ?

Our final goal aims at identifying the most suitable set of 25 spectral bands (defining both their position in spectrum and their width), in order to design a superspectral camera system dedicated to urban land cover applications, that is to say more particularly to identify urban materials. It has namely been shown by (Herold et al., 2004) that it was possible to select a subset of spectral bands making it possible to discriminate between most urban materials classes.
Such sensor could be adapted (especially in case of bands in the VNIR domain) from IGN CamV2 aerial cameras (Souchon et al., 2010), which offer a very modular system, making it possible to use adapted spectral filters.
Such superspectral system could offer some advantages compared to most hyperspectral sensors. It would first offer the possibility to combine the use of suitable spectral bands for a specific application with a high spatial resolution. It would also offer a larger swath. It would be a photogrammetric system, making it possible to obtain 3D models (DSM). Besides, using a CCD array sensor instead of a push-broom sensor, it would make it possible to capture multistereoscopic images, offering thus a possible calculation of BRDF models (Martinoty, 2005).
The choice of optimal band sets will be processed here from a set of airborne hyperspectral data captured during a data acquisition campaign named UMBRA (Adeline et al., 2013).

## 3. THE UMBRA CAMPAIGN

The UMBRA campaign (Adeline et al., 2013) was carried out thanks to the French collaboration of IGN and ONERA, and took place on 23th-25th October 2012. It aims at acquiring a new reference dataset representative of two different kinds of French cities. This data set is first devoted to two main applications : on one hand, the development and validation of a new atmospheric correction method in sunlit and shaded urban areas and, on the other hand, to the definition of a future superspectral camera system for high resolution urban land cover classification, as explained above. However, several secondary studies have also been considered: target detection, sensor radiometric calibration, fusion ( ~ pan sharpening) of hyperspectral images with very high spatial resolution IGN CamV2 images in the context of the preparatory program of the HypXim satellite, aerosol and smoke analysis and other various applications aiming at evaluating the human influence on urban ecosystems.

Images were captured over two French cities: Toulouse and Amiens. These two cities had been chosen for their difference in building architecture, urbanization plan and their variety in urban materials. On one hand, they are sufficiently important cities to offer distinct kinds of urban land covers with dense downtowns, residential areas with individual or collective housings, industrial/commercial areas, transport infrastructures highway, railway, airport), vegetated (parks, gardens) and water areas. On the other hand, these two cities can be considered as typical of most French cities: Amiens as an example of Northern French cities and Toulouse for the South-Western part of the country.

Airborne images were acquired at high spatial and spectral resolution by panchromatic, multispectral and hyperspectral cameras. Images were indeed captured simultaneously by two distinct sensors mounted on a same aircraft: very high spectral resolution images were captured by an hyperspectral Hyspex sensor (wavelength is between 400 and 2500nm, ground sample distance (GSD) ~ 80cm for VNIR and 1.6m for SWIR) while very high spatial resolution images were acquired by the IGN CamV2 system (Souchon et al.,

2010) (4 bands red-green-blue-near infrared, GSD ~ 12.5cm). Thus, both remote sensing data and photogrammetric data have been acquired, which will make it possible to calculate 3D models.

Radiometric field measurements were also collected during the whole aerial acquisition, aiming both at characterizing the atmosphere, acquiring a ground truth for reflectance retrieval, and collecting spectra of some urban materials.

## 4. VERY FIRST CLASSIFICATION RESULTS FROM THE UMBRA DATA SET

This paper intends to present very first land cover classification results obtained using the UMBRA data set. It must be kept in mind that at present the data set has still not been fully pre-processed. Therefore, **only raw radiance VNIR** hyperspectral images have here been used.
The nomenclature retained for this classification remains quite simple, with 9 material/land cover classes : red tiles – slates – metal 1 based roofing material - metal 2 based roofing material – asphalt – cobblestone pavements – bare soil – high vegetation – low vegetation. We are aware that this legend remains quite simple for a study of urban materials and that other important classes should be added, as for instance railway areas, gravels (which will here be classified as bare soil or cobblestone pavements), cement and water areas.

All the land cover classification results presented above have been obtained using a per pixel linear SVM classifier. The ability of SVM to perform good classification of hyperspectral data has indeed already been shown (Melgani et al., 2004 ; Camps-Valls et al., 2005). The libSVM implementation (Cheng et al., 2011) has here been used and trained by 200 pixels per class. Obtained classification results have been evaluated from a small test data set, plotted with the help of aerial very high resolution images (texture information) and “streetview” images.

