MULTI-SCALE METHODOLOGY TO MAP GREY AND GREEN STRUCTURES IN URBAN AREAS USING PLÉIADES IMAGES AND EXISTING GEOGRAPHIC DATA

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Résumé

L'identification et le suivi des extensions urbaines ainsi que la préservation des écosystèmes en milieu urbain sont devenus des enjeux majeurs de nos sociétés. Dans un contexte de consommation d'espace toujours plus importante et de croissance constante de la population urbaine, la pression sur les milieux semi-naturels en milieu urbain est de plus en plus forte. Les enjeux autour des trames vertes et bleues comme la demande sociale de « nature » imposent de développer des méthodes novatrices et adaptées à ce type de milieux pour maintenir ou augmenter la biodiversité dans les zones urbaines de la plupart des villes européennes. De nombreuses études ont déjà été menées sur la cartographie et l'analyse des villes européennes et leurs évolutions au moyen de données de télédétection mais une méthodologie consolidée et reproductible manque encore. Dans le cadre du projet VALI-URB, une méthodologie multi-scalaire basée sur des images Pléiades et des données géographiques existantes (bases de données vectorielles de type OSM et BDTOPO ® IGN) est proposée pour cartographier les surfaces bâties et vertes dans les zones urbaines et périurbaines. L'objectif est montrer l'intérêt d'utiliser une information d'occupation et d'utilisation des sols dérivée des images Pléiades combinées à des données vecteurs pour cartographier de manière semi-automatique les structures grises et vertes à l'échelle locale (1/10 000) par une classification orientée-objets. Les premiers résultats sont présentés sur deux villes de taille moyennes aux formes urbaines différentes: Strasbourg et Rennes (France).

Mots-clés: morphologie urbaine, imagerie Pléiades, Données auxiliaires, classification d'images orientées-objets

Abstract

Identification and monitoring of urban fabric and preservation of existing ecosystems have become major issues to maintain or increase biodiversity in areas under urban influence in most of European cities. While many studies have shown the interest of using optical remotely sensed data for that purpose, a consolidated and reproducible methodological framework was still missing. In this context, a multi-scale methodology has been proposed in the framework of the project VALI-URB to map built-up and vegetated land features in urban and suburban areas based on Pléiades images and existing ancillary data (vector databases or the Open Street Map database). The objective of this paper is to highlight the interest of using land cover/use maps derived from Pléiades images and vector databases to semi-automatically characterize grey and green infrastructures at a scale of 1:10,000. First results are presented on two medium-sized cities with different urban forms: Strasbourg and Rennes (France).

Keywords: *urban structure, Pléiades imagery, ancillary data, object-based image classification*

1. Introduction

Improving our knowledge on the urban patterns with their grey and green structures and their dynamics at multiple spatial scales (from the urban block to the morphological urban zone) plays an important role for a wide range of applications, such as urban planning and management (Herold et al., 2005), disaster management (Okada et al., 2000), or energy consumption modelling in urban environments (Heiple et al., 2008). Many studies have mapped and analysed European cities and their evolution using optical remote sensed data but a consolidated and reproducible methodological framework is still missing. In the context of the VALI-URB Project, a multi-scale methodology based on Pléiades images and existing ancillary data (vector databases or the Open Street Map - OSM - database) has been proposed to map built-up and vegetation land features in urban and suburban areas.

The mapping of grey and green elements at local scale performed with an object-based image analysis using Pléiades satellite images with a generic methodology on two test sites (Strasbourg, Rennes) is provided. The second section presents the study site and data, and the third one details the flowchart of the general methodology. Section 4 shows first results obtained on Strasbourg and Rennes. Conclusions and discussion of the results are expressed in section 5.

2. Study sites and datasets

Two medium-sized cities with different urban forms have been chosen to apply the standardized methodological approach (Figure 1). Both cities present several typical morphological urban characteristics representative of some western urban areas.

