HYPERSPECTRAL IMAGERY AND URBAN AREAS: RESULTS OF THE HYEP PROJECT

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Résumé

Le projet HYEP (ANR HYEP 14-CE22-0016-01 *HYperspectral imagery for Environmental urban Planning* - Programme Mobilité et systèmes urbains - 2014) a permis de confirmer l'intérêt d'une approche globale du milieu urbain par télédétection et notamment en utilisant l'imagerie hyperspectrale (IH). L'intérêt des images hyperspectrales réside dans la gamme d'informations fournies sur des longueurs d'onde de 0.4 à 4 µm ; elles fournissent ainsi un accès aux grandeurs spectrales d'intérêt et aux paramètres chimiques ou biophysiques de la surface. HYEP avait pour objectif de préciser ceci et de proposer un panel de méthodes et de traitements en tenant compte des caractéristiques des autres capteurs existants afin d'en comparer les performances. Les développements réalisés ont été appliqués et évalués sur des images aéroportées hyperspectrales acquises sur Toulouse (France) et Kaunas (Lituania), utilisées également pour synthétiser des systèmes spatiaux : Sentinel-2, Hypxim/Biodiversity et Pleiades. Parmi les verrous identifiés, ceux liés à l'amélioration des capacités spatiales des capteurs et aux changements d'échelle spatiale ont été en partie levés par des approches de fusion, qui se sont avérées concluantes. Après une présentation de l'offre de données hyperspectrales pour les études urbaines et la présentation des sites d'étude, un point a été fait sur la disponibilité et l'utilisation des bases de données spectrales mobilisables au travers de travaux internationaux et nationaux ou de démarches institutionnelles. Ensuite les méthodes mises en place dans un parti pris d'utilisation ou du développement de méthodes déjà existantes sont présentées. Ainsi des méthodes d'extraction, de fusion ou de classification ont été appliquées à différentes résolutions spatiales afin de qualifier les gains et la complémentarité de l'IH par rapport à d'autres capteurs. Ces évaluations ont porté sur des « domaines » d'intérêts pour les gestionnaires et aménageurs du milieu urbain : les surfaces imperméables, la végétation ou encore la détection de panneaux solaires. L'article se termine sur une discussion et des pistes de perspective.

Mots-clés : *Image Hyperspectrale, Toulouse, surfaces imperméables, végétation, panneaux photovoltaïques, fusion, classification*

Abstract

The HYEP project (ANR HYEP 14-CE22-0016-01 Hyperspectral imagery for Environmental urban Planning - Mobility and Urban Systems Programme - 2014) confirmed the interest of a global approach to the urban environment by remote sensing and in particular by using hyperspectral imaging (HI). The interest of hyperspectral images lies in the range of information provided over wavelengths from 0.4 to 4 µm; they thus provide access to spectral quantities of interest and to chemical or biophysical parameters of the surface. HYEP's objective was to specify this and to propose a panel of methods and treatments taking into account the characteristics of other existing sensors in order to compare their performance. The developments carried out were applied and evaluated on hyperspectral airborne images acquired in Toulouse and Kaunas (Lithuania), also used to synthesize space systems: Sentinel-2, Hypxim/Biodiversity and Pleiades. Among the locks identified were those related to improving the spatial capabilities of the sensors and spatial scale changes, which were partially overcome by fusion and sharpening approaches, which proved to be successful. After a description of our hyperspectral data set acquired over Toulouse, an analysis is conducted on several existing and accessible spectral databases. Then, the chosen methods are presented. They include extraction, fusion and classification methods, which are then applied on our dataset synthetized at different spatial resolution to evaluate the benefits and the complementarity of hyperspectral imagery in comparison with other traditional sensors. Some specific applications are investigated of interest for urban planners: impervious soil map, vegetation species cartography and detection of solar panels. Finally, discussion and perspectives are presented.

Keywords: *Hyperspectral imagery, Toulouse, impervious surface, vegetation, solar panels, fusion, classification*

1. Introduction

The urban population is increasing globally, and the number of millionaire or multimillionaire urban centres is more and more numerous. Nearly 84% of the world's population is expected to live in cities by 2050 (Fargkias, 2013). According to demographic projections, over the next decade, about 2.6 billion people will impact urban developments (United Nations, 2018).

The consequences of this increase are profound, with impacts on the environment (Bai et al., 2018; Garcia et al., 2018). These large urban areas are characterized by land artificialization at the expense of natural or agricultural ecosystems (Angel et al., 2011; Seto et al., 2010; Seto et al., 2013), and urban densification. These two combined processes have major impacts on the functioning of atmospheric (Vargo et al, 2013; Shafri et al., 2012), hydrological and biotic processes at different scales (Hahs, 2009; Wanga, 2019; Grimm et al., 2008; Grimmond, 2007; Oke, 1982) which already recorded temperature increases or air pollution related to urban activities.

This evolution induces a need to understand the complexity of these relationships; a need reinforced by sustainable development logic (Sustainable Development Objectives). This understanding must be done at different spatial and territorial governance scales (Nimela, 1999; Alberti, 2015; Grove et al., 2016; Selberg et al., 2017).

Although territorial planning standards regulate land use, zoning or land management, it is only recently that the consideration of sustainability and resilience objectives has reinforced the need for quantitative inventories and monitoring, as well as the need for a holistic understanding of how urban systems work (Alberti, 2015). To this end, it must be possible to collect relevant information on biodiversity and vegetation, impervious surfaces and elements influencing urban microclimates or hydrological flows (Carlson and Arthur, 2000; Heldens et al., 2017; Huang et al. 2013; Voogt and Oke, 2003).

However, the specific characteristics of urban areas make the collection of this information complex. Indeed, the city is characterized by strong internal dynamics, a very large spatial heterogeneity of its elements, its geometric shapes (horizontal and vertical) (Small et al., 2003), its great variety of materials (Small, 2005) and the presence of shadows due to its three-dimensional geometry (Zhou et al., 2005). Understanding the functioning of the urban system requires the identification and characterization of specific observables such as buildings and their morphology, mineral surfaces, wastelands, aquatic surfaces or vegetation at different levels. These observables are essential for establishing an inventory and mapping of urban surfaces, for monitoring the health of urban vegetation or its biodiversity, and for analyzing the ageing of materials (Miller and Small, 2003) or infrastructures.

In addition, the need for very fine mapping of urban land cover has increased very rapidly to meet the requirements of evaluating actions taken, collaborating with city dwellers, implementing various environmental monitoring applications such as flow measurements, roof pollution, road condition surveys, microclimate models and their integration into climate-energy planning, detection of hazardous materials, toxic smoke analysis or plant health analysis, etc. All this influences the quality of life and health of urban dwellers (Pauleit et al., 2005; Tan et al., 2010; Wania, 2007).