### 4.1 Results obtained using raw VNIR radiance hyperspectral data

Encouraging results are obtained directly from the whole raw hyperspectral VNIR spectra. No optimisation of the “*c*” parameter of the SVM (i.e. the penalty associated to classification errors during training phase) has been performed, in order to better compare the influence of input data. Almost 92.5 % of ground truth test pixels have been well classified (see confusion matrix in table 1, user and producer accuracies in table 2 and examples of classification results in figure 1).
It can be noticed from figure 1, that because of slope effect, some roof parts covered by red tiles have been misclassified as cobblestone pavement areas. Because of their specular behaviour, slates are sometimes misclassified with other classes, such as metal when they are enlighten, or asphalt, which is also a “dark” class.
Some misclassification between cobblestone pavements and bare soils occurs: it can be caused by the fact that there is no specific gravel class, and that some gravel areas have been included in the bare soil ground truth, while they sometimes tend to be classified as concrete. There are also sometimes misclassifications between asphalt and concrete (but some of them could correspond to the presence of mixed pixels).

| GT/classif | RedTile | Slates | Metal1 | HighVeget | LowVeget | Asphalt | BareSoil | Metal2 | Cobblestone |
|---|---|---|---|---|---|---|---|---|---|
| RedTiles | 10371 | 41 | 6 | 0 | 17 | 31 | 564 | 23 | 160 |
| Slates | 0 | 692 | 15 | 0 | 0 | 62 | 0 | 3 | 5 |
| Metal 1 | 0 | 88 | 1111 | 0 | 0 | 12 | 1 | 53 | 2 |
| HighVeget | 0 | 0 | 0 | 8174 | 1020 | 0 | 1 | 0 | 0 |
| LowVeget | 79 | 8 | 0 | 1407 | 37364 | 1 | 10 | 0 | 2 |
| Asphalt | 6 | 62 | 0 | 7 | 47 | 9209 | 13 | 110 | 650 |
| Bare soil | 4 | 0 | 3 | 0 | 8 | 2 | 1348 | 9 | 3 |
| Metal 2 | 0 | 1 | 19 | 0 | 0 | 9 | 14 | 831 | 5 |
| Cobblestone | 19 | 61 | 4 | 0 | 37 | 1394 | 43 | 50 | 7146 |

Table 1. Confusion matrix obtained from classification of raw radiance VNIR spectra

| | User accuray | Producer accuracy |
|---|---|---|
| RedTiles | 98.97 | 92.49 |
| Slates | 72.61 | 89.06 |
| Metal 1 | 95.94 | 87.69 |
| HighVeget | 85.25 | 88.90 |
| LowVeget | 97.07 | 96.12 |
| Asphalt | 85.90 | 91.14 |
| Bare soil | 67.60 | 97.89 |
| Metal 2 | 77.02 | 94.54 |
| Cobblestone | 89.63 | 81.63 |

Table 2.User and producer accuracies of classification of raw radiance VNIR spectra

