Conference Proceedings Paper

Classification of Sentinel-2 Images Utilizing Abundances Representation

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Published: date
Academic Editor: name

Abstract: This paper deals with (both supervised and unsupervised) classification in multispectral Sentinel-2 images, utilizing the abundances representation of the pixels of interest. The latter pixel representation uncovers the hidden structured regions which are not often available in the reference maps. Additionally, it encourages class distinctions and bolsters accuracy. The adopted methodology, which has been successfully applied on hyperpsectral data involves two main stages: (I) the determination of the pixels abundance representation and (II) the employment of a classification algorithm applied on the abundance representations. More specific, stage (I) incorporates two key processes namely: (a) **endmember extraction** utilizing spectrally homogeneous regions of interest (*ROIs*) and, (b) **spectral unmixing**, which hinges upon the endmember selection. The adopted spectral unmixing process assumes the Linear Mixing Model (*LMM*), where each pixel is expressed as a linear combination of the endmembers. The pixel's abundance vector is estimated via a variational Bayes algorithm that is based on a suitably defined hierarchical Bayesian model. The resulting abundance vectors are then fed to stage (II) where two off-the-shelf supervised classification approaches (namely nearest neighbor (*NN*) classification and support vector machines (*SVM*)) as well as an unsupervised classification process (namely online adaptive possibilistic c-means (*OAPCM*) clustering algorithm), are adopted. Experiments are performed on a Sentinel-2 image acquired for a specific region of the Northern Pindos National Park in the northwestern Greece containing water, vegetation and bare soil areas. The experimental results demonstrate that the ad-hoc classification approaches utilizing the abundance representations of the pixels outperform the ones utilizing the spectral signatures of the pixels, in terms of accuracy.

Keywords: spectral unmixing; classification; clustering; Sentinel-2 imagery; land cover.

1. Introduction

Land cover analysis and classification is essential for various environmental and mapping applications. Land classification yields to thematic maps which integrate land cover materials. Sentinel-2 data has gained leverage in the remote sensing community due to the high spatial and the high temporal resolution. Sentinel-2 multispectral high-resolution sensor (*MSI*) operates on thirteen different bands of which four have a resolution of ten meters, six a resolution of twenty meters and three a resolution of sixty meters. Hence, Sentinel-2 data provide information on the reflectance of the land surface for many different wavelengths on a local and regional scale. Regardless of the sensor's spectral resolution, these images are challenged by the presence of mixed pixels, which depict mixtures of distinct materials.

Each mixed pixel is associated with the electromagnetic reflection of various materials measured in numerous spectral bands belonging to the surface depicted by the pixel, measured in numerous spectral bands. These measurements constitute the spectral signature of the pixel. Two processes are fundamental in analysis such as: (a) the detection of the constituent components of mixed pixels as well as the proportions in which they appear and, (b) the identification of homogeneous regions. The first objective is tackled via spectral unmixing and the second via the use of classification algorithms.

Classification [1]-[4] partitions the set of pixels from the input image into compact, homogeneous groups. It is performed in either supervised or unsupervised way usually operating in the spectral signatures of the pixels. Hitherto, mixed surface features are tackled by supervised classification approaches, which require the availability of a labeled set of pixels. These pixels form the training set that is used for teaching the classifier the underlying pixel classification task in order to further classify the unlabeled pixels. Popular classification methods proposed in literature include the nearest neighbor classifier [5],[6] and the support vector machines (*SVMs*) [7].

Several classification methods have been applied on Sentinel-2 images. In this work we assess the performance of a recently proposed classification method [2], originally proposed for hyperspectral images on Sentinel-2 data. The main idea of the methodology is to perform first spectral unmixing based ona asuitably selected set of endmembersd and represent each pixel by its associate abundance vector (constituting from the corresponding abundance values). Then, the classification of the pixels is performed on the abundance vectors of the pixels and not on their spectral signatures (actually two supervised and one unsupervised classification algorithms are utilized). To assess the performance of the adopted methodology on Sentinel-2 data, we compare with the case where spectral signature pixel representations are considered. To the best of our knowledge this is the first attempt of utilizing a combination of both spectral unmixing and classification tasks on Sentinel-2 data.

The area on which the methodology will be assessed is that of Northern Pindos National Park-Greece (Sentinel-2 data). Section 2 describes the adopted algorithm. Section 3 demonstrates the results obtained by ad-hoc classification algorithms utilizing the spectral signatures and the abundances representations. Conclusion is summarized in Section 4.