The interest of satellite imagery as a complement to *in situ* and cartographic information to study urban environments is increasing, particularly with the increase of multispectral satellites with very high spatial resolution currently in use and the variety of usable spectral characteristics (Briottet et al., 2006; Demarchi et al., 2014; Small et al., 2018). Many studies have been conducted in different cities around the world (Phinn et al., 2002; Powell et al., 2007; Pu et al., 2008; Rashed et al., 2003), using information from various sensors. Their objectives were also varied, ranging from research to more operational objectives, with work on urban canopy models needed to understand urban micro-climates (Shashua-Bar et al., 2004; Taleghani et al., 2015) to land use mapping or surface temperature conditions (Sobrino et al., 2013).

Various methods have been developed or transferred regarding the urban heterogeneity (mixed pixels) and shadow (Adeline, 2013) by extracting fractions of cover using unmixing methods or extracting urban objects with fusion or pan sharpening methods.

Indeed, the spatial resolution of current and future hyperspectral sensors is not fine enough to distinguish some urban objects in classification applications. There is therefore an interest in cross-referencing this information with data that are less spectrally rich, but better spatially defined, thanks to advanced pansharpening methods (Loncan et al., 2015) aiming at preserving the rich semantic information of the hyperspectral sensor while managing the difference in spatial resolution with the VHR (Very High Resolution) data.

2. Imaging spectroscopy and urban areas

Imaging spectroscopy gives access to new parameters to characterize urban areas. Indeed, such data can more accurately discriminate the heterogeneity of urban materials (anthropogenic or natural) and thus allow new applications such as monitoring health of ecosystems, biodiversity or material ageing and delivering complementary information to better understand and control urban heat islands (UHI) for instance.

Although multi- and hyperspectral data have the same physical basis (Transon et al., 2018) and cover the same spectral ranges from the visible to the near infrared (VNIR; 400-1000 nm) and from the near infrared to the shortwave infrared (SWIR: 1000-2400 nm) domains, they differ in their number of bands and their spectral resolution allowing a continuous spectral reflectance with hyperspectral sensors. Further, a key instrument characteristic to sense urban areas is the ground sampling distance.

A lot of efforts have been done during the last decades to promote hyperspectral airborne sensors (Figure 1) like HyMAP, CASI, AVIRIS, DAIS, ROSIS, AISA, HYDICE, MIVIS, or space borne sensor like Hyperion-EO-1 (Cavalli et al., 2008; Weng and Lu, 2008; Weng et al., 2008; Xu and Gong, 2007), CHRIS-PROBA platform (Demarchi et al., 2012; Duca and Del Frate, 2008), GAOFEN-5 launched in 2018, PRISMA (Labate, 2009), EnMAP (Guanter, 2016) and HISUI (Kashimura, 2013).

Imaging spectroscopy can discriminate urban materials by their spectral behavior but also deliver a fine map of the classes composing the scene (Jilge et al., 2016). Such a technique is also able to provide by-products (Behling et al., 2015) useful to build a strategy for energy planning (e.g. inventory of solar panels, man- made materials identification) (Myint et al., 2013), for reducing impervious surfaces in urban area, for dimensioning hydraulic infrastructures, for greening cities or for improving the quality of life, especially air quality (Brackx, 2017).

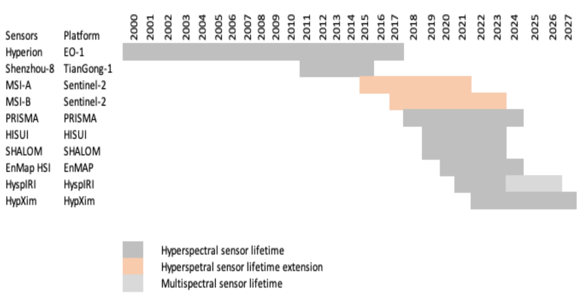

Figure 1: List of the main hyperspectral space sensors. See Transon et al. (2018) for spectra range of each sensor.

Remote sensing in the optical domain is limited by the recurrent problems caused by the strong variability of the signal due to (1) the varying irradiance depending on the viewing and incident angle but also on the local slope of the scene, (2) the abiotic material heterogeneity (roughness, use, ageing (Briottet et al., 2005); (Jilge et al., 2017) (van der Linder, 2009); (3) the biotic variations between vegetation, bare soil or water with, for the same object type, intraclass and interclass variabilities due to species, ageing, height. Further urban morphology is also problematic as buildings and infrastructures exhibit very different shapes and sizes (Gadal et al., 2015; 2016) with various volumes inducing an important spatial variability (Heiden, 2012). Rules on urban planning, construction procedures, geographical area affect the city morphology, the vegetal biodiversity and therefore may compromise any processing transfer from one town to another. Finally, the huge diversity of urban materials coupled to its important intraclass variability require a very representative database which does not exist now. Thus, this renders difficult to achieve a good learning phase in classification or for validation purpose as existing database a not sufficiently representative.

The HYEP (HYperspectral imagery for Environmental urban Planning - ANR) project aimed (1) to deliver answers about the resilience and the suitability of urban ecosystems in order to reduce anthropic pressure on the environment and (2) to strength targeted accompanying actions for sustained developments. This context is exacerbated by a quick and powerful transition to digital technology able to deliver new information to better understand these territorial challenges. Thus, new approaches are required to propose tools and services in order to be able to measure the impact of urban planning policies from classification map and change detection tools using imaging spectroscopy. In particular, such tools can propose useful information for solar panels installation, for urban sprawl policies, for run-off prediction using impervious soil map or for the monitoring of urban biodiversity. HYEP has focused on three applications:

- - Quantification and description of urban surface materials
- - Mapping and identification of urban vegetation
- - Detection of solar panels and estimation of their surfaces.

These applications cover several urban environmental issues, and the related parameters will be integrated at different scales for urban planning. This required accurate and representative databases of spectral optical properties of manmade and natural materials present in cities. Some urban databases already exist but are not sufficiently representative of the materials found in the south of France, thus efforts have been made to complete them. Furthermore, the benefits of imaging spectroscopy (Hypxim future space mission and Hyspex airborne sensor) in urban areas for these three applications were evaluated by comparing their performances to several space borne sensors (Pléiades, Sentinel-2). A consortium of several laboratories with complementary skills contributed to the HYEP project: CNRS (TETIS, ESPACE, LETG, IRAP, GIPSA), ONERA (Dota) and IGN (LaSTIG) representing about twenty researchers, 4 PhD’s and 5 MsC students. This paper aims at summarizing the main findings of HYEP and highlighting the pros and cons of hyperspectral satellite images and techniques for urban environmental applications.