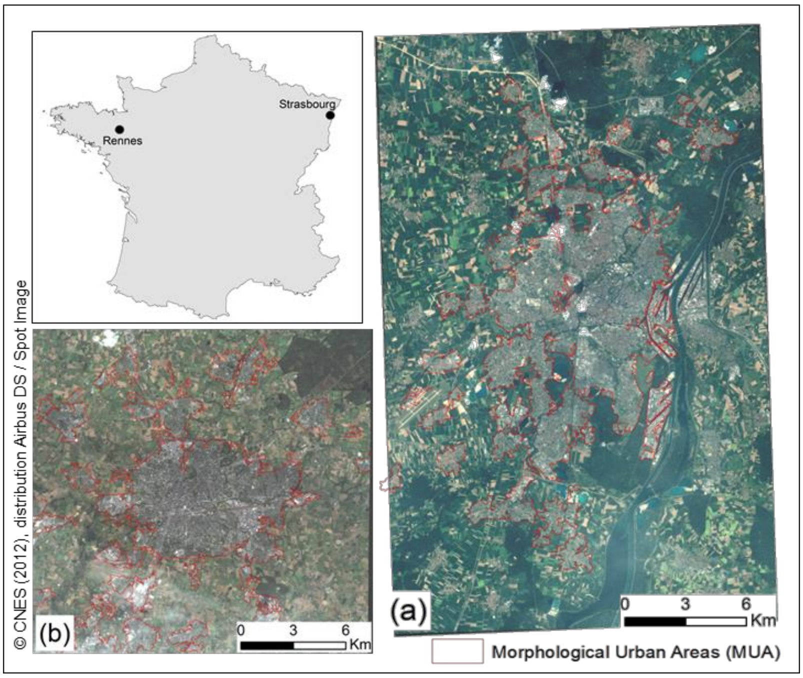

Figure 1: Location of the study sites. Pléiades images are displayed as a true color composition (RGB).

Strasbourg is a compact urban city of 415,000 inhabitants (2013) which covers an area of 316 km with a density of 1498 inhab./km. This city is organized as a concentric dense city centre inherited from the Middle-Ages with surroundings organized in some rings (Figure 1a). Rennes is a multi-nodal city of 473,187 inhabitants (2013) surrounded by a green-belt and covering an area of 705 km with a density of 587 inhab./ km. The city is structured as a polycentric city (Figure 1b). Both cities are submitted to a gradual urbanisation process since the last century with an urban sprawl achieving the third ring (Strasbourg) and the peripheric cities (Rennes). Thus, several urban patterns or Urban Fabrics (UF) can be observed in both cities along a gradient of urbanization from the city-centre and its suburbs (Figure 2).

A bundle (MS + P) Pléiades image has been acquired in both cities during leaf-on period (Figures 1a and 1b and Table 1). Radiometric and atmospheric corrections are applied to Pléiades images using the 6S model (Second Simulation of a Satellite Signal in the Solar Spectrum vector code) proposed by Vermote et al. (1997). Corrections are performed with the Orfeo Tool Box (OTB) using the Optical Calibration/6S module. Both images are orthorectified by the French National Geographic Institute. Pan-sharpened ortho-images with a 0.5m spatial resolution are created based on the combination of panchromatic and multi-spectral bands.

Study site	Acquisition date	Resampled Spatial resolution	Cloud cover (%)
Rennes	10/04/12	2 m, 0.5m	10-15
Strasbourg	08/14/12	2 m, 0.5m	5-10

Table 1: Characteristics of Pléiades images (MS – Multispectral / P – Panchromatic).

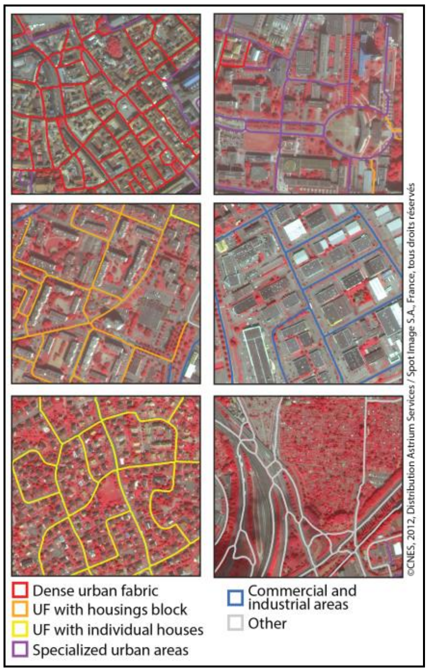

Figure 2: Typology of urban patterns (urban fabrics).

