URBAN MORPHOLOGY ANALYSIS BY HIGH AND VERY HIGH SPATIAL RESOLUTION REMOTE SENSING

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ABSTRACT:
Improving our knowledge on the urban patterns and their dynamics at multiple spatial scales (from the Morphological Urban Area - MUA, the urban fabric to the urban materials) is a real challenge for research, but also a necessity to manage the territory. Satellite imagery with high and very high spatial resolutions is a real opportunity and is a very relevant data source in this domain. Since recent years, the object-oriented classification approach is largely developed and applied for urban interest. In this context, this paper proposes a general workflow to mapping urban patterns at different scales. High spatial resolution imagery is firstly used to extract impervious surface based on supervised object-oriented classifier and to delineate the morphological urban area at the scale of 1:25,000. Based on this first mapping, a second workflow is proposed to introduce ancillary data (communication network) to produce a mapping of urban fabrics by using both a bottom and a top-down approach. In the bottom-up approach, urban blocks and materials are also classified by object-oriented processing. In the top-down approach, the previous results are used to produce a mapping of urban fabrics at 1:10,000. These classifications are based on membership function classifier which is dependant of the users's expert knowledge that can define rules and constraints in the membership function to control the classification procedure. Results produced at different scales (MUA, to the urban fabric and urban materials) on the urban area of Strasbourg (East of France) achieve high overall accuracy and show the possibility to apply the workflow to other cities with similar morphology and characteristic typical of our western cities.

1. INTRODUCTION

Improving our knowledge on the urban patterns and their dynamics at multiple spatial scales (from the urban block to the morphological urban zone) is a real challenge for research, but also a necessity to design master plans, to monitor consumption of agricultural fields, woodland and natural lands, to plan infrastructure development (drinking water, sewage, roads, etc.), to locate slum development in rapid expanding cities, to manage risk and security, to handle environment protection, to assess urban services (waste, health, post, transportation, etc.).

Satellite imagery with different spatial resolutions is a real opportunity and is a very relevant data source in this domain. Since recent years, the object-oriented classification approach is largely developed and applied for urban interest (Burnett and Blaschke, 2003; Jacquemin et al., 2007; Hanson et Wolff., 2010). Since several decades, a wide range of techniques has been applied on high spatial remote sensing images to delineated Morphological Urban Area (MUA) at scales ranging from 1/50 000 to 1/25 000 (Weber, 2001, Tatem, et al, 2004). At a finer scale (from at scales ranging from 1/10 000 to 1/25 000), urban geographers and planners are subdividing the city in morphological homogeneous neighbourhoods, sometimes named Homogeneous Urban Patch (HUP) to characterise, manage and plan the city. These HUP were defined by Herold et al. (2003) as (a) a morphogenetic regions, homogeneous in texture and visibly different from their neighbouring HUP, (b) composed of several landcover classes, but only one single landuse classes, (c) where possible their boundaries follows roads or others natural or artificial features, (d) of a relatively large size. These HUP called here urban fabrics group several similar urban blocks.

In this context, the first objective of this paper is to improve the mapping of the MUA by using object-oriented classification on high spatial resolution image (Spot 10m) compared to classical per-pixel supervised classification. The second objective is to propose a bottom-up methodology combining supervised and ruled-based classification methods to classify urban fabrics from very high spatial resolution imagery (Quickbird, 2.4m) by using ancillary data allowing to delineate urban blocks. The experiments have been performed on the urban area of Strasbourg for the calibration of feature selection and classification. The proposed workflow has been also applied on a subset of the Toulouse urban area to validate the approach allowing to produce a multiscale mapping of urban forms.

The first section presents the study site and data. The second section of this paper details the workflow. Section 3 presents results obtained on the Strasbourg area completed with results on Toulouse area. Validation and discussion of the results are expressed in section 5, before conclusions and perspectives in section 6.

2. STUDY SITES AND DATA

The urban area of Strasbourg and Toulouse (more than 400 000 inhabitants) are located respectively on the East of France, in the floodplain of Rhine river (Figure 1a) and on the South-West of France in the floodplain of the Garonne river (Figure 1b). These both cities present several typical morphological urban characteristics representative of some western urban areas: a concentric dense city centre inherited from the Middle Ages with surroundings organised in some rings characterized by typical urban fabrics (Table 1). They are also submitted to a gradual urbanisation process since the last century with an urban sprawl achieving the third ring.