2. Methods

2.1 Test Area

The test area is a specified region of the Northern Pindos National Park in the northwestern Greece. This region is the largest protected forestry region with high topographical diversity. The image has a resolution of 30m consisting of 333×333 pixels and is depicted in Fig. 4(a). We utilized the image at 30m resolution instead of the one at 10m resolution in order to compare the results obtained by the proposed algorithm with the reference classification map provided at 30m resolution [6]. The image depicts the artificial lake of Aoos on the northwest of Metsovo and a small part of the mountains of Pindos. The region is dominated by grassland, prickly oaks and hornbeams, beech, black pine and deciduous oak. The verge of the mountain slopes is covered by Bosnian pine. Human agricultural activities are also present along the water basin. The image is atmospherically corrected and this process yielded to the reduction of the number of bands from 13 to 10, namely band 1 (443 nm), band 9 (945 nm) and band 10 (1375 nm) have been removed. Four basic classes, namely Water, Dense Vegetation, Soil and Sparse Vegetation are specified.

2.2 Adopted Methodology

The adopted methodology is motivated by the properties of the abundances of ground materials present in the pixels of a Sentinel-2 image. Each pixel is represented by a vector of ten spectral bands and the original space is reshaped to the dimensionally reduced space of abundances. (see Figure 1).

In addition, since the abundance representation of a pixel unveils sub-pixel level information, this allows the proposed algorithm to identify possible refined structures within each region, which is usually not available in the ground truth maps.

The scope is to employ first endmember extraction (*EE)* by identifying spectrally homogeneous regions (regions of interest, *ROIs*) and extracting the mean endmembers of the image based on the collected *ROIs*. Secondly, it employs a *SU* method that is based on the endmembers extracted by *EE*, in order to produce the abundance fractions for each pixel, which in turn form the so-called abundance vector of the pixel. These vectors from all pixels are fed to the classification process that groups pixels according to abundance representations.

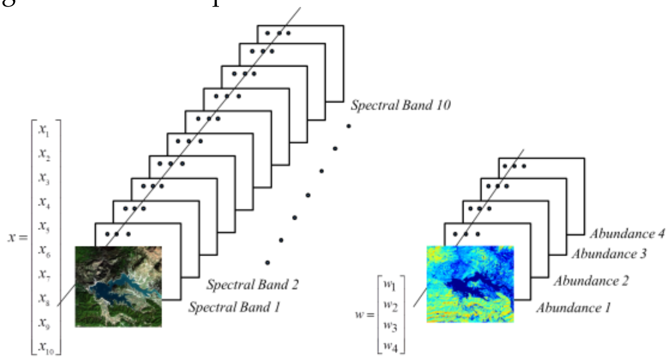
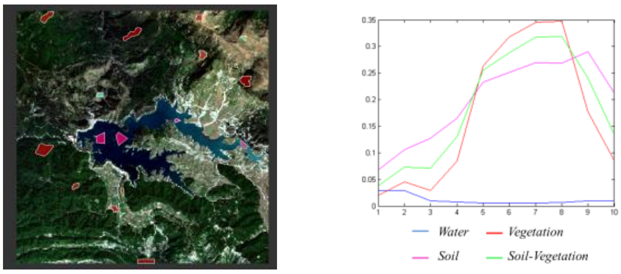


Figure 1. Spectral bands from the original spectral band space are dimensionally reduced to the less correlated abundance space.

2.2.3. A. EE

Aiming at selecting representative endmembers for each class, suitable regions of interest (*ROIs*) were selected. In our experiments we use four main land cover classes, namely (a) Water, (b) Dense Vegetation, (c) Soil and (d) Sparse Vegetation. All endmembers are calculated as the average values of the spectral signatures of the pixels in each *ROI*. Figure 2 depicts (a) the appropriate *ROIs* selected on the Sentinel-2 image (*see* Section 3: Fig. 4(a)), (b) the endmembers of four main classes, water, dense vegetation, soil, sparse vegetation.



(a) (b)

Figure 2. (a) *ROIs* selection for endmember extraction, (b) endmembers of four classes, water, dense vegetation, soil, sparse vegetation.