A list of urban objects (Table 2) was firstly defined to map the urban areas at 1/10,000 according to (Puissant et al., 2005). In this study, urban objects are defined as homogeneous units in the Pléiades image by two attributes: (1) the first one refers to the spectral response of the object (material) and (2) the second refers to its spatial dimension (shape) (Puissant, 2003). Based on this definition, twenty-three urban objects were defined. These objects were grouped into three object categories (Table 2–level 1: water, vegetation, artificial/mineral) according to classical and standardized land cover nomenclature (Corine Land Cover or Urban Atlas datasets).

Level 1	Level 2	Level 3	Level 4
1 Water	11 water surface	111 pond / lake	
		112 swimming pool	
	12 linear water	121 brook	
		122 small river	
		123 big river	
		124 channel	
2 Vegetation	21 tree /shrub	211 isolated tree (crown surface)	2111 isolated deciduous tree 2112 isolated coniferous tree
		212 tree group (copse)	2121 deciduous tree group 2122 coniferous tree group 2123 mixed tree group
		213 tree alignment	2131 deciduous tree alignment 2132 coniferous tree alignment 2133 mixed tree alignment
		214 other	
	22 grass	221 square / rectangular grass	
		222 square linear grass	
		223 round grass	
		224 grass with other form	
3 Artificial/ mineral	31 above ground surface	311 orange roof building 312 dark grey roof building 313 light grey/white roof building	
	32 ground surface	321 dark to light grey surface 322 orange surface 323 'green' mineral surface 324 beige surface	
	33 linear element	331 linear dark to light grey 332 linear beige	
4 Shadow			
5 Cloud/haze			
6 Artefact			

Table 2: Nomenclature of urban objects in four level (in grey – typology used for the land cover classification).

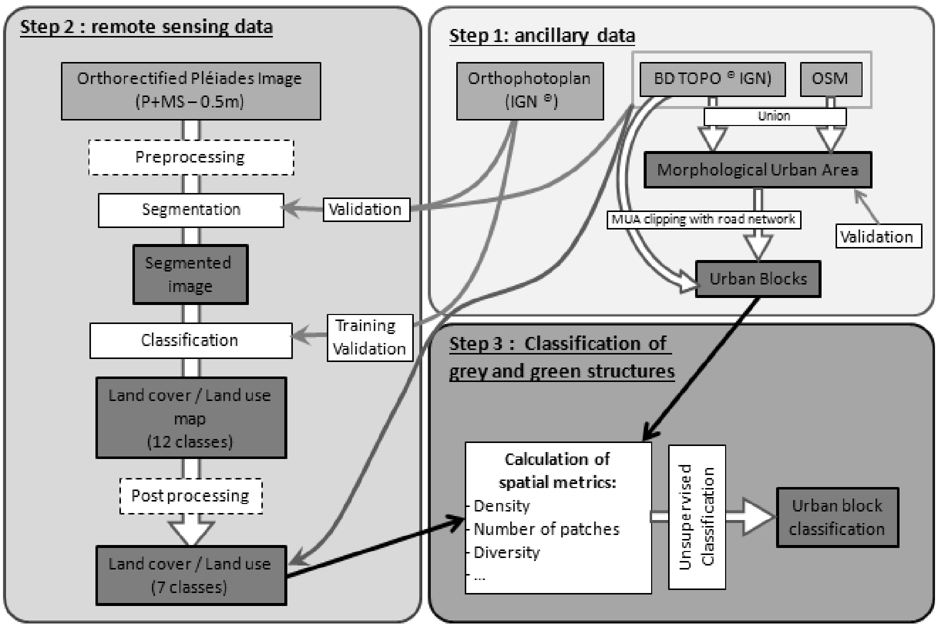

Figure 3: Flowchart of the general methodology.