3. Materials

3.1. Study site and data

Two sites were selected: Toulouse (France) and Kaunas (Lithuania). Only results obtained for the former are presented here.

For Toulouse, the ground and airborne data were collected during the 2012 UMBRA experiment (Adeline et al., 2013) and one trial in 2015. The 2012 image was captured by Hyspex sensor, providing 408 spectral bands ranging from 400 to 2500 nm. The study area covers 2 km^2.These experiments focused on a zone covering the Toulouse downtown and peri-urban Montaudran district (Adeline, 2013, Aguejdad, 2017, Le Bris 2019). Two Hyspex hyperspectral cameras covering the VNIR and SWIR spectral ranges with a 0.8 m GSD (Ground sampling Distance) for the VNIR and 1.6 m GSD for the SWIR for the dataset acquired in 2012, and 2 m GSD for the dataset acquired in 2015.

Figure 2: Toulouse downtown area - RGB representation acquired with Hypsex – ONERA sensor.

From these hyperspectral images, several synthetic images simulating multi or hyperspectral space sensors were generated and detailed in Table 1.

Several atmospheric corrections to retrieve the surface reflectance were tested at different spatial resolutions. Indeed, the most popular atmospheric methods suppose the surface as flat as possible, which are not valid in urban areas due their strong 3D heterogeneity. Lenot et al. (2009) proposed an alternative method, SIERRA, by considering the topography. But its modelling is not accurate enough to consider the multiple scattering phenomena present in a town. On the other hand, ATCOR4 (Richert and Schlapfer, 2002), (Richter et al., a & b, 2011) and ICARE (Lacherade et al., 2008) developed similar atmospheric correction tools adapted for cities and able to estimate the TOA reflectance by considering the surface digital model (SDM). ICARE can retrieve the spectral reflectance in both sunny and shadowed areas but this method is very time consuming. Two other methods were tested: COCHISE (Miesch et al., 2005) and an empirical atmospheric correction method developed by Chen et al. (2013). COCHISE supposes the scene is flat and spatially heterogeneous, but cannot retrieve the reflectance in shadowed areas. On the other hand, Chen et al. (2013) proposed an alternative by estimating the radiative components with the flat scene assumption and then by weighting them with empirical laws. (Roussel et al., 2018) conducted this comparison on the 2015 Toulouse dataset at different spatial resolutions by analyzing the classification performances using two classifiers: k-means (non-supervised) and Support Vector Machine (SVM, supervised).

Date of acquisition	**Sensor configuration**	**GSD (m)**	**Processing level**	**Area**
2012	Hyspex	1.6	TOA (Cochise + Chen)	Downtown + Montaudran
	Pléiades	1.6		
	Biodiversity / Hypxim (simulated)	4		
		8		
	Sentinel-2	1.6		
2015	Hyspex	2	TOA Cochise	Downtown
	Biodiversity / Hypxim (simulated)	4		
		8		
	Sentinel-2 (simulated)	10		

Table 1: Acquired images and synthetic images simulating different space sensors (TOA: Top of Atmosphere).

The main results showed the best choice of the atmospheric corrections depends on the spatial resolution. For very high spatial resolution (GSD < 2 m), ICARE has to be chosen whereas for medium spatial resolution (GSD > 8 m), COCHISE is recommended (Roussel et al., 2018).

3.2 Spectral sample database

Remote sensing can describe urban objects from their morphology or geometry and their optical properties. Spectral databases are increasingly used in order to train and validate image processing results. Several types of databases might be exploited: spectral libraries created: in laboratories on small samples of materials; those obtained in field campaigns or those extracted from images. In HYEP, databases were built including these three types of information. A database of reflectance spectra of different urban materials has been compiled from existing spectral libraries: Aster (Baldridge et al., 2009), SLUM - Spectral Library of impervious Urban Materials (Kotthaus et al., 2014), MEMORIES (Means of Exchange and Valuation of

Measurements of Thermal, Optical and Infrared Properties of Samples and Scenes-ONERA) (Martin and Rosier, 2012), Santa Barbara (Herold et al., 2003; 2004), Tel- Aviv Ben Dor (Ben-Dor et al., 2001), DESIREX (Sobrino, 2008). The spectra offered by these different libraries have been sorted and reshaped according to a common nomenclature, but it appears, however, that the different classes are very unevenly distributed (Le Bris et al., 2017) and the heterogeneity of the collected spectra in various countries and with various field spectra devices makes their use in image processing very delicate. This spectral information is required to assess the performance of unsupervised unmixing methods. But the results of the supervised classification show that a database built only from spectra of very different geographical origins does not give good results regardless of the classification method used.

Thus several options were investigated to build an effective database. First, pure spectra were directly selected on the images acquired by Hyspex sensor. Second, the database was filled with synthetic pure spectra on the acquired images. Last, the database was completed from existing spectra coming from in-lab or on-ground measurements. However, the different classes are present in very different proportions in this study area. In fact, the roofs in the study area are mostly covered with tiles, the other materials being rarer and, in some cases, difficult to identify (Le Bris et al., 2016).

Pure spectra have been collected on 2015 Toulouse image in coherence with the Corine Land Cover database - 4th level for urban categories (Zinko et al., 2016; Le Bris 2019). The study of the spectral variability was carried out to extract interclass (among materials) and intraclass (same material) variability. At the end, 33 spectra were obtained for Toulouse (Table 2), compared to spectra from existing field campaign databases and used for the learning step of the classification or for the validation phase. An example of spectral reflectance of solar panel is given in Figure 3.

For the solar panel application, on-ground measurements were achieved using an ASD FieldSpec 3 on the Sept. 21 2015, when 130 spectral signatures were collected with different viewing angles and spot sizes (Figure 3).

For the vegetation mapping applications, two investigations were conducted to retrieve spectral reflectance to enrich previous ones at various scales. One consisted in measuring spectra at leaf and canopy levels with an ASD spectroradiometer covering the 0.4-2.5 µm range. Most of the spectral reflectance of leaves were measured simultaneously with two airborne acquisitions. However, for the two prominent species, Aesculus hippocastanum and Tilia tomentosa, their spectra at canopy levels were measured 6 days before the airborne experiment. No rain event happened. The other approach consisted in extracting spectra from images thanks to high precise localization of tree species acquired with a DPGS exhibiting an absolute geometric accuracy below 10 cm. More than 600 spectra were thus extracted (see (Brabant et al. 2019 for details).

