Retrieval of vegetation understory information fusing hyperspectral and panchromatic airborne data

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ABSTRACT
The knowledge of the characteristics of the vegetation cover is of great interest in climate change process understanding due to its important role in controlling water and carbon cycles. The properties of vegetated surfaces are usually estimated from remote observations through semi-empirical regression models or using radiative transfer models, which simulate the interactions of solar radiation with the vegetated medium. In real domain the spectral responses measured by the sensor in forested area are strongly influenced by the different natural understory conditions that limit the possibility of applying both retrieval methods to predict overstory vegetation parameters. Understory information is therefore needed for trees parameter estimation; moreover from a biodiversity point of view and forest management perspective understory represents a critical component of forest ecosystem that needs a better characterization. An experiment was conducted using multisensor hyperspectral and panchromatic data to study the typology and status of different vegetated understory under a sparse poplar plantation. The salient aspect of the method is the integration of spectral (multisensor) domain fusion and spatial domain fusion techniques within a Multi-Layer Perceptron model. Ground data and airborne hyperspectral imagery were collected during DARFEM experiment, EU-funded HySens project (DLR-Germany). The achieved results show that this methods is able to solve “operatively” the problem of a volumetric mixture typical of natural forest ecosystems identifying the different surfaces present under the tree canopy. The understory maps produced represent effective input for the inversion of radiative transfer models (SAIL) and general useful information for forest ecological studies.

Keywords: Hyperspectral, Neural Network, Multi source, radiative transfer model, forest understory.

1 INTRODUCTION
Radiometric measurements collected from Earth observation sensors onboard of airplane and satellite platforms offer the opportunity to describe the terrestrial biosphere at different spatial scales. Remote sensing techniques have been used with success to characterize the state and properties of vegetation compound. Satellite remote sensing nowadays represents basic data for forest inventories providing information about structure and typology of forest over wide area [1] and for crops monitoring [2]. Aerial surveys with hyperspectral images can be used to produce cover mapping that give a detailed spatial distribution of natural forest species in complex and heterogeneous areas [3,4]. Moreover hyperspectral images allow to achieve a spatial quantitative estimation of vegetation biophysical structural properties, such as the leaf area index (LAI) and fractional cover (Fc), and biochemical, such as total chlorophyll concentration (Cab) and water content (W) [5,6].

Those parameter are generally retrieved using semi-empirical regression models, in which a limited number of \textit{in situ} measurements of the biophysical parameter examined are correlated with a spectral vegetation index. An alternative to this approach is offered by the use of radiative transfer models such as PROSAIL [7,8,9], which simulate the interactions of solar radiation with the vegetated medium, in inverse mode. This techniques allow to retrieve both biochemical and structural vegetation parameter in predictive mode without \textit{in situ} measurements [10]. Previous experiments [5,6,11,12,13] have demonstrated the strong influence of different backgrounds on the remote sensing spectra recorded at the sensor when forest canopy presents low fractional cover and low LAI values reducing the predictivity and operability of regression models. This “understory effect” was also found when inverting radiative model such as PROSAIL yielding consequently an error in the estimation of green LAI [5].

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On the other hand the natural understory represents an important element in forest ecosystem: different understory typology and status control suitable habitats for animals, affect microclimatic condition and govern potential fire activity. In remote sensing field few works have been conducted for the estimation of understory characteristics while many papers treat the problem as a noise to be minimized.

The aim of this work is to test the potentiality of neural network models to define an efficient method of analysis capable of both -fusing multisensor multispectral information and -exploiting the spatial relationships of neighboring pixels to extract high accuracy information of forest ecosystem. Spatial and spectral relationships are not explicitly formalized in an attempt to limit design and computational complexity; raw data are instead presented directly as input to the neural network classifier. Neural network model has been chosen for its characteristic of solve non liner problem typical of the spectral mixture caused by multiple scattering that occur in a forest volume.

