

Using object-oriented classification and high-resolution imagery to map fuel types in a Mediterranean region

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[1] Knowledge of fuel load and composition is critical in fighting, preventing, and understanding wildfires. Commonly, the generation of fuel maps from remotely sensed imagery has made use of medium-resolution sensors such as Landsat. This paper presents a methodology to generate fuel type maps from high spatial resolution satellite data through object-oriented classification. Fuel maps were derived from QuickBird imagery, which offers a panchromatic and four multispectral bands ranging from 0.61 to 2.44 m resolution. The image used for this paper dated from July 2002 and is located in the NW region of Madrid, Spain. The Prometheus system, a fuel type classification adapted to the ecological characteristics of the European Mediterranean basin, was adopted for this study. Viewed with high-resolution imagery, fuel-related features are often aggregations of pixels exhibiting a variety of spectral properties. Correct identification and classification of these objects requires an explicit consideration of spatial context. We used an object-oriented approach, which allowed context consideration during the classification process, as a complement to traditional pixel-based methods. The map created with this approach was assessed to have greater than 80% accuracy for the prediction of six fuel classes. Results suggested that object-oriented classification of high-resolution imagery has the potential to create accurate and spatially precise fuel maps.

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1. Introduction

[2] Wildfires are frequent in Mediterranean ecosystems, and they can become a major cause of land degradation [Maselli *et al.*, 2000]. Understanding the spatial variation of fire risk is essential for forest resource management. Fuel conditions are a primary component of fire risk; spatially accurate fuel models are critical in fire management, particularly at the urban-wildland interface (WUI) where the risk to life and property is acute [Andrews and Queen, 2001]. Wildfires in the WUI have recently gained attention due to the explosive growth of WUI areas and some catastrophic events in the last decades, such as the Southern California fire of October 2003, which burned 300,000 ha, destroyed 3361 homes and killed 26 people [Keeley *et al.*, 2004]. This concern about the impact of WUI wild fires has

led to interest in the potential of very high resolution (VHR) satellite imagery to improve the accuracy and precision of the fuel maps used to prevent and fight such fires.

[3] In the past, the use of remotely sensed data to map fuel was limited by the relatively coarse spatial resolution of the available data sources. The majority of the work in this area used sensors such as SPOT HRV (Système Pour l'Observation de la Terre-Haute Resolution Visible) and Landsat MSS (Multispectral Scanner) or TM (Thematic Mapper), with a ground instantaneous field of view (GIFOV) on the order of 10 to 100 meters [De Wulf *et al.*, 1990; Castro and Chuvieco, 1998; Maselli *et al.*, 2000; Riaño *et al.*, 2002]. Newer sensors such as QuickBird and IKONOS provide a submeter GIFOV, but few studies [e. g. Wang *et al.*, 2004; Ozdemir *et al.*, 2005] have investigated the potential for higher-resolution imagery to improve vegetation mapping or fuel classification accuracy.

[4] One shortcoming of traditional pixel-based methods may be their inability to process the additional within-field spectral variability present in high-resolution data. If the classes sought in a fuel map can be recognized only through the aggregation of multiple pixels, pixel-based classification must rely on postprocess filtering to identify those classes. This approach may become prohibitively complex; a number of potentially contradictory operations would be necessary, for example, to aggregate pixels to identify basic scene elements such as tree crowns, and then to consider the

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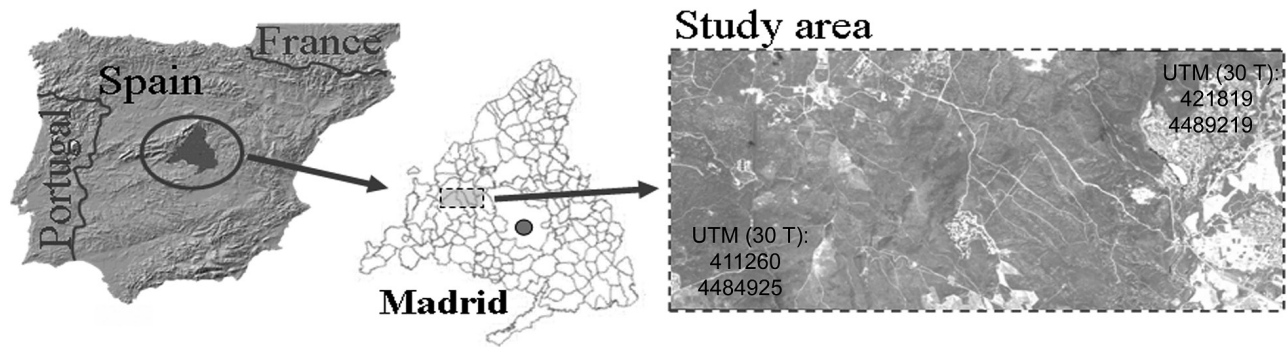


Figure 1. Study area in NW Madrid region.

spatial distribution of those elements in order to recognize particular fuel conditions.

[5] Object-oriented classification is an alternative to pixel-based methods. In this approach, pixels are aggregated before classification, not after. Thus classification is performed on groups of pixels (“objects”) identified according to predetermined rules. Objects can be classified on the basis of spectral values, spectral variability, size, shape or in relation to neighboring objects. Classification can also be hierarchical, with the arrangement of objects on one level informing the creation of higher-order objects. The use of objects allows direct labeling of classes such as fuel conditions that may be both spectrally heterogeneous and spatially complex.