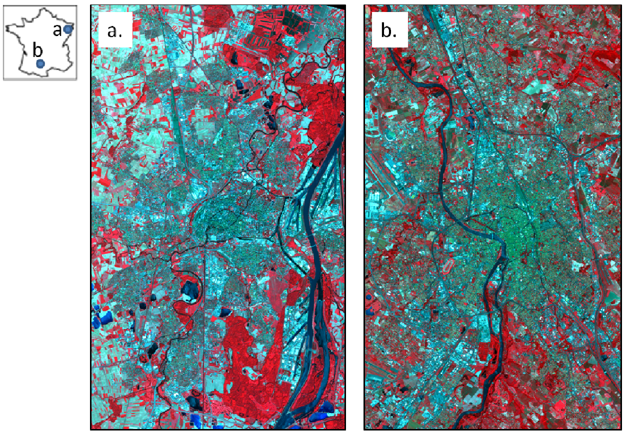

Figure 1. Study sites (a) Strasbourg and (b) Toulouse (©CNES)

	1. Dense urban fabric (city center)
	2. Urban fabric with individual houses
	3. Urban fabric with housing blocks
	4. Mixed urban fabric *Urban fabric composed of individual housed and housing blocks*
	5. Mixed urban area *Area composed of housing classes (class 1, 2, 3) and specialised areas (class 6)*
	6. Specialised or specific areas *Surfaces dedicated to specialised activities: e.g commercial and industrial activities, etc.*
	7. Green surfaces *Urban park, sport fields, etc*
	8. Communication ways
	9. Hydrographic network and water surfaces

Table 1. List of relevant urban fabrics for mapping urban area at 1:10,000

The Strasbourg and Toulouse datasets are composed of two multispectral images with different spatial resolutions (2.4 m and 10 m) acquired respectively by the QuickBird satellite (c)DigitalGlobe) and the SPOT-5 (c)CNES (Table 1). The SPOT-5 image (figure 1a,b) have four spectral bands (green, red, near-infrared, middle infrared). The QuickBird multispectral image (figure 1c,d) is available in four spectral bands (blue, green, red, and near-infrared). All the data are geometrically corrected in the same cartographic projection (RGF93).

3. METHODOLOGY

The proposed methodology is organized in four steps (Figure 2). The first step concerns the MUA extraction based on HRS imagery. The modified watershed segmentation implemented in the ENVI EX 4.8 was adapted to extract impervious surfaces (housing, communication ways, commercial or industrialised zones) on the SPOT5 image (10m). Features characterizing spectral, spatial and textural information have been calculated. This segmentation is following by a supervised classification where two algorithms (implemented in ENVI EX) are compared: the Nearest Neighbourhood (NN) and the Support Vector Machine (SVM). These classification results are also compared to a per-pixel supervised classification (maximum likelihood algorithm).

The MUA is then delimited (on the most relevant result in terms of global accuracy assessment) by using a classical threshold of distance (200m defined by the European level) between urban patches. For the third following steps based on VHRS imagery, the multi-resolution image segmentation (MRIS, Baatz and Schäpe, 2000) and the classification algorithm implemented in eCognition®8.64 was adopted (NN algorithm).

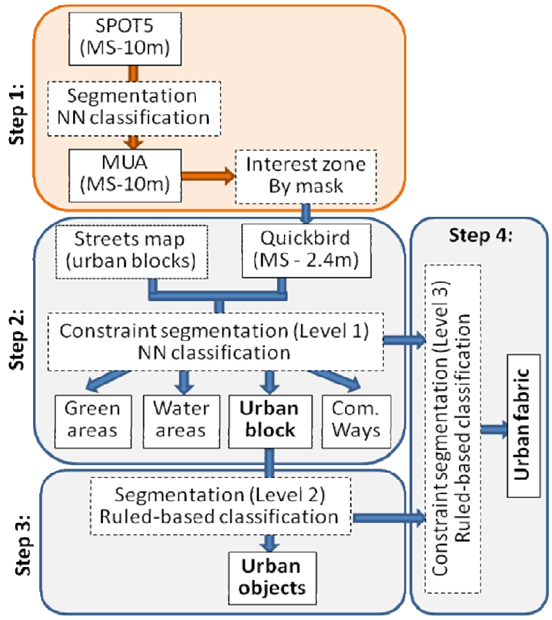

Figure 2. General workflow applied on HR (step1) and VHR imagery (step 2 to 4)

