URBAN AREA PRODUCT SIMULATION FOR THE ENMAP HYPERSPECTRAL SENSOR

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ABSTRACT

Low spatial resolution is a major limitation for remote sensing classification, especially in a urban environment. In this work, we will focus on the simulation of urban area environment at a low spatial resolution, comparable to the new hyperspectral sensors that will be launched in the next few years. The aim is to better understand the possibility offered by the new sensors, in a challenging scenario like the one represented by a highly mixed image. Particular attention is placed on the characteristics of the sensor EnMap, produced by DLR. The experiments conducted on a real data set confirm the challenges posed by low spatial resolution when analyzing a urban environment.

1. INTRODUCTION

Urban areas are currently the most rapidly changing types of land covers, even though they represent only a low percentage of the global land surface [1]. The possibility to monitor these areas is therefore one of the most relevant issues concerning the evaluation of the human impact on the environment. For this purpose, the use of satellite remote sensing imagery can provide a timely and relatively cheap view of urban land covers, as well as a tool to monitor changes in urbanizing landscapes. The most common approach for characterizing urban areas using remote sensing imagery is the land-cover classification, that is assignment of an area to a class which corresponds to the material covering the area or the main purpose for which the land is used. However, the remote sensing characterization of urban environments can be complicated for several reasons: (i) usually, urban land-cover classes are not well spectrally distinct, resulting in considerable confusion between classes [2], (ii) the physical structure of land-use classes varies from site to site due to the different roofing and paving materials and building typology [1], (iii) urban areas are heterogeneous and most pixels, at the satellite spatial resolution which can vary from few to tens of meters per pixel, appear mixed with varying proportions of different components and/or materials [3].

The use of hyperspectral sensors for land cover monitoring is receiving continuosly growing attention due to the advantageous characteristic of such data and to the already planned civilian space missions which will make available in the next future a huge quantity of hyperspectral data (amongst the others, PRISMA, planned by the Italian Space Agency ASI in 2014, EnMap planned by German Space Agency DLR in 2014, Hyper-J and HyspIRI, planned respectively bt the Japan Space Agency and NASA in the next future, besides the already on orbit sensors like the widely used Hyperion and AVIRIS, both of NASA). The potentialities offered by the new generation of hyperspectral satellite imagery for urban applications is a challenging aspect that this paper intends to deal with, as it is still not fully investigated [4]. In this paper, particular attention is placed on the characteristics of the sensor EnMap, produced by DLR [5, 6].

The remainder of the paper is as follows. Section 2 introduces the characteristics of the EnMap sensor. Section 3 describes the experimental design followed in this work, while Sections 4 and 5 present a discussion of the results and the conclusions of the work.

2. CHARACTERISTICS OF THE ENMAP SENSOR

The Environmental Mapping and Analysis Program (EnMAP) German hyperspectral mission is intended to provide new quality spectral information about the Earth surface, exploiting the state-of-the-art hyperspectral sensor technology. The sensor is designed to acquire areas of 30 $\times$ 30 km with a ground sampling distance (GSD) of 30 m, measuring in the 420-2450 nm spectral range with more than 240 bands by means of two entirely independent prism-based spectrometers that cover the spectral regions from the visible to near-infrared (VNIR) and the short-wave infrared (SWIR). The mean spectral sampling interval is 6.5 nm in the VNIR and 10 nm in the SWIR.

Despite the modular architecture of the EnMAP scene simu-

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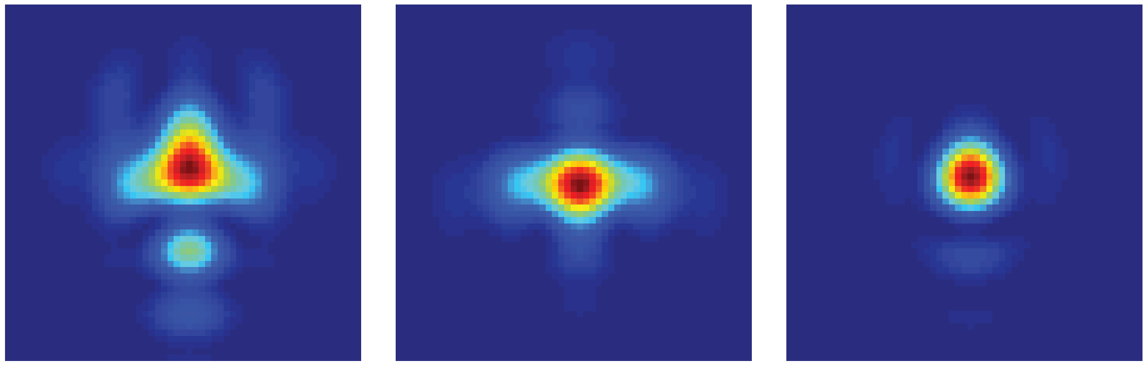


