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Comparison of sampling strategies for object-based classification of urban vegetation from Very High Resolution satellite images

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ABSTRACT

Vegetation monitoring is becoming a major issue in the urban environment due to the services they procure and necessitates an accurate and up to date mapping. Very High Resolution satellite images enable a detailed mapping of the urban tree and herbaceous vegetation. Several supervised classifications with statistical learning techniques have provided good results for the detection of urban vegetation but necessitate a large amount of training data. In this context, this study proposes to investigate the performances of different sampling strategies in order to reduce the number of examples needed. Two windows based active learning algorithms from state-of-art are compared to a classical stratified random sampling and a third combining active learning and stratified strategies is proposed. The efficiency of these strategies is evaluated on two medium size French cities, Strasbourg and Rennes, associated to different datasets. Results demonstrate that classical stratified random sampling can in some cases be just as effective as active learning methods and that it should be used more frequently to evaluate new active learning methods. Moreover, the active learning strategies proposed in this work enables to reduce the computational runtime by selecting multiple windows at each iteration without increasing the number of windows needed.

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1. Introduction

With the increasing urbanization, urban green spaces become more important for urban environments and urban ecosystems, notably for the services they procure (Tzoulas et al., 2007). These services are numerous and allow for instance, reducing pollutants from transportation and the effect of urban heat islands, to maintain biodiversity in cities or to develop leisure facilities. In Europe, urbanisation results in urban sprawl that is fragmenting natural and agricultural landscapes (European Environment Agency, 2006) and the developing green infrastructures at the European level is a permanent task for several decades (Jongman et al., 2004). In France, the implementation of the Grenelle 1 (2009) and Grenelle 2 (2010) environmental policy aimed at creating through regional schemes of ecological coherence, a network of green and blue networks. The Green and Blue Infrastructure consists of a green component, i.e. natural and semi-natural environments on land, and a blue component, i.e. the water and wetland network (rivers, streams, canals, ponds, wetlands, etc.) (COMOP, 2009). In France, the topographic database produced by the French National Geographic Institute (BD Topo®—IGN) is often used to map the green part of these networks (Hubert-Moy et al., 2012). This database is not necessarily regularly updated and is not complete for the whole national territory. Only tree areas of over 0.5 ha are represented and herbaceous vegetation is not considered. Thus this database is not accurate enough or sufficiently up to date to map ecological continuities at the infra-communal scale (Hubert-Moy et al., 2012). The development of satellites at Very High Resolution (VHR) providing images with a resolution of less than a metre has continued since the early 2000s, allowing up to date maps to be obtained that are exhaustive in terms of the type of vegetation.

With the increasing availability of satellite images, numerous methods have been developed to retrieve the urban vegetation. These methods may be supervised or not and are often uniquely based on spectral values of pixels (Xie et al., 2008). However, with VHR images, the spectral values of objects of the same type become more heterogeneous and it may become necessary to use new features such as texture or neighbourhood to improve the results of classifications (Tuominen and Pekkarinen, 2005; Sheeren et al., 2009). Rather than using a per-pixel classification, object-

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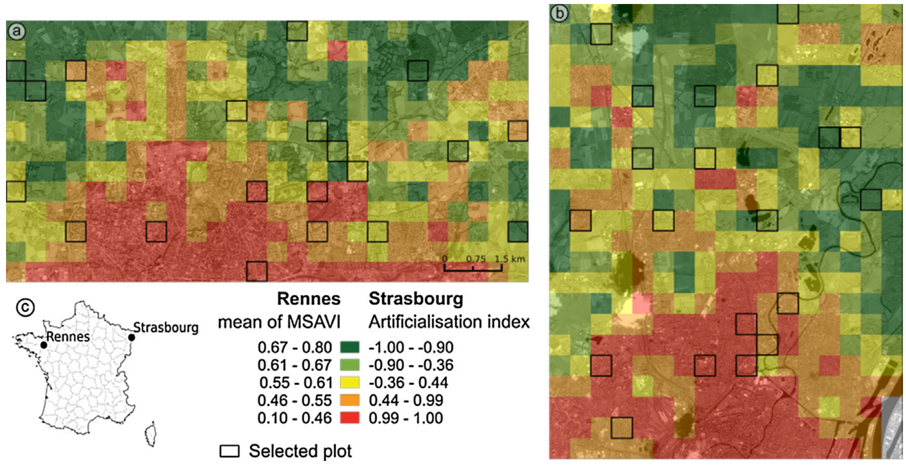

Fig. 1. Localisation of the study sites (c) of Rennes (a) and Strasbourg (b), along with their urbanisation index and the localisation of photo-interpreted plots (black outlines).