3. Methodology

The proposed methodology is organized in three steps (Figure 2) and follows a bottom-up approach in order to be close to the visual interpretation process. The first step (Figure 3 – step 1) concerns the extraction of the Morphological Urban Area (MUA) and the delineation of 'urban blocks' based on ancillary data. A protocol based on Loriot (2008) was proposed to extract impervious surfaces (housing, communication ways, commercial or industrialized zones). The MUA was firstly delineated using (1) the built-up layer derived from the combination of the BD TOPO ® IGN and the OSM databases and (2) the road, railway and hydrographic network layers, extracted from the BD TOPO ® IGN database. In this study BD TOPO ® IGN database is considered as the reference layer to be updated by the OSM database. Comparison of the two layers allowed us to extract the elements present only in the OSM database, to validate them by photo-interpretation and update the BD TOPO ® IGN database. Each limit (Figure 1) is validated using MUA's limits derived from aerial photographs and cadastres provided by the urban agencies of both cities. Then, units called 'urban blocks' were delineated in using the MUA limits previously defined and the main roads, rivers and all the railways.

In the second step, the MUA is classified using an object-based image analysis (Figure 3 – step 2). The Pléiades images are firstly segmented before being classified to identify the urban objects defined in the nomenclature (Table 2 in grey). Three supervised classification algorithms were tested. The segmentation and classification results are then evaluated. The training and validation schemes proposed are detailed in section 3.1. Section 3.2 explains the segmentation and classification algorithms. In the step 3, the grey and green structures are analysed at the 'urban block' scale (Figure 3, step 3). This analysis is based on a series of metrics classically used in landscape ecology. Eight spatial metrics (% of land cover per class, number of patches, mean and standard deviation of patch size, patch and edge density, shape index, Shannon index) are calculated on the land cover classification (Figure 3, Step 2) at the scale of the urban blocks. These blocks were previously classified into six classes of urban fabrics. In Rennes, a supervised photo-interpretation process is applied to build these classes. In Strasbourg, a regional land use database is available ®CIGAL (Figure 2). This exploratory analysis has to allow classifying urban blocks into urban fabrics. In this paper, only preliminary results of unsupervised classification of these urban blocks based on four metrics are presented. Validation step is performed using the Kappa Index (Congalton, 1991).

3.1 Training and validation steps

A rigorous statistical accuracy assessment generally requires suitable reference data, an appropriate sampling scheme and independence between the training and validation datasets (Congalton, 1991). Training and validation samples are generated through a stratified random sampling scheme adapted from Puissant et al. (2014). The stratification is based on an urbanization index, which represents the complexity of a city with several density levels. The urbanization index was built using three land cover classes ('vegetation areas' (A_V), 'non-vegetation areas' (A_{NV}) and water areas (A_w)). Vegetation areas are extracted in thresholding a NDVI computed from the Pléiades images. Water surfaces were derived from the BD TOPO ® IGN database and other areas that did not belong to A_V or A_w are considered as non-vegetation areas. Study zones are sub-divided into squared plots with a respective area A_T of 0.25km^2 (500m x 500m). For each plot the urbanization index I_u is computed using:

$$I_U = \frac{A_{NV} - A_V}{A_T - A_w}$$

This urbanization index ranges from -1 for the totally vegetation surfaces to 1 for the totally artificialized plots. The proposed index is classified by quantiles in five classes in order to obtain diverse and representative samples. This type of discretisation is particularly adapted, as each class is equally represented. For the two most urbanized plots, a random selection of 1000 segments per class is labelled. For the three least urbanized plots, only 600 segments are considered since their spatial organization is less complicated and composed of objects fewer. Classification methods prsented in next part are then evaluated by cross-validation technique. 2/3 of labelled segments are randomly chosen and considered for the training, and 1/3 for the validation. Kappa indexes are also calculated to assess classification results.

3.2 Segmentation and classification methods

The Pléiades images are segmented using the Multiresolution segmentation algorithm of eCognition® software (Baatz and Shäpe, 2000; Burnett and Blasche, 2003). The optimal parameters (shape, compactness, smoothness) are performed using two methods: an unsupervised method, the Estimate Scale Parameter (ESP) tool (Drăguţ et al., 2010; eCognition® software, 2012) and a supervised method, the distance index (Levine and Nazif, 1985; Clinton et al., 2010). The supervised method is validated using one hundred and eighty reference polygons randomly selected from the OSM or the BD TOPO ® IGN databases, or digitized from the orthophotoplan (IGN®) (Belgiu and Drăguţ, 2014). In total, 28 parameter combinations were tested to determine the optimal scale, smoothness and compactness values (Tables 3 and 4).