In the second step, the MUA (extracted in the step 1) is firstly used as a mask to extract the area of interest on the Quickbird image. The segmentation algorithm is then constrained by communication ways map (streets, railway and hydrography) in order to produce blocks on the image. These blocks are then classified by using the supervised NN classification algorithm. Features used for this classification are chosen to characterize both the block itself (shape index) and its general composition (means of the fourth spectral bands, brightness and texture).

In the third step, only the urban blocks are then segmented with a fine scale parameter (Table 2) and classified with a rule-based fuzzy algorithm in order to extract landcover classes defined by their materials roofing. For instance, ceramic tile roofing is called ‘orange’ roof and slate tile roofing called ‘dark grey’ or ‘light grey’ roof in the paper, etc.

	Scale parameter	Color / Shape	Compacity/Smothness
Level 1	Constrained by street map		
Level 2	10	0.7/0.3	0.5/0.5
Level 3	Constrained by street map		

Table 2. Parameters using in the segmentation process.

For this classification level (level 2), the hierarchy of landcover classes/urban materials is created by using a ‘deduction’ approach (Figure 3). Some previous tests have shown that the order of the object extraction and the rules application are controlling classification results (Puissant et al, 2006). Urban materials which are considered as 'easy' to extract in term of number of features (minimal) are on the top of the hierarchy. For example, vegetation is the first class that can be easily extracted by using spectral index as MSAVI which is considered in the literature as more relevant in urban context (REF). In summarize, features rules are chosen in order to follow the principle of visual interpretation (color, shape, texture, vegetation index) and their number is then most restricted as possible to allow the reproducibility of the method. The proposed landcover class hierarchy is then presented in Figure 3. Features thresholds are chosen by empirical tests and visual interpretation for each class.

