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Reliable, accurate and timely forest mapping for wildfire management using ASTER and Hyperion satellite imagery

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Abstract

The present study aims to explore the potential and effectiveness of new Earth Observation data for mapping the vegetation composition and structure and thus provide accurate forest maps to be used in fire propagation simulation models and fire risk assessment. Land cover classification of ASTER and Hyperion images is performed in a detailed nomenclature including different vegetation types and densities since the same vegetation type may give fires with different behaviour as a result of differences in fuel continuity.

The results suggest that both datasets can provide highly accurate maps with an overall accuracy of 85% for ASTER and 93% for Hyperion classification. Although Hyperion is superior to ASTER in terms of overall accuracy, the latter provided a higher thematic accuracy identifying one additional class compared to Hyperion. The evaluation of the classification results in terms of cost and technical characteristics suggest that both datasets are suitable for use in wildfire management tools, depending on the specific user needs, and they could also be used complementary if a combination of high thematic accuracy and locally high spatial accuracy is needed.

Keywords: Earth Observation; Mapping; Forest; Classification; Wildfires; ASTER; Hyperion; Fire propagation model

1. Introduction

Fire is an ecological factor with a long presence in the Mediterranean region as well as in other regions with Mediterranean type climate. Once an uncontrollable force of nature and later tamed for use by humans, fire currently constitutes a major ecological disturbance factor threatening ecosystem sustainability but also an important management tool for many ecosystems around the globe, such as Savannas where fire forms a significant component of their ecology (Bond and Keeley, 2005). Fire can be considered the largest ‘‘herbivore’’ on Earth with very broad dietary preferences (Bond and Keeley, 2005) that determines the structure and composition of vegetation in many regions of the world (Bond et al., 2005).

Over the last five decades much attention has been paid on the ecological impacts of fire, which are determined to a large extent by fire behaviour. Fire behavior is of particular importance not only because fires with different behaviour result in different ecological impacts, but also because it determines the optimal suppression strategy of any given fire. Thus, various efforts have been made to develop tools and models that could assess, on the one hand, the risk of fire accurately, and, on the other hand, the behaviour of a given or potential fire (e.g. Rothermel, 1972; Keramitsoglou et al., 2004; Vakalis et al., 2004a,b).

The two most important determinants of fire behavior are fire intensity and rate of spread, and are both affected by, among other factors, the type of fuel, the fuel load and the fuel continuity (Whelan, 1995). Different species produce different types of fuel with some species, such as *Pinus halepensis*, being more flammable than others (Vakalis et al., 2004a) due to the high content of flammable oils and resins, producing fires of high intensity. The fuel load and fuel continuity are both related to the percentage of the surface covered by vegetation and thus by potential fuel (Whelan, 1995).

The effectiveness and accuracy of any tool to be used for fire risk assessment or simulation of fire behavior depends on the availability and accuracy of data related to the above ecosystem properties, as demonstrated in the fire simulation models

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developed by Vakalis et al. (2004a,b). Thematically and spatially accurate land cover maps and information on the percentage of vegetation cover are thus critical for the prevention and suppression of fire in fire-prone areas and ecosystems.

Carlson and Burgan (2003) review users' needs in operational fire danger estimation and have discussed the role of Earth Observation (EO) in determining fuel which may also be used for fire propagation models. Multitemporal series of vegetation indices, including NDVI, to monitor vegetation stress have been used (Paltridge and Barber, 1988; Lopez et al., 1991), whilst other researchers have used thermal infrared data as an indicator of water stress in vegetation (Vidal et al., 1994; Desbois and Vidal, 1996). Other researchers have combined vegetation indices with thermal data to estimate fire potential (e.g. Chuvieco et al., 2004). Riano et al. (2002) used Landsat^{TM} images to generate fuel type maps at a spatial and temporal scale adequate for operational fire management applications. It should be noted, however, that even in cases of less dense canopies the discrimination by the sole use of optical sensors becomes difficult, especially between forest classes or forest and shrubs classes representing similar spectral characteristics. EO multispectral and hyperspectral sensors, such as ASTER and Hyperion, have substantially increased the potential to obtain timely, detailed and accurate information on land cover. Indeed, the exploitation of their spectral capabilities through application of various classification methods is discussed in the literature with promising results. In the few studies that utilise ASTER data, these have been used to perform land cover classification using object-oriented methods, and have produced satisfactory results (Kato et al., 2001; Lewinsky, 2005). Nonetheless, in some cases there are still difficulties in discriminating certain forest types (Yamaguchi et al., 1998). However, up to now, researchers have not paid enough attention to the potential of ASTER data in fuel type and properties mapping. Recently, Lasaponara and Lanorte (2007) showed that ASTER data may provide a valuable tool for characterization and mapping of fuel types achieving classification accuracy higher than 90% even for heterogeneous areas characterized by a complex topography and mixed vegetation covers.