Scale	shape	Compactness
70	0.5;0.9	0.5;0.9
80	0.5;0.9	0.1;0.5;0.9
90	0.5;0.9	0.1;0.5;0.9
100	0.5;0.9	0.5;0.9
110	0.5;0.9	0.5;0.9
120	0.5;0.9	0.5;0.9

Table 3: Test of segmentation parameters.

Site	Scale	Shape	Compactness
Rennes	80	0.9	0.5
Strasbourg	90	0.9	0.1

Table 4: Optimal segmentation parameters.

Three supervised classification methods are applied to the segmented images: K-Nearest Neighbor (KNN) (Cover and Hart, 1967), Random Forest (RF) (Breiman, 2001) and Support Vector Machine (SVM) (Vapnik, 1998). The classifications are performed using 14 image features with spectral information (mean and standard deviation values), indexes (NDVI, MSAVI, and brightness), geometric information (area, compacity, asymmetry) and textural parameters (Homogeneity and entropy). Spatial post-processing is then conducted by crossing the classifications with the ancillary data (Figure 2, step 2). Seven classes of landcover are considered: building from OpenStreetMap or from BD TOPO ® IGN, network (roads and railways) and water from BD TOPO ® IGN, agricultural parcel from 'Registre Parcellaire Graphique' (RGP), tree, grass and other artificialized surfaces with classification of Pléiades images.

4. Results

4.1 Step 1: Morphological Urban Area with ancillary data

The maps of the MUA created with the protocol (Figure 2, Step1) are very close to the MUAs provided by the planning agencies in both cities (Figure 4). For instance, the MUA of Rennes shows a slight difference (less than 10%) between the surfaces of the two MUAs. The main differences can be explained by scattered housing along some roads, which were aggregated during the layer elaboration. These results show that this semi-automatic method for mapping the MUA can be reproducible and should be adaptable to different types of city.

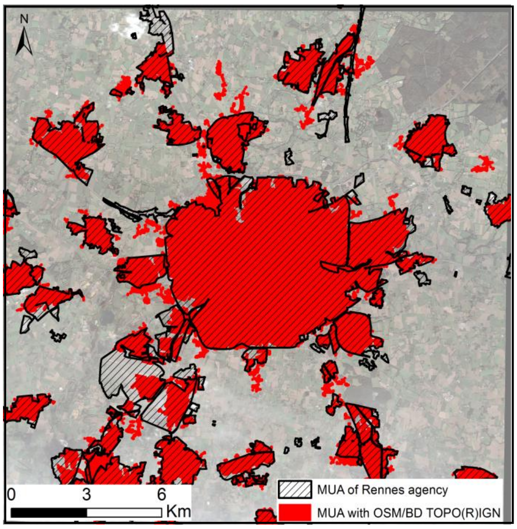

Figure 4: Comparison of MUAs on Rennes The MUA produced using OSM/ BD TOPO ® IGN databases and the MUA provided by the planning agency (AUDIAR).

4.2 Step 2: Classification results

Kappa values for the three classification algorithms are satisfactory (Table 5) with values always superior to 0,7. Though, RF and SVM classifiers give better results than the KNN technique. The best classification result is obtained with the SVM classifier for Strasbourg (Kappa: 0.8) and with the RF classifier for Rennes (Kappa: 0.79). RF classifier and SVM show greater robustness in some class discrimination (shadows/water, shadow/gray object) (Figure 5). Shadow discrimination requires more specific methods, the three classification methods showing the same limits to correctly extract them.

	KNN	SVM	Random Forest
Strasbourg	0.72	0.80	0.78
Rennes	0.73	0.78	0.79

Table 5: Classification Kappa values.