(a) (b) (c)

Fig. 1. Point spread function of the EnMap sensor at different wavelengths: (a) 420 nm (b) 900 nm (c) 1000 nm. If a point in figure is red (blue), it will have a high (low) influence on the final pixel value.

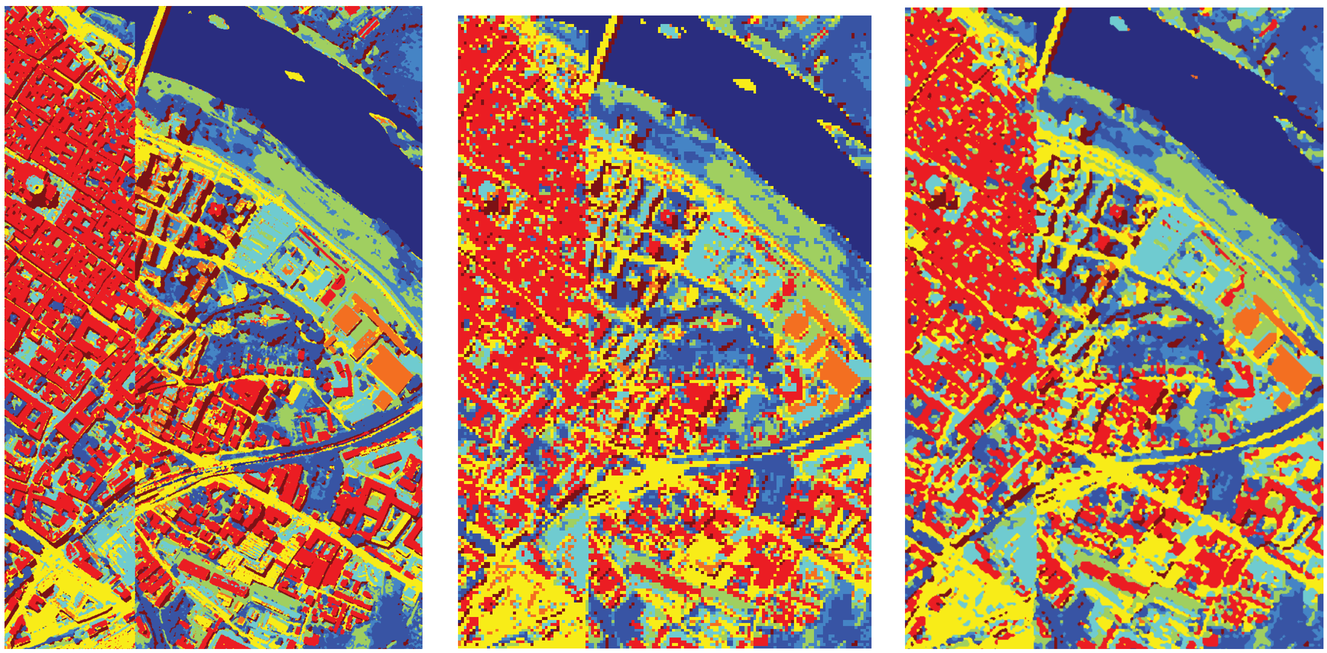
lator, it is acknowledged that the spectral and spatial dimensions are always coupled in real spectrometers. The coupling appears as optical aberrations in the two domains that can be seen as different consequences of non-uniformities in the instrument point spread function (PSF) (see Fig. 1). They can be simultaneously described by a spectrometer-intrinsic distortion matrix, which specifies the position of each spatial and spectral pixel in the detector array with respect to the instrument slit. However, the EnMAP scene simulator performs a separate modeling of the two dimensions, since only this way can the computationally required simplification be achieved. Additionally, it enables the separate analysis of different types of instrumental factors.
Preliminary works trying to create accurate simulations of the sensor images were shown in [6, 7]. In this paper, we will focus on urban area environments, to investigate the influence of low spatial resolution on the data classification accuracy.