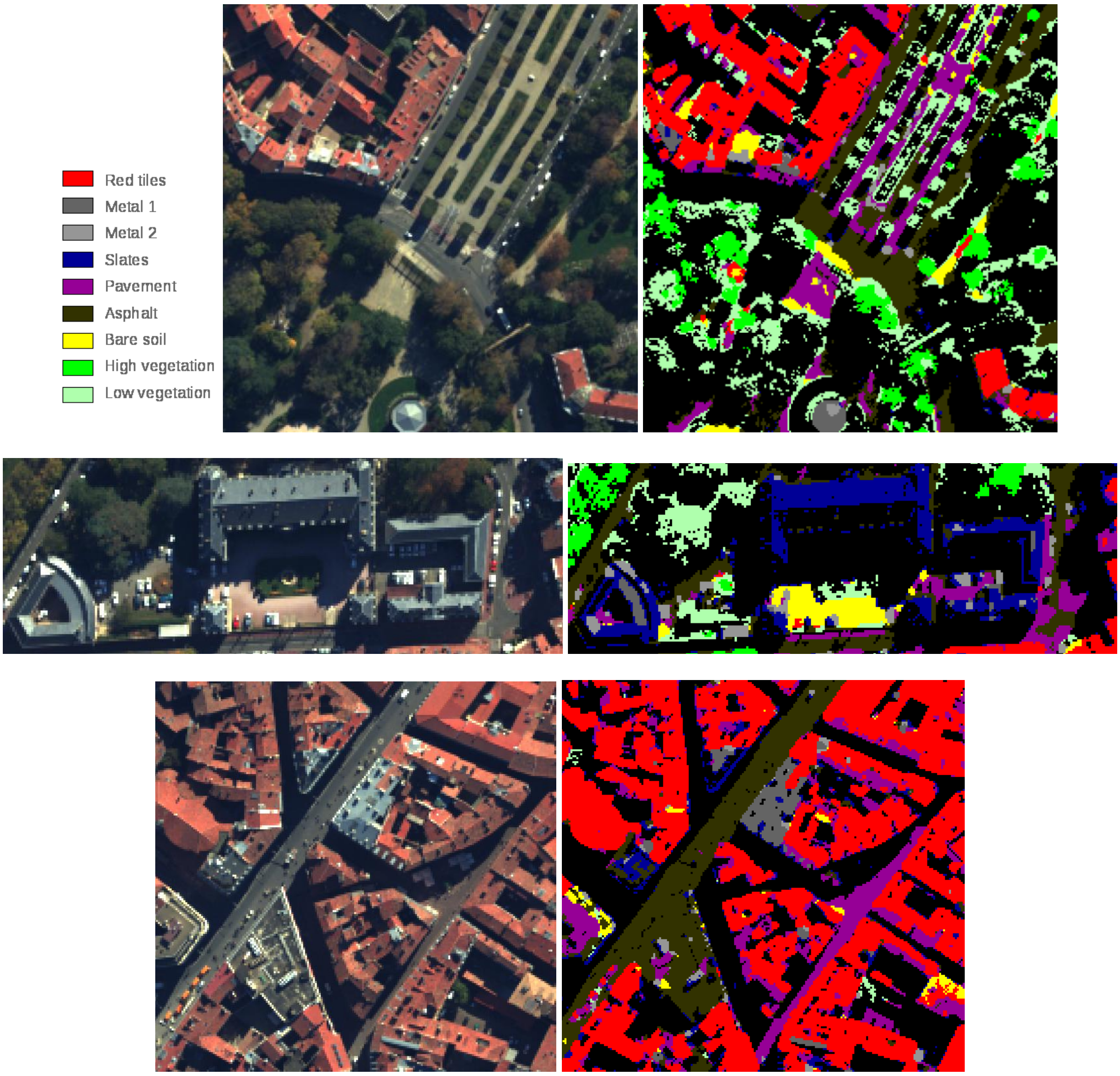


Figure 1. Examples of classification results on the Toulouse data set. Only raw radiance VNIR images have been used. On these illustrations, classification results have been regularized: the label given to a pixel is decided after a vote of pixels belonging to a 5x5 neighbourhood window around the current pixel.

### 4.2 Results obtained using normalized VNIR radiance hyperspectral data

In order to try to take into account slope effects, an other classification experiment has been performed on normalized radiance spectra. Overall accuracy has not changed a lot (92.9% well classified pixels), but discrimination of red tiles has been improved. On the opposite, more asphalt areas have been misclassified as slates, and more bare ground areas have been considered as cobblestone pavements. As for previous test, no optimisation of the c parameter of the SVM has been performed.

| GT/classif | RedTile | Slates | Metal1 | HighVeget | LowVeget | Asphalt | BareSoil | Metal2 | Cobblestone |
|---|---|---|---|---|---|---|---|---|---|
| RedTiles | 10531 | 33 | 12 | 0 | 5 | 52 | 462 | 7 | 111 |
| Slates | 0 | 713 | 32 | 0 | 0 | 23 | 0 | 1 | 8 |
| Metal 1 | 0 | 35 | 1202 | 0 | 0 | 8 | 1 | 12 | 9 |
| HighVeget | 0 | 0 | 0 | 8477 | 716 | 2 | 0 | 0 | 0 |
| LowVeget | 42 | 66 | 0 | 1081 | 37606 | 25 | 51 | 0 | 0 |
| Asphalt | 7 | 465 | 2 | 28 | 16 | 9113 | 13 | 15 | 445 |
| Bare soil | 1 | 1 | 5 | 0 | 5 | 3 | 1327 | 1 | 34 |
| Metal 2 | 0 | 0 | 20 | 0 | 0 | 5 | 5 | 847 | 2 |
| Cobbelstone | 15 | 96 | 5 | 1 | 35 | 1325 | 515 | 9 | 6753 |

Table 3. Confusion matrix obtained from classification of normalized radiance VNIR spectra

| | User accuray | Producer accuracy |
|---|---|---|
| RedTiles | 99.39 | 93.92 |
| Slates | 50.60 | 91.76 |
| Metal 1 | 94.05 | 94.87 |
| HighVeget | 88.42 | 92.19 |
| LowVeget | 97.98 | 96.75 |
| Asphalt | 86.33 | 90.19 |
| Bare soil | 55.90 | 96.37 |
| Metal 2 | 94.96 | 96.36 |
| Cobblestone | 91.73 | 77.14 |

Table 4. User and producer accuracies of classification of normalized radiance VNIR spectra

### 4.3 Results obtained using only 4 bands belonging to red-green-blue-near infrared

Classification was also performed on only 4 bands corresponding to red-green-blue-near infrared bands. An overall accuracy of 73% is obtained without optimizing the "*c*" parameter of the SVM (i.e. the penalty associated to classification errors during training phase), and reached 85% after having optimized this parameter.

### 4.4 Results obtained using a subset of ACP components

An ACP of the VNIR data set has been calculated. Classification has been performed using only 10 and 20 bands of the PCA.
Using the 20 first bands of the PCA, 86% of ground truth pixels have been well classified, without optimizing the "*c*" parameter of SVM. This rate has increased to 90.5% when this parameter is optimized. Classification result from the 10 first bands of the PCA, the overall accuracy has reached almost 75% without optimization of the "*c*" parameter of the SVM and has also increased to 90%, after optimization.

### 4.5 Conclusion and future work

Obtained results are encouraging, even if some misclassifications between some classes have occurred. Nevertheless, it must be kept in mind that these are very first results, and that further investigations must be led, to improve the classification nomenclature and the ground truth reference data set.

Other classifiers, such as Spectral Angle Mapper, Import Vector Machines (Zhu et al., 2005) which have been shown to perform well when applied to hyperspectral data (Braun et al., 2012), or Random Forest (Breiman, 2001) should also be tested. Further investigation will also strongly focus on band selection.

The SWIR spectra of the airborne acquisition is also available and should be used.

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