[6] Although it emerged as early as the 1970s [e.g., Kettig and Landgrebe, 1976], object-based analysis was not used extensively within the field of remote sensing until recently [Flanders et al., 2003; Laliberte et al., 2004; Ivits et al., 2005]. As commercial software has become available, several works have used segmentation of Landsat images as an alternative to per pixels methods [e.g., Barlow et al., 2003; Dorren et al., 2003; Wulder and Seemann, 2003]. Other authors have specifically shown the benefits of segmenting the image into homogeneous objects to reduce the inherent complexity of high-resolution imagery [Giakoumakis et al., 2002; Baatz and Schäpe, 2000]. Object-oriented analysis has become a valuable and complementary approach that creates regions as carriers of features that are then introduced in the classification stage.

[7] The focus of this paper is to evaluate the potential of object-oriented processing to discriminate Mediterranean fuel types using high-resolution QuickBird imagery. The fire-prone forest type in the study area, coupled with a mix of homes and forest exemplify conditions where high spatial resolution may be most valuable in a fuel map. It is hoped that the methods developed and tested in this study will inform and support future high-resolution fuel mapping activities in the Mediterranean and in other regions.

2. Site Description

[8] The study area in Figure 1 is located in the NW region of Madrid, Spain. It includes the municipalities of Galapagar, Colmenarejo, Villanueva del Pardillo and Valdemorillo, and covers an area of 5048 hectares. The mean elevation is

850 m. The region has experienced population growth that has led to a number of new urban/suburban settlements. These areas are particularly vulnerable to wildfires.

[9] The climate is typically Mediterranean, with a rainy winter, short wet spring and fall, and a long arid summer period with high temperatures [Thornthwaite, 1933]. Under these circumstances, fire weather is common throughout the summer. Only 7–12% of annual rainfall takes place during the summer, and mean temperatures for the season range from 22 to 25°C.

[10] Soils are siliceous on granite parent material. The area is mostly covered by Mediterranean vegetation: mainly shrublands and a typical Mediterranean formation called “dehesa”. Shrubland areas contain Spanish greenwood (*Genista scorpius*), Spanish broom (*Retama sphaerocarpa*) and juniper (*Juniperus oxycedrus*) in a mixed distribution that depends on factors such as terrain, slope, and humidity. Dehesa refers to a savanna-like woodland with large grazing pastures and scattered old trees. It appears in areas where tree growth is limited by livestock, typically cattle. Isolated tree stands remain surrounded by grass and shrubs in places that would likely be forested in the absence of livestock. In areas of elevated human impact, trees are completely replaced by grass formations.

[11] Part of the region was reforested in the 1950s with stone pine trees (*Pinus pinea*), but these plantations did not succeed in many areas. This process led to the present situation, where pine-forested patches and small nonadapted pines appear between dehesa formations and natural shrubbery.

3. Methods

3.1. Fuel Type Classification

[12] Because it is difficult to describe all physical characteristics for all fuels in a particular area, a classification system is often created whereby different types of vegetation are grouped together according to their fire behavior. Such classification is normally based upon the size, species, form, arrangement, and continuity of constituent fuel elements [Merrill and Alexander, 1987]. Two well-known fire behavior fuel type systems are the Northern Forest Fire Laboratory system (NFFL) [Albini, 1976] and the Canadian Forest Fire Behavior Prediction system (FBP) [Lawson et al., 1985]. Within Europe, the system referred to as “Pro-