3. EXPERIMENTAL DESIGN

The idea of the paper is to consider a very high resolution image (acquired by the airborne hyperspectral sensor ROSIS), and to artificially degrade its spatial resolution, according to the physical characteristics and the point spread function (PSF) of the EnMap sensor. Preliminary experiments were conducted on a ROSIS data set representing the center of Pavia. The image is 1096 by 715 pixels. 102 spectral dimensions were processed in the experiment. Nine classes of interest are considered, namely: water, tree, meadow, brick, soil, asphalt, bitumen, tile and shadow. The original spatial accuracy of the image is 1.3 m. In order to have a simulated urban area with lower spatial resolution, we have artificially degraded the spatial resolution of the original image. Two different down-scaling factors were tested: 3 and 5 (that is, each pixel of the low-resolution image corresponds to 9/25 pixels of the original data set), according to the point spread function of the EnMap sensor, at 1000 nm, shown in Fig. 1(c). Therefore, each pixel has not only the weighted contribution of the 9/25 pixels it corresponds to, but also from neighboring pixels, in order to simulate the possible inefficiencies of a hyperspectral sensor. The relatively low spatial resolution of the new created images (3.9 and 6.5 m), although higher with respect to common satellite hyperspectral sensors, represents a challenging test for the traditional approaches used to perform classification in urban areas, due to the high number of mixed pixels which are jointly occupied by more than one class.
The low resolution image was classified with one of the state of the art classifiers for hyperspectral remote sensing images, the Support Vector Machines (SVM) [9], in order to obtain a flavor of the problem encountered by a traditional remote sensing classifier. A comparison with an approach recently proposed in [8] to deal with data containing mixed pixels was also performed. The method proposes a joint use of probabilistic classification techniques and spectral unmixing in order to handle mixed pixels. Due to lack of space, we refer to [8] for further details on the method.

4. DISCUSSION

The two classifiers considered in this work were trained by randomly choosing 100 samples per class. Preliminary results obtained in the data set down-sampled of a factor 5 are shown in Fig. 2 and 3. The classification maps show how challenging is the classification of urban area in the case of (relatively) low spatial resolution. Fig. 3 shows a small part of the image where several ground truth classes are present. It can be noticed that the method proposed in [8] provides slightly better results as compared to a traditional SVM, especially when looking at the structure borders, where usually mixed pixels appears. However, due to intrinsic nature of the scenario, the quality of the classification map is far from the



(a) (b) (c)

