Evaluating EO1-Hyperion capability for mapping conifer and broadleaved forests

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Abstract
The objective of the present study is the comparison of the combined use of Earth Observation-1 (EO-1) Hyperion Hyperspectral images with the Random Forest (RF), Support Vector Machines (SVM) and Multivariate Adaptive Regression Splines (MARS) classifiers for discriminating forest cover groups, namely broadleaved and coniferous forests. Statistics derived from classification confusion matrix were used to assess the accuracy of the derived thematic maps. We demonstrated that Hyperion data can be effectively used to obtain rapid and accurate large-scale mapping of main forest types (conifers-broadleaved). We also verified higher capability of Hyperion imagery with respect to Landsat data to such an end. Results demonstrate the ability of the three tested classification methods, with small improvements given by SVM in terms of overall accuracy and kappa statistic.

Keywords: Hyperspectral images, image classification, support vector machine, random forest, multivariate adaptive regression splines, mediterranean areas.

Introduction
From the launch of the first Landsat satellite (ERTS-1) in 1972, space borne images have become even more suitable in providing sound and updated information for monitoring Earth’s environmental conditions. Distinctively, they are the central source for implementing land use/cover (LULC) thematic maps. Remotely sensed imagery provides valuable information for defining the extent of LULC classes, their temporal changes at various scales, as well as for coarsely depicting landscape patterns, useful to understand the effects of the interactions between environment and human activities [Kavzoglu and Colkesen, 2009; Maselli et al., 2009; Corona, 2016].

For discriminating broad land-cover classes (e.g., forests, water, crops, urban areas), the relatively small number (5-10 bands) of acquisition channels that characterizes multispectral sensors may be sufficient [White et al., 2010]. However, their discrimination
capability is rather limited when different groups or conditions of the same broad class (e.g., different types of forest) are to be distinguished. Conversely, due to their relatively narrow bandwidth (5-10 nm) and large number of spectral bands (usually more than 100), hyperspectral sensors have the ability to resolve subtle absorption and reflectance features of plant species, facilitating land cover classes discrimination and mapping. Under this perspective, Hyperion, a hyperspectral sensor mounted on-board the Earth Observing-1 (EO-1) platform, offers great opportunities for improving the quality of LULC classification. On the other hand, the analysis of hyperspectral data is a complex task, principally because of the large spatial variability of the hyperspectral signature of each land-cover class, the atmospheric effects, and the curse of dimensionality [Melgani and Bruzzone, 2004].

A variety of classification approaches has been applied to remotely sensed hyperspectral data [Lu and Weng, 2007]: Spectral Angle Mapper [Vyas et al., 2011], Linear Discriminant Analysis [Clark et al., 2005], Decision Tree Classifier [Lawrence et al., 2004], Artificial Neural Networks [Erbek et al., 2004], Support Vector Machine [Dalponte et al., 2009] and Random Forest [Chan and Palinkx, 2008] are some of the advanced methods for hyperspectral data classification. Recently, Hyperion imagery data was used to map LULC in the Mediterranean context [Pignatti et al., 2009; Petropoulos et al., 2012]. Despite their interesting results, the main limitation of these experimental studies is due to the little training and validation subsets, entailing the inability to extend their findings on wider areas.

The present study was conducted to evaluate the potential of EO-1 Hyperion data for supporting Land Cover classification on large areas. We tested three machine-learning techniques, namely Support Vector Machine (SVM), Random Forest (RF), and Multivariate Adaptive Regression Splines (MARS), to distinguish and classify conifer and broadleaved forests. In particular, we aimed to assess the ability of these techniques in classifying hyperspectral data over areas characterized by complex landscapes, both in terms of species mixture and interactions between environment and human activity. We firstly defined the best Hyperion wavebands for discriminating conifers and broadleaved forests, and then we compared the performances by SVM, RF, and MARS.

**Study site**

The study area is located in Tuscany Region, Italy, and covers approximately an area of 1100 km² (Fig. 1). This area exhibits a very particular landscape structure with various ecosystems ranging from typical Mediterranean to more mountainous habitats. This variety is principally due to the climate differences because the complex orography and the influence of the sea from the West. The elevation of the area ranges from sea level to the top of the Apennines mountain range (1400 m a.s.l.). Steep slopes characterize the North-Eastern part of the area, while gentle hills can be found towards the South-Western end.