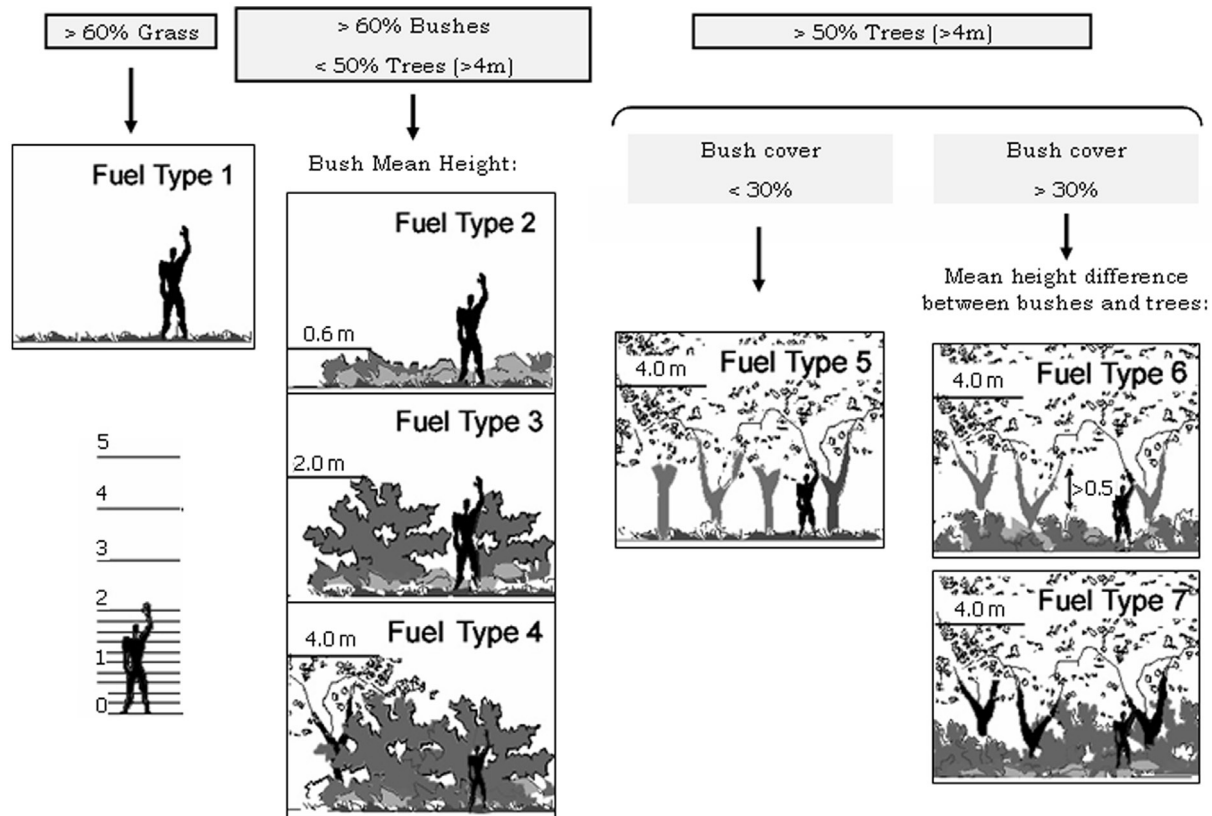


Figure 2. Prometheus fuel classification system for Mediterranean systems.

metheus” deals with the composition and sorting of various types of vegetation found in Mediterranean ecosystems [Riaño *et al.*, 2002]. According to this standardization, fuels are divided into seven types (<http://www.firegrowthmodel.com/index.cfm>) (Figure 2).

[13] Fuel type 1 (grass cover >50%) is land fuel. This category comprises grasslands consisting of agricultural and herbaceous vegetation.

[14] Fuel type 2 (shrub cover >60%, tree cover <50%) is surface fuels. This category comprises grasslands, low-lying shrubs (30–60 cm) and a high percentage (30–40%) of herbs. This category includes clear-cuts, where slash was not removed.

[15] Fuel type 3 (shrub cover >60%, tree cover <50%) is medium-height shrubs. It comprises medium- to large-sized shrubs (0.6–2.0 m), as well as young trees resulting from natural regeneration or forestation.

[16] Fuel type 4 (shrub cover >60%, tree cover <50%) comprises tall shrubs (between 2.0 and 4.0 m) and regenerating trees.

[17] Fuel type 5 (shrub cover <30%, tree cover >50%) is forest areas with no understory. It includes areas where ground fuel was removed either by prescribed burning or by mechanical means.

[18] Fuel type 6 (shrub cover >30%, tree cover >50%, distance between the canopy base and surface fuel layer >0.5 m) is forest areas with medium understory. The surface fuel consists essentially of small shrubs, grass, litter, and duff.

[19] Fuel type 7 (shrub cover >30%, tree cover >50%, distance between the canopy base and surface fuel layer

<0.5 m) is forest areas with high and dense understory. Tree stands with heavy surface fuels, a very dense surface fuel layer and with a very small vertical gap to the canopy base.

3.2. Field Sampling

[20] A total of 80 field plots were distributed throughout the study area. The sampling campaign was conducted between July and September 2004. Because public access in the area was limited, it was impossible to obtain a random sample of the area. However, an effort was made to ensure that the sample was representative of potential fuel types. A coarse classification-based stratification roughly corresponding to fuel type was created using the QuickBird imagery. Plot locations were chosen in situ based upon access and stratum; at least five plots were located in each fuel stratum. Once established, plots were carefully collocated with the imagery in the field.

[21] Plots were relatively small, 5 × 5 m, to match the potentially small grain size of fuel information available from QuickBird. Measurements at each site included: species and height of all trees and shrubs, substrate type, the distance between the top of the understory and the crown base, and a general landscape description. Afterward, the scheme shown in Figure 2 was applied to identify the Prometheus fuel type of each plot.

3.3. Data Preprocessing

[22] Object-oriented classification was carried out using ten image layers derived from QuickBird imagery dated from July 2002. QuickBird is the highest-resolution commercial remote sensing satellite now operating, offering a