Goodenough (2002) compared forest classification accuracies between EO-1's Hyperion and ALI sensors and Landsat 7 ETM+, and concluded that compared to Landsat, hyperspectral sensors provide greater accuracies and better discrimination in several forest types. In particular, Hyperion hyperspectral data have been used to produce high operational accuracies for forest mapping with different classification methods (Gomez-Chova et al., 2004; Goodenough et al., 2002; Minguillon and Serra-Sagrista, 2003; Benediksson and Kanellopoulos, 1999).

In this paper, we propose a comparative study between ASTER and Hyperion data using the same coverage area, training sets and classification method in order to evaluate their accuracy, effectiveness, complementarity and relative advantages for forest mapping as far as (i) vegetation type and (ii) percentage of vegetation cover are concerned. The ultimate aim is to provide a reliable map representing simultaneously vegetation type and percentage coverage for use in a decision-support system (DSS) during forest fire fighting. The pilot application area is the forested east side of Mount Parnitha, in the prefecture of Attiki, which includes the city of Athens (Greece).

2. Materials and methods

2.1. Satellite images and pre-processing

Two satellite images were used in this study, namely one ASTER image acquired in autumn 2003 (October 13) and one Hyperion acquired in autumn 2004 (September 20). The ASTER image provided scene coverage of 60 km by 60 km whilst the Hyperion image covered 7.6 km by 86 km. Both images were subset to a common area of interest covering 7.6 km by 25 km with 25 m pixel size and were geometrically corrected and georeferenced to the Hellenic Geodetic Reference System 1987 (EGSA87). ASTER data are recorded in 14 spectral bands from visible to thermal infrared. Spectral bands in the visible and near infrared (ASTER product AST2B05V), and in the shortwave infrared (ASTER product AST2B05S) were used for vegetation mapping.

Due to intense striping in several Hyperion bands, particularly in the shortwave infrared spectral area, the following processing was applied in order to reduce data dimensionality, preserve useful spectral information and minimize striping. For each spectral area, a first band elimination was performed by visual inspection. Subsequently, principal component analysis (PCA, Jensen, 1996) was performed in order to retain bands that presented only random noise. For these bands, the correlation matrix was calculated and the less correlated bands were finally retained. In addition, bands where random noise affected more than 5% of the total number of pixels were excluded. The processing was performed separately for visible, near infrared and shortwave infrared spectral bands and 63 spectral bands were finally retained: 23 in the visible, 12 in the near infrared and 28 in the shortwave infrared. The retained bands were subsequently stacked to a single file for further processing.

2.2. Classification

On the basis of the CORINE land cover (CLC) 2000 database (Heymann et al., 1993), the stratum "Forest" (according to the 1st hierarchical level of CLC) was extracted from ASTER and Hyperion images for classification. Fig. 1a shows a pseudo-coloured view of the ASTER image utilising bands 2–3–4 whilst Fig. 1b presents Hyperion image with band combination 24–45–117 for blue–green–red, respectively. Both figures show the stratum 'Forest' for the common area covered by ASTER and Hyperion scenes.