2.2.4. B. SU

The selection of appropriate endmembers is crucial so as to correctly estimate the abundance fractions. The spectral signature of the pixel, denoted by x, is assumed to follow the Linear Mixing Model (*LMM*). The latter adopts the hypothesis that the spectrum of a mixed pixel is a linear combination of its endmembers' spectra as follows:

$$x = \Phi w + n \quad (1)$$

where $\Phi = [\phi_1, \phi_2, \ldots, \phi_p] \in \Re_+^{L \times p}$, $L >> p$, is the mixing matrix comprising the endmembers' spectra in its columns (L-dimensional vectors $\phi_i, i = 1, 2, \ldots, p$), $\boldsymbol{w}$ is a $p \times 1$ vector consisting of the corresponding abundance fractions, named abundance vector, and $\boldsymbol{n}$ is an $L \times 1$ additive noise vector, which is assumed to be a zero-mean Gaussian distributed random vector with independent and identically distributed elements.

The abundance fractions for each pixel should be non-negative and sum to one. The abundance vector for each pixel is estimated via a variational Bayes algorithm, called *BiICE* which is based on an appropriately defined hierarchical Bayesian model [8]. In algorithmic form the abundance vector can be written as:

$\boldsymbol{w}$ = *BiICE* ($\boldsymbol{\Phi}$, $\boldsymbol{x}$).

BiICE is computationally efficient, provides sparse solutions without requiring the fine-tuning of any parameters and converges fast to accurate values even for highly correlated data. The determined abundance vector $\boldsymbol{w}$ is further used for each pixel representation at the classification process. Then, the abundance representations resulting from *BiICE* are fed to the classification process.

2.2.5. C. Classification

The classification is carried out in both supervised and unsupervised terms. Sepcifically, for the former case the nearest-neighbour classifier (*NN*) is employed, where every training example is stored with its label and a prediction is made for a test example by computing its distance to every training example. In addition to *NN*, *SVMs* are also utilized since they show , in general, superior performance to other classification methods. The advantage of *SVM* is that it successfully works with small number of training samples. Finally, for the unsupervised case, a clustering algorithm, called online adaptive possibilistic c-means (*OAPCM*), is exploited [9]. In *OAPCM*, pixels are being processed one by one and their impact is memorized to suitably defined parameters. Hence, the algorithm is flexible in tracking variations during the clustering formation. *OAPCM* starts with a zero number of clusters and during evolution it creates new clusters or merges existing ones.

Figure 3 depicts a flowchart of the two case studies: A) spectral signatures classification and B) abundances representation classification.

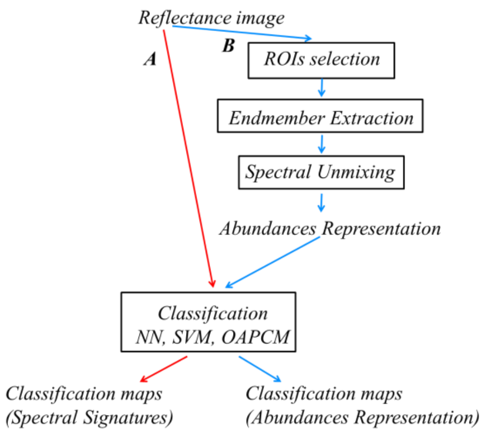


Figure 3. Flowchart of the two case studies: A) spectral signatures classification (red line), B) abundances representation classification (blue line).

3. Results and Discussion

Aiming at a quantitative evaluation, ad-hoc classification approaches proposed in literature such as the nearest neighbor (*NN*) classifier, the support vector machines (*SVMs*) and the unsupervised

OAPCM algorithm are utilized. The obtained results (classification maps) are validated in terms of accuracy based on the obtained confusion matrix as can be seen in Tables I and II. In both cases of supervised classification (*NN*, *SVM*), the four endmembers extracted in the *EE* process are used to train the classifiers whereas the remaining pixels are used for validation. It should be noted that, in the case where the abundances representations are used as input for classification, spectral unmixing is applied on the four endmembers as well as on the remaining pixels. The abundances representations are used to train the classifiers. As a result, classification maps are generated, providing information of the area of each land class. The classification utilizing the abundances representation (*see* Fig.3 case study *B*) achieves an average accuracy which is higher to the classification that utilizes the spectral signatures (*see* Fig. 3 case study *A*). The water and soil classes are successfully identified by the two case studies since the average classification accuracies are similar. However, the dense vegetation and sparse vegetation classes are not successfully identified. Results are shown in Fig. 4.