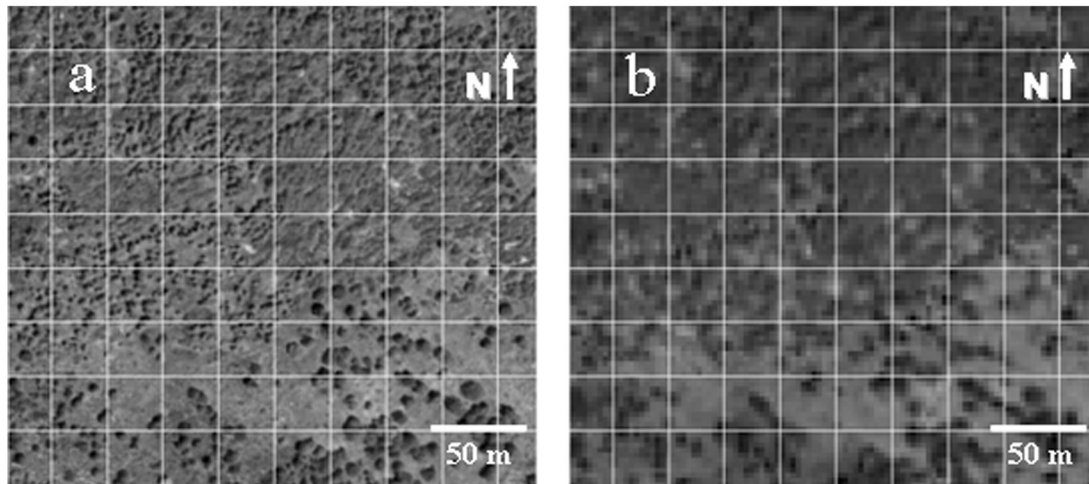


Figure 3. QuickBird image subset presented with (a) the panch sharpened bands and (b) the original 2.44 m resolution bands. The grid signifies Landsat resolution.

panchromatic channel (from 0.61 m resolution) and 4 multispectral channels (2.44 m resolution) from the red, blue, green and near-infrared (NIR) portions of the spectrum. Preprocessing consisted of orthorectification using digital elevation models and field-collected ground control points located by differentially corrected global positioning system; root mean square error (RMSE) of this process was less than 1 pixel.

[23] The image layers consisted of (1) four multispectral bands with 2.44 m GIFOV, (2) these same bands resampled to 70-cm pixels, (3) a normalized difference vegetation index band ($NDVI = (NIR - red) / (NIR + red)$) [Kriegler *et al.*, 1969; Rouse *et al.*, 1974]), and (4) a pixel-based classification of vegetation cover class.

[24] The resampled bands (2 above) were obtained through a resolution merge with the panchromatic data to produce high-resolution multispectral imagery. This method [Welch and Ehlers, 1987] involved resampling the original multispectral bands to 0.7 m resolution, performing a Principal Component transformation using these bands, rescaling the 0.7 m panchromatic band to match the range of the first principal component (PC1, assumed to represent overall scene luminance), and substituting the rescaled panchromatic band for PC1 in a back transformation to the original multispectral bands. This method makes use of the higher-resolution panchromatic band while maintaining the general characteristics of the original multispectral histograms [Chavez *et al.*, 1991].

[25] NDVI values were calculated using the 2.44 m resolution bands and were resampled to 70 cm resolution afterward. The cover layer, consisting of 10 classes, was produced using supervised classification on the 0.70 m multispectral bands. Finally, an additional thematic layer delimiting areas of pine plantation was used in the classification process. It should be noted that many of the areas marked as “planted” in this layer have failed since their establishment in the 1950s.

3.4. Object-Oriented Classification

[26] Image segmentation is a process by which pixels in an image are grouped together using a stated system of

rules. These pixel groups are the unit of analysis in object-oriented classification. The analyst may create differing segmentations of the same image by changing band weights and altering preferences for the type of segments sought. In eCognition[®], the software used in this analysis, one may specify the general size, shape, and spectral heterogeneity of the objects to be produced in a segmentation [Flanders *et al.*, 2003; Benz *et al.*, 2004; Laliberte *et al.*, 2004]. The general approach tested here was hierarchical.

[27] The first step in this approach was a multiscale image segmentation. In iterative steps, a three-level network of image objects was developed. We first created a segmentation (the “fuel type level”) that was eventually to be classified according to the Prometheus fuel types. This segmentation was the result of a two-step process. First, the relatively coarse 2.44 m multispectral data were segmented with weights favoring regularly shaped segments. Adjacent regularly shaped segments that had similar spectral characteristics were then merged in a second segmentation process. The segments resulting from this two-step process were consistent with fuel type boundaries identified on the imagery using professional judgment. Objects with extremely high spectral heterogeneity at the fuel type level were classified as “urban” and not considered for further segmentation. A second (“intermediate level”) segmentation was independently created incorporating the NDVI image and the pine plantation thematic layer. The last segmentation (“pixel level”) corresponded to the classification of cover type. This pixel level layer was produced using supervised maximum likelihood classification performed upon the panch sharpened 0.70 m bands (blue, green, red, NIR) to produce ten simple cover classes: tree, high shrubs, medium shrubs, low shrubs, grass, wet grass, soil, road, rock, and shadow. The panch sharpening process was necessary in this step because small or narrow surfaces like roads and isolated trees would have been difficult to classify using the original 2.44 m bands. Figure 3 shows the difference in the level of detail obtained.

[28] Objects created in the intermediate and fuel type level segmentations were then classified using eCognition’s nearest neighbor classifier, considering both the spectral and

Table 1. Selected Context-Based Rules for Classifying Each Level Toward Fuel Type Classification