Vegetation in the study site is a result of the lasting interaction between man and the environment. At lower elevations, with a climate subject to summer drought, forest vegetation is mainly sclerophyllous and connected to agricultural areas. As altitude grows and temperature slowly decreases, the land is mainly covered by conifer and deciduous broadleaved forests, with a certain degree of mixture between them. The prevailing tree
species are *Quercus pubescens* Willd. and *Q. cerris* L. (≈60%), *Castanea stiva* Miller (≈11%), *Q. ilex* L. (≈7%), *Fagus sylvatica* L. (≈6%), *Abies alba* Mill. (≈3%), *Picea abies* (L.) H.Karst (≈3%), *Pinus nigra* J.F.Arnold (≈3%) and *P. sylvestris* L. (≈3%).

**Hyperion data**
The Earth Observation-1 (EO-1) imagery of September the first 2011 was obtained at no costs from the United States Geological Survey [USGS, url: glovisusgs.com] archive. The Hyperion sensor has a 30-m ground sample precision over a 7.5 km swath and provides 242 spectral bands ranging from 357 to 2576 nm at a spectral resolution of 10 nm with a 16-bit dynamic range [Thenkabail et al., 2004]. The imagery was received as a full long scene of 185 km strip and at a processing level of 1 L1T (terrain corrected and georeferenced image) in GeoTIFF format. Hyperion is the first hyperspectral sensor for civil purpose aboard the EO-1 to merge spatial resolution of common satellite remote sensors with spectral resolution of the airborne hyperspectral instruments.

**Methods**
A pixel-based supervised classification was carried out on the Hyperion image, following the main steps reported in Figure 2.
Since many of the 242 bands of Hyperion are not usable for the classification due to high noise ratio [George et al., 2014], a pre-processing phase was applied [Petropoulos et al., 2012]. In the first step, the Level 1 L1T GeoTIFF Hyperion imagery was converted into ENVI format files using the Hyperion_tools.sav toolkit available in ENVI image processing environment [ITT Visual Information Solutions, 2008]. The non-calibrated bands were then removed (i.e. bands 1-7, 58-78, 225-242). 50 out of 70 bands of Hyperion VNIR spectrometer were calibrated, as well as 148 out of 172 bands of the SWIR spectrometer. The resulting 198 calibrated bands covered the entire spectrum from 426 to 2395 nm [USGS, 2008]. In addition, the Hyperion imagery water absorption bands (i.e. bands 120-132, 165-182, 185-187, 221-224) were removed to reduce the influence of atmospheric scatter and water vapour absorption due to mixed gases.
In a subsequent phase, the bands with vertical stripping were identified and removed by visual inspection (i.e. bands 8-12, 54-57, 79-84, 96-103, 118-119, 133-138, 163-164, 183-184, 188-220). The at-sensor radiance from the raw Digital Number (DN) values was computed for all the remaining spectral bands. This measure of radiance was obtained by dividing the pixel’s DN by the constant value of 40 for the visible and infrared (bands 8-57) and by 80 for the short-wave infrared (bands 79-224) [USGS, 2008]. No further correction for topographic effects was necessary, since Hyperion imagery was already terrain-corrected. Finally, a total of 90 bands were used for analysis.

In order to reduce possible edge effects, the original EO-1 imagery was clipped, and its margins were reduced of approximately 500 meters on average. Moreover, the study area was also reduced to avoid cloudy areas.

**Ground truth**

The established classification scheme has three main classes: Conifer forests (CF), i.e. land mainly covered by conifer forest stands, Broadleaved forests (BF), i.e. land mainly covered by broadleaved forest stands, and Other land (OL), i.e. any different kind of land cover. Ground truth was established by on-screen interpretation of airborne orthophotos (spatial resolution of 0.5 m) made available by WMS service of Tuscany Region [http://www.regione.toscana.it/-/geoscopio-wms, map-code rt_ofc.10k10.4R2G3B], integrated by inspection of Google Earth, Bing Maps and dedicated field surveys. In the end, a total of 309 polygons (92 from conifer forests, 73 from broadleaved forests and 144 from other land), with an average size of 50 ha, were detected.