This research belong to the DARFEM (DAIS and ROSIS for Forest Ecosystem Monitoring) experiment, conducted in the framework of the EU-funded project HySens coordinated by DLR - Germany, that has been designed for a better understanding of the capability of hyperspectral and directional data in the retrieval of physiologically relevant vegetation parameters [14]. In particular the aim of the test is to produce an understory typology map over a forested area fusing DAIS and ROSIS through the mean of neural network model.

2 MIXTURE PROBLEM

Remote sensing application are based on the spectral discrimination of objects present in the acquired image. The measured spectra of a pixel is the integration of the reflected energy from all the objects and surfaces within the ground instantaneous field of view (IFOV) and generally the wider is the pixel size the more heterogeneous are the classes present. However spectral mixture is inherent in any finer-resolution even analyzing the same land cover; natural vegetation intra class variability, caused by several factors such as age, microclimatic condition, soil type, health condition and species distribution, often adds additional complexity to the theoretical spectral separability [15]. Moreover the application of remote sensing data for forestry ecosystem study can be heavily influenced by the understory presence, the spectral signatures recorded at the sensor are in fact affected by the presence of different background (vegetation species, density of plant, soil type , ecc.).

2.1 Spatial mixture

Mixture analysis and hyperspectral data should permit to identify in the images the end member spectra of the different surfaces, however the spectral mixture is not always easy to model and solve. The spectra recorder at the sensor for the pixel in the figure can be theoretically considered as a linear combination, equation (1), of the spectral contribution of the single components as they would be recorded for pure pixels:

\[
\rho_{pixel} = fctree \cdot \rho_{tree} + fcgrass \cdot \rho_{grass} + fcsoil \cdot \rho_{soil}
\]

(1)

where

- \(\rho_{pixel}\) is the reflectance recorded by the pixel
- \(fctree, fcgrass\) and \(fcsoil\) are the fractional cover relative respectively to the class Tree, Grass and Soil and
- \(\rho_{tree}, \rho_{grass}\) and \(\rho_{soil}\) are the spectral response end-member for the single class Tree, Grass and Soil.

![Pixel Tree Grass Soil](image_url)

**Figure 1.** The spectral signature of the pixel (black box) can be considered as the combination of the single spectral response of the different surfaces (tree, grass and soil).

2.2 Volumetric mixture

In the case of a forestry stand the signature recorded by a pixel is the result of the scattering and absorption of the different elements present in the volume, figure 2. Under this condition the contribution of the different
components cannot be considered linear and a simple linear un-mixing approach cannot be useful in detecting the contribution of the different compartments.

Prior research [13,15,16] has demonstrated that non-linear spectral mixing takes place when multiple reflection occurs and that non-linear decision rule models can produce better results. In this context we propose a neural network model to approach the problem due to its capability of treating non-linear problems. An experimental test was therefore conducted on real domain to test the potentiality of neural network in solving volumetric mixture detecting different background under a forest canopy.

3 TEST AREA

The study area, figure 3, is represented by a poplar plantation located in the Ticino regional park north west of Pavia in Lombardia region, Italy. This site belongs to the CARBOEUROFLUX project and is equipped by a permanent flux tower, managed by the Joint Research Centre (JRC), to study the full balance of carbon dioxide when fast-growing forests are planted for sequestering greenhouse gases according to the Kyoto Protocol.

The poplar plantation represents a simplification of a natural forest, where the trees correspond to a single specie and the plant are positioned in order to maximize the tree grown. The typical 6 meters distance between the trees determines consequently a sparse canopy forest. Under this situation the vegetated understory or the bare soil strongly influences the remote sensing spectra recorded at the sensor and represents a good controlled situation to test the potentiality of the method.

Figure 2. The spectral signature of the pixel (black box) are a non-linear combination of the response of the different background, soil for stand 1 and understory for stand 2, and of the overstory characteristics.