Urban Class	Group of materials	Materials	Nb of spectra
Man-made	Mineral	tile, fibrocement, tar	17
	Metal	copper, zinc, aluminium	9
	Hydrocarbon	glass, PVC, polyethylene, asphalt, bitumen	10
	Infrastructure	road	2
		rail	2
		pavement, square	7
Natural	Vegetation	tree	3
		short grass	1
	Water surface	canal	2

Table 2: Nomenclature of spectra collected over the 2015 Toulouse hyperspectral image.

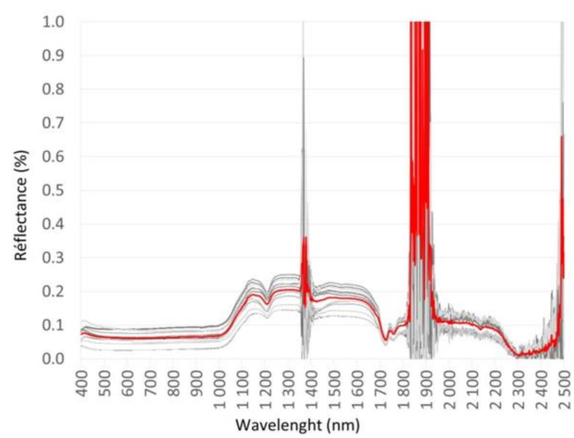

Figure 3: Spectral reflectance of solar panels

For urban buildings the geometric parameters are essential to identify the type of buildings or any manmade objects using very high spatial resolution sensors (ideally a few cm GSD). The spatial resolution is the key parameter for a correct any urban object classification result. The better the spatial resolution, the better classification performances are.

In conclusion the performances of spectra databases depend on the representativeness of a given material or tree *species in the cities. Indeed, some can have a very weak distribution in the cities and therefore not be represented in the database, leading to errors in the city characterization.*

4 Methods

Hyperspectral sensors are characterized by their high spectral resolution, but their spatial resolution is often lower than for multispectral sensors with low spectral resolution. Thus, it is necessary to improve spatial resolution of hyperspectral data using spatial information of multispectral images, keeping as much as possible spectral characteristics (Cavalli et al., 2008). Applied methods to overcome this issue can be roughly split into two main parts (see Figure 4): (1) pixel-based and object-based classifications (including dimension reduction by reducing spectral richness) and unmixing called low level methods; (2) High-level methods that may integrate one or various outputs of above-mentioned techniques: pan and multi-sharpening multi-sensor classification and change detection (Chang, 2013; Lu et al., 2004; Radke et al., 2005; Hussain et al., 2013).

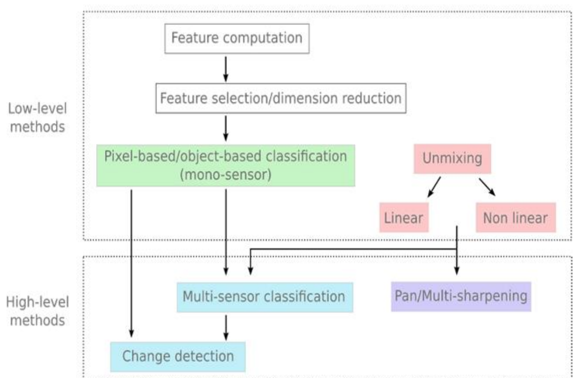

Figure 4: *Workflow of the main techniques studied during the HYEP project.*

Thus, three groups of methods were especially studied in HYEP: supervised classification (pixels and object oriented), unmixing (pan/multisharpening) and fusion approaches. The objectives were to assess the interest of hyperspectral imagery toward multispectral imagery through classification regarding spatial resolution (8 and 30m) and the gain in fusion processing regarding multispectral imagery or 3D LIDAR data. More details in the various referenced publications and final report.

4.1 Supervised classification

Classic supervised classification methods have been used (Support Vector Machine SVM Random Forest-RF). We compared classifiers results regarding spatial and spectral resolution, complementarity of sensors or of sets of bands. Results are detailed in section 5.

4.2 Unmixing

Unmixing methods aim to estimate the abundances of materials composing a scene delimited by a pixel projected to the ground. Benhalouche et al. (2017) tested three multisharpening approaches to enhance the spatial resolution of urban hyperspectral remote sensing images. These approaches, related to linear- quadratic spectral unmixing techniques, use a linear- quadratic nonnegative matrix factorization (NMF) multiplicative algorithm. These methods begin by unmixing the observable high-spectral/low-spatial resolution hyperspectral and high-spatial/low-spectral resolution multispectral images. The obtained high- spectral/high-spatial resolution features are then recombined according to the linear-quadratic mixing model to obtain an unobservable multisharpened high-spectral/high-spatial resolution hyperspectral image (Benhalouche et al., 2017; Karoui et al., 2018 and 2019).

4.3 Fusion approaches

Several fusion approaches were tested. See Loncan et al. (2015) for a state of the art of pan-sharpening methods on several set of images. Two families of fusion methods were evaluated in HYEP: (1) by fusing hyperspectral images with multispectral data with a better GSD at pixel level and by fusing, (2) at object level, a hyperspectral image with 3D images (Lidar, DSM). Further, an extension of these methods was also investigated by Hervieu et al. (2016) and Ouerghemmi et al. (2017) to (3) fuse multispectral and hyperspectral images for classification. In the latter work, a "decision fusion" was applied for classification purposes to very high spatial resolution (VHR) multispectral (MS) images (3-4 bands) and lower spatial resolution images with rich spectral configuration. MS VHR images offer a precise delineation of urban objects while hyper-spectral images (hundreds of bands) offer a better spectral characterization of these objects. A two-step decision fusion strategy was developed to merge them; it includes a per pixel fusion step followed by a contrast sensitive regularization step. Experiments were performed for urban materials classification issues on the Toulouse dataset with an MS image at 1.6m GSD (RGB) and hyperspectral image resampled at 8 m GSD (405 bands from VNIR-SWIR). Fuzzy "Min", "compromise" and Dempster-Shafer rules give the best results: overall accuracy (OA) increased from 71.2% for hyperspectral image alone and 69.2% for MS VHR image alone to 73.5% after fusion.

5. Applications

As mentioned previously, HYEP aims to deliver answers on the benefits of remote sensing and in particular hyperspectral imagery to urban applications. HYEP focused on the three following applications.

(1) Impervious surfaces: due to its fine spectral resolution

and its large spectral range, imaging spectroscopy can better discriminate a larger variety of materials (roof, road, tar, asphalt…) than multispectral ones.

