Multiscale fuel type characterization by using multisensor remote sensing data for the Mediterranean ecosystems of Southern Italy

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Abstract: In the context of fire management, fuel maps are essential information requested at many spatial and temporal scales for managing wildland fire hazard and risk and for understanding ecological relationships between wildland fire and landscape structure. Remote sensing data provide valuable information for the characterization and mapping of fuel types and vegetation properties at different temporal and spatial scales from global, regional to landscape level.
Fuel types is one of the most important factors that should be taken into consideration for computing spatial fire hazard and risk and simulating fire growth and intensity across a landscape. In the present study, forest fuel mapping is considered from a remote sensing perspective. The purpose is to delineate forest types by exploring the use of remote sensing data. For this purpose, multisensor and multiscale remote sensing data such as, Landsat-TM and Spaceborne Thermal Emission and Reflection Radiometer (ASTER) were analyzed for a test area of southern Italy that is characterized by mixed vegetation covers and complex topography. Fieldwork fuel types recognitions, performed at the same time as remote sensing data acquisitions, were used as ground-truth dataset to assess the results obtained for the considered test areas.
Two different approaches have been adopted for fuel type mapping: the well-established classification techniques performed at the pixel level and spectral mixture analysis performed at the subpixel level.
Results from our investigations showed that remote sensing data can provide valuable information for the characterization and mapping of fuel types and vegetation properties at different temporal and spatial scales from global, regional to landscape level.

***Keywords**: fuel type mapping, satellite, airborne, sub-pixel classification*

1. INTRODUCTION

Yearly, forest fires affect vast areas and cause devastating damages at European and Global scales so that they are considered a very relevant factor of environmental degradation. Fire danger estimation plays an important role in the framework of programs for fire damage mitigation. It is a valuable support for designing strategies related to the use and the distribution of the available fire fighting resources, which can prevent or at least minimize fire effects.
In the context of fire management, fuel maps are essential information requested at many spatial and temporal scales for managing wildland fire hazard and risk and for understanding ecological relationships between wildland fire and landscape structure. Remote sensing data provide valuable information for the characterization and mapping of fuel types and vegetation properties at different temporal and spatial scales from global, regional to landscape level.
The characterization of fuel types is very important for computing spatial fire hazard and risk and simulating fire growth and intensity across a landscape. However, due to the complex nature of fuel characteristic a fuel map is considered one of the most difficult thematic layers to build up. The advent of sensors with increased spatial resolution may improve the accuracy and reduce the cost of fuels mapping. The objective of this research is to evaluate the accuracy and utility of imagery from Quickbird and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data for remotely

fuel typing. In order to ascertain how well such satellite data can provide an exhaustive classification of fuel properties.

Two different approaches have been adopted for fuel type mapping: the well-established classification techniques and spectral mixture analysis. Fieldwork fuel type recognition, performed at the same time as remote sensing data acquisitions, was used to assess the results obtained for the considered test area.

Our investigations constitute a baseline for quantifying potential errors resulting from classification of lower spatial resolution images by using re-sampled classifications of higher spatial resolution data.

2 STUDY AREA AND DATA SET

The selected study area (figure 1) extends over a territory of about 6,000 hectares inside the National Park of Pollino in the Basilicata Region (Southern Italy). It is characterized by complex topography with altitude varying from 400 m to 1900 m above sea level (asl) and mixed vegetation covers. Between 400 and 600 m natural vegetation is constituted by the Mediterranean scrubs, xeric prairies and Mediterranean shrubby formations. In the strip included between 600 and 1000-1200 m the characteristic vegetation is represented by poor populations of Quercus pubescens and from extensive woods of Turkey oaks (Quercus cerris); evident degradation forms are present, in the form of xerophytic prairies and substitution bushes. The higher horizons are constituted by beech woods (Fagus sylvatica) which arrive up to 1900 m: the deforested areas in this strip are generally engaged by mesophytic prairies used for pasture.

