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Fire type mapping using object-based classification of Ikonos imagery

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Abstract. Distinguishing and mapping areas of surface and crown fire spread has significant applications in the study of fire behaviour, fire suppression, and fire effects. Satellite remote sensing has supplied a suitable alternative to conventional techniques for mapping the extent of burned areas, as well as for providing post-fire related information (such as the type and severity of burn). The aim of the present study was to develop an object-based classification model for mapping the type of fire using very high spatial resolution imagery (Ikonos). The specific objectives were: (i) to distinguish between surface burn and canopy burn; and (ii) to assess the accuracy of the classification results by employing field survey data. The methodology involved two consecutive steps, namely image segmentation and image classification. First, image objects were extracted at different scales using multi-resolution segmentation procedures, and then both spectral and contextual object information was employed to classify the objects. The accuracy assessment revealed very promising results (approximately 87% overall accuracy with a Kappa Index of Agreement of 0.74). Classification accuracy was mainly affected by the density of the canopy. This could be attributed to the inability of the optical sensors to penetrate dense canopy to detect fire-affected areas. The main conclusion drawn in the present study is that object-oriented classification can be used to accurately distinguish and map areas of surface and crown fire spread, especially those occurring in open Mediterranean forests.

Additional keywords: canopy burn; fuzzy analysis; image segmentation; surface burn.

Introduction

Forest fires are an integral part of many terrestrial ecosystems such as boreal forests, temperate forests, Mediterranean ecosystems, savannas, and grasslands, among others (Pausas and Vallejo 1999). The type of fire, the main focus of the present study, is related to environmental conditions such as topography, wind, fuel type, and condition of the fuel. Fire scientists and managers distinguish the following three general types of wildland fire: ground, surface, and crown, depending on the fuel stratum in which the fire burns (Scott and Reinhardt 2001). More specifically:

- A ground fire is one that burns in ground fuels such as duff, organic soils, roots, and rotten buried logs;
- A surface fire is one that burns in the surface fuel layer, which lies immediately above the ground fuels but below the canopy or aerial fuels; and
- A crown fire is one that burns in elevated canopy fuels.

Distinguishing and mapping areas of surface and crown fire spread has significant applications in the study of fire behaviour, fire suppression and fire effects (Albini and Stocks 1986; Stephens 1998; Alexander 2000; Rogan and Yool 2001; Scott and Reinhardt 2001; Graham 2003).

Although remotely sensed data have been shown to provide accurate post-fire information shortly after the fire event (Smith and Woodgate 1985; Milne 1986; Chuvieco and Congalton 1988; Jakubauskas *et al*. 1990; Karteris 1995; White *et al*. 1996; Patterson and Yool 1998; Beaty and Taylor 2001; Escuin *et al*. 2002; Pollet and Omi 2002), the mapping of the type of fire seems to be in its early stages. However, new types of satellite data such as Ikonos imagery, whose high spatial resolution is comparable with that of an aerial photo, are opening up a new frontier in remote sensing (Tanaka and Sugimura 2001). One major application in which very high resolution images are expected to bring new insight is in the provision of post-fire related information (Gitas and Rishmawi 2003).

Moreover, new classification techniques such as object-based classification have recently been developed. The concept here is that information necessary to interpret an image is not represented in single pixels, but in meaningful image objects. Segmentation, the first step in the object-oriented

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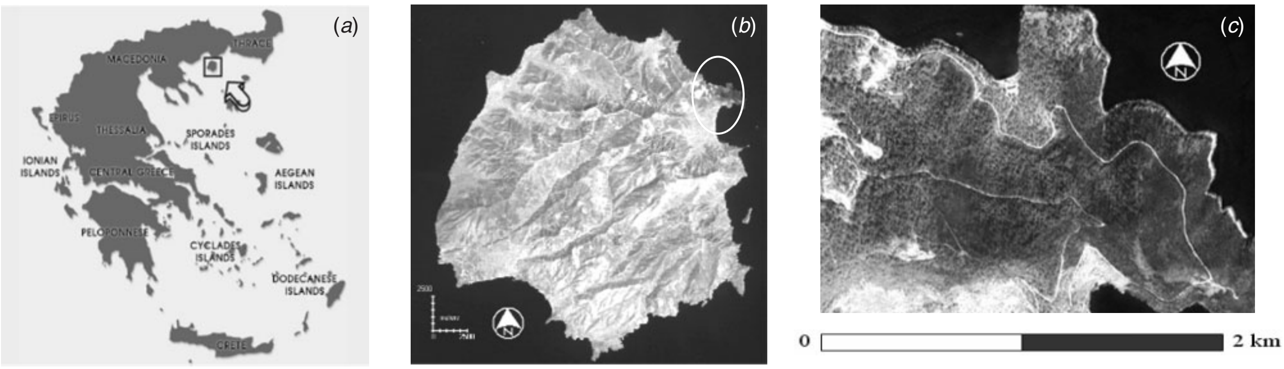