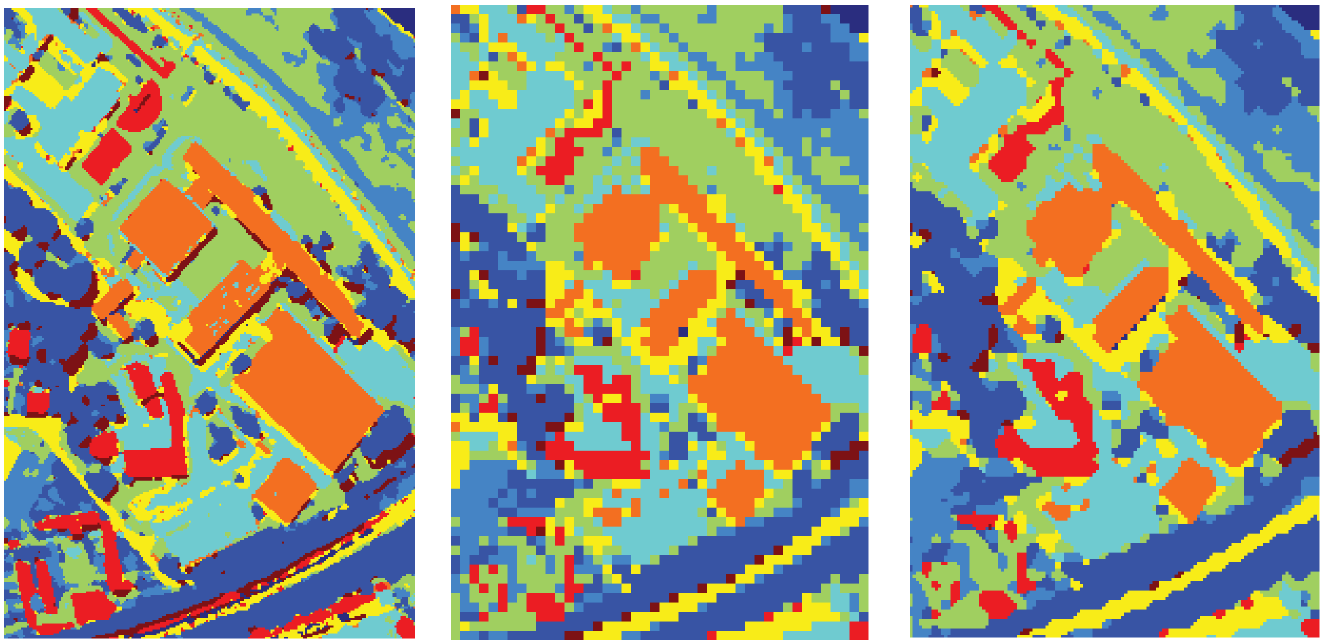
Fig. 2. ROSIS center data classification map: (a) SVM classification map on original resolution data (b) SVM classification on lower resolution data (c) Classification map obtained by applying the method presented in [8] to the low resolution data

case of high spatial resolution.
From a quantitative point of view, the comparison of the low resolution maps obtained with SVM to the high resolution ground truth was not straightforward due to the different number of pixels of the two images. However, we know that every pixel of the low resolution image corresponds to $n \times n$ pixels of the high resolution image. By comparing a pixel of the low resolution classification map with the $n \times n$ corresponding in the high resolution ground truth map, we can compute per-pixel classification accuracy. In the experiment conducted with a data set downsampled of a factor three, the SVM classifiers provide a classification accuracy of 79.56%, while the method proposed in [8] 81.89%. When the spatial accuracy is decreased of a factor 5, the SVM obtains a classification accuracy of 70.97%, while the method proposed in [8] 74.32%. For comparison, the classification accuracy obtained by training an SVM with 100 samples per class on the original data is 98.11%.

As a conclusion of this preliminary work, we can assess that spatial resolution is a major limitation for the analysis of urban environments with traditional techniques. When downscaling the spatial resolution of a factor 3, the classification accuracy decrease of about 20%. The difference is almost 30% when the downscaling factor is equal to 5. The comparison of the classification accuracies should be carefully considered, since the decrease of spatial resolution introduces a number of mixed pixels which cannot be correcty classified by a traditional classifier like an SVM. However, the large difference of classification accuracy with respect to the original case shows the importance of a high spatial resolution for the classification of urban environment. The joint use of spectral unmixing and classification methods provides both qualitative and quantitative improvements, thus opening new perspectives for the development of suitable approaches for urban area classification.

5. CONCLUSIONS AND FUTURE WORKS

In this paper, we have shown preliminary results on a urban area product simulation for satellite hyperspectral sensors, intended to investigate the potentiality of new hyperspectral sensors generation in urban environment.
The experiments show that, even in a relatively low spatial resolution case, the task of urban area classification becomes very challenging. Future developments of this work will be a more realistic simulation of urban data and a careful assessment of the possibilities offered by recently developed methods like [8] to provide possible solutions for the problem of mixed pixels. In particular, more physical properties of the EnMap sensor will be taken into account to simulate the data, and a lower spatial resolution will be tested.



(a) (b) (c)

Fig. 3. Right bottom part of the classification image: (a) SVM classification map on original resolution data (b) SVM classification on lower resolution data (c) Classification map obtained by applying the method presented in [8] to the low resolution data

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