The remotely sensed characterization of fuel types was performed by adopting as reference the fuel types classification (Table 1) developed for Mediterranean ecosystems in the framework of the Prometheus project (Prometheus Project 1999).

ASTER is a high resolution imaging instrument that is flying on the Earth Observing System (EOS) Terra satellite. It has the highest spatial resolution of all five sensors on Terra and collects data in the visible/near infrared (VNIR), short wave infrared (SWIR), and thermal infrared bands (TIR). Each subsystem is pointable in the crosstrack direction. The VNIR subsystem of ASTER is quite unique. One telescope of the VNIR system is nadir looking and two are backward looking, allowing for the construction of 3-dimensional digital elevation models (DEM) due to the stereo capability of the different look angles. ASTER has a revisit period of 16 days, to any one location on the globe, with a revisit time at the equator of every four days. ASTER collects approximately eight minutes of data per orbit (rather than continuously).

Among the 14 ASTER bands (see table 2b) we only considered the 3 channels in the VNIR region and 6 channels in the SWIR region, while the TIR channels were excluded. Both ASTER and MIVIS data used for this study were acquired on June 1998.

A LANDSAT TM image was sensed on 18 November 1998. Such data were acquired from a nominal altitude of 705 kilometers (438 miles) in a near-circular, sun-synchronous orbit at an inclination of 98.2 degrees, imaging the same 185-km (115-mile) swath of the Earth's surface every 16 days. All the TM reflectance bands (1 to 5 and 7) were used for our investigations

All of the remote sensed data were georefered in the UTM projection..

Additionally, photos and air photos were obtained for the investigated area at the same time as MIVIS data acquisition. Fieldwork fuel typing were performed using a global position system (GPS) for collecting geo-position data (latitude and longitude). Air photos and fieldwork fuel types were used as a ground-truth dataset firstly to identify the fuel types defined in the context of Prometheus system, and secondly, to evaluate performance and results obtained for the considered test area from the remote sensing data processing.

3 DATA ANALYSIS

Two different approaches have been adopted for fuel type mapping: the well-established classification techniques performed at the pixel level and spectral mixture analysis which allows a sub-pixel analysis. Among the classifications performed at the pixel level, two different techniques, parametric and non parametric were considered in this study.

The K NN (nearest neighbour) was applied to obtain a non parametric classifications of fuel types; whereas the maximum likelihood classification (MLC) (Lillesand and Kiefer 2000) was adopted for performing a parametric analysis. The K NN and MLC were adopted because both of them are “conventional classifiers” widely used for remote sensed imagery. Moreover, both of them are supervised classifications, thus, allowing the use of the same training data and then a direct comparison of their performances. The selection of training data is a key step that strongly influence the accuracy levels.

The selection of training data for the current analysis was performed on the basis of ground surveys and air photos, that allowed the identification of region of interest (ROI) corresponding to the seven fuel types (see Figure 4), plus two additional classes related to no fuel and unclassified regions. Pixels belonging to each of the considered ROI were randomly separated into training data and testing data, used for classifications and accuracy evaluations.

Among the parametric classification, the MLC is considered one of the most important and well-known image classification methods due to its robustness and simplicity (Richards, 1986). It is widely used in vegetation and land cover mapping. Moreover, it was also tested for fuel model distributions by (Riaño, Chuvieco et al. 2002). The ML method quantitatively evaluates the variance and the covariance of the spectral signature when classifying an unknown pixel assuming at the same time a Gaussian distribution of points forming a cluster of a vegetation class. Under this assumption the distribution of a class is described by the mean vector and the covariance matrix which is used to compute the statistical probability of a given pixel value being a member of a particular class. The probability for each class is calculated and the class with the highest probability is assigned the pixel (Lillesand and Kiefer 2000). The ML classifier is based on the assumption that different variables used in the computation are normally distributed. This assumption is generally considered acceptable for common spectral response distributions.