(2) Urban vegetation mapping: the characterization of the tree vegetation (species, hydric stress, health…) and its monitoring is essential to evaluate its influence on human well-being, to predict urban heat islands or for the preservation of the biodiversity. Such mapping is crucial for end users to manage urban planning.

(3) Roof characterization and solar panel detection: cities have to promote sustainable energy production (Grenelle 2). But as a first step, communities request an inventory of existing solar panels (location, size) in public and private areas.

5.1 Classification of impervious surfaces

The detection of impervious surfaces is achieved using a supervised classification method at pixel level. At first, existing literature over spectral reflectance literature has been collected: (Wan et al., 1994), MODIS UCSB emissivity Library (Ben-Dor et al., 2001; Heiden et al., 2007; Herold et al., 2003b) for the learning phase. Unfortunately, results did not lead to satisfactory classification performances. The reasons are the insufficient number of samples in some classes, the large, unbalanced amount of samples for each class and the non-similarity between spectra of a given class and the corresponding ones in the image. For this last limitation, an explanation might be that spectral reflectances are usually measured in laboratory or on-ground but at a very different spatial scale from the image. Better results are obtained when the database is directly built from the image itself.

The analysis continued by evaluating the benefits of the spectral and spatial resolutions for the classification.

The comparison of classification performances from Pleiades, Sentinel 2 and 8m / 30m GSD hyperspectral space sensor highlights the benefits of the SWIR spectral range. In addition, it has been shown that using a subset of spectral bands well adapted to a classification problem makes it possible to obtain as good results as using the whole spectrum. Experiments on the automatic determination of these well-suited bands (position, width) for different case studies, have been performed (Le Bris et al., 2016), (Le Bris et al., 2019). SVM classifier applied with a Gaussian kernel (Le Bris et al., 2019; Oltra-Carrio et al., 2015) provide satisfying results. The larger the spectral range is for a 10 nm spectral resolution, the better the classification performs.

With a Hypxim-like configuration, although the classification performances are similar between images simulated at 4 m and 8 m GSD in terms of overall accuracy (OA), a visual analysis is easier with the 4 m GSD image.

5.1.1 Benefits of the spectral resolution

Several spectral configurations were tested (Le Bris et al., 2019). Comparing Pléiades images (GDS = 1.6m), classification results, Hypxim hyperspectral images (GSD= 4 and 8 m) in the range 400 – 1000 nm, authors showed that adding the SWIR range to the VNIR one, increases classification performances. In fact, the SWIR is essential to classify manufactured materials, as most of their spectral features are located in these ranges. Le Bris et al. (2019) selected 10 spectral bands in the VNIR-SWIR domain and demonstrated the benefits of this spectral configuration compared to Pleiades or to a 0.4 -1.0µm hyperspectral sensor. Visually, such improvements are easily detected as illustrated in Figure 5 where the classification map is less noisy although results presented here are derived from pixel classification and have not been spatially regularized in this case. Morphometric approaches have been applied on Kaunas site.

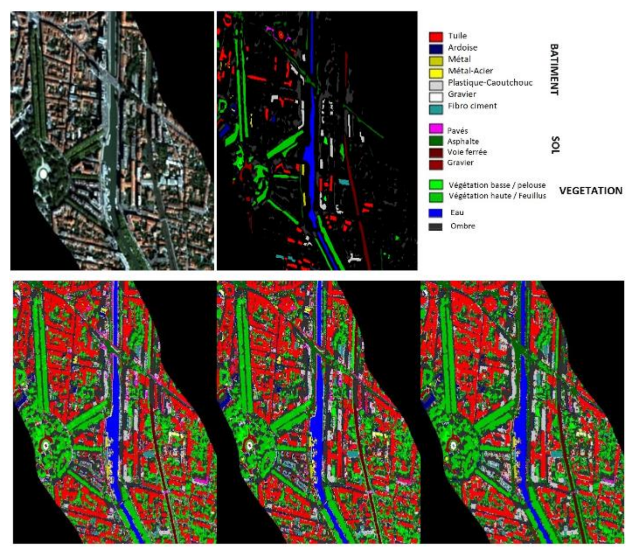

Figure 5: From left to right and from top to bottom, ortho-image on a part of the test zone, associated ground truth, classification results for Pléiades, Hyspex VNIR and Hyspex SWIR spectral configurations at 2 m spatial resolution

The hyperspectral configuration limited to the 400-1000 nm range gives better results than the Pleiades configuration. Adding bands from the SWIR domain improves these results, with the best results being achieved for the configuration covering the 400-2500 nm range. The importance of the SWIR can also be noted through the improvements observed in some classes when comparing the results obtained for a set of 10 bands from the 400-2500 nm range with the Pleiades configuration, or even between classes results with the 400-1000 nm hyperspectral configuration.

The main confusions that remain concern the following classes:

- The slates are very badly classified. This was to be expected, because this class is poorly represented, presents an important specularity, which can make it similar to other classes with the consequence of confusions with shadows, water, metal.
- High and low vegetation tend to merge. This can be explained by the fact that for each of these classes, there is an important intraclass variability
- Confusions between asphalt, paving stones and roof gravel also occur.

5.1.2 Benefits of the spatial resolution

The impact of the spatial resolution on classification performances was also investigated by comparing classification results obtained from Hypxim images at 4 and 8 m GSD.

At 8 m spatial resolution, only the urban objects of large size are well classified. But as seen in Table 5, the results are similar for some classes when the pixel size changes from 4 m to 8 m. In fact, at 8 m GSD, the detected classes are rougher and smoother than small objects which tend to disappear to the benefits of the neighbors but in a different class.

Finally, a comparison was achieved aiming to compare the performances of classification from different sensors: Pleiades, Sentinel-2 and HYPXIM (Table 5 and Figure 6). As such at the same spatial resolution, Hyper_1.6m and Sentinel-2_1.6m deliver the best performances (OA ~ 87.9 % and 89.7 %, respectively) in comparison with Pleiades also simulated at 1.6 m GSD. These results illustrated the benefits of using the SWIR bands.

At their nominal spectral resolution, the best results are obtained with Pléiades (OA ~ 82.6 %) and HYPER_8m (OA ~ 80.7 %). A visual analysis shows false detection rates differ between Pleiades and HYPER_8 m suggesting the benefits to fuse these two types of data to improve the classification (Table 3; Figure 6).

Although the differences are not spectacular, it is observed that better results are obtained when the spectral configuration is improved.

However, the experience remains limited because the study area is not very large (risk of over-adjustment of the model), and some classes are not well represented (learning and evaluations on the same areas).