Class	Level	Parameters
Cover type	pixel	multispectral mean and standard deviation
Broadleaf tree (stand)	intermediate	relative area of “tree” cover type at pixel level, pine plantation thematic layer
Broadleaf tree (isolated)	intermediate	mean NDVI, mean difference with neighbors’ NDVI, pine plantation thematic layer
Pine tree (stand)	intermediate	relative area of “tree” cover type at pixel level, pine plantation thematic layer
Pine tree (isolated)	intermediate	mean NDVI, mean difference with neighbors’ NDVI, pine plantation thematic layer
Trail	intermediate	segment length ÷ segment width, mean NDVI, relative area of “bare ground” cover type at pixel level
Urban	fuel types	spectral heterogeneity, relative border with other “urban” objects
Bare soil	fuel types	relative area of “trail” + “rock” + “road” lower-level objects
Fuel type 1	fuel types	relative area “grass” + “irrigated grass” lower-level objects, relative border with other “fuel type 1” objects
Fuel type 2	fuel types	relative area of “short shrubs” lower-level objects, relative border with other “fuel type 2” objects
Fuel type 3	fuel types	relative area of “medium shrubs” lower-level objects, relative area of “shadow” lower-level objects, relative border with other “fuel type 3” objects
Fuel type 4	fuel types	relative area of “high shrubs” lower-level objects, relative area of “shadow” lower-level objects, relative border with other “fuel type 4” objects
Fuel type 5	fuel types	relative area of “pine tree” (stand and isolated) objects, relative border with other “fuel type 5” objects
Fuel type 7	fuel types	relative area of “broadleaf tree” (stand and isolated) objects, relative border with other “fuel type 7” objects

spatial properties of those objects and the lower level objects contained within them. The training areas supporting this supervised classification were independent of the validation data set and were identified visually using expert interpretation of the imagery. The simultaneous representation of image information on different scales allowed the propagation of many different kinds of relational information. This information was used to create the context-based semantic and spatial rules (summarized in Table 1) that governed the use of pixels to classify intermediate objects and then the use of both intermediate objects and pixels to classify fuel class level objects. The final fuel map was simply composed of the classified objects in the fuel type level.

3.5. Accuracy Assessment

[29] The field plots were used to validate two stages of the fuel type classification. In the first, the cover type (tree, high shrubs, medium shrubs, low shrubs, grass, wet grass, soil, road, rock, or shadow) was estimated for a 1-m square area corresponding to the coordinates at the center of each plot. Large-scale printouts of the imagery were brought into the field to aid in the registration of the plot to the imagery. The recorded cover type was later checked against the cover type mapped through the pixel level classification. Only 77 of the 80 plots were used for this purpose since no cover type was recorded in the 3 plots located in urban areas. The other validation effort was a plot level assessment (covering 25 m²) of fuel type that was based upon the tree, shrub and ground cover list from each plot. These field-based assessments were then compared to the mapped fuel type for the majority of the pixels within the plot area (all plots turned out to be homogenous with respect to final fuel classification). Error matrices were derived for both validation exercises. In addition to overall accuracy, Kappa statistics

[Hudson and Ramn, 1987; Congalton, 1991, 2001] were calculated for both cover type and fuel class.

4. Results

4.1. Pixel-Based Classification of Cover Type

[30] Results of the pixel-based supervised classification are shown in Figure 4. Visual inspection and our validation exercise brought to light several attributes of the cover classification. Individual trees were correctly distinguished, as in Figure 4e which shows a dehesa (open woodland) formation. Riparian forest were distinguished from the neighboring vegetation (Figure 4d), and the roads and tracks were also properly assigned (Figures 4b and 4d). Overall accuracy, presented in Table 2, was relatively high. Values corresponding to “producer’s accuracy” indicate the probability of a reference sample being correctly classified and “user’s accuracy” is indicative of the probability that a sample classified on the map/image actually represents that category on the ground [Congalton, 2001].

[31] According to our error assessment (Table 2), the main sources of error came from the “high shrub” class, with a users accuracy of 50%. The “bare ground” class was over-estimated and some trees were misclassified as irrigated grass, which is normally found within riparian areas, like the one shown in Figure 4d. Identification of pine trees was somewhat problematic. In addition, urban areas, such as the one depicted in Figure 4c, resulted in a complex mix of cover classes. Global classification accuracy according to the validation plots was 75%, with a Kappa coefficient was 0.69.

4.2. Object-Oriented Classification of Fuel Type

[32] The context-dependent process of object classification allowed the labeling of the coarsest-level objects thought to conform to fuel type boundaries. Figure 5 shows several

