Characterization and Mapping of Fuel Types for the Mediterranean Ecosystems of Pollino National Park in Southern Italy by Using Hyperspectral MIVIS Data

Rosa Lasaponara,* Antonio Lanorte, and Stefano Pignatti

National Research Council, Institute of Methodologies of Environmental Analysis, Potenza, Italy

Received 14 April 2005; accepted 16 December 2005

ABSTRACT: The characterization and mapping of fuel types is one of the most important factors that should be taken into consideration for wildland fire prevention and prefire planning. This research aims to investigate the usefulness of hyperspectral data to recognize and map fuel types in order to ascertain how well remote sensing data can provide an exhaustive classification of fuel properties. For this purpose airborne hyperspectral Multispectral Infrared and Visible Imaging Spectrometer (MIVIS) data acquired in November 1998 have been analyzed for a test area of 60 km^2 selected inside Pollino National Park in the south of Italy. Fieldwork fuel-type recognitions, performed at the same time as remote sensing data acquisition, were used as a ground-truth dataset to assess the results obtained for the considered test area. The method comprised the following three steps: 1) *adaptation of Prometheus fuel types* for obtaining a standardization system useful for remotely sensed classification of fuel types and properties in the considered Mediterranean ecosystems; 2) *model construc-*

* Corresponding author address: Antonio Lanorte, National Research Council, Institute of Methodologies of Environmental Analysis, C. da S. Loja, Tito Scalo, Potenza 85050, Italy.

E-mail address: alanorte@imaa.cnr.it

tion for the spectral characterization and mapping of fuel types based on a maximum likelihood (ML) classification algorithm; and 3) *accuracy assessment* for the performance evaluation based on the comparison of MIVIS-based results with ground truth. 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 being that the achieved classification accuracy was higher than 90%.

KEYWORDS: Fire; Hyperspectral MIVIS data; Fuel type mapping

1. Introduction

Wildland fires are considered one of the most important disturbance factors in natural ecosystems. In the Mediterranean regions, fires are considered a major cause of land degradation. Every year, around 45 000 forest fires break out in the Mediterranean basin causing the destruction of about 2.6×10^6 ha (FAO 2001). Several studies (see, e.g., Vila et al. 2001) dealing with the effects of fires on the vegetation within the Mediterranean basin found that fires induce significant alterations in short- as well as long-term vegetation dynamics.

Prevention measures, together with early warning and fast extinction, are the only methods available that can support fire fighting and limit damages caused by fires, especially in regions with high ecological value, dense populations, etc. To limit fire damage, fire agencies need to have effective decision support tools that are able to provide timely information for quantifying fire risk. In particular, fire managers need information concerning the distribution, amount, and condition of fuels in order to improve fire prevention and modeling fire spreading and intensity. Geographic information systems (GISs) and remote sensing (RS) are considered useful tools for supporting prevention activities (see, e.g., Chuvieco et al. 2004). Remote sensing can provide valuable data on type (namely, distribution and amount of fuels) and status of vegetation in a consistent way at different spatial and temporal scales. Since the description of fuel proprieties is usually very complex, fire managers have tried to summarize the physical parameters and spatial distribution of fuel in different classes also known as “fuel models” (Anderson 1982; Burgan and Rothermal 1984). More specifically, a fuel model has been defined as “an identifiable association of fuel elements of distinctive species, form, size, arrangement, and continuity that will exhibit characteristic fire behaviour under defined burning conditions” (Merrill and Alexander 1987). The spatial distribution of the fuel characteristics can be displayed as fuel type maps.

The Northern Forest Fire Laboratory (NFFL) system (Albini 1976) is the most common and well-known fuel model that was developed taking the vegetation structure and characteristics of the North American floras into account. Recently, in the framework of the 1999 Prometheus project, a new fuel type classification system was specifically developed to better represent the fuel characteristic of the Mediterranean ecosystems (Algosystems SA, Greece). This classification is principally based on the height and density of fuel, which directly influence the intensity and propagation of wildfire. The Prometheus system is briefly described in Table 1.

Because of the complex nature of fuel characteristics, a fuel map is considered

Table 1. Characteristics of the MIVIS spectral bands.