Classification was based on a supervised approach, which is predicated upon training samples whose spectral characteristics are known with certainty. A field campaign to the sampling sections resulted in the collection of ground-truth samples, by

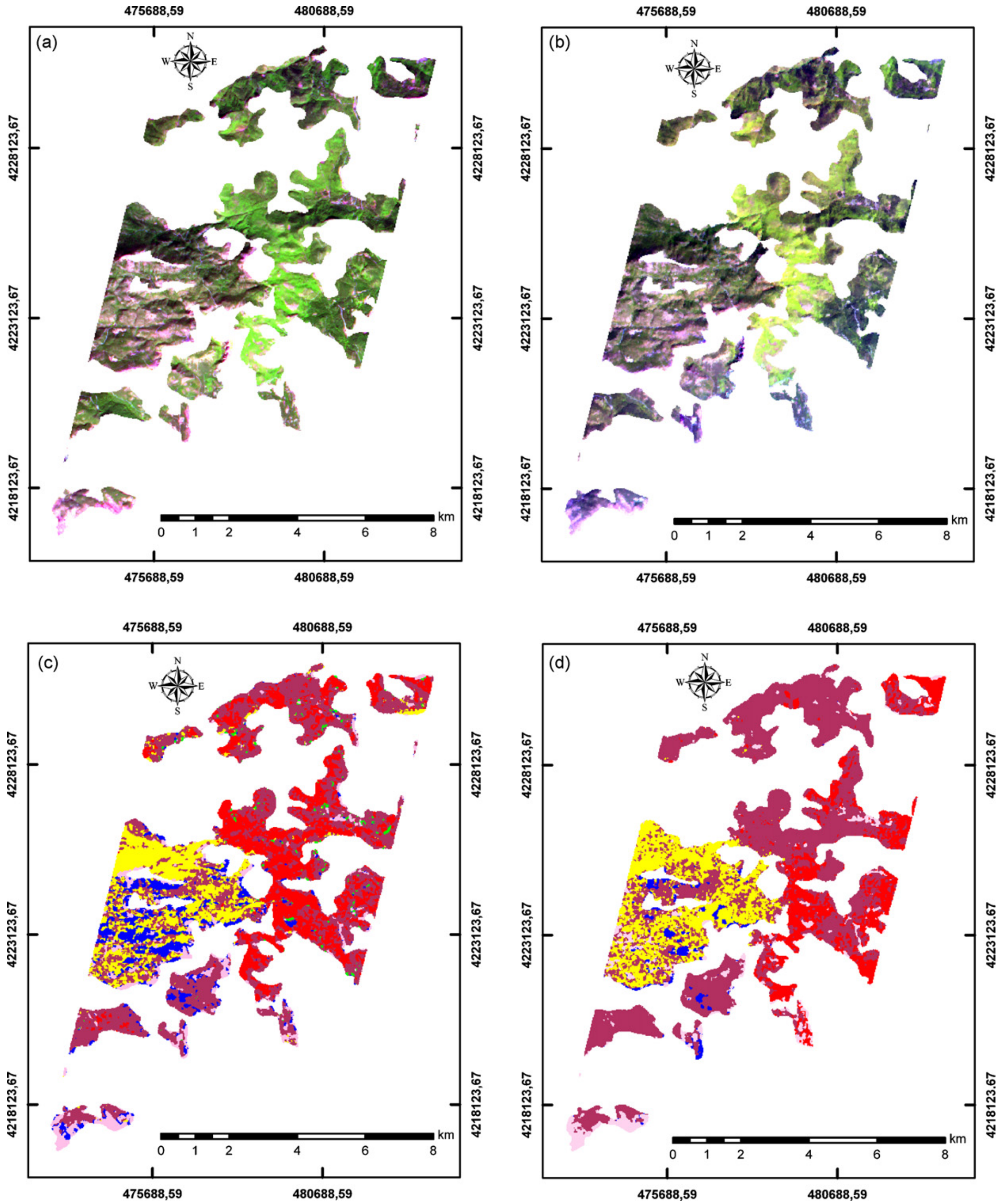

Fig. 1. (a) False colour composition of the ASTER image masked in order to only cover the study area (blue: band 2; green: band 3; red: band 4). (b) False colour composition of the Hyperion image using the same mask (blue: band 24; green: band 45; red: band 117). (c) Classification map produced using the ASTER image. (d) Classification map generated from the Hyperion image. Both classification maps use the same nomenclature and colours: maroon: aleppo pines; red: evergreen broad leaved trees; yellow: firs; blue: coppice; pink: bare soil; green: grasslands.