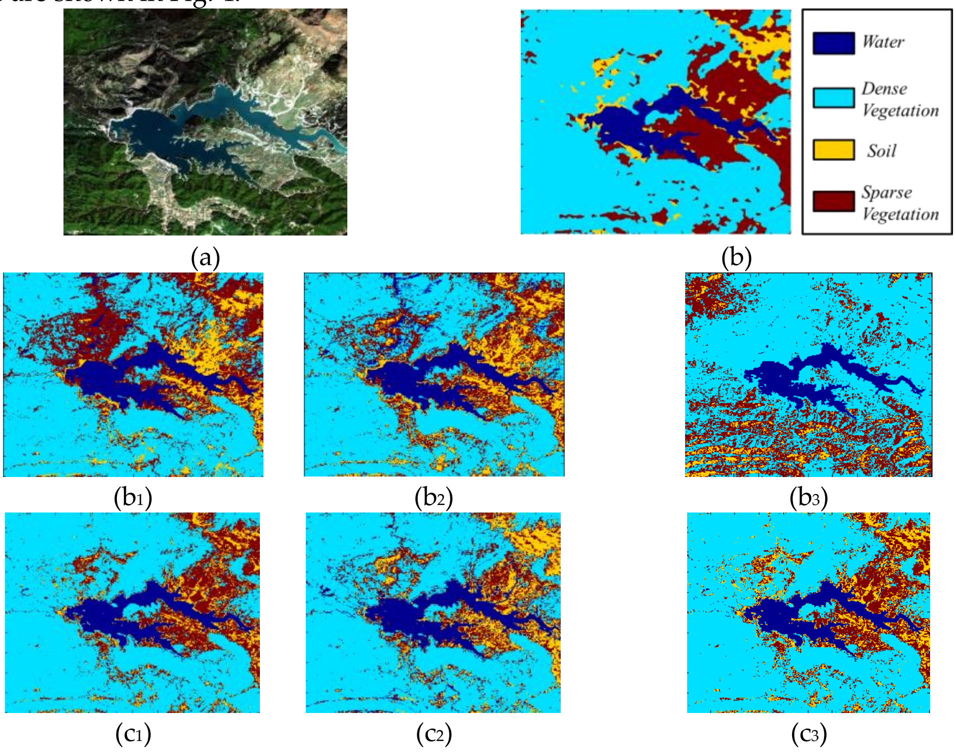


Figure 4. (a) Band 8th of the Sentinel-2 image, (b) Reference map of four classes: water, vegetation, bare soil and soil-vegetation, (b_1), (b_2), (b_3) classification results obtained by *NN*, *SVM*, *OAPCM* on spectral signatures, (c_1), (c_2), (c_3) classification results obtained by *NN*, *SVM*, *OAPCM* on abundances representation.

TABLE I Comparative Results of Classification Algorithms in Terms of *AA* for Spectral Signatures

	Water	*Dense vegetation*	*Bare Soil*	*Sparse vegetation*
NN	93,49	80,44	86,86	76,26
SVM	93,16	80,90	87,25	76,77
OAPCM	94,89	55,25	86,41	65,99

TABLE II **C**omparative Results of Classification Algorithms in Terms of *AA* for Abundances Representation

	Water	***Dense vegetation***	***Bare Soil***	***Sparse vegetation***
NN	94,68	86,39	87,12	82,04
SVM	94,90	84,73	88,00	79,41
OAPCM	96,81	86,20	87,79	80,65

4. Conclusion

The objective of this study is to assess the performance of a methodology that has been successfully applied on hyperspectral data on Sentinel-2 data when supervised and unsupervised classification approaches are employed. The advantage of this methodology is that it integrates the abundances representation instead of the basic spectral signatures representation of the pixels. The abundances representation provides sub-pixel level information and in principle is capable of a more accurate mapping of land cover. The adopted methodology has been experimentally evaluated on a Sentinel-2 image of Northern Pindos National Park (Greece) which comprises water, vegetation (dense and sparse) and bare soil areas. The performance of (two supervised and one unsupervised) classification algorithms proposed in literature utilizing the abundance representations is compared with the ones utilizing the spectral signatures in terms of accuracy. The experimental results demonstrate that the proposed algorithm is able to (a) correctly estimate the abundance vectors using a sparsity promoting unmixing scheme that produces the relevant abundance maps and (b) generate more accurate classification maps based on the available reference map.

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