Bands	Lower edge (μm)	Upper edge (μm)	Bandwidth (μm)
1–20	0.43	0.83	0.02
21–28	1.15	1.55	0.05
29–92	1.983	2.478	0.009
93–102	8.18	12.7	0.34–0.54

one of the most difficult thematic layers to build up (Keane et al. 2000), especially for large areas. Aerial photos have been the most common remote sensing data source traditionally used (Morris 1970; Muraro 1970; Oswald et al. 1999) for mapping fuel types distribution. Nevertheless, remote sensing multispectral data can be an effective data source available at different temporal and spatial scales that can be fruitfully adopted for building up fuel type maps from global, regional, and down to local scale. For this purpose, up to now, several satellite sensors have been used in the last decades. For example, National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (NOAA AVHRR) data were used by McKinley et al. (McKinley et al. 1985) for mapping fuel types in the western United States. Landsat Thematic Mapper data were used for mapping fuels models in the Yosemite National Park in the United States (van Wagtendonk and Root 2003) and in Spain (Cohen 1989 in California; Riaño et al. 2002; Salas and Chuvieco 1994). A multisensor approach based on Spot and Landsat imager was adopted by Castro and Chuvieco (Castro and Chuvieco 1998) to perform a classification of fuel types for Chile by using an adapted version of Anderson's system. The accuracies obtained from these researches ranged from 65% to 80% (Chuvieco 1999). The accuracy level is strongly related with fuel presence and spatial distribution (how many and where) and with specific environmental conditions (topography, land-cover heterogeneity, etc.).

The importance of using a multisensor data source to map a fuel model was emphasized by many authors (see, e.g., Keane et al. 2001). Nevertheless, fire researchers did not pay enough attention to the potentiality of using hyperspectral data to map fuel types and properties. Hyperspectral data can be used to detect narrow spectral variation between different fuel types and thus to emphasize small differences not distinguishable by using multispectral sensors. This research aims to investigate the usefulness of hyperspectral data to characterize and map fuel types. This objective is achieved by analyzing Multispectral IR and Visible Imaging Spectrometer (MIVIS) data by using a maximum likelihood (ML) classifier for a test case located in the south of Italy that is highly representative of Mediterranean-like ecosystems.

2. Study area

The selected study area (Figures 1a and 1b) extends over a territory of about 6 000 ha inside Pollino National Park in the Basilicata Region (southern Italy). Figure 1a shows the location of Pollino Park and Figure 1b shows a red–green–blue (RGB) composition of MIVIS spectral channels for the study area.

The selected study area constitutes a complex morphological unit in which mountain landscapes are close to the Sinni River alluvial plan. It is characterized