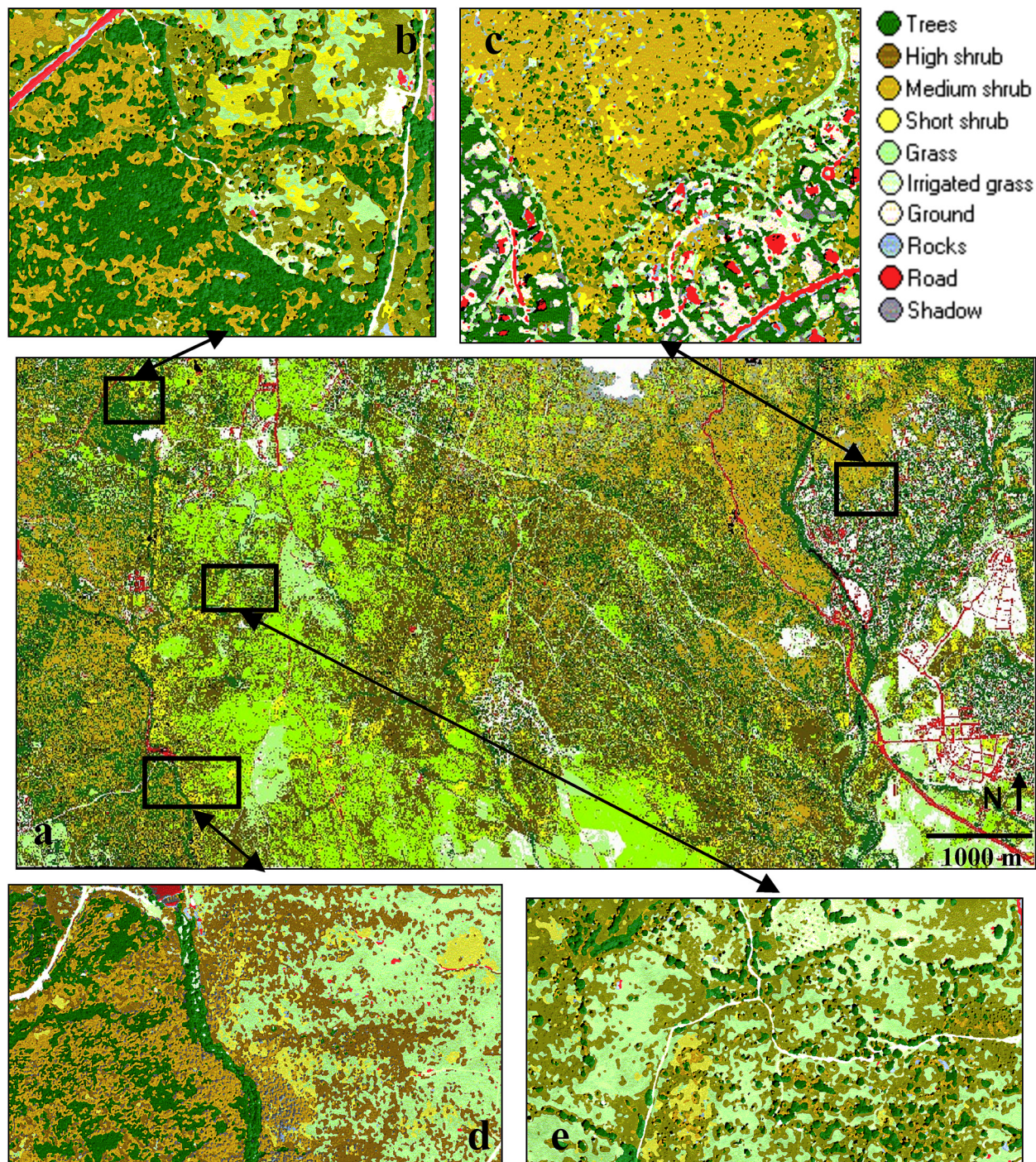


Figure 4. (a) Pixel-based classification of cover type. Detailed examples of (b) an oak forest, (c) an urban settlement, (d) a reforested area, and (e) a riparian forest.

examples of this fuel type classification. Figure 5b corresponds to an oak forest. Depending on the relative area of oak trees or shrubs, objects were assigned to fuel type 3 or 7. Areas where grass was dominant were allocated to fuel type 1. Figure 5c illustrates the cover type complexity of urban settlements that was used in the identification and ultimate removal of urban objects from the fuel classification. Figure 5d shows an area previously planted with pine; fuel types 3 and 5 were assigned

depending on the relative area of shrubs or pine trees in lower-order objects. A riparian corridor (in red) was also properly identified in that subset. Finally, Figure 5e corresponds to a dehesa formation, where isolated oak trees were combined with other covers, showing a mixed fuel distribution.

[33] Sixty-five out of 80 plots were correctly identified to one of 6 fuel types using object-oriented classification (both field inspection and image classification suggested no occur-

Table 2. Quantitative Accuracy Assessment for Pixel-Based Cover Type Classification^a

	Reference Data										User's Accuracy	
	Tree	Height of Shrubs	Medium Shrubs	Short Shrubs	Grass	Wet Grass	Ground	Road	Rock	Shadow		Sum
Classified Data												
Tree	19	0	2	0	0	1	0	0	0	0	22	86%
High shrubs	2	9	3	1	3	0	0	0	0	0	18	50%
Medium shrubs	2	0	14	0	0	0	0	0	0	0	16	88%
Short shrubs	0	0	1	4	0	0	0	0	0	0	5	80%
Grass	0	0	0	1	8	0	0	0	0	0	9	89%
Wet grass	0	0	0	0	0	2	0	0	0	0	2	100%
Ground	0	0	1	0	0	1	2	0	0	0	4	50%
Road	0	0	0	0	0	0	0	0	0	0	0	—
Rock	0	0	0	0	0	0	0	0	0	0	0	—
Shadow	0	0	0	0	1	0	0	0	0	0	1	—
Sum	23	9	21	6	12	4	2	0	0	0	77	
Producer's Accuracy	83%	100%	67%	67%	67%	50%	100%	—	—	—		

^aOverall classification accuracy is 75.3%.

rence of Prometheus fuel type 6 in the study area). Table 3 suggests that error was relatively well distributed across fuel types. Fuel type 3 was predicted with the lowest accuracy and appeared to be confused with type 7. This error may be traced to the pixel level classification, in which there was confusion of medium and high shrubs with trees (Table 2). The cover classification precision therefore influenced the fuel type classification. The overall accuracy of the fuel type classification was 81.5%, with a Kappa coefficient of 0.78.