The kNN classifier is based on non-parametric density estimation techniques, that decides the class of an object by analyzing its k nearest neighbors within the training objects. The main advantages of KNN classifier are that (I) It don not need prior knowledge and frequency distribution of spectral values, (II) It is analytically tractable with simple implementation, (II) It uses local information, which can yield highly adaptive behaviour. The main disadvantages of KNN classifier are that (I) vast training samples result to large computational intensity, (II) large storage requirements; (III) computationally intensive recall (IV) Highly susceptible to the curse of dimensionality.

Both the MLC and KNN algorithms, as with other conventional classification (hard classification) techniques developed for per-pixel analysis, assumes that all image pixels are pure. Nevertheless, this assumption is often untenable. In mixed land cover compositions, as pixels increase in size, the proportion of mixed cover type distributed at pixel level will likewise increase and information at the sub-pixel level will be of increasing interest. Consequently, in fragmented landscapes conventional “hard” image classification techniques provide only a poor basis for the characterization and mapping of fuel types giving, in the best case, a compromised accuracy, or, in the worst case, a totally incorrect classification.

The use of spectral mixture analysis (SMA) can reduce the uncertainty in hard classification techniques since it is able to capture, rather than ignore, subpixel heterogeneity. The SMA allows for classifying the proportions of the ground cover types (end-member classes) covered by each individual pixel. End-member classes can be taken from “pure” pixels within an image or from spectral libraries. Over the years, different models of spectral mixtures have been proposed (Ichku and Karnieli 1996). Among the available models, the most widely used is the Mixture Tuned Matched Filtering (MTMF) (Harsanyi and Chang 1994, Boardman et al. 1995, Boardman 1998) that is based on the assumption that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixels.
variability and complexity of fuels.

4 RESULTS

Results from our analysis showed that the use of remotely sensed data at high spatial and spectral resolution provided a valuable characterization and mapping of fuel types. The overall accuracy levels (see table 1,2,3) obtained for the test case using the different classification approach are shown in Table 1 to 3.

In particular, for ASTER data the different classification approaches substantially provided very close results (see table 1). High accuracy levels were achieved, thus, showing that the spectral ASTER property and its spatial resolution allowed to obtain satisfactory results even for extremely heterogeneous areas as those under investigations.

For TM data processing performed at the pixel level, the accuracy was 62% and 64% from MLC and KNN respectively. Whereas, the use of unmixing techniques allowed an increase in accuracy at around 7%. This results that can be considered highly satisfactory considering the fact that the sample area is characterized by high variability and complexity of fuels.

The fuel typing obtained from TM-based MLC exhibited an overall accuracy of 62,48% (2). The obtained level of accuracy can be considered highly satisfactory considering that the sample area is characterized by high variability and complexity of fuels. Results for each of the nine classes are discussed below.

Fuel Type 1 – This class showed a producer accuracy equal to 70.83% and an user accuracy equal to 83.61%. The major classification problems arisen from the high mixing with Fuel Type 3. Thus, inducing a remarkable pixel transition from Fuel type 1 towards Fuel type 3 (almost 19% of the pixels) and vice versa. The "transfer" pixels from Fuel type 3 towards Fuel type 1 is actually much more limited (3.45%).

Classification	MLC	KNN	MTMF

Overall Accuracy (%)	82,22	82,27	82,32
Kappa Coefficient	0,7849	0,7853	0,7861

Table 1. ASTER Confusion Matrices

Classification	MLC	KNN	MTMF
Overall Accuracy (%)	62.48	64.49	68.85
Kappa Coefficient	0.5735	0.5905	0.6443