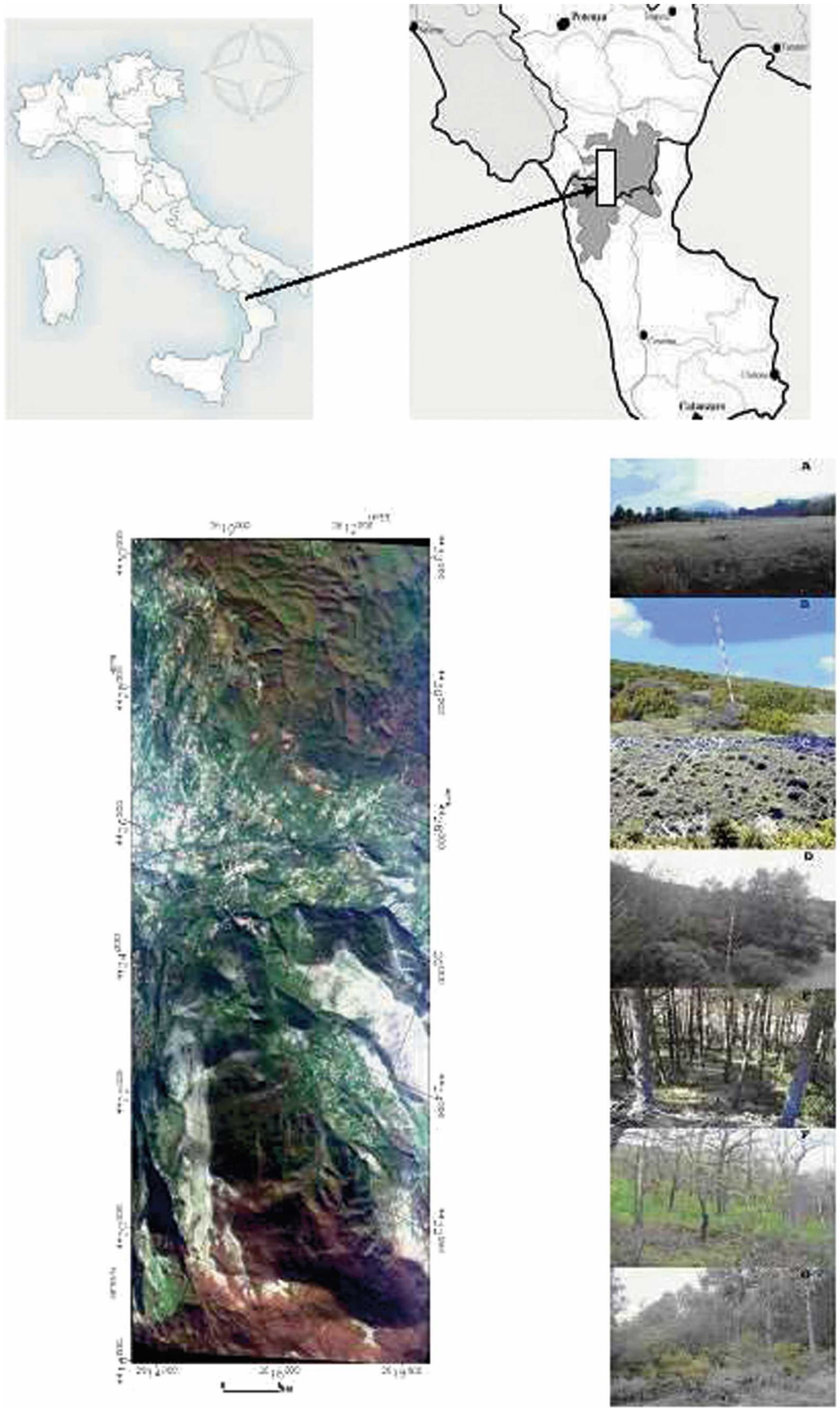

Figure 1. (a) Study area location. (b) MIVIS RGB picture from 13–7–1 spectral channels. (c) Prometheus system adapted for the study area: fuel type 1 (A), fuel type 2 (B), fuel type 3 (C), fuel type 4 (D), fuel type 5 (E), fuel type 6 (F), and fuel type 7 (G).

by complex topography with altitude varying from 400 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 by 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.

3. Data analysis

3.1. Dataset MIVIS

The hyperspectral data were acquired by the airborne MIVIS scanner (on board a Spanish aircraft: CASA 212) that is owned and managed by the Italian National Research Council in the context of the Airborne Laboratory for Environmental Study (LARA) Project. MIVIS acquired information in 102 spectral bands characterized by a noncontinuous spectral coverage between 0.4 and 12.7 μm (Table 1). The survey was executed on 9 November 1998 at an altitude of 4000 m ASL (corresponding to a ground resolution varying from 7 to 3.5 m with respect to altimeter variations) at a scan rate of 16.5 Hz. Additionally, aerial photos were acquired for the investigated region. Among the 102 MIVIS bands only the 28 channels in the visible and near infrared (VNIR) were considered, while the thermal infrared region (TIR; having a different ground resolution), and the shortwave infrared (SWIR) channels were excluded because of the low signal-to-noise ratio due to solar irradiance in the autumn season.

Additionally, ground-based and aerial photos were obtained for the investigated region at the same time as MIVIS data acquisition. Fieldwork fuel typing occurred during and after the acquisition of remote sensing data. A global positioning system (GPS) was used for collecting geoposition data (latitude and longitude). Aerial photos and fieldwork fuel types were used as a ground-truth dataset, first to identify the fuel types defined in the context of the Prometheus system, and second, to evaluate performance and results obtained for the considered test area from the MIVIS data processing.

3.2. Prometheus adaptation

The seven fuel type classes standardized in the context of the Prometheus system (see Table 2) were detailed, identified, and carefully verified for the study area on the basis of field works performed before, during, and after the acquisition of MIVIS remote sensing data. In particular, photos and air photos, taken for the investigated region at the same time as MIVIS data acquisition, along with the fuel types recognized in the field were used for this purpose. Figure 1c and Table 3 show the results obtained from the adaptation of the Prometheus system to the characteristics and properties of fuel types present in the investigated test area. Significant patches corresponding to areas representative for each fuel class were

Table 2. Fuel type classification developed for Mediterranean ecosystems in framework of the Prometheus project (1999).