The performances of classification by class expressed with the F-measures appear unequal (Table 6). In general, F-measures are significantly higher than 0.7 which express good performances for classification model for both cities. But mistakes exist for classes like scrubs in the two sites due to misclassification with wooded elements. This class is very under-represented in the landscape and few examples are taken into account for the training step. Other classes, like orange areas in Rennes or herbaceous vegetation in Strasbourg, have same problems. Most classifiers under class-imbalance, like SVM or RF, tend to be biased in favour of the majority class, and vice versa, and may underestimate the number of cases belonging to the minority class (He and Garcia, 2009).

	Strasbourg (SVM)	Rennes (RF)
Water bodies	0,968	0,839
Wooded areas	0,914	0,87
Scrubs	0,142	0
Orange area	0,869	0,25
Herbaceous areas	0,591	0,817
Grey area	0,853	0,874
White areas	0,667	0,776
Beige areas	0,757	0,704
Crops	0,879	0,825
Bare soils	0,84	0,853
Shadows	0,808	0,766
Clouds	0,958	0,889

Table 6: Classification F-measures.

The nomenclature presented in Table 2 is organized in 4 levels of detail. In this work, the classification results show that objects are well classified at Level 2 for vegetation and water classes, and at Level 3 for the class “artificial areas”. However, the classification failed to identify classes at level 4. This is probably due to the difficulty to extract shape indexes from the segmented images that could be used to refine the classification.

4.3 Step 3: Exploratory analysis of urban blocks and classification

The series of metrics are computed at two scales: the MUA and the urban blocks. First, the distribution of urban fabrics is not the same in the two cities (Table 6). Dense urban fabrics and individual residential areas are more present in Strasbourg whereas specialized urban areas are more numerous in Rennes. Some errors about the identification of urban blocks can be observed because urban block classes were assigned differently in the two cities, i.e. by photo-interpretation and using a regional land cover database respectively for Rennes and Strasbourg. This explains why some small blocks delimited by roads, like places or roundabouts, are affected to urban classes whereas this kind of objects are classified as other objects in the case of Rennes.

At the urban fabric scale, part of land cover objects in urban blocks appears similar in both cities (figure 6). Only the urban fabric with individual houses presents different patterns with more “tree vegetation” in Strasbourg and “grass” in Rennes. Trees in this block are bigger and fewer in Strasbourg than in Rennes. Artificial areas are also larger in Strasbourg, which can be explained by the data source used to of assign the urban blocks to a given class. Moreover, buildings are larger but less numerous in Rennes due to the size of urban blocks in this city (Table 6). Urban fabrics in Rennes appear more fragmented for all blocks probably owing to the classification results. The combination of the three metrics presented in figure 6 allows differentiating urban fabrics based on their composition. First result of unsupervised classification of urban blocks is presented in Figure 7. The result is encouraging with an overestimation of two classes: ‘others surfaces’ and mixed UF.

	Mean Area (ha)		Proportion of each class (%)		Number of patches	
	Rennes	Strasbourg	Rennes	Strasbourg	Rennes	Strasbourg
Dense urban fabrics	0.83	1.05	1	4	88 (2%)	520 (11%)
UF with housing blocks	1.08	1.86	12	8	651 (13%)	494 (11%)
UF with individual houses	1.04	1.80	18	26	993 (19%)	1746 (39%)
Specialized urban areas	2.51	1.20	24	6	570 (11%)	296 (6%)
Industrial and commercial areas	5.45	2.68	16	13	177 (3%)	304 (3%)

Table 6: Composition of urban blocks.

Figure 5: Comparison of the classified images produced in Rennes (a) RGB original image of Rennes, (b) classification map using RF, (c)) classification map using KNN, (d)) classification map using SVM.