Fig. 1. (*a*) Location of the study area in Greece; (*b*) post-fire Landsat-Thematic Mapper of Thasos (near infra-red band); (*c*) Ikonos image of the fire-affected area (near infra-red band).

approach, involves merging the pixels in the image into image object primitives called objects or segments with a certain heterogeneous and homogeneous criterion. In comparison with pixels, image objects carry much more useful information and, therefore, can be characterised by far more properties, such as form, texture, neighbourhood or context, than pure spectral or spectral-derivative information (Baatz and Shäpe 2000).

Object-oriented image analysis, which is based on the fuzzy concept, is an approach that uses not only spectral information, but also spatial information of image objects. The fuzzy concept uses a degree of membership or a probability to express an object's assignment to a class. Fuzzy theory replaces the 'yes' or 'no' in the binary theory with the continuous (0–1), where 0 means 'exactly no' and 1 means 'exactly yes'; thus all values between 0 and 1 represent a more or less certain status of yes and no. Thereby, the degree of membership or probability depends on the degree to which the objects fulfil the class-describing properties or conditions. A major advantage of these soft methods lies in their ability to express uncertainties about the classes' descriptions. They also make it possible to express each object's membership in more than just one class. In contrast, classic classifiers in remote sensing (e.g. maximum likelihood) assign a membership of 1 or 0 to the pixels, expressing whether a pixel belongs to a certain class or not.

Object-based classification models have been developed and applied on Landsat-Thematic Mapper (Mitri and Gitas 2004*a*, 2004*b*) and NOAA-AVHRR images (Gitas *et al.* 2004), resulting in the accurate mapping of burned areas in the Mediterranean. When comparing the results obtained from the object-based classification with those derived from a pixel-based classification technique (maximum likelihood) for burned area mapping (Mitri and Gitas 2004*a*), it was found that the use of fuzzy classification applied to image objects resulted in a reduction in the number of misclassified pixels and that the accuracy of the classification results was improved by a minimum of 18%.

The aim of the present study was to develop an object-based classification model to map the type of fire using very high spatial resolution imagery. The specific objectives were:

- To distinguish between surface burn and canopy burn using a post-fire Ikonos image; and
- To assess the accuracy of the classification results by employing field survey data.

Study area and dataset description

The study area is the island of Thasos, Greece's most northerly island (Fig. 1). Its surface area is 399 km^2, and its perimeter is approximately 102 km. It is almost circular in shape, with a length from north to south of 24 km and a width of 19 km, extending from 24°30′ to 24°48′ East and 40°33′ to 40°49′ North. Elevation ranges from sea level to 1217 m (0–300 m in the area of interest). The major forest species, *Pinus brutia* and *Pinus nigra*, often form open stands with a canopy cover ranging from 10 to 40% (FAO 1999). *Pinus brutia* is the dominant vegetation at the lower elevations between 0 and 800 m, whereas *Pinus nigra* is found at higher altitudes (Gitas 1999). In addition to the forests, other types of Mediterranean vegetation, such as *maquis* and *garrigue*, are also present. The specific area under study was burned on 13 July 2000 by a mixed (crown and surface) fire that affected an area of 187 ha covered by *Pinus brutia* forest.

An Ikonos multi-spectral 1-m pan-sharpened image captured on 14 July 2000, one day after the fire, was obtained. Prior to mapping of the fire type, the image was pre-processed. This involved atmospheric and geometric correction.

From an operational point of view, the darkest pixel method, which derives its input parameters from the image itself and is relatively easy to implement, is preferred over more sophisticated techniques that require the acquisition of atmospheric or meteorological data (Hadjimitsis *et al.* 2004). Based on the above, atmospheric correction in the present work involved a simple darkest pixel correction,

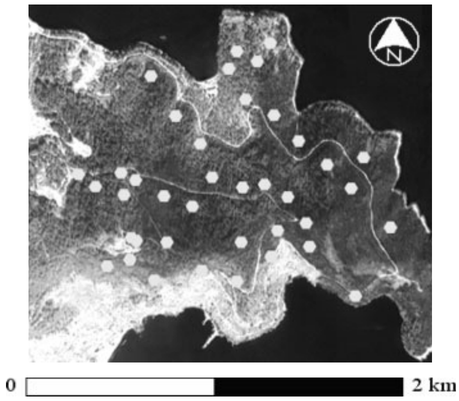

Fig. 2. Field plots located over the satellite image.

which subtracted the minimum value of each spectral channel from each pixel's brightness in that channel. The Ikonos image was geometrically corrected and projected to the Greek grid. A set of 20 ground control points, which were evenly distributed over the image, was used in the procedure, and the nearest neighbour interpolation method was employed to resample the image. An overall root mean square error of 0.24 was obtained using the simple polynomial rectification technique. The fact that it was low could be attributed to the absence of high relief in the terrain.