Fuel type		
1	Ground fuels (cover >50%)	Grass
2	Surface fuels (shrub cover >60%; tree cover <50%)	Grassland, shrubland (smaller than 0.3–0.6 m and with a high percentage of grassland), and clear-cuts, where slash was not removed.
3	Medium-height shrubs (shrub cover >60%; tree cover <50%)	Shrubs between 0.6 and 2.0 m.
4	Tall shrubs (shrub cover >60%; tree cover <50%)	High shrubs (between 2.0 and 4.0 m) and young trees resulting from natural regeneration or forestation.
5	Tree stands (>4 m) with a clean ground surface (shrub cover <30%)	The ground fuel was removed either by prescribed burning or by mechanical means. This situation may also occur in closed canopies in which the lack of sunlight inhibits the growth of surface vegetation.
6	Tree stands (>4 m) with medium surface fuels (shrub cover >30%)	The base of the canopies is well above the surface fuel layer (>0.5 m). The fuel consists essentially of small shrubs, grass, litter, and duff.
7	Tree stands (>4 m) with heavy surface fuels (shrub cover >30%)	Stands with a very dense surface fuel layer and with a very small vertical gap to the canopy base (<0.5 m).

carefully identified over the MIVIS images by using geo-position data (latitude and longitude) collected during the ground surveys by means of GPS. Pixels relating to these areas were exploited in order to perform the selection of adequate region-of-interest (ROI) point (ground-truth dataset) for the seven classes (fuel type) with the addition of one class concerning areas having no fuel and one class concerning areas having unclassified pixels. The sample points of the ground-truth dataset were selected in the same areas subject to a direct check in the field in order to be used first to identify the fuel types defined in the context of the Prometheus system, and second, to evaluate performance and results obtained for the considered test area from the MIVIS data processing. For this reason, pixels corresponding to the given ground-truth areas were subdivided into testing data (50%) and training data (50%) through randomization of the pixels for every class.

3.3. Model construction and comparison

The mapping of fuel types was obtained by using a supervised classification based on the ML algorithm. The ML classifier is considered one of the most important and well-known image classification methods because of its robustness and simplicity. It is widely used in vegetation and land-cover mapping. Moreover, it was also tested for fuel model distribution (Riaño et al. 2002). The ML method quantitatively evaluates the variance and covariance of the spectral signatures when classifying an unknown pixel assuming at the same time that a Gaussian distribution of points is forming a cluster of a vegetation class. Under this assumption the distribution of a class is described by the mean vector and 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). As reported above, the ML classifier is based on the assumption that

Table 3. Fuel type and vegetation typologies adapted from the Prometheus system for the study area.

No fuel	Roads and houses	
	Plowed and bare soils	Areas at present or permanently presenting soils with no vegetation cover because of plowing or erosion phenomena.
	Woody cultivations	Arboreal cultivations (mainly orchards, olive groves, and vineyards).
	Calcareous cliffs and detritus	Emergine rocks, landslides, and generally melted sediments.
	Course and water bodies	Natural water and artificial courses besides natural water stretches and artificial basins.
Fuel type 1	Xerophytic prairies	Grassy vegetation of primary and secondary origin with a prevalence of *Bromus sp.*
	Mesophytic prairies	Grassy vegetation developing when water availability is good. Middle-altitude prairies and peak prairies with a prevalence of *Cynosurus cristatus*.
Fuel type 2	Substitution bushes	*Small shrubs* with predominant presence of *Cistus sp.*
	Uncultivated soils, ferns, field boundary vegetation, woods, meadows, roads	Vegetation growing in areas no longer agriculturally used or in any case at borders of lands used for a definite and consolidated purpose.
Fuel type 3	Substitution bushes, broom vegetation	Mediterranean formations of secondary origin with predominant presence of *Prunus sp., Spartium junceum* transition states toward forestry vegetation referable to mixed oak woods.
	Mediterranean scrubs, garigues, and shrubby prairies	Vegetation types referable to evergreen sclerophylls mainly degradated; Mediterranean formations with prevalence of medium-height shrubs and secondary formations scarcely covering areas no longer used for pasture.
Fuel type 4	Mediterranean scrubs	Vegetation types referable to evergreen sclerophylls Mediterranean formations with prevalence of tall shrubs.
	Beech woods and mixed oak woods	Young trees or small height formations of beech woods and mixed oak woods.
	Ilex woods	Wood formations with a prevalent presence of *Quercus ilex*, of which there are in the study area scarce pure stands at altitude lower than 600 m
Fuel type 5	Beech woods	Forestry formations with predominant presence of *Fagus sylvatica* of great relevance in the study area since these trees cover most parts of the belt between 1200 and 1800 m.
	Reforestation conifer woods	Areas that have been reforested mainly with *Pinus nigra* and *Pinus halepensis.*
Fuel type 6	Oak woods	Forestry formations with prevalence of *Quercus pubescens* in lower areas and *Quercus cerris* and *Quercus frainetto* in higher areas up to 1000–1200 m.
	Chestnut woods	Chestnut tree formations (*Castanea sativa*).
Fuel type 7	Mixed oak woods and reforesting trees	Forestry formations in which *Quercus sp.* is associated with numerous other forestry species belonging to *Acer, Fraxinus, Ostrya, Alnus, Sorbus, Malus, Crataegus, Pinus, Picea,* and *Abies.*