means of polygons and a detailed description of land cover. An example of a sampling section is given in Fig. 2. These polygons had a twofold role: part of them was used as training samples to classify ASTER and Hyperion images, and the rest as evaluation data for assessing the classification performances, i.e., the final map products which will serve as input to fire propagation models. The sampling sections covered 5.6% of the total area taking into consideration the trade-off between the size of each section and the distance between them. If the sections are too small, it usually takes more time to travel between the sections than to survey each of them. In addition, the smaller the section, the less representative it is for the global

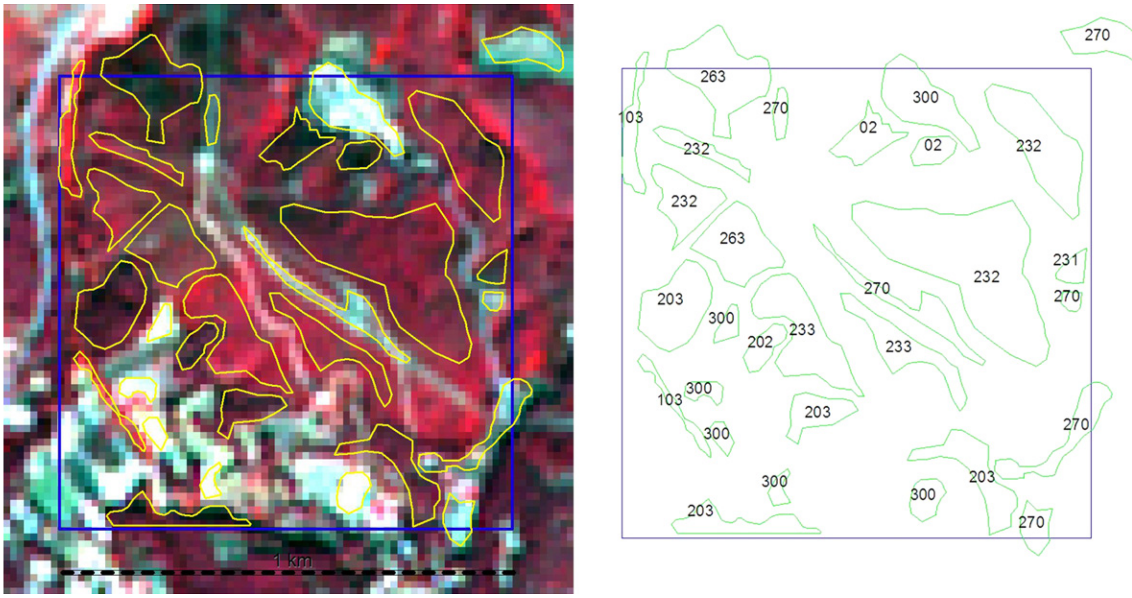

Fig. 2. A sampling section (in blue) of the 'Forest' stratum. On the left is the ASTER image with the digitised polygons and on the right the same polygons with their properties related to vegetation cover and density (coded) in a GIS environment.

vegetation population and the greater the variance between sections. Based on the above criteria and taking into account the budget restrictions, sampling between 5 and 6% of the total area was considered adequate. It is noteworthy that this can be considered as one of the highest rates used for operational mapping. For instance, MARS project sampling was set at 2.5% for agricultural areas and 1% for forest areas (Tsiligirides, 1998; see also Torrna and Harma, 2004, for CLC in Finland).

Four classes were defined according to the percentage of vegetation cover: 0–25%, 25–50%, 50–75% and 75–100%, and were coded as 0, 1, 2 and 3, respectively. The definition of the above classes was imposed by the fire propagation model used (Vakalis et al., 2004a,b) and was considered of enough detail to represent the densities present in the area of study. In total, 12 vegetation and land-cover classes were identified in the satellite scenes.

The training samples were digitized (Fig. 2), checked thoroughly and modified accordingly to ensure homogeneity within the polygons. Subsequently, a number of tests are applied including:

- ellipses separability in feature space;
- transformed divergence (Jensen, 1996); and
- contingency matrix, which is similar to Conglaton's (1991) confusion matrix, but was applied here only to the training pixels.

Classification was performed according to the parametric maximum likelihood algorithm (e.g. Schowengerdt, 2007). This same method was applied to both data sets in order to obtain comparable results. A majority 3×3 kernel was subsequently applied in order to create a context-based classification to reduce undesirable noise.