**Training and validation subsets**

From each class, training pixels were randomly selected, while the remaining pixels were used as validation subset (Tab. 1). The training pixels were used to calibrate the RF, SVM and MARS classifiers. Data preparation and statistical analyses were performed in R GNU statistical software environment [R v3.1.2, R Core Team, 2014]. raster package was used to manage the Hyperion image.

| Land Cover class   | Training set | Validation set | Total  |
|--------------------|--------------|----------------|--------|
| Conifer forest     | 6847         | 2935           | 9782   |
| Broadleaved forest | 6956         | 2982           | 9938   |
| Other LC           | 8374         | 3589           | 11963  |
| Total              | 22177        | 9506           | 31683  |

**Bands selection**

After pre-processing, a total of 90 bands remained from the original 242. Despite this reduction, the dimensionality was still too high and the number of bands was further reduced through a step-wise discriminant analysis procedure based on Wilk’s lambda test statistic [Green and Caroll, 1978] applied to the training set. The analysis was carried out using the greedy.wilks function of klaR package of R statistic software.
Spectral separability
In order to ascertain that the multiple endmembers of different classes taken for the study were quite distinct and separable, a class separability analysis using Jeffries-Matusita (J-M) distance was applied on the selected endmembers. The J-M distance is a commonly applied measure to quantify the degree of dissimilarity. The J-M distance value ranges from 0 (i.e. identical distributions) to 2 (i.e. complete dissimilarity). Values higher than 1.8 indicates a good degree of dissimilarity. ENVI software was used for this analysis.

Classification methods
Support Vector Machine
Support vector machine (SVM) is a supervised non-parametric statistical learning technique, which is known for the ability to generalize well even with limited ground truth, and often used to improve the classification of remotely sensed imagery, including airborne hyperspectral data [Mountrakis et al., 2011; Paneque-Gálvez et al., 2013]. Training multidimensional data are used to find the so-called optimal separation hyperplane, i.e. the hyperplane that separates the dataset into a discrete predefined number of classes in a way consistent with training sample, maximizing the distances between different classes in order to minimize misclassifications [Burges, 1998]. Gamma and cost are the parameters needed to be set [Melgani and Bruzzone, 2004]. To this end, the e1071 R package was used, and the optimal gamma and cost parameters were identified using the tune.svm function. Gamma resulted equal to 0.1 and cost equal to 10. e1071 package [Leisch et al., 2012] was used for SVM classification.

Random Forest
The Random Forest method [Breiman, 2001] requires two parameters to be set: 1) mtry, the number of predictor variables performing the data partitioning at each node and 2) ntree, the total number of trees to be grown in the model run. Based on earlier experiences and recommendations from literature we set the number of ntree to 500. For categorical classifications based on the RF algorithm, the default value for the mtry parameter is \( \sqrt{p} \), where \( p \) equals the number of predictors within a given dataset [Liaw and Wiener, 2002]. After some trials, mtry was fixed to 7 in this work. randomForest package [Liaw and Wiener, 2002] was used to perform Random Forest classification.

Multivariate Adaptive Regression Splines
MARS is a recursive-partitioning algorithm, incorporating a multi-stage regression that uses spline functions [Friedman, 1991]. MARS is based on regression functions, but methods have been developed to adapt it to classification purposes. In MARS, knots are responsible to break the independent variables into subsets [Menéndez et al., 2010]. The goal of MARS is to establish a data-driven procedure for simultaneous estimation of an unknown function. The best MARS model is chosen using generalized cross-validation (GCV). It consists of a first forward process that leads to the building of specific pairs of basis functions (BFs). For GCV, that takes into account not only estimation errors, but also the complexity of the model, those pairs of BFs that contribute less to the goodness-of-fit are eliminated in a backward phase of modelling. For further details, see Lawrence and Moran [2015]. Earth package [Milborrow, 2014] was utilized for MARS classification. At
the best of our knowledge, MARS is here used for the first time to classify hyperspectral imagery.

**Accuracy assessment**

Accuracy of classified images was assessed in terms of omission (OE) and commission (CE) errors for the three considered classes. The overall classification accuracy (OA), Producer’s Accuracy (PA) and User’s Accuracy (UA) were also computed using information from the contingency matrix [Congalton, 1991].