different variables used in the computation are normally distributed. This assumption is generally considered acceptable for a common spectral response distribution.

In our case, on the basis of ground surveys and aerial photos, we selected the ROIs corresponding to the considered seven fuel types, plus two additional classes related to no-fuel and unclassified regions. Pixels belonging to each of the considered ROIs were randomly separated into training data and testing data, used for the ML and accuracy evaluation, respectively.

Figure 2 shows the mapping of fuel type obtained for the investigated test area from the MIVIS images. Such a map presents very high user's accuracy. For the accuracy assessment we consider the producer accuracy, user accuracy, and overall accuracy, which are defined as follows.

- The producer accuracy is a measure indicating the probability that the classifier has correctly labeled an image pixel, for example, into the fuel type 1 class given that the ground truth is the fuel type 1 class.
- The user accuracy is a measure indicating the probability that a pixel belongs to a given class and the classifier has labeled the pixel correctly into the same given class.
- The overall accuracy is calculated by summing the number of pixels classified correctly and dividing by the total number of pixels.

Table 4 shows the accuracy coefficients as well as the omission and commission errors. The achieved overall accuracy was 90.39%. Thus, showing that the use of remotely sensed MIVIS data at high spatial and spectral resolution provided a valuable characterization and mapping of fuel types.

In particular, fuel type 5 exhibited the best user accuracy (99.92%), whereas the worst values were related to fuel type 2 (71.71%), fuel type 4 (73.04%), and fuel type 3 (84.13%). These results suggest that a light mixing of fuel type exists between the different classes that are made in prevalence of shrubs. This behavior may be a consequence of the high variability of these vegetation typologies that, in the considered area, is due to the typical microclimatical, orographical, and pedological characteristics. A further confirmation of this is given by the producer accuracy values also reported in Table 4. Such values are generally very high for all the classes (about or superiors to 90%) except for the fuel type 3, which presents a value of the producer accuracy equal to 49.09%; for this class only 50% of the pixels are classified correctly.

Finally, Table 4 also shows the commission and omission errors that are tighly correlated to the user accuracy and producer accuracy, respectively. In fact, for example, the worst user accuracy values (fuel types 2, 3, and 4) correspond to the higher commission values. (respectively, 28.29%, 15.87%, and 26.96%), just as the worst producer accuracy (fuel type 3) corresponds to the higher omission values (50.91%).

4. Conclusions

Hyperspectral MIVIS data acquired in November 1998 have been analyzed for a test area of southern Italy to ascertain how well remote sensing data can characterize fuel type and map fuel properties. Fieldwork fuel type recognitions, per-