Figure 3. The study area, IR false color composite of DAIS data (RGB: 19,11,4) and relative position of field measurement collected. For each point, derived by GPS position, it is possible to know the canopy and the understory condition, the relative field spectra and the LAI measurements.
3.1 Field campaign

The field campaign of the DARFEM experiment were addressed to the forestry characterization measuring structural and optical properties of poplar stands and understory. Tree height, diameter, crown area, leaf area index (LAI) and vegetation fractional cover (Fc) of the overstory were measured. Moreover the underground status and typology were described for each forest stand; nadiral digital RGB photography allows to evaluate the characteristics and the relative fractional cover (Fcu) for each background. FieldSpec FR spectroradiometer, operating in a wavelength range from 350 to 2500 nm, has been used to collect the different understory and soil reflectance using the Spectralon TM panel as a reference. Each site, where ground measurements were collected during the field campaign, was geo-located using a GPS system: in this way it was possible to realize a GIS that describes the canopy and understory condition, the field spectral data and the overstory LAI (LAIo) measurements as described in figure 3.

4 DATA AND METHODOLOGY

In nature different micro-climatic conditions (radiance, moisture, wind, soil type, ecc.) determine the presence of diverse vegetated understory. These local conditions are controlled, in a forest, by the structural characteristic of the different stands such as canopy closure, crown radius, trees density etc. The use of a panchromatic high spatial resolution images (≈ 1 m) could allow to take into account these stand forest parameters; moreover contemporary hyperspectral information could consent to discriminate different background categories.

This scheme nowadays can be operationally achieved using traditional aerial hyperspectral survey coupled with low cost panchromatic camera images acquired at the same time; in the future high resolution satellite data such as IKONOS or QuickBird could be fused with hyperspectral satellite images from the new sensors (Hyperion, ChrisPoba, Spectra, etc.).

4.1 Definition of Classes

The classes selected correspond to the underground characteristic of the study area. Two vegetation communities indicated by the prevalent specie (Artemisia Vulgaris and Poa Trivialis), and two main soil type with sand or gravel texture were chosen. In order to encompass all the different situations a fifth class corresponding to a sparse vegetation situation has been added.

![Figure 4. Picture of different understory present in the poplar plantation](image-url)
4.2 Remote sensing data

The remote sensing data used were acquired from 10.30 to 11 am the 20th of June 2001 using two spectrometers of DLR (tab. 1): DAIS 7915 (Digital Airborne Imaging Spectrometer) and ROSIS (Reflective Optics System Imaging Spectrometer). The flight height was 1800 m determining a pixel size for DAIS of 2.5 m and for ROSIS of 1 m.

Table 1 - Spectral and geometric characteristics of the different sensors. DAIS 7915 operates in 79 spectral channels in the range from visible to thermal infrared wavelengths while ROSIS spectral range is limited to the visible and near infrared wavelengths (430 - 850 nm).

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Scanner Type</th>
<th>Fov (°)</th>
<th>Pixel size</th>
<th>Bands</th>
<th>Spectral range</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAIS</td>
<td>Whisk broom</td>
<td>2115 m ±26°</td>
<td>2.5 m</td>
<td>79</td>
<td></td>
</tr>
<tr>
<td>ROSIS</td>
<td>Push broom</td>
<td>420 m ±8°</td>
<td>1 m</td>
<td>115</td>
<td></td>
</tr>
</tbody>
</table>

The data were geometrically and atmospherically corrected by DLR using ATCOR4 [17] at the correction level 2b. In the further analysis DAIS stripe, acquired in the principal plain, and a mosaic of ROSIS data, recorded on the same area, were utilized.

4.1.1 Multipsectral set selection

The input data for the neural network were extracted from two types of plans: hyperspectral information by DAIS sensor and spatial contextual data from a panchromatic high resolution image (~1 m) simulated by ROSIS images. 25 DAIS band considered more important were selected: 2 in the visible range (2,6), 17 in the red edge position range (8-24), 2 in the NIR plateau (28,32), 3 in the SWIR region (33,38,52) and 1 as thermal band (76).