based image analysis has been proposed as an alternative (Blaschke, 2010). These approaches allow pixels to be re-grouped within homogenous segments and a large set of features to be computed, which can be spectral, textural, contextual or spatial (Mathieu et al., 2007; Blaschke et al., 2011). The use of these approaches for the detection of urban vegetation allows increased performance compared to per-pixel approaches (Cleve et al., 2008; Zhang et al., 2010). Rule-based classifications are often used to retrieve the vegetation from VHR images (Pham et al., 2011; Van Delm and Gulink, 2011). The relevant features and thresholds are often determined by trial and error, which can be very time-consuming and is strongly influenced by the knowledge of the expert (Belgiu et al., 2014). Additionally, the created rule sets are difficult to transpose to other sites or images, whether they come from the same sensor, or not and need to be adapted (Hussain and Shan, 2016).

Supervised classifications with statistical learning techniques have provided good results for the detection of urban trees (Cleve et al., 2008; Zhang et al., 2010; Tigges et al., 2013; Rougier and Puissant, 2014). These methods have the advantage of being easily reproducible, regardless of the study site or the image considered. However, to obtain good results with a supervised algorithm, it is often necessary to collect large amounts of training data, particularly for the most heterogeneous classes (Chen and Stow, 2002) or require representative training data which allow to consider the whole diversity of the space or the classes studied (Foody and Mathur, 2004). The collection of this data is typically obtained by field survey or visual image interpretation which can be an important work and cost. The image interpretation is very time consuming and may vary depending on the interpreter or external and technical factors (Van Coillie et al., 2014). To obtain representative examples, several schemes are traditionally used in remote sensing, such as stratified random sampling (Congalton and Green, 2009). This strategy generally allow to reduce the size of the training data needed but require prior knowledge on the study site to construct the stratification.

More recently, active learning methods have been proposed, to reduce the cost needed for the production of training data by reducing the training set size and thus the labelling time. Using an iterative process, the aim of this approach is to select the most informative and representative examples for the active classifier at each iteration, so that they can be annotated by the user (Settles, 2010). Using these methods generally allow to obtain more accurate results than with simple random sampling (Settles, 2010; Tuia et al., 2009). These methods also permit to increase interaction with the user (Hichri et al., 2013) and are recently used with good results, both for multispectral and hyperspectral image classification (Tuia et al., 2009; Demir et al., 2011). Tuia et al. (2011) identified three major families of strategies that are commonly used for the selection of new examples: strategies based on the disagreement of a model committee, on the distance to the separators and on posteriori probability measurements.

A problem of the active learning strategies is the computational runtime needed to carry out the classification, as the number of iterations can sometimes be large. Several solutions have been proposed to reduce the number of iterations by selecting a batch (Demir et al., 2011) or a window (Stumpf et al., 2014) at each iteration. Other algorithms have been proposed, to integrate diversity criteria and to reduce redundant information of new examples and obtain more rapidly a series of examples that represent the full complexity of the image being studied (Demir et al., 2011; Tuia et al., 2009; Volpi et al., 2012; Stumpf et al., 2014). Different methods have been also proposed to take spatial constraints into account (Liu et al., 2009; Xu et al., 2014; Pasolli et al., 2014) or to take terrain specificities into account (Demir et al., 2014) to obtain less correlated and thus more representative examples.

In this context, the main objective of this work is the mapping of urban vegetation (tree and herbaceous vegetation) from VHR images extending to multiclass classifications an active learning method initially proposed by Stumpf et al. (2014) for the detection of landslides. Most applications of active learning in the field of remote sensing compare these methods to simple random sampling. Moreover, as it has been shown that other selection strategies allow obtaining better results, this work addresses this issue and provides a benchmark of different sampling strategies for the mapping of urban vegetation. To challenge random stratified sampling, three strategies of active learning are evaluated. They are based on a committee model to select the most informative windows in the framework of an object based analysis. The first will choose the most uncertain window and the second integrates a diversity criterion. The third method proposes to combine active leaning and

Table 1
The part of the classes considered by surface and segments for Strasbourg and Rennes.

	Strasbourg		Rennes	
	Area	Segment[a]	Area	Segment[a]
Tree	21.14 %	19.09 %	20.96 %	24.04 %
Herbaceous	13.29 %	9.68 %	9.98 %	9.87 %
Other	65.57 %	71.23 %	69.06 %	66.08 %

[a] The classes have been attributed from the digitized ground truth to the objects coming from segmentation (1st level) according to the majority class represented in each segment.

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