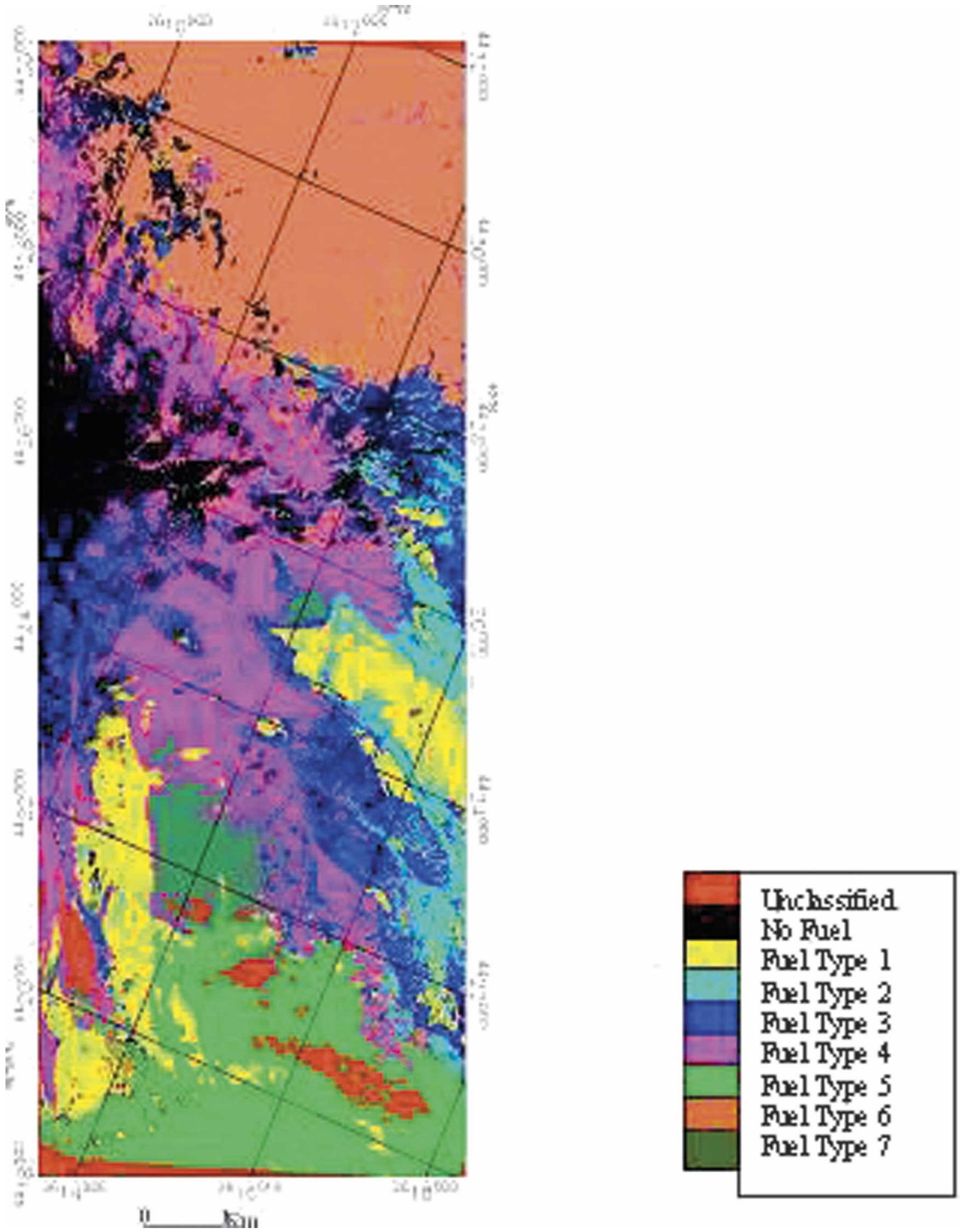

Figure 2. MIVIS ML classification.

formed at the same time as remote sensing data acquisitions, were used as a ground-truth dataset to assess the results obtained for the considered test area. Results from our analysis showed that the use of remotely sensed data at high spatial and spectral resolution provided a valuable characterization of fuel types, being that the classification accuracy was higher than 90%. Results obtained from these investigations can be directly extended to Mediterranean-like ecosystems.

The approach proposed in this work can be fruitfully applied to different remotely sensed data, such as the Landsat Thematic Mapper, or Enhanced Thematic

Table 4. Confusion matrix.

Class	Producer accuracy (%)	User accuracy (%)	Commission (%)	Omission (%)
Fuel type 1	98.29	88.41	11.59	1.71
Fuel type 2	89.20	71.71	28.29	10.80
Fuel type 3	49.09	84.13	15.87	50.91
Fuel type 4	96.24	73.04	26.96	3.76
Fuel type 5	100.00	99.92	0.08	0.00
Fuel type 6	95.44	99.52	0.48	4.56
Fuel type 7	94.64	98.35	1.65	5.36
No fuel	99.14	98.68	1.32	0.86
Unclassified	99.38	100.00	0.00	0.62
	Overall accuracy = 90.3964%		Kappa coefficient = 0.8905	

Mapper, NOAA AVHRR, *Terra–Aqua* Moderate Resolution Imaging Spectroradiometer (MODIS), characterized by different spatial and spectral resolution for mapping fuel properties at a different spatial scale from the landscape to regional level as it is often requested by National and International Environmental Protection Agency Forestry and Environmental Managers.