Table 1. TM Confusion Matrices

Classification	MLC		MTMF	
Class	Producer Accuracy (%)	User Accuracy .(%)	Producer Accuracy (%)	User Accuracy (%)
Fuel type 1	70.83	83.61	80.56	70.30
Fuel type 2	46.60	41.03	48.54	52.08
Fuel type 3	56.47	67.88	54.31	68.11
Fuel type 4	62.96	46.48	74.60	59.75
Fuel type 5	78.77	42.59	77.40	53.05
Fuel type 6	44.33	76.22	52.84	75.25
Fuel type 7	54.00	63.68	71.60	69.92
No fuel	95.68	94.51	95.68	94.51
Unclassified	89.13	73.21	89.13	100.00
Overall Accuracy (%)	62.48		68.85	
Kappa Coefficient	0.5735		0.6443	

Table 3. TM Confusion Matrices

pixels) and vice versa. The "transfer" pixels from Fuel type 3 towards Fuel type 1 is actually much more limited (3.45%).

Fuel Type 2 – This class showed very low producer's (46.60%) and user's (41.03%) accuracy values. The confusion occurred over all with Fuel type 3, Fuel type 4 and Fuel type 5. Between Fuel type 2 and Fuel type 3 there is a large "exchange" of pixels: ML Classifier "moves" 15.53% of the pixels from Fuel type 2 toward Fuel type 3 and 12.07% in adverse sense. The major classification problems arisen from the fact that the high variability and complexity of fuels makes the selection of distinct ground-truth points impossible at the TM spatial resolution.

Fuel Type 3 - This class showed a producer accuracy equal to 56.47% and an user accuracy equal to 67.88%. The major classifications problems come from the high mixing with Fuel Type 2, Fuel Type 4 and Fuel Type 1. In this case it is necessary to consider that Fuel type 3 presents a few analogous vegetation elements as Fuel Type 2 and Fuel Type 4. They are substantially differentiated by their highs, so that the mixing is unavoidable. The mixing with Fuel Type 1 is mainly due to the subpixel distribution of these fuel types.

Fuel Type 4 – This class showed a producer accuracy equal to 62.96% and an user accuracy equal to 46.48%. Confusion exist above all with Fuel type 7. The mixing between the two classes consists in a strong pixel "transfer" from Fuel type 4 toward Fuel type 7 and vice versa. ML Classifier "moves" 19.05% of the pixels of Fuel type 4 (according to ground-truth dataset) toward Fuel type 7 and 11.20% of Fuel type 7 (according to ground-truth dataset) toward Fuel type 4.

Fuel Type 5 – Relatively high producer accuracy (78.77%), low user accuracy (42.59%). The analysis of the user accuracy showed a high mixing with Fuel Type 7 and Fuel Type 6. Thus, causing the "transfer" of a big number of pixels toward Fuel type 5 (respectively 27.60% and 19.86%).

Fuel Type 6 – Low producer accuracy (44.33%), relatively high user accuracy (76.22%). The analysis of the producer accuracy showed that there was a high mixing above all with Fuel Type 5 (see Fuel Type 5). Instead, the mixing with Fuel Type 4 and Fuel Type 2 was due to the complexity of fuel types distribution.

Fuel Type 7 – Moderate producer (54.00%) and user accuracy (63.68%). Confusion exists with Fuel Type 5 and Fuel Type 4 (see above).

No Fuel – Very high producer (95.68%) and user accuracy (94.51%). This class does not present significant mixing with other classes.

Unclassified – High producer accuracy (89.13%) and relatively high user accuracy (73.21%). Some confusion occurred with Fuel Type 4. This is mainly due to the subpixel distribution of the different classes.

The overall accuracy was 62% that can be considered highly satisfactory considering that the test area is characterized by high variability and complexity of fuels. For all the considered fuel types, the major problem was the subpixel distribution. These problems were overcome using a sub-pixel level classification.

The application of MTMF to TM data allowed an improvement of the overall accuracy from 62.48% to 68.85% (see table 4). A net increase in the user accuracy emerged for the following six classes, Fuel Type 2,3,4,5,7 and also for the unclassified pixels. In particular, Fuel Type 2 class increases its user accuracy from 41.03% to 52.08%, Fuel Type 4 from 46.4% to 59.75% and, finally, Fuel Type 5 from 42.59% to 53.05%.