In addition to the image data, field data were also collected in the summer of 2002 (2 years after the fire) from 39 plots (10×10 m). The location of each plot was determined using a handheld global positioning system device, in addition to a hard copy print out of the Ikonos image (Fig. 2). The effects of the fire on the vegetation were assessed and categorised into two classes of fire type, namely, canopy and surface. Other data employed included the official fire perimeter published by the Greek Forest Service.

Methodology

The development of the object-oriented model (Definiens Imaging 2002) involved two steps: segmentation and classification. Image objects were extracted from the image in the segmentation procedure prior to classification. The methodology is detailed below.

Segmentation

The segmentation used was a bottom-up region-merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects were merged into bigger ones. Segmentation parameters were determined empirically in order to produce highly homogeneous objects in specific resolutions and for specific purposes. A series of segmentations was generated by adjusting the parameters of scale, band weights, colour, and shape. As burned areas appeared to be more visible in Ikonos bands 3 and 4 than in bands 1 and 2, a weight number of '2' was assigned to bands 3 and 4, and a weight number of '1' was assigned to bands 1 and 2. The sum of all chosen weights for image layers was normalised to 1. Additionally, segmentations based on higher colour weights (80%) and lower shape weights (20%) appeared to better match the ground features of the image.

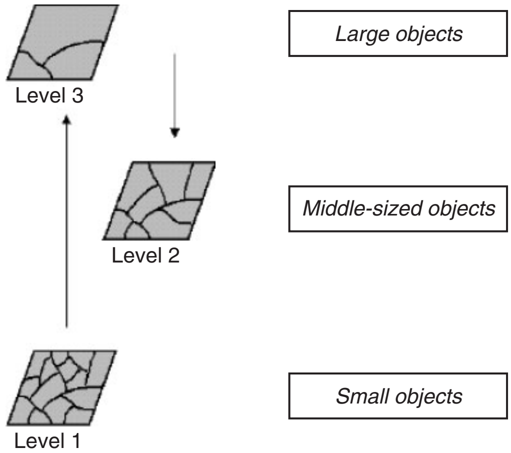

Fig. 3. Different levels of image segmentation.

Next, a three-level graded scale (15, 60, and 150) of segmentation (Fig. 3), namely small objects (level 1), middle-sized objects (level 2), and large objects (level 3), was created. The scale parameter here is an abstract term that determines the maximum allowed heterogeneity for the resulting image objects. Super-objects at levels 3 and 2 would provide information about the classification of the sub-objects at level 1.

Classification

Classification was based on fuzzy logic and consisted of a combination of several conditions (Fig. 4) that had to be fulfilled for an object to be assigned to a class (Civanlar and Trussell 1986; Tsatsoulis 1993). The fuzzy sets were defined by membership functions that identify those values of a feature that are regarded as typical, less typical, or not typical of a class, i.e. they have a high, low, or zero membership, respectively, of the fuzzy set. Classifications were carried out at the three segmentation levels. The classes were:

- Level 1: 'surface burn', 'canopy burn', 'healthy vegetation', and 'other';
- Level 2: 'water', 'bare soil', and 'other'; and
- Level 3: 'healthy vegetation', 'heavily burned', and 'slightly burned'.

Features based on object spectral information (image digital numbers) as well as object contextual information, such as neighbourhood and relation to super-objects and to sub-objects, were used in the classification. The features based on object spectral information were: the Normalized Difference Vegetation Index (NDVI)-like index (digital numbers have been used instead of reflectances or radiances) and the

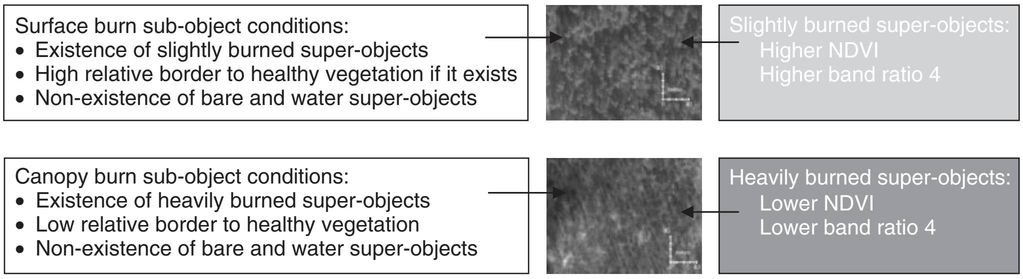

Fig. 4. Fire type class descriptions (middle: Ikonos subsets in false colour). NDVI, Normalized Difference Vegetation Index.