The basic principle followed during the classification was that the output should include both vegetation types and densities. However, in cases where density classes could not be separated they were merged and named appropriately. For instance, class "Coppice density 2" was spectrally confused with "Coppice density 3". These two classes were, therefore, merged in one, namely "Coppice densities 2–3".

3. Results

Classification maps resulting from both datasets are shown in Fig. 1. Fig. 1c and d show the maps produced using ASTER (Fig. 1a) and Hyperion (Fig. 1b), respectively. In terms of vegetation type and cover the results are presented in Table 1. The total accuracy of each image is evaluated by means of overall performance and kappa statistics. The accuracy results

Table 1
Confusion matrices for ASTER and Hyperion classifications

Species	Density	Accuracy (%)			
		ASTER		Hyperion	
		Producer's	User's	Producer's	User's
Aleppo pine	0	83.33	95.24	98.70	98.70
Aleppo pine	1	91.67	84.62	99.53	97.53
Aleppo pine	2	45.45	93.75	96.97	97.97
Aleppo pine	3	97.18	85.19	98.25	98.20
Coppice	0	99.11	98.80	90.16	64.29
Coppice	1	70.00	92.90	92.45	92.45
Coppice	2–3	77.78	77.78	60.20	99.14
Evergreen broad leaved	2–3	73.81	65.96	96.88	96.88
Fir	0	95.00	90.48	85.71	85.71
Fir	3	97.52	84.38	75.00	85.71
Bare soil	–	98.50	98.50	80.00	72.73
Grasslands	3	100.00	100.00	–	–

Density numbers correspond to 0 = 0–25%, 1 = 25–50%, 2 = 50–75%, and 3 = 75–100% of vegetation surface coverage. Classes with density numbers 2–3 correspond to a merged class of densities 2 and 3.

Table 2
Overall classification results for ASTER and Hyperion sensors

Sensor	Number of classes	Overall performance (%)	Overall Kappa statistics
ASTER	12	84.50	0.8212
Hyperion	11	92.59	0.9191

for both classification experiments are presented in Table 2. The overall accuracy of the maps shows that both classifications present satisfactory results in terms of overall performance and kappa coefficients. Hyperion classification with overall classification accuracy of 93% over-performed ASTER classification where an overall accuracy of 85% was achieved. ASTER, however, identified one more class than Hyperion (grasslands, covering 1.1% of the total area). The lower thematic accuracy of Hyperion classification was probably due to the limited training set for this particular class (small number of training pixels) that seemed to be insufficient for Hyperion to classify.

The classification accuracy was based on the ground-truth data. Producer's accuracy and user's accuracy for each vegetation type and density from the corresponding confusion matrices are also shown in Table 1. Producer's accuracy reflects errors issued from the sampling data. User's accuracy reflects the percentage of correctly classified pixels. Both classifications present acceptable levels of accuracy.

The classification maps have been finally integrated into a fire propagation model based on Vakalis et al. (2004a). By replacing the existing forest maps with the new classification products derived in the framework of this study the model returned a fire simulation output that was more sensitive to fuel variations at cell level and generated more irregular shapes in response to these variations. This could be attributed to the fact that the model input consisted of up-to-date detailed vegetation maps of forest species and vegetation density types.

4. Discussion

ASTER and Hyperion imaging data have similar spatial resolution, which indicates practically the same scales for vegetation mapping. Classification gave satisfactory results in both cases. However, Hyperion, due to its superiority in spectral information, provided better classification accuracy results (see Table 2) that exceeded 90%.

For both data sets the ability to discriminate vegetation type and cover depends on the spectral characteristics of the species and the size of the training set. The minimum number of pixels required for a signature when using a maximum likelihood classifier is the number of bands plus one. The minimum number of pixels of a sample size used to estimate the mean vector and covariance matrix for a N-dimensional normal distribution is $(N + 1)$, which is the necessary condition for the matrix to be positive definite (ERDAS, 1997). As ASTER is a multispectral and Hyperion is a hyperspectral sensor, it becomes clear that it is easier to extract a reliable training set for ASTER than for Hyperion. In this study, ASTER seemed to be able to provide one more class with the limited training samples. As a result, Hyperion required more intense sampling in order to provide distinct classes of all vegetation types. Despite the limitations of training samples, the classification of Hyperion renders higher overall accuracy and minimum spectral confusion in all cases of classes returned.