**Results**

Table 2 reports the 50 optimal Hyperion bands selected by the Wilk’s lambda test. These bands are included within the 477 nm to 1770 nm wavelength region: 14 bands are from visible, 23 bands from NIR, and 13 bands from SWIR regions. The J-M separability test on these hyperspectral bands resulted in values higher than 1.99 between both CF and BF versus OL, while for the separability between CF and BF a J-M value of 1.86 was reached. The land cover map produced from the implementation of the SVM classifier is presented in Figure 3. RF and MARS classifications upon the validation set resulted in high overall accuracy, always greater than 93%. However, SVM worked better, with an OA of 96.4%.

![Figure 3 - The acquired Hyperion image (left) in false colour (R: band 29, G: band 14, B: band 7 as from Table 2); the Hyperion subset (centre) covering the study area; (right) SVM classified image covering orthophotos on a zoomed portion of the scene.](https://example.com/figure3.png)
Table 2 - List of the 90 bands obtained after pre-processing (noise removals). The ones marked with a star (*) are those selected by the Wilk’s lambda test.

| Band | Wavelength | Band | Wavelength | Band | Wavelength |
|------|------------|------|------------|------|------------|
| #n   | nm         | #n   | nm         | #n   | nm         |
| B1*  | 477.7      | B31* | 783.0      | B61* | 1265.6     |
| B2   | 487.9      | B32  | 793.1      | B62* | 1275.7     |
| B3   | 498.0      | B33* | 803.3      | B63  | 1285.8     |
| B4*  | 508.2      | B34* | 813.5      | B64* | 1295.9     |
| B5*  | 518.4      | B35  | 823.7      | B65  | 1306.0     |
| B6*  | 528.6      | B36  | 833.8      | B66  | 1316.1     |
| B7*  | 538.7      | B37* | 844.0      | B67* | 1537.9     |
| B8   | 548.9      | B38  | 854.2      | B68* | 1548.0     |
| B9*  | 559.1      | B39  | 864.4      | B69  | 1558.1     |
| B10  | 569.3      | B40* | 874.5      | B70  | 1568.2     |
| B11  | 579.4      | B41* | 884.7      | B71* | 1578.3     |
| B12* | 589.6      | B42* | 993.2      | B72* | 1588.4     |
| B13  | 599.8      | B43  | 1003.3     | B73* | 1598.5     |
| B14  | 610.0      | B44  | 1013.3     | B74* | 1608.6     |
| B15* | 620.1      | B45* | 1023.4     | B75  | 1618.7     |
| B16* | 630.3      | B46  | 1033.5     | B76* | 1628.8     |
| B17* | 640.5      | B47  | 1043.6     | B77* | 1638.8     |
| B18  | 650.7      | B48  | 1053.7     | B78* | 1648.9     |
| B19* | 660.8      | B49* | 1063.8     | B79* | 1659.0     |
| B20* | 671.0      | B50* | 1073.9     | B80  | 1669.1     |
| B21* | 681.2      | B51  | 1084.0     | B81* | 1679.2     |
| B22* | 691.4      | B52* | 1094.1     | B82  | 1689.3     |
| B23  | 701.5      | B53  | 1184.9     | B83  | 1699.4     |
| B24  | 711.7      | B54  | 1195.0     | B84  | 1709.5     |
| B25* | 721.9      | B55* | 1205.1     | B85* | 1719.6     |
| B26* | 732.1      | B56  | 1215.2     | B86  | 1729.7     |
| B27* | 742.2      | B57  | 1225.2     | B87  | 1739.7     |
| B28* | 752.4      | B58* | 1235.3     | B88* | 1749.8     |
| B29* | 762.6      | B59  | 1245.4     | B89  | 1759.9     |
| B30* | 772.8      | B60* | 1255.5     | B90  | 1770.0     |

The accuracy statistics are shown in Table 3.
Table 3 - Accuracy by SVM, RF and MARS classifiers applied to the validation set. PA, producer’s accuracy; UA, User’s Accuracy; CE, Commission Error; OE, Omission Error. In brackets the standard error of OA.