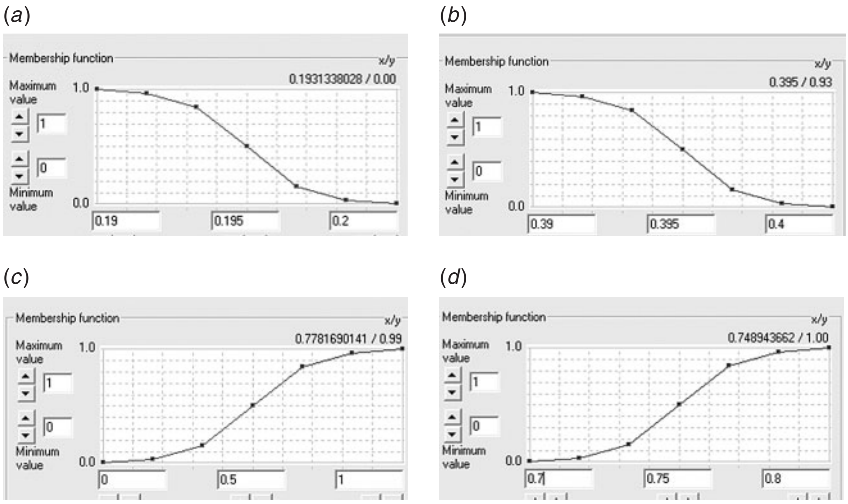

Fig. 5. Membership functions of heavily burned super-objects for the features (*a*) 'Normalized Difference Vegetation Index' and (*b*) 'band ratio 4', and of canopy burn sub-objects for the features (*c*) 'existence of' and (*d*) 'high relative border to'.

band ratio of near infra-red (NIR). The object NDVI was calculated from the NDVI values of all *n* pixels forming an image object, whereas the object band ratio of NIR corresponded to the NIR mean value of an image object divided by the sum of all spectral layer mean values. Membership functions (Fig. 5) were adapted for each chosen classification feature. They offered a transparent relationship between feature values and the degree of membership to a class.

Classification results and discussion

The classification at level 1 resulted in the production of a fire type map of the study area (Fig. 6). An area of 80 ha, representing 43% of the total burned area, was classified as canopy burn, whereas an area of 106 ha, representing 57% of the total burned area, was classified as surface burn. The results of the classification were compared to the data collected during the field survey. The comparison resulted in the production of a classification error matrix (Table 1). The overall accuracy of the classification was 0.87, whereas the total Kappa Index of Agreement was 0.74. The examination of the error matrix revealed a slight confusion between the surface

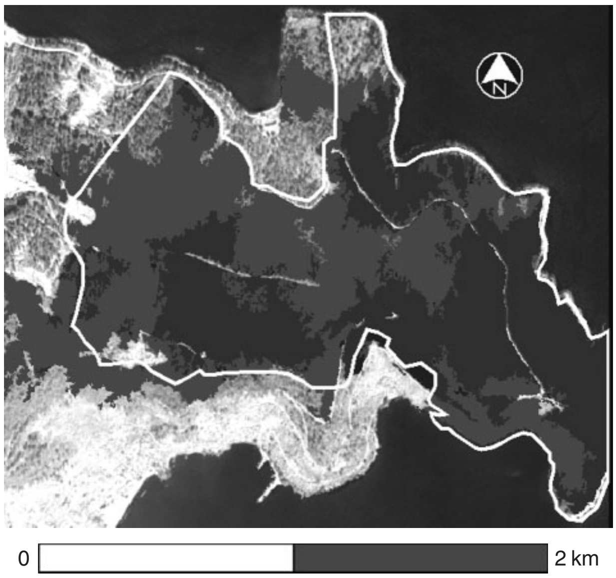

Fig. 6. Ground mapped fire perimeter (white line) and final classification results of the Ikonos image (burned canopy in dark grey and burned surface in light grey).