References

Albini, F. A., 1976: Estimating wildfire behavior and effects. General Tech. Rep. INT-30, Intermountain Forest and Range Experiment Station, USDA Forest Service, Ogden, UT, 92 pp.

Anderson, H. E., 1982: Aids to determining fuels models for estimating fire behavior. General Tech. Rep. INT-122, Intermountain Forest and Range Experiment Station, USDA Forest Service, Ogden, UT, 22 pp.

Burgan, R., and R. C. Rothermal, 1984: BEHAVE: Fire behavior prediction and fuel modeling system-FUEL subsystem. General Tech. Rep. INT-167, USDA Forest Service, 126 pp.

Castro, R., and E. Chuvieco, 1998: Modelling forest fire danger from geographic information systems. *Geocarto Int.,* **13,** 15–23.

Chuvieco, E., 1999: *Remote Sensing of Large Wildfires in the European Mediterranean Basin.* Springer-Verlag, 122 pp.

——, X. Cocero, I. Aguado, A. Palacios, and E. Preado, 2004: Improving burning efficiency estimates through satellite assessment of fuel moisture content. *J. Geophys. Res.,* **109,** D14S07, doi:10.1029/2003JD003467.

Cohen, W. B., 1989: Potential utility of the TM tasseled cap multispectral data transformation for crown fire hazard assessment. *ASPRS/ACSM Annual Convention Proc.: Agenda for the 90's.* Vol. 3, Baltimore, MD, ASPRS/ACSM, 118–127.

FAO, 2001. Global forest fire assessment 1990–2000. Forest Resources Assessment Programme, Working Paper No. 55.

Keane, R. E., S. A. Miincemoyer, K. A. Schmidt, D. G. Long, and J. L. Gardner, 2000: Mapping vegetation and fuel for fire management on the Gila National Forest Complex, New Mexico. General Tech. Rep. RMRS-GTR-46-CD, USDA Forest Service, 126 pp.

——, R. Burgan, and J. van Wagtendonk, 2001: Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modelling. *Int. J. Wildland Fire,* **10** (3–4), 301–319.

Lillesand, T. M., and R. W. Kiefer, 2000: *Remote Sensing and Image Interpretation.* Wiley, 724 pp.

McKinley, R. A., E. P. Chine, and L. F. Werth, 1985: Operational fire fuels mapping with

NOAA-AVHRR data. *Proc. Tenth Pecora Memorial Remote Sensing Symp.: Remote Sensing in Forest and Range Resource Management,* Bethesda, MD, American Society for Photogrammetry and Remote Sensing, 295–304.

Merrill, D. F., and M. E. Alexander, 1987: *Glossary of Forest Fire Management Terms.* National Research Council of Canada, Committee for Forest Fire Management, 91 pp.

Morris, W. G., 1970: Photo inventory of fine logging slash. *Photogramm. Eng.,* **36,** 1252–1256.

Muraro, S. J., 1970: Slash fuel inventories from 70 mm low-level photography. Canadian Forest Service Publication 1268, Canadian Forest Service, Ottawa, ON, Canada, 63 pp.

Oswald, B. P., J. T. Fancher, D. L. Kulhavy, and H. C. Reeves, 1999: Classifying fuels with aerial photography in East Texas. *Int. J. Wildland Fire,* **9** (2), 301–319.

Riaño, D., E. Chuvieco, J. Salas, A. Palacios-Orueta, and A. Bastarrika, 2002: Generation of fuel type maps from Landsat-TM images and auxiliary data in Mediterranean ecosystem. *Can. J. For. Res.,* **32,** 1301–1315.

Salas, J., and E. Chuvieco, 1994: Geographic information system for wildland fire risk mapping. *Wildfire,* **3** (2), 7–13.

van Wagtendonk, J. W., and R. R. Root, 2003: The USE of multitemporal Landsat Normalized Difference Vegetation Index (NDVI) data for mapping fuels models in Yosemite national Park, USA. *Int. J. Remote Sens.,* **24,** 1639–1651.

Vila, M., F. Lloret, E. Ogheri, and J. Terradas, 2001: Positive fire-grass feedback in Mediterranean: Basin shrubland. *For. Ecol. Manage.,* **147,** 3–14.