5. Discussion

[34] In pixel-based analyses, spatial resolution should approximately match the spatial scale of the features to be measured [Woodcock and Strahler, 1987]. If resolution is too coarse, signatures of interest become convolved with neighboring signatures; if resolution is too fine, signatures correspond only to components of the features of interest, leaving the post facto task of combining components. The GIFOV of QuickBird imagery is considerably smaller than the spatial dimension of fuel type units, but the imagery may be used to resolve objects such as isolated tree crowns, paths and other cover types that are fuel class constituents [Giakoumakis *et al.*, 2002]. The approach tested here linked these pixel level fuel constituents to higher-order fuel class polygons through an object-oriented hierarchical framework.

[35] In the context of an object-oriented analysis, the pixel may be thought of as the most basic in a continuum of increasingly complex objects. Pixels may be assigned a class value, as happens in traditional pixel-based classification, and they may also be combined using spectral, spatial or relational rules to form more complex objects. As such, the pixel level accuracy displayed in Table 2 represents an assessment of the accuracy of the analysis' simplest objects. As simple objects are part of larger objects at higher levels of organization, it is possible that initial accuracies may rise as contextual rules become a factor. In other words, the final fuel classification makes use of the cover type information present at the pixel level without necessarily being limited by the pixel level accuracy of those objects. This is particularly encouraging because of the spectral limitations of currently available VHR imagery. Neither QuickBird nor IKONOS carries a shortwave infrared band, although work with Landsat TM and ETM+ has highlighted the importance of that spectral region for forest structure studies [Cohen and Goward, 2004].

[36] There are several ways in which contextual information enhanced object classification in this analysis. Urban areas have a characteristic disaggregated aspect, with a mix of cover patterns. Pixels within urban and suburban sectors present a broad range of spectral values that make them difficult to classify through a pixel-based approach, leading to alternative techniques such as texture analysis [Puissant *et al.*, 2005]. In object-oriented classification, by contrast, such areas are relatively simple to identify because they contained such a diversity of subobjects. Contextual benefits were also seen in the classification of linear objects such as roads, tracks, and riparian areas. Consideration of the ratio of segment length to width enabled the relatively accurate classification of such objects despite internal spectral variability. Similarly, the relative area of "shadow" in lower-order objects was successfully used to delimit tall shrubs and trees. External contextual information may also be used to enhance classification. A spatial record of established pine plantations was used to refine intermediate objects classified as pine forest.

[37] The principal drawback to the object-oriented process described here was the amount of time spent in creating the hierarchy of semantic rules needed to build objects relevant for fuel classification. It is hoped, though, that the insights gained through this process will provide a template for classifying fuel in this and other Mediterranean ecosystems. The software used for this analysis (eCognition) allows for the recording and editing of complex processing protocols, so the mapping process may be streamlined in the future. It should also be noted that the computing resources needed for this process were significant: several layers were considered simultaneously, and even a single QuickBird image is relatively large (approximately 1 gigabyte). The application of the complete processing algorithm, which was developed on subsets of the imagery, ran for 10 days using a 3.2 Ghz. desktop computer. However, since this processing took no personnel hours and since developments in the computing field are likely to continue, processing time should not be considered limiting.

[38] The spectral properties of fuel classes can become quite complex and heterogeneous when studied with high spatial resolution imagery. This inherent heterogeneity is difficult for pixel-based approaches to accommodate in a single class. The object-oriented classification paradigm allows the systematic and knowledge-driven combination