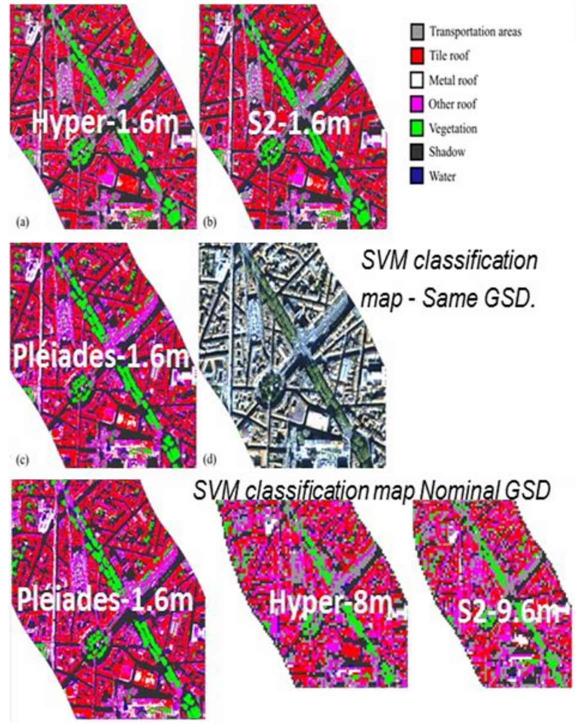

Figure 6: Supervised classification (SVM) over Toulouse on different synthetic images simulating HYPXIM, Sentinel-2 et Pleiades spectral configurations with 1.6 m GSD (first two top rows) and with their nominal GSD (last row): (see figure).

Image	Kappa	Overall accuracy (%)
SENTINEL 2_1.6m	0.88	89.7
Hyper_1.6m	0.86	**87.9**
PLEIADES_1.6m	0.80	82.6
HYPER_8m	0.77	80.7
SENTINEL-2_9.6m	0.66	71.4

Table 3: Global classification results depending on simulated images (5 classes are considered: asphalt, gravel, tile, vegetation, and water). The training sets are composed of 2% of the samples included in the ground truth on Toulouse case study**.**

Object-oriented approaches might also be applied in urban areas (Mohammadi, 2012) due to the characteristics of urban landscape (heterogeneity, density, volume). Such an object-oriented study has been conducted (Aguejdad et al., 2019) using NDVI, MNF, principal component analysis channels extracted from our 2015 hyperspectral image, complemented with a digital elevation model. Confusion persists between on the one hand, the road network and associated structures such as car parks, and buildings with asphalt roofs on the other hand. However, the use of 3D information and its inclusion in the classification process helps to overcome this problem.

5.2 Urban vegetation mapping

5.2.1 Various methodologic approaches

Regarding the issues of vegetation in urban areas (Wania, 2007; Selberg et al., 2018; Seto, et al., 2013), several approaches were carried out to discriminate tree species.

The PhD thesis of Aval (2018) has been the occasion to deepen various experiments. A first experiment with a pixel-based approach evaluated the performances of spectral classification using several classification methods. It is shown that a number of 15 spectral bands located in the VNIR range are able to discriminate deciduous trees, with an increase of 15 % in the classification performances. Several machine learning classification methods were also tested showing the best performances were obtained with SVM but also by performing a previous characteristic selection by Minimum Noise Fraction (MNF) transformation.

A second study aimed to classify tree species using an object-oriented approach throughout three experiments. Thus, Aval et al., 2018a evaluated the complementarity of four different sources (3D lidar, panchromatic, VNIR hyperspectral and SWIR hyperspectral data), fused with several decision rules. The VNIR hyperspectral image is the major source for species classification, which is then improved by adding the SWIR range. The two other data sources have a marginal contribution on the classification. Nevertheless, 3D lidar is useful to discriminate the low and high vegetation. The learning phase was conducted on a reference area of Toulouse and then applied on another area delivering similar performances with respect to the detection of the majority species.

This previous work was extended by using a set of classifiers, specific to each species, composed of a triplet of vegetation indices. This method was compared to another one using either a set of vegetation indices or the full spectral signature. Three different learning databases with different spatial scales were thus generated: leaf scale, tree canopy scale and directly from the image. The comparison of the results showed that triplets method leads to the best results and has low sensitive to the scale of learning datasets thanks to the use of vegetation indices. *The best results are obtained using the full spectral signature acquired from the image itself.*

A third experiment was conducted aiming to detect tree alignment composed of the same species and of similar height (Aval et al., 2018b). The proposed method was based on Marked Point Process (MPP) by using simultaneously information on the spectral signature, the tree height, a linear alignment and GIS to select only trees on the border of road. Applied on Toulouse dataset, 100% of the 69 *Platanus x hispanica* trees were detected whereas classical methods were only able to detect 51 ones (Figure 7).

Finally, classification performance depends on the precision of the tree species nomenclature. The “Tree Family” nomenclature (12 to 19 classes) is well discriminated with SVM but the tree species nomenclature (14 to 27 classes) are better identified with RF. The more important samples per class, better are the performances. Finally, a learning method based on stratified k-folds significantly improved the results in comparison with classifiers or dimension reduction methods.

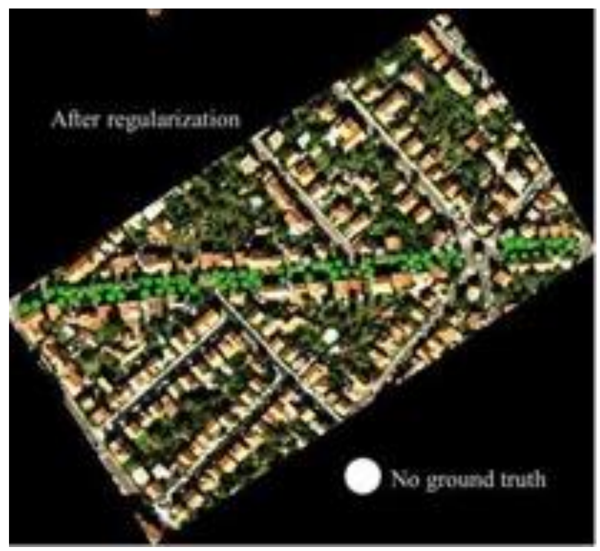

Figure 7: *Detection of alignement tree over an area in Toulouse. Classification: Platanus x hispanica (100% of trees are detected) - ONERA. Aval et al. (2018)*

5.2.2 Benefits of spatial & spectral resolutions

In order to support the future HYPXIM mission, the benefits of high spatial and spectral image sensor to sense urban urea had to be demonstrated.