4.1.2 Panchromatic image simulation

The panchromatic image was obtained simulating the response of the Landsat-7 sensor, the reflectance spectra of the ROSIS image were converted into the band equivalent reflectance for the investigated panchromatic band of ETM+[18]. The band equivalent reflectance \( R_{ETMPan} \) was derived by integration over each band’s spectral response function as follows:

\[
R_{ETMPan} = \frac{\sum_{j=\lambda_{\text{min}}}^{\lambda_{\text{max}}} r_j \rho_j}{\sum_{j=\lambda_{\text{min}}}^{\lambda_{\text{max}}} r_j}
\]  

where \( R_{ETMPan} \) is the band equivalent reflectance for the Panchromatic band, \( \lambda_{\text{min}} \) is the starting wavelength of band’s filter function, \( \lambda_{\text{max}} \) is the ending wavelength of band’s filter function, \( r_j \) is the relative response for band at wavelength \( j \), \( \rho_j \) is the reflectance measured by ROSIS at wavelength \( j \).

This panchromatic band was created in order to simulate a low cost high resolution band to be used in addition to multispectral data selected by DAIS.

4.3 Multisource approach

The understory map was generated using a neural network multi-sourcing approach able to integrate the contextual information of a high resolution panchromatic image with the spectral information of a selection of hyperspectral bands. The explicit representation/description of spatial relationships among neighboring pixels usually involve complex analytical measures that contribute to increase the accuracy in classification, but on the other side...
determine the side effect of an increase of computational and design complexity. This results in a significantly
decrease of the operational character and applicability of the automated procedures.

The use of windows directly presented in input to a neural classifier without analytical, local measures extracted
from the neighbor pixels has been experimented in previous works [19]. Results obtained show that presenting the
network with the entire window of pixels allows the network to infer an arbitrary measure of spatial context,
through the adjustment of its weights during learning, as necessary to discriminate classes.

4.3.1 Neural network approach
The structure of the network in accordance with the multilayer perceptron model was composed of input, hidden
and output layer with fully connection between adjacent layers.

The input layer was composed of 53 neurons: 28 representing contextual features associated with pixels from
high resolution panchromatic image and 25 representing spectral features associated with hyperspectral imagery.

The size of the hidden layer reflected a compromise between specialization (more hidden nodes) and
generalization (fewer hidden nodes). Following Kannelopoulos and Wilkinson [20] we applied an empirical rule to
implement this criteria: the number of hidden neurons must not exceed the largest value obtained by doubling the
sum of the input and output nodes. An hidden layer composed of 15 neurons was obtained experimentally by
applying a trial and error procedure in agreement with the criteria specified above.

The output layer was composed of 5 neurons each of one associated with an understory class.

Our strategy employed the MLP model as a soft classifier: the output of the network, conventionally interpreted
as crisp class assignment applying the winner-take-all rule to the output neurons, was softened here, considering the
values of the output neurons directly as the possibility or likelihood of a class. Soft maps represent an unmixing
method to provide for the same pixel fraction of the understory classes presented. After the production of soft
results, a hardening process was performed to obtain a useful result for subsequent GIS analysis. The understory
map was then linked to the spectral understory database in order to map for each pixel the theoretical understory
spectral response. Further analysis intend to use the soft information produced by the neural model to generate, by
linear combination, a weighted understory spectral response for each pixel of the image combining the spectral end-
member collect in the field for the different categories.

The neural classification model requires a supervised learning procedure. In our context the training set is
composed of labeled pixels. Using the information collected in the field, geo-located using a GPS system, it was
possible to realize a GIS that describes the position of all field measurements and that integrates these data with
ancillary topographic and thematic maps of the study area. The multisource approach was based on geocoded data;
the different input were extracted by the images using geographical coordinates of the training pixels corresponding
to the different understory classes. The training set presented to the network was composed of 289 patterns; the
learning process was based on back propagation algorithm with momentum. The network was trained for 1500
epochs; in figure 4 the error graph showing a convergence trend is illustrated. The target output element was set at a
single pixel corresponding to the geographical coordinates of the DAIS image.