As a whole, results from the sub-pixel analysis showed that the use of unmixing technique allows an increase in accuracy at around 7% for both the overall accuracy and the Kappa Statistic (k) compared to the accuracy level obtained by applying a widely used classification algorithm.

These results delineate that the use of TM data can provide a useful characterization and mapping of fuel types for fragmented ecosystems as in the case of Mediterranean landscape.

4 FINAL REMARKS

Landsat-TM, and ASTER were processed for fuel type mapping performed in the fragmented landscape of Pollino national park. Fieldwork fuel types recognitions, performed at the same time as remote sensing data acquisitions, were used as ground-truth dataset to assess the results obtained for the considered test areas. As expected, results from the higher spatial resolution data namely ASTER imagery substantially provide very close levels of accuracy from both MLC and MTMF. In particular, for ASTER data the different classification approaches substantially provided very close results (see table 1). High accuracy levels were achieved, thus, showing that the spectral ASTER property and its spatial resolution allowed to obtain satisfactory results even for extremely heterogeneous areas as those under investigations.

For TM data processing performed at the pixel level, the accuracy was 62% and 64% from MLC and KNN respectively. Whereas, the use of unmixing techniques allowed an increase in accuracy at around 7%. This results that can be considered highly satisfactory considering the fact that the sample area is characterized by high variability and complexity of fuels.

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REFERENCES

BOARDMAN, J.W., 1998, Leveraging the high dimensionality of AVIRIS data for improved sub-pixel target unmixing and rejection of false positives: mixture tuned matched filtering. Summaries of the Seventh JPL Airborne Geoscience Workshop. JPL Publication 97-1, 55-56. NASA Jet Propulsion Lab., Pasadena, Calif.

CONGALTON, R. G., and GREEN, K., 1998, Assessing the accuracy of remotely sensed data: principles and practices. Lewis Boca Raton, Florida, USA.

FAO, (2001). Global forest fire assessment 1990-2000. Forest Resources Assessment Programme, working paper n.55, http://www.fao.org:80/forestry/fo/fra/docs/Wp55_eng.pdf.

HARSANYI, J.C., and CHANG, C., 1994, Hyperspectral image classification and dimensionality reduction: an orthogonal subspace projection approach. IEEE Trans. Geosci. Remote Sens., 32,779–785.

ICHKU, C., and KARNIELI, A., 1996, A review of mixture modelling techniques for sub-pixel land cover estimation. Remote Sensing Reviews, 13,161–186.

Lasaponara R., A. Lanorte, S. Pignatti, 2005Multiscale fuel type mapping in fragmented ecosystems: preliminary results from Hyperspectral MIVIS and Multispectral Landsat TM data, Int. J. Remote Sens., 587-593.