Several efforts have been done to evaluate the impact of the higher spectral and spatial resolutions, of the dimension reduction, of the classifier on the tree species classification performances (Brabant et al., 2019).

First, using the dataset on Toulouse acquired in 2015 (see Table 2**,** a supervised classification method was applied on the different synthetic sensors and the performances evaluated with the Overall Accuracy citeria. The best performances were obtained with the best spectral (10 nm) and spatial resolution images (4 m).

Finally, the best classification method is Support Vector Machine (SVM), followed by Random Forest (RF), coupled with Minimum Noise Fraction (MNF). Indeed, a better spatial resolution improved the classification on HYPXIM 4 m compared to 8 m images and significantly improved the tree discrimination compared a multispectral sensor like Sentinel-2, even if its 10 m GSD SWIR band was considered.

Different dimension reduction methods were compared: Principal Component Analysis (PCA), MNF, methods based on a selection of uncorrelated vegetation index. The comparison was applied on hyperspectral images at three GSD (2.4 and 8 m). Interestingly the more contributive vegetation indices for the tree species discrimination vary among the spatial resolution.

5.3 Detection of solar panels

Two methods were proposed to detect solar panels in urban areas and then to estimate their surfaces (Karoui et al., 2018 and 2019). Indeed, solar panels have an important role in energy systems in such area and in particular in developed countries (Malof et al., 2016). Governmental agencies, electric network operators or decision-makers support the development of such facilities, considered as green energy from non- pollutant resources, by funding them or by reducing tax.

Therefore, to prevent malicious activity with this alternative energy, numerous organizations are seeking accurate information upon this facility: location, surface, energy production.

One method is based on field investigation, but it is very cost effective and time consuming. On the other side, remote sensing is an opportunity, which can overcome these drawbacks.

Recently, Malof et al. (2016) and Puttemans et al. (2016) proposed approaches to detect and locate solar panels using a high spatial resolution sensor with VNIR airborne or space borne multispectral data. Limitated results came from geometric viewing conditions causing in some cases specular reflection making their detection difficult. Hyperspectral data can overcome this while exhibiting a lower spatial resolution with pixels composed of a mixture of pure solar panel material spectra, hindering their direct detection and then the estimation of their surfaces.

Fortunately, using the spectral richness of imaging spectroscopy, unmixing methods can discriminate spectra inside a mixed pixel and estimate their corresponding abundances, giving access to their surfaces.

Two linear unmixing methods were tested to this end. At present, spectral signatures of solar panels they are based on *a priori* knowledge of. They consisted in factorizing the observed data matrix in non-negative matrices (Cichoki et al., 2009), similar to partial factorization (Limem et al., 2013; Tong et al., 2016). Developed algorithms aimed to minimize a cost function by means of iteratively updated rules.

The first algorithm, named GRD-Part-NMF, used a gradient-based descent resolution method whereas the second one used multiplicative update rules (Multi-Part-NMF). They both guaranteed the non-negativity constraint of the data, and involved: the observed data, prior information on the solar panel spectra, the unknown spectra of the other materials and the abundances of the materials.

These tools were tested on synthetic and real hyperspectral images and the results compared to standard approaches (Karoui et al., 2018 a and b), as illustrated in Figure 8.

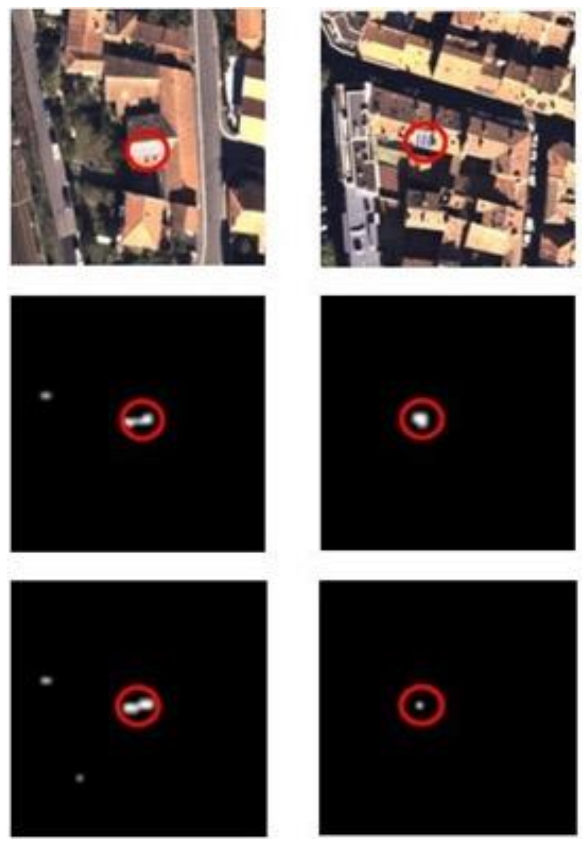

Figure 8: ***Detection of solar panel (a) Ortho-image. Maps of*** *fractions of abundance of photovoltaic panels: (b) Multi-Part-NMF, (c) Multi-NMF. Circles in red include photovoltaic panels.*

It is shown that all the solar panels are detected with no false alarm and the proposed approaches yield better performances than the existing methods. Moreover, the estimation of the surface area is obtained with a good accuracy in comparison with very high spatial resolution ortho-image (Table 4).

	Manual delineation	*Multi Part NMF*
Sub image 1	*15*	*15.27*
Sub image 2	*12*	*13.06*

Table 4: Surfaces of solar panels in m²

6. Conclusions and perspectives

6.1 Discussion

Several items covering spectral and spatial characteristics and advances in various application domains (urban material, vegetation, solar panels…) might be highlighted.

6.1.1 Spectral resolution

The spectral range (0.4-0.9 µm) is essential for discriminating vegetation species; however, extending the range to 2.5 µm improves discrimination performance. Moreover, a spectral resolution of 10 nm does not significantly affect performances.

6.1.2 Spatial resolution

Different spatial resolutions were studied: 2, 4 and 8 m GSD. The best performance is obtained with a resolution of 2 m. Although slightly lower, the quality of the classification on 4 m and 8 m images is similar in part because the 8 m image is less sensitive to local heterogeneities.

The Hyspex resolution (2 m) is very interesting for urban elements detection while it allows discriminating the majority of urban structure elements. The Hypxim resolution (8m) will only be interesting if there are possibilities of multisensors enhancing approaches through fusion or pansharpening.