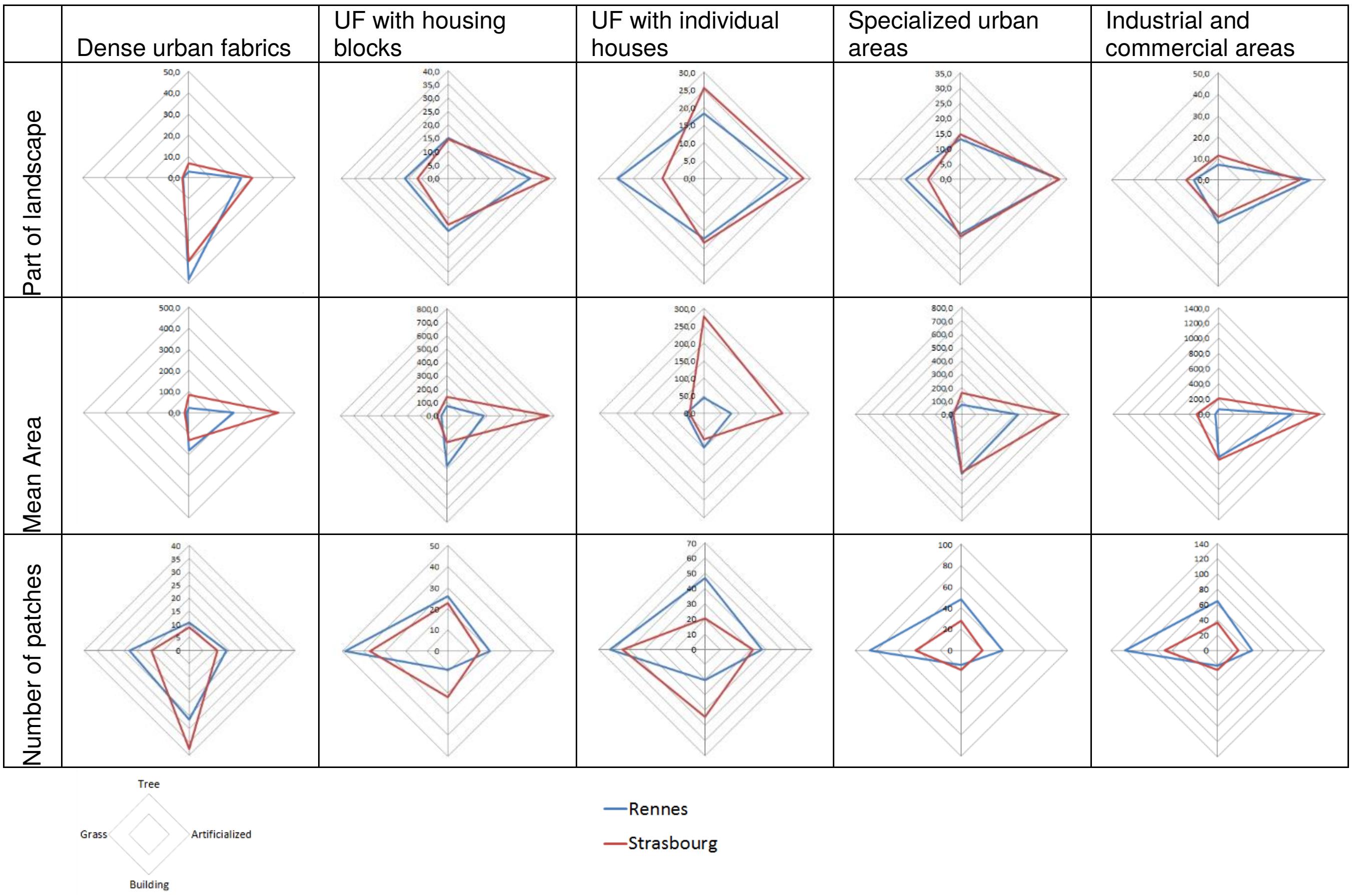

Figure 6: Composition of urban fabrics characterized by three metrics.

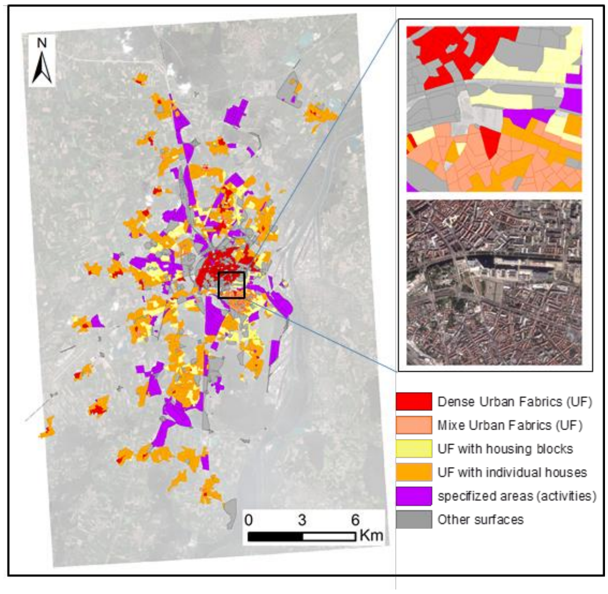

Figure 7: First result of unsupervised classification of urban blocks in Strasbourg with four metrics (% of landcover per class, number of patches, standard deviation of patches and Shannon index).