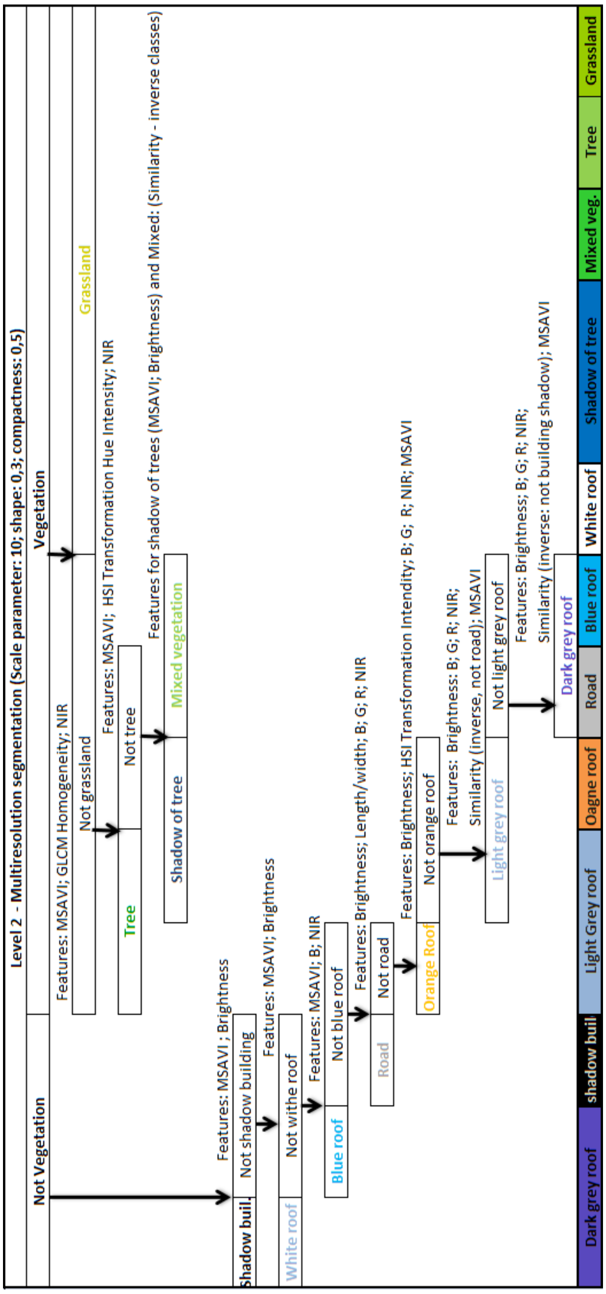

Figure 3. Workflow for the classification at the level 2 (landcover or materials classes).

At the fourth level, the urban blocks (built at the second step by the constraint segmentation) are classified into landuse classes characterising the urban morphology in six classes of urban fabrics (Table 1). The classification is based on the sub-level 2 by using rules of composition. The arrangement of landcover classes observed by an expert is confirmed by a statistical analysis of some urban blocks (based on the ground survey knowledge of the expert). This analysis allows highlighting some rules of spatial arrangement of landcover classes to describe an urban fabric. For example, Figure 4 shows that in our western cities, an individual urban fabric is characterized by an important proportion of vegetation with a high percentage of 'orange' roofing, however in an urban fabric with urban blocks (high building for housing) the proportion of dark and light grey roofing is higher than the orange roofing with the same proportion of vegetation. For this experience, all thresholds of landcover classes at level 2 are defined by integrating this knowledge.

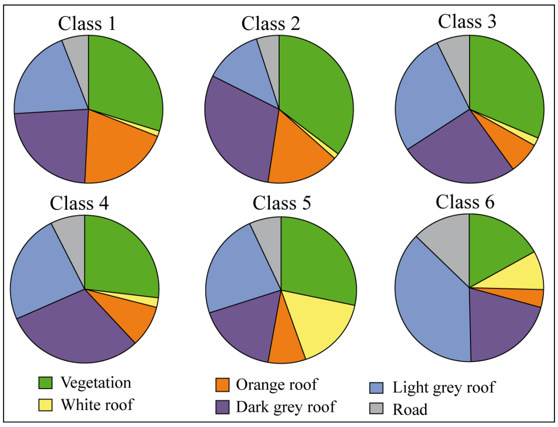

Figure 4. Composition of urban fabric classes (described in Table 1) based on landcover classes of the sub-level 2

An accuracy assessment of each classification is operated at each level and is based on confusion matrix associated indicators: overall accuracy, user’s and producer’s accuracy and Kappa coefficient. Field survey mapping or visual interpretation of aerial photographs was performed to obtain data for validation of the classifications.

4. RESULTS AND VALIDATION

All the steps of the workflow have been performed on the urban area of Strasbourg for the calibration of feature selection and classification process (sections 4.1, 4.2, 4.3). Except for the step 1, some experiments have also been applied on a subset of the Toulouse urban area to validate the approach allowing to produce a multiscale mapping of urban forms (from objects to urban fabrics).

4.1 Classification of the MUA (step 1)

For the segmentation step at 10m, we found out that a scale parameter of 25 (with a merge parameter of 90) was the optimal scale to extract impervious surfaces. To classify image objects using NN or SVM classifier, a feature space and training samples have to be defined. After testing many different band combinations, composite bands, textural and spatial parameters, the following features were used in the expert system rule to extract urban patches: mean bands 1,2,3, band ratio, brightness, entropy, length and area. The training samples were chosen to be statically relevant by using more than 30 samples for each class (110 in total). These both results have also been compared to a per pixel classification where all classes of impervious surface have been summarized.

Table 3 shows producer's accuracy, user's accuracy, overall accuracy and the kappa index generated for the third classifiers. As expected, the SVM classifier produces the highest accuracy (93,35%). The improvement can be noted specially for the user's accuracy related to impervious surfaces. This demonstrates that the SVM classifier can reduce some confusions between impervious and other classes over the two others algorithms.

	Maxlike		NN		SVM	
	%prod	%user	%prod	%user	%prod	%user
Impervious surf.	89.62	58.32	66.24	67.25	84.49	86.45
Other	80.11	99.48	94.89	94.34	98.23	94.34
Overall acc. (%)	*83.25*		*91.14*		***93.35***	
Kappa index	*0.66*		*0.78*		***0.83***	

Table 3. Accuracy assessment on the classification results of urban patches.