6.1.3 Urban elements

Some urban indices are interesting for urban planning purposes and can be extracted according to the targeted urban elements. Specific footprint rates of various indices are likely to be provided according to usable area units (building blocks, districts, etc.) like: Density ratio, surfaces of buildings ratio, typo- morphology of urban areas, location and surfaces of solar panels ratio.

Vegetation indicators can be proposed according to defined area units (canopy crowns, tree alignments, districts, etc.): vegetation density, shaft linear length, surface and type of vegetation, tree species and biodiversity

It has to be noticed that it is necessary to define carefully the observable elements, particularly for vegetation. Depending on 3 categories (leaf – canopy-landscape or genus - species - family), the results may be different for both detection and characterization and have strong implications on field measurements to extend the proposed method to wider areas.

6.1.3.1 Urban Materials

Characterization of roofs according to color and certain materials is feasible. But some urban materials are still difficult to differentiate because the similarity of their composition (for e.g.: asphalt, paving stones and gravel or bare ground, roof gravel and cement). Other potential difficulties of discrimination are linked to shade, slopes and roof orientations. The use of 3D makes it possible to differentiate the elements (roofs, trees, structures) and thus to separate the ground observable (meadows for instance) from other elements.

Urban materials could also be better discriminated by using morphological shape indices and building characteristics. It would be interesting to define possible typological indications of urban areas through geometric and topologic measurements.

Among interesting outcomes, the detection of solar panels is a success that needs to be reinforced on larger and more varied images. The operationality of this work will then have to be evaluated with socio economic partners.

6.1.3.2 Vegetation

Species classification results are satisfactory but can be improved. The major problem comes from the difficulty of having consistent plant spectra (between laboratory, field and image) that allow species discrimination. Moreover, databases are unbalanced with regard to the diversity of species present in cities.

The homogenization or even over-representation of certain planted species biases the choice of elements used to train methods and validate them. Variations in scale between the landscape and the leaf also induce biases in the consideration of spectral signatures measured in the laboratory, on the ground or extracted from the image. The foliar structures of the tree crown, their density induce different results depending on the species. Methods for species discrimination should therefore better account for their physico-chemical and geometric characteristics in order to obtain greater

statistical and modelling efficiency. Another solution would be to jointly exploit temporal information from the Sentinel-2 time series providing information on vegetation phenology and hyperspectral THR information. The results confirmed the possibility of distinguishing species present on aligned sites even if some are not easily distinguishable.

The fusion of hyperspectral data with 3D Lidar measurements or GIS, allows better detection of mature vegetation and consideration of context (alignments along the roads).

Processing rules for supervised classification are also emerging to promote cartographic products. The databases must be representative of the plant species present in terms of both the number of species and the number of samples per species. Different learning spectral databases were tested. The ones extracted from images give the best performance but it has also been shown that for trees with high leaf densities, similar classification performance is obtained with bases built at the leaf or canopy level.

6.1.4 Methods

The HYEP project can be considered as a success. It has made it possible to measure the need for a global approach of a very constrained environment both by its complexity and by the obstacles. The project has led to the improvement of methods used by the various partners, the lifting of a number of scientific obstacles and encouraged interdisciplinary dialogue between partners.

The methods of classification with a pixel-based approach directly from spectral reflectance are not very efficient; it is preferable to have an object-oriented approach, which is confirmed by existing work in the literature.

The fusion of hyperspectral data with a higher spatial resolution image having a reduced number of spectral bands improves classification results.

Locks related to improving sensor spatial capabilities and spatial scale changes have been partially addressed by the fusion, sharpening approaches, which have proven to be successful. And the project provided answers to the current locks that reside in the determination of optimal bandwidth resolution in the selected and/or developed methods.

6.2 Perspectives

Technical perspectives have been considered by partners such as the development since 2017 of a superspectral camera by the IGN team (with the addition of the SNIR) or camera design capable of being mounted on drones.

Research perspectives such as the creation of a collaborative platform is under development. It should allow classification results to be validated through participatory individual feedbacks. This realization responds to the difficulty in an urban environment to collect training or validation samples on the field in private areas. The aim would be to supplement *in situ* measurements identified with instruments and information collected through a web interface. This approach is in line with the need to stabilize methods through larger units (for training and validation). The project raised this important gap that is not being filled: the sharing of spectral databases collected from various parts of the globe. The Genlib project (Genlib project) might be an answer to this point. Among the most important perspectives, the possibility of having a global approach considering the constraints of the environment through a clear definition of collection methods and the implementation of pre-processing stages seem to us a priority to continue to develop the use of hyperspectral imaging (knowing that such an achievement would be more broadly applicable to other types of imaging).

From a methodological point of view, questions arise concerning the minimum amount of information to be collected and the necessary resources (Time/Man, computing power and resources); this question raise up more and more in current within scientific communities.

The physical simulation of observables by radiative transfer model (such as DART for example) could be a solution and would make it possible to estimate biochemical quantities to monitor them and to constitute simulated reflectance data that can be used to process hyperspectral images adapted to the resolution of the instruments. This direction would reduce the lack of spectral signatures mentioned above and would facilitate the extraction and identification of urban observables.

Another important point of attention is the existence of massive datasets and current learning methods (deep or shallow). These methods are data-intensive methods that need to be able to be calibrated for learning. So if the current ESA Copernicus sensors (Sentinel 1, 2 and other multispectral sensors) provide images with intensive revisit times, this is not the case for airborne data. Henceforth the question would be to study the complementarity between hyperspectral sensors with low revisits with sensors with sustained revisit times. From then on the use of deep learning methods, for example, would be justified and would certainly make it possible to focus on an aspect that was not developed in the HYEP project, that of hyperspectral time series.

For operational perspectives, the extraction of specific observables such as solar panels, or even tree species has led us to identify points of interest that could be useful for the management of a city. For instance, in Kaunas, the asbestos roofs are particularly numerous and require regular monitoring; determining the degree of impermeability is also a crucial issue for local authorities involving complementary sources. Finally, to support or inform questions about plant biodiversity, establishment of islands of freshness or temporal and sanitary monitoring of vegetation areas (trees, shrubs, meadows, and green spaces) these types of results might be relevant.

The question of temporality would most certainly require a review of some methodological choices made in the context of HYEP due to source variability and seasonality effects. Thus, in the case of a time series approach involving complementary sources (sensors), fusion aspects remain important locks due to seasonal change, shadows presence or urban dynamic.

Finally, imaging spectroscopy is a tool to deliver urban cartography of urban natural and manmade materials which could be used to improve the land surface temperature estimation from remote sensing acquisitions as such methods require the knowledge of their optical properties. Future thermal infrared missions like TRISHNA (Lagouarde et al., 2018) or LSTM could benefit of such information.

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