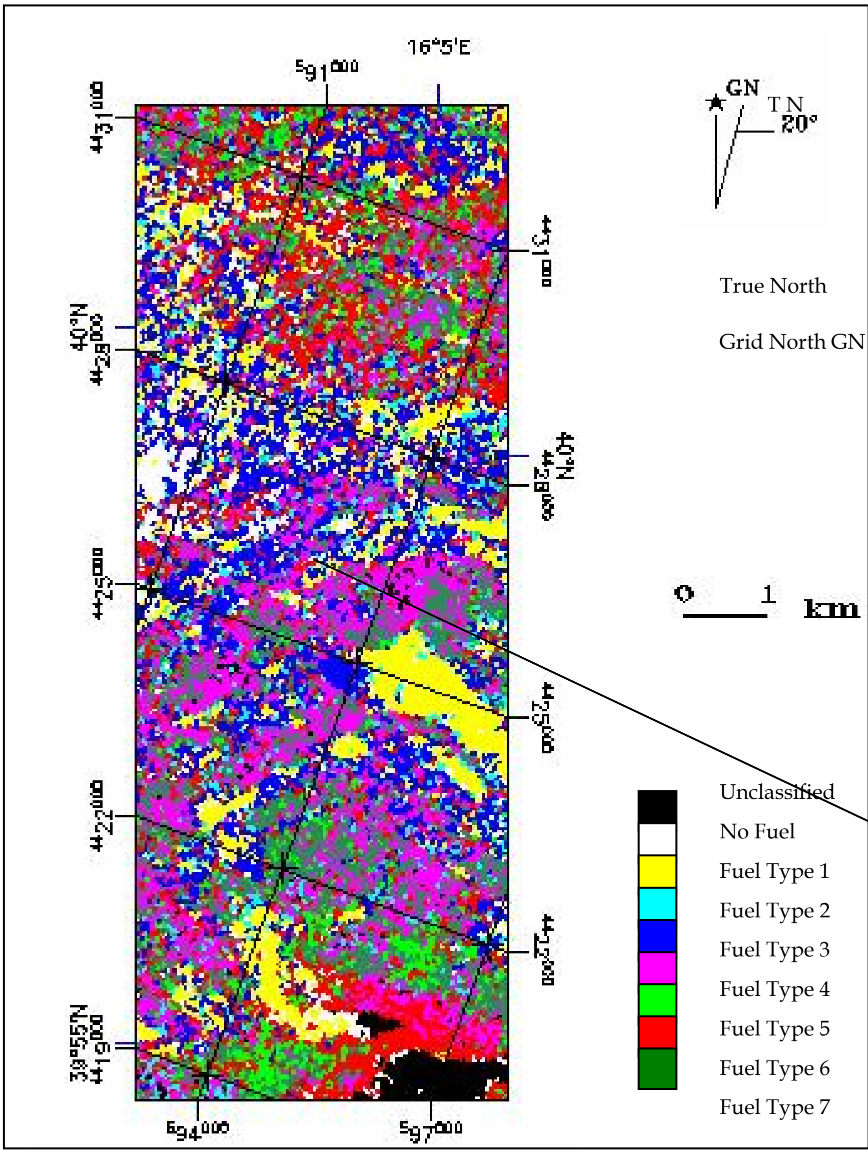
Lasaponara R., A. Lanorte, S. Pignatti, 2005. Characterization and mapping of fuel types for the Mediterranean ecosystems of Pollino National Park in the Southern Italy by using Hyperspectral MIVIS data Earth Interactions (2005EI000165R in press)

LILLESAND, T. M., and KIEFER, R.W., 2000, Remote sensing and image interpretation (New York: Wiley).

PROMETHEUS, S.V. PROJECT, 1999, Management techniques for optimisation of suppression and minimization of wildfire effects. System Validation. European Commission. Contract number ENV4-CT98-0716.

VAN WAGTENDONK, J. W., and ROOT, R.R., 2003, The USE of multitemporal Landsat Normalized Difference Vegetation Index (NDVI) data for mapping fuels models in Yosemite national Par k, USA, International Journal of Remote Sensing, 24, 1639-1651.

Vila M., Lloret, F., Ogheri, E., and Terradas, J., (2001), Positive fire-grassfeedback in Mediterranean. basin shrubland. Forest Ecology and Management, 147, 3-14.



Fuel Type class	Fuel Type description in terms of percentage of cover
1	Ground fuels (cover >50%)
2	Surface fuels (shrub cover >60%, tree cover <50%)
3	Medium-height shrubs (shrub cover >60%, tree cover <50%)
4	Tall shrubs (shrub cover >60%, tree cover <50%)
5	Tree stands (>4 m) with a clean ground surface (shrub cover <30%)
6	Tree stands (>4 m) with medium surface fuels (shrub cover >30%)

Table shows a description Fuel types

The Study area is located selected inside the Pollino National Park

Fuel type mapping obtained from TM data using MTMF.