From the classification result the MUA is produced by some spatial analysis described in section 3 (Figure 5a). This MUA is then selected to be used as a mask to the Quickbird image with a fine spatial resolution (2.4m) for the next step.

4.2 Classification of urban blocks (level 1) and urban materials (level 2)

The masked image is used as an input for the segmentation step. The classification is performed on segmented blocks corresponding to the minimal system built from the communication ways. Training samples are chosen to apply the NN classifier and the classification result (level 1) is expressed in four thematic classes of blocks: (1) green spaces (agricultural lands, urban park, sport fields, etc), (2) communication ways related to surfaces, (3) water surfaces (river and lake) and (4) urban blocks related to housing or commercial activities. Classification results of these blocks (Figure 5b) obtained an overall accuracy assessment of 86% with a kappa index of 0,87. Some confusions related to urban blocks have been manually corrected in order to use this result to classify the sub-level 2. Some blocks have not been classified because they do not cover the Quickbird image.

The classification of urban materials is defined in 11 classes where accuracy assesment is presented in Table 4.

	%Prod Acc.	%User Acc.
Grassland	100.00	88.24
Tree	69.23	69.23
Mixed vegetation	89.75	86.23
Shadow of tree	89.69	79.58
Shadow of building	86.67	79.10
White roof	100.00	86.67
Blue roof	75.54	100.00
Road	60.50	68.12
Orange roof	97.80	98.89
Light grey	63.41	55.32
Dark Grey	68.63	94.6
Overall accuracy (%)	*78.88*	
Kappa Index	*0.75*	

Table 4. Accuracy assessment of classification at level 2.

Producer's and user's accuracy are generally highest on urban materials on the top of the hierarchy which is presented in ascending order of difficulty (described in Figure 3). As expected, the main confusions appear between objects with similar materials such as roads and light or dark grey roof. Classification result is presented on a subset of the urban area of Strasbourg (Figure 5c).

4.3 Classification of urban fabrics (level 3)

For the level 3, the accuracy assessment is 76,6% with a kappa index of 0,70. Three urban fabrics seems particularly well identified (dense, individual and specialised urban fabrics). The producer's and user's accuracies of 100% for the dense urban fabric can be explained due to the low representatively of this thematic class in periurban area. Indeed in your experiment we have chosen to exclude the city centre because some clouds and shadows appear on the Quickbird image. Accuracies are low for complex urban fabric such as mixed urban fabric and area. Their composition is not clearly different as shown at Figure 3. However, classification results (Figure 5d) are very encouraging results allowing to help end-users to produce automatically interest maps of the territory at the scale of urban fabrics.

	%Prod Acc.	%User Acc.
1. Dense Urban Fabric (UF)	100.00	100.00
2. UF with individual houses	100.00	76.92
3. UF with housing blocks	81.82	83.56
4. Mixed urban fabric (housing)	57.14	66.67
5. Mixed urban area (activities)	33.34	54.21
6. specialised areas	100.00	86.67
Overall accuracy (%)	*76.60*	
Kappa Index	*0.70*	

Table 5. Accuracy assessment of classification at level 3.

4.4 Validation of the workflow on Toulouse area

Only a subset of Toulouse area localised in the first ring of urbanisation has been used to validate the workflow allowing to map blocks (level 1), objects (level 2) and urban fabrics (level 3) as vector datatbase on communication ways is easily available. Segmentation parameters have been identified as relevant for their application to this second city and hvae been applied without changes. In the features space chosen for the classifcation step, only the thresholds of parameters have to be adapted for a better adequation with the spectral and spatial variability of the local context of Toulouse. The overall accuracy assessment at the different steps (Table 6) shows the same confusions or omissions errors and shows the reproductibility of the proposed workflow with the unique condition to have date on communication ways.

	Level 1	Level 2	Level 3
Overall acc. (%)	*83.25*	*91.14*	***93.35***
Kappa index	*0.66*	*0.78*	***0.83***

Table 3. Accuracy assessment for each level of classification on Toulouse area.