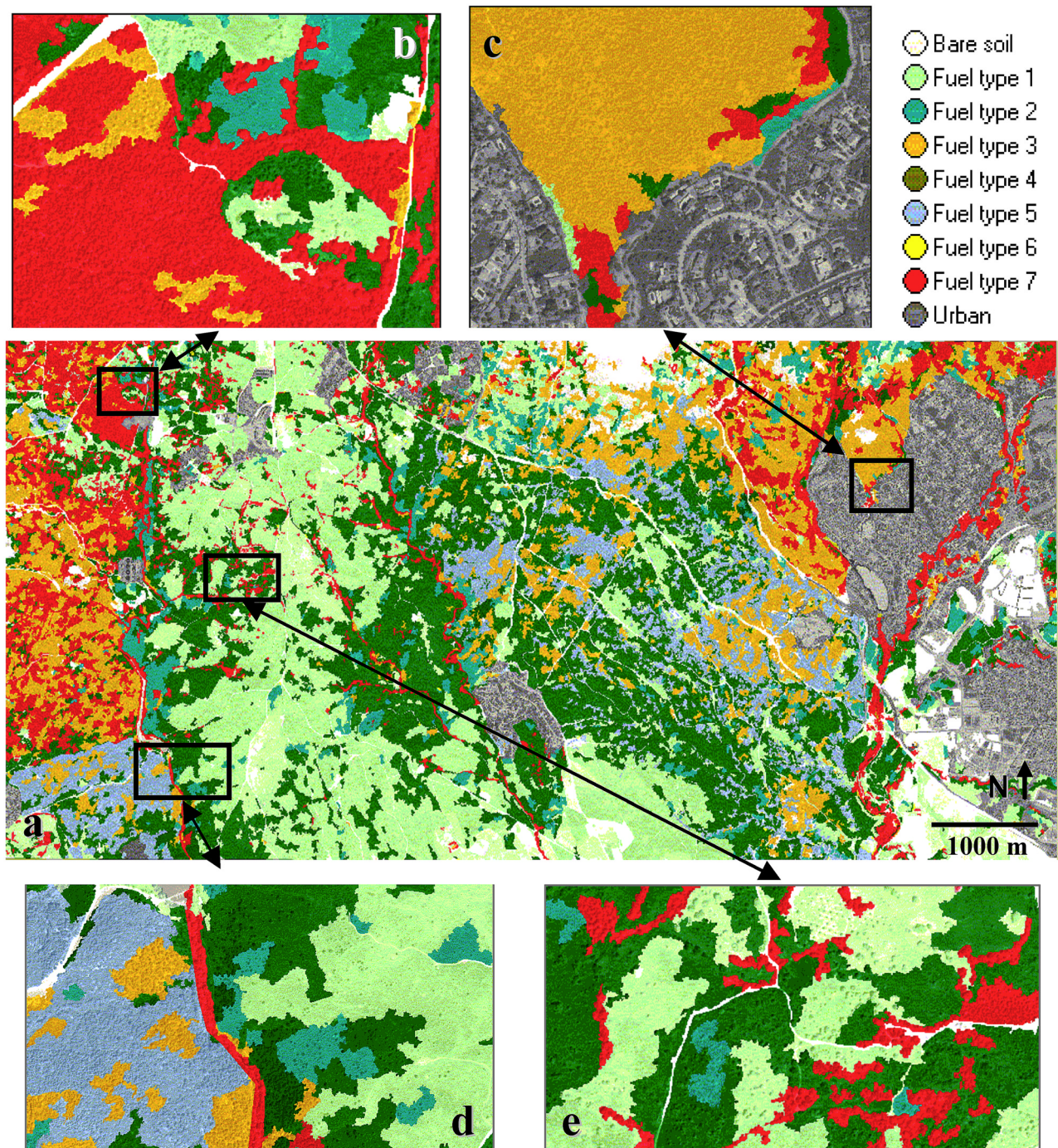


Figure 5. (a) Fuel map obtained with object-oriented processing. The subsets correspond to examples of (b) oak forest, (c) urban settlement, (d) reforested area, and (e) riparian forest.

of spectrally diverse pixels in a way that is directed toward the production of map units matching the desired classification scheme. The work reported here confirms that the combination of both approaches is capable of producing relatively accurate results in the field of fuel mapping.

6. Conclusions and Implications

[39] A primary use of remotely sensed fuel information has been as an input to fire spread simulation tools such as

BehavePlus or FARSITE for purposes of fighting wildland fire [Andrews *et al.*, 2003] or evaluating the effect proposed fuel reduction treatments [Stratton, 2004]. While the wildland-urban interface may provide scenarios where running such simulations at the single-meter grain is justified, the scale of interest for the spread of wildland fires will be considerably coarser in many cases. The primary value of VHR imagery for fuel mapping therefore lies not only in its ability to produce high-resolution maps but also in its potential to improve fuel map accuracy with its ability to

Table 3. Quantitative Accuracy Assessment for Object-Oriented Fuel Classification^a

	Reference Data								User's Accuracy
	Bare Soil	Urban	Fuel Type 1	Fuel Type 2	Fuel Type 3	Fuel Type 4	Fuel Type 5	Fuel Type 7	
Classified Data									
Bare soil	4	0	0	0	0	0	0	0	100%
Urban	0	3	0	0	0	0	0	0	100%
Fuel type 1	0	0	10	0	0	0	0	0	100%
Fuel type 2	0	0	1	7	1	0	0	0	78%
Fuel type 3	0	0	0	0	9	1	0	0	90%
Fuel type 4	0	0	2	1	1	12	1	0	71%
Fuel type 5	0	0	0	0	1	0	5	1	71%
Fuel type 7	0	0	1	0	3	1	0	15	75%
Sum	4	3	14	8	15	14	6	16	
Producer's Accuracy	100%	100%	71%	88%	60%	86%	83%	94%	

^aOverall classification accuracy is 81.5%.

detect submetric fuel components (see Figure 3). The mapping process employed here allowed the recognition of fuel components (individual trees and shrubs) and the production of an accurate and relevant fuel classification. Results of this polygon-based classification may be rasterized and resampled to any appropriate resolution.

[40] While more research is needed to identify the relative effects on accuracy of object- versus pixel-oriented classification and VHR versus moderate-resolution imagery, our results establish object-oriented processing as a viable method of producing fuel maps with QuickBird imagery. The ability to create protocols defining the interrelationships between objects at different scales, from pixel level cover types to larger spectrally heterogeneous polygons representing fuel class units, allowed the large volume of data present in a VHR scene to be processed efficiently and accurately with respect to fuel classification. While creation of the protocols used here was labor intensive, processing time should decrease as studies such as this one solve more of the critical issues in hierarchical classification. Commercially available software such as eCognition allows extensive automation of object identification and organization, meaning that lessons learned in one scene may extend to others across the region. This cross-scene efficiency would address a practical barrier to the wider use of VHR imagery: the large amount of data that must be processed for a relatively small area. While further investigation is needed into the relative costs and benefits of the regional use of VHR data for fuel mapping, this project has demonstrated that submeter remotely sensed data can be used to create fuel classifications that are potentially useful in the prediction of fire behavior and effects.

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