| Land cover class   | Support Vector Machine | Random Forest | Multivariate Adaptive Regression Splines |
|--------------------|------------------------|---------------|-----------------------------------------|
|                    | PA         | UA    | CE   | OE | PA    | UA    | CE   | OE | PA    | UA    | CE   | OE |
| Conifer forests    | 94.7       | 92.5  | 5.3  | 4.8| 90.5  | 92.8  | 9.5  | 7.2| 89.0  | 91.4  | 11.0 | 8.6 |
| Broadleaves forests| 95.2       | 94.7  | 4.8  | 5.3| 93.2  | 90.4  | 6.8  | 9.6| 91.1  | 89.6  | 8.9  | 10.4|
| Other lands        | 99.3       | 99.3  | 0.7  | 0.7| 98.6  | 99.0  | 1.4  | 1.0| 99.0  | 97.9  | 1.0  | 2.1 |
| Overall accuracy (%) | 96.4 (±0.0016) | 94.1 (±0.0021) | 93.0 (±0.0023) |

In terms of individual classes’ accuracy, similar patterns were observed among the three classification approaches. The highest accuracies were obtained by the other land class, despite its wide ranging from urban land to agricultural land and waterbodies, followed by broadleaved forests and conifer forests. The class with the lowest PA and UA was conifer forests for all the three classifiers. Conifer species were predominantly present in mixed forest stands, probably suffering a strong reflectance influence from broadleaved species.

Discussions

The study area is characterized by a complex landscape, characteristic of Mediterranean areas. To obtain reliable land cover maps in complex ecosystems and on large areas represents one of the main goal in remote sensing applications for earth monitoring [Maselli et al., 2009]. Previous works [e.g. Pignatti et al., 2009; Petropoulos et al., 2012; George et al., 2014] have highlighted the usefulness of hyperspectral satellite imagery to improve forest cover classification. However, the experimental trials have resulted in low classification accuracy (even lower than 70% in some cases), not suitable for operative uses. We argue that these results were due to a too small fraction of study area (≈0.4%) used as training and validation set while trying to discriminate a large number of forest types. As recommended by Van Niel et al. [2005] and Li et al. [2014], training sample size for each class should not be fewer than 10-30 times the number of bands. Our results are in accordance with this suggestion. By reducing the number of land cover classes to three (conifer forest, broadleaved forest, other land) and by adopting a relevant number of training and validation pixels (Table 1), we have obtained accurate classifications from Hyperion EO-1 data and the three different classifiers. The classification accuracy using SVM classifier of Hyperion bands was better than the other classifiers, despite very good accuracy was reached by them too.

When dimensionality is high, like in the case of hyperspectral imagery, it must be reduced. Our study has confirmed that the Wilk’s lambda test statistic optimally performs the task of waveband selection, obtaining the (lowest) suitable amount of bands for discriminating forest types. Most of the identified bands belonged to NIR region of the electromagnetic spectrum, demonstrating sensitivity of the two forest types here considered with respect to leaf and canopy structure. In addition, bands in the visible region exert a key role in discriminating forest and non-forest classes. Finally, reliable LULC classes discrimination was achieved also due to the optimal selection of time of acquisition of satellite data, in this
case the end of summer.
As a practical application of our findings, the methodology here tested results in suitable
LULC classes discrimination at large scales. The current most used approach worldwide to
perform LULC classification is based on computer-assisted visual interpretation of Landsat
data [Corona et al., 2015]. In order to assess the additional value of Hyperion imagery as
a powerful tool to discriminate LULC classes compared with Landsat data, we conducted
the above-described SVM classification approach on Landsat 8 imagery over the same
area, in the same seasonal timespan. The analysis resulted in an OA of 71.3%. We can
experimentally confirm that classification of narrow band data, like those from Hyperion,
can return significantly better forest type classification than classical broadband data, like
Landsat.

Conclusions
As Hyperion combines the advantages of medium spatial resolution - ideal for covering
large areas - with the ones of high spectral resolution imagery - ideal for discriminating
land cover and forest classes -, it is highly suitable and to be recommended as a tool
for supporting LULC classifications, e.g. on a regional level. Under such a perspective,
we highlight the importance that must be given to a careful selection of wavebands for
producing high accuracy forests maps reducing, at the same time, the computational efforts.

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