Figure 5. Input configuration for the neural network (left) and the MSE error after 1500 epochs (right).
5 RESULTS

The trained neural network was tested over the whole image producing the map represented in the following figure. A visual control of the results by the expert show a good agreement with the real situation more over several test sampled were selected to compared the ground truth information, digital photography and ancillary data, with the classification results.

![Figure 6](image)

**Figure 6.** Multisource images for to be classified (a); trained neural network (b); output image (c).

5.2 Application of the product: Inversion results

The neural network seems therefore to be able to solve the problem of volume un-mixing producing a map of distribution of different understory. The next step is to test the contribution of this method to enhance the performance of inversion of radiative transfer models in the retrieval of overstory green LAI. PROSPECT [10] and SAIL [8,9] models were used to describe the radiative transfer in the leaf and in the canopy respectively. The inverse problem was solved by minimizing a cost function defined by the distance of the modeled reflectance from the observed one (for details [5]). The inversion procedure requires the definition of an input set (for details see [11]). Among these inputs, the spectral signature of the vegetation background is to be specified. To overcome this problem, this information can be usually set to a nominal vector of values for all the inversion (i.e. average soil spectral signature of the study area) allowing the variation of a multiplicative “correction factor” (soil brightness parameter) in the inversion process and thus assuming a single background type. The use of an understory map avoids this assumption by identifying the estimated background type and understory associated field spectra (acquired during the field campaign) for every inversion.

![Figure 7](image)

**Figure 7.** Inversion procedure: background spectra input were selected according to the understory map.
5.2.1 Green LAI estimation

Our results show that, supplying a plausible background signature to the inversion, PROSAIL provides an accurate estimation of the green LAI of the overstory (gLAIo). The accuracy of the estimates was evaluated in terms of SDEP (Standard Deviation Error in Prediction) calculated on the basis of all the available LAI field measurements in the test area (n=35). Different strategies were explored in order to assign a background spectral signature to each inversion. The accuracy of each strategy (ordered on the X axis by increasing elaboration and sampling cost) is reported in Table 2 together with a description of the available dataset of LAI field measurements.

Table 2. Summary of spectral background assignment strategies and relative results (Standard Deviation Error in Prediction, SDEP), of gLAIo estimation by PROSAIL inversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>B.S.</td>
<td>Spectral signature of Bare Soil was provided to every inversion</td>
</tr>
<tr>
<td>Under-map</td>
<td>The background map was used as a criterion to assign the background signature</td>
</tr>
<tr>
<td>Exact</td>
<td>The most appropriate background for each inversion was supplied</td>
</tr>
</tbody>
</table>

It is worth noting that the “exact” strategy is an abstraction representing the best accuracy obtainable with such approach and that it’s not operatively applicable (all the background types were assigned according to the in-field inspection). Nevertheless, the accuracy provided by the other strategies seems reasonable for most of the environmental applications (e.g. SVAT and BCG modeling). Moreover under story map seems to be an operational methods able to almost double the performance of the model.

6 DISCUSSION AND CONCLUSION

Forest ecosystem can be successfully monitored with remote sensing data even if the volumetric mixture of the different vegetated layers can affect the results. Understory presence effects the spectral response acquired by the sensor invalidating mapping techniques and retrieval of overstory biophysical parameters. In particular the inversion of radiative transfer model is strongly affected by presence of vegetated understory.

Under this condition traditional linear un-mixing does not represent a useful method to take into account the role and influence of the different understory while neural network approach can represent a suitable technique to solve the problem. A neural network model was therefore used to produce an understory map indicating five different categories of background typical of the study area. From a visual interpretation, overlapping the ground truths in a GIS environment, the map seems to reproduce accurately the spatial distribution of the understory categories.

The application of this product for the local assignment of the spectral background in the PROSAIL inversion procedure shows a strong increase in the accuracy of the green LAI estimation. Moreover these mapping method allows to give information about the complex characteristic of a forest representing a useful tool for monitoring the whole ecosystem. Understory map can be very important for wildlife studies and for supply elements of fire risk in natural area.

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