Table 1. Fire type mapping contingency matrix

Classified data	Reference data			
	Canopy burn	Surface burn	Total	Commission error
Canopy burn	13	0	13	0
Surface burn	3	21	24	0.125
Unclassified (non-burned)	0	2	2	–
Total	16	23	39	–
Producer's accuracy	0.813	0.913		
User's accuracy	1	0.875		
Kappa Index of Agreement per class	0.719	0.774		

burn and the healthy vegetation classes. This confusion is related to the presence of dense healthy vegetation on the image, which completely covers areas of surface burn. This confusion could be attributed to the inability of the optical sensor to penetrate dense canopy to detect fire-affected areas.

Close examination of the map produced revealed the spatial distribution of the two classes of burn to be highly homogeneous. Also, the border line between surface burn and canopy burn appeared to be very irregular as a result of fire transition from surface burn to canopy burn, and vice versa. In addition, the road network seemed to control the extent of the surface fire, but not the canopy fire.

The resulting map of the total burned area (surface burn plus canopy burn) was compared with the fire perimeter map generated by the Forest Service using traditional survey methods. The vectorised fire perimeter from the classified image was overlaid onto the official fire perimeter. The area measured by the Greek Forest Service was 187 ha, whereas that of the classification result was 186 ha, i.e. a difference of only 1 ha. The common area between the fire perimeter from the classification and that of the Forest Service was 87%. The boundary derived from the classification was rather more detailed than that derived by the Forest Service.

Conclusions

In the present study, an object-oriented model was developed using very high spatial resolution Ikonos imagery to map fire type on the Mediterranean island of Thasos. The main conclusion drawn is that object-oriented classification can be used to accurately distinguish and map areas of surface and crown fire spread (overall accuracy of 87% and Kappa Index of Agreement 0.74), especially that occurring in open Mediterranean forests.

Classification accuracy was mainly affected by the density of the canopy. This could be attributed to the inability of the optical sensors to penetrate dense canopy to detect fire-affected areas. In such a case, a combination of the Ikonos imagery with other types of data such as RADAR, which is able to penetrate the forest canopy, might be worthy of investigation in the future.

Finally, the ability of the object-based classification to combine spectral with contextual information seemed to be the main advantage of the method not only when mapping fire type, but also when mapping the total burned area. Another advantage is its ability to derive other information of particular interest to forest scientists and managers.

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References

Albini F, Stocks B (1986) Predicted and observed rates of spread of crown fires in immature jack pine. *Combustion Science and Technology* **48**, 65–76.

Alexander M (2000) Fire behaviour as a factor in forest and rural fire suppression, Forest Research Bulletin No. 197, Forest and Rural Fire Science and Technology Series Report No. 5. Forest Research, Rotorua in association with New Zealand Fire Service Commission and National Rural Fire Authority, Wellington, New Zealand.

Baatz M, Schäpe A (2000) Multi-resolution segmentation – an optimization approach for high quality multi-scale image segmentation. In 'Angewandte geographische Informationsverarbeitung XI. Beiträge zum AGIT-Symposium Salzburg 2000', Karlsruhe. (Ed. J Strobl) pp. 12–23. (Herbert Wichmann Verlag: Heidelberg)

Beaty R, Taylor A (2001) Spatial and temporal variation of fire regimes in a mixed conifer forest landscape, Southern Cascades, California, USA. *Journal of Biogeography* **28**, 955–966. doi:10.1046/J.1365-2699.2001.00591.X

Chuvieco E, Congalton RG (1988) Mapping and inventory of forest fires from digital processing of TM data. *Geocarto International* **4**, 41–53.

Civanlar R, Trussell H (1986) Constructing membership functions using statistical data. *Fuzzy Sets and Systems* **18**, 1–13. doi:10.1016/0165-0114(86)90024-2

Definiens Imaging (2002) Object-oriented image analysis, eCognition user guide. Munich. Available at http://www.definiens-imaging.com [Verified 17 January 2005]

Escuin S, Navarro R, Fernandez P (2002) Using remote sensing and GIS to assess wildfire damage throughout the Mediterranean. *Earth Observation Magazine* **11**, 19–22.

FAO (1999) Mediterranean forests. *Unasylva* **50**, 35–41.

Gitas I (1999) Geographical information systems and remote sensing in mapping and monitoring fire-altered forest landscapes. PhD Thesis, University of Cambridge, UK.

Gitas I, Rishmawi K (2003) Burned area mapping with the use of low, medium-high and very high resolution satellite imagery. *Geotechnical Scientific Issues* **44**, 4–15.

Gitas I, Mitri G, Ventura G (2004) Object-oriented image analysis for burned area mapping using NOAA-AVHRR imagery in Creus Cape, Spain. *Remote Sensing of Environment* **92**, 409–413. doi:10.1016/