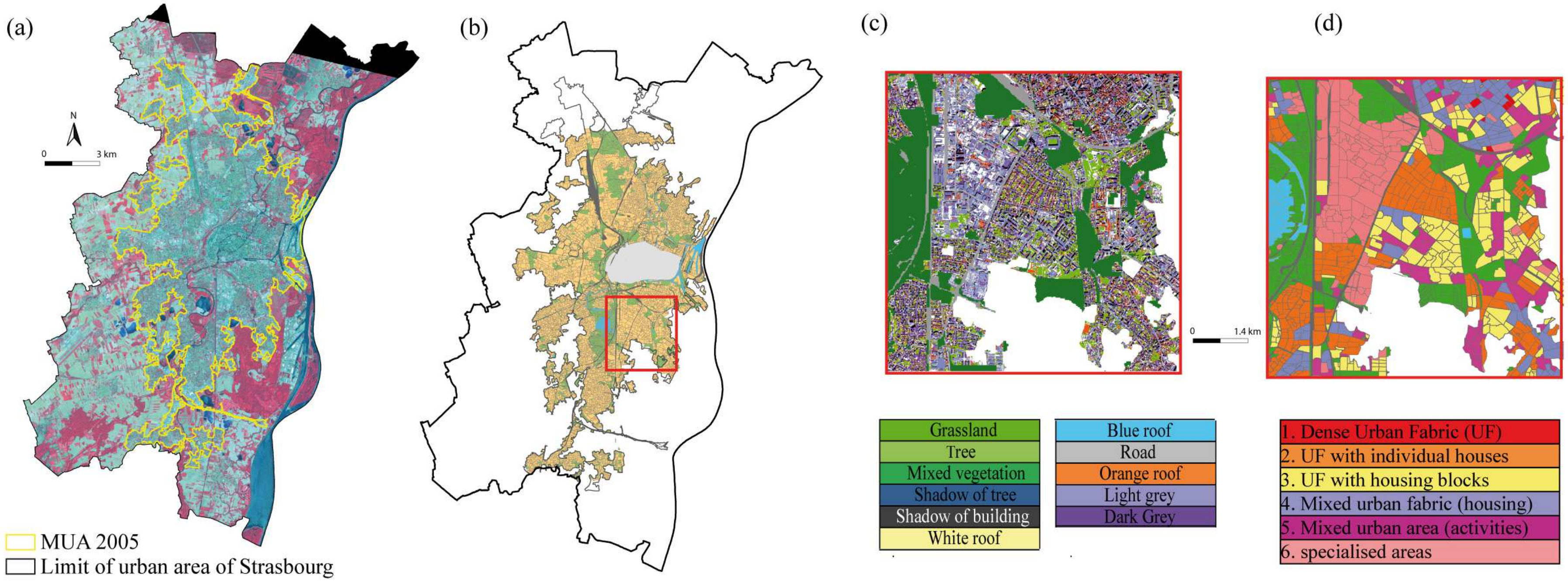

Figure 5. Results on Strasbourg area: (a) Morphological Urban Agglomeration (MUA), (b) classification of urban blocks, (c) classification of landcover/materials classes and (e) classification of urban fabrics.

5. CONCLUSION AND PERSPECTIVES

The proposed methodology in this research based on HRS and VHRS imagery allows producing some information related to MUA and urban fabrics. For this level of analysis, no database exists and it is important to help end-users to produce automatically with a generic methodology these information's. In order to do that, the proposed methods using existing data on street map showed good results on Strasbourg. To highlight the reproducibility of the method, combining all the workflow but also the features sets, the both workflow have been tested on the Toulouse urban area. Results are shown also their soundness proving that it is possible to apply this methodology to an other site of interest (with the same morphological development).

Some researchers have been enables in two domains: for the segmentation methods and parameters and for the features selection and thresholding. In order to choose the optimal resolution(s) and segmentation parameters, the spatial heterogeneity could be measured using average local variance function (Woodcock and Stralher, 1987, Nijland et al, 2009, Tran et al.,2011) on a set of images with different resolutions (from VHRS to HRS). The spatial analysis of the composition of each urban fabric could do also of an more precise statistical analysis by calculate these information on a great number of urban fabric. 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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