Table 3 summarises the ASTER versus Hyperion technical specifications and their evaluation in terms of suitability for forest mapping according to the methodology and the results

Table 3
ASTER vs. Hyperion technical specifications and evaluation of suitability for mapping forested areas

Parameter	ASTER	Hyperion	Advantage
General			
Satellite/sensor characteristics			
Launch date	December 1999	November 2000	
Spatial resolution	Bands 1–3: 15 m; Bands 4–9: 25 m; Bands 10–14: 90 m	30 m	ASTER
Temporal resolution	4–16 days	16 days	ASTER
Spectral resolution	60–700 nm, 14 bands	10 nm, 242 bands (196 effective)	Hyperion
Spectral range	VIS, NIR, SWIR, TIR	VIS, NIR, SWIR	ASTER
Radiometric resolution	8 bits	12 bits	Hyperion
Area covered by scene (swath)	60 km × 60 km	7.7 km × 86 km	ASTER
Stereoscopic observation	Yes	No	ASTER
Case study (data used)			
Cost/time requirements			
Cost for per km^2	0.02 € per km^2	9–36 € per km^2	ASTER
Pre-processing	Standard (resampling & geometric correction)	Standard (resampling & geometric correction) & band and noise reduction	ASTER
Data	1 archived scene	1 scene after satellite programming	–
Classification map			
Overall classification performance	84.50%	92.59%	Hyperion
Overall Kappa statistics	0.8212	0.9191	Hyperion

obtained from this study. The comparison between the two satellite sensors showed that ASTER images have lower cost, they are faster and easier to process, they cover a larger area within a single scene and they provide acceptable classification accuracies (80–85%) in the framework of operational projects that require costly field works for training (5–6% of the study area). On the other hand, Hyperion has a higher data cost and needs more computational time due to increased data volume and inherent noise. However, whenever superior thematic accuracy is required, hyperspectral data are the best choice or they can be used as a complement in order to locally increase classification accuracy. In the latter case, it is important to note the necessity for additional and detailed field information. It is also noteworthy that the two satellites overpass the same area with an approximately 40-min time lag, which ensures that their images can be acquired under the same atmospheric conditions, thus increasing a synergistic use.

5. Concluding remarks

The current study explored the potential of using ASTER multispectral and Hyperion hyperspectral satellite Earth Observation data and methods for mapping vegetation composition and structure that can become potential fuel in a wildfire incident. The results suggest that both datasets can provide highly accurate and easily updatable products, which can be used as components in the various models and tools developed for wildfire management. However, each of the two satellite sensors presents certain advantages that may render it more or less suitable or even complementary to one another depending on the specific conditions.

Datasets and methods, such as the ones presented in the current study, gain significant importance for wildfire management due to the changing environment in which forest fires occur as a result of the altered fuel properties as well as of the climatic change. The fire suppression strategy, applied in most fire prone areas for almost a century is thought to have increased the fuel load (Dodge, 1972; Bonnicksen, 1980; Minnich, 1983), increasing the risk of high intensity and more difficult to control forest fires. Furthermore, the predictions of climatic change, as reported by Christensen et al. (2007), for the Mediterranean region suggest that summer temperature will increase and precipitation will decrease, increasing the regional aridity and the potential for more frequent, of higher intensity and subsequently more catastrophic fires (Clark, 1988; Mouillot et al., 2002; Pierce et al., 2004; Whitlock et al., 2003).

Under the situation of increased fuel load and increased potential for intensive hot fires the development and use of accurate tools for early assessment of fire risk and the potential behaviour of fire is of particular importance. It could lead to the adoption of appropriate measures for managing the most vulnerable areas, towards decreasing the fuel load or developing appropriate strategies for the effective suppression of fire. Therefore, accurate fire propagation models can be used in the operational support of forest fires suppression, in the development of fire propagation scenarios, in the training of volunteer fire fighters, in the planning of actions to be taken by Civil Protection Agencies, and in the decision support of local competent authorities.

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