5. Conclusion and perspectives

The proposed methodology in this research based on Pléiades imagery allows producing some information related to MUA and urban fabrics related to grey and green structures. The proposed methods using existing data at different levels in the process produce multi-scale information and showed preliminary good results on Strasbourg and Rennes. Some developments on Brussels have done same results. The spatial analysis of urban fabric could be also completed by others indexes and has to be evaluated on a great number of urban fabrics. However, the same type of approach could also be applied to cities characterized by other morphology development by adapting features selection and composition.

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References

Baatz M., Schäpe A., 2000. Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation. in: Strobl, J. (Ed.). XII., 12–23.

Belgiu M., Drăguţ L., 2014. Comparing supervised and unsupervised multiresolution segmentation approaches for extracting buildings from very high resolution imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 96(0), 67–75.

Breiman L., 2001. Random Forests. Machine Learning, 45, 5–32.

Burnett C., Blaschke T., 2003. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. Ecological Modelling 168, 233–249.

Clinton N., Holt A., Scarborough J., Yan L., Gong P., 2010. Accuracy Assessment Measures for Object-based Image Segmentation Goodness. Photogrammetric Engineering and Remote Sensing, 76(3), 289–299.

Congalton R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment 37(1), 35–46.

Cover, T., Hart, P., 1967. Nearest neighbor pattern classification. Information Theory, IEEE Transactions on Information Theory, 13(1), 21–27.

Drăguţ L., Tiede D., Levick S.R., 2010. ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data. International Journal of Geographical Information Science 24(6), 859–871.

He H., Garcia E.A., 2009. Learning from Imbalanced Data. IEEE Transactions on Knowledge and Data Engineering 21(9), 1263 –1284.

Heiple S., Sailor D.J., 2008. Using building energy simulation and geospatial modeling techniques to determine high resolution building sector energy consumption profiles. Energy Build. 40(8), 1426–1436.

Herold M., Hemphill J., Dietzel C., Clarke K.C, 2005, Remote sensing derived mapping to support urban growth theory, Proceedings of ISPRS, vol. XXXVI-8/W27., 6p., California, USA.

Levine M.D., Nazif A.M., 1985. Dynamic Measurement of Computer Generated Image Segmentations. Pattern Analysis and Machine Intelligence, IEEE Transactions on PAMI-7, 155–164.

Loriot P., 2008. Etude expérimentale : détermination d'un MOS et calcul d'une tache urbaine à partir de la BD TOPO® d'IGN. CETE du Sud Ouest, 70p

Okada S.; Takai N., 2000, Classifications of Structural Types and Damage Patterns of Buildings for Earthquake Field Investigation. In Proceedings of the 12th World Conference on Earthquake Engineering, Auckland, New Zealand.

Puissant A., 2003. Information géographique et images à très haute résolution : utilité et application en milieu urbain. Thèse de doctorat, Université Louis Pasteur - Strasbourg I, Strasbourg, France.

Puissant A., Hirsch J., Weber C., 2005. The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery. International Journal of Remote Sensing, 26(4), 733–745.

Puissant A., Rougier S., Stumpf A., 2014. Object-oriented mapping of urban trees using Random Forest classifiers. International Journal of Applied Earth Observation and Geoinformation, 26, 235–245.

Vapnik V.N., 1998. Statistical Learning Theory. Wiley(Ed.), 768p, New York.

Vermote E.F., Tanre D., Deuze J.L., Herman M., Morcette J.-J., 1997. Second Simulation of the Satellite Signal in the Solar Spectrum, 6S: an overview. IEEE Transactions on Geoscience and Remote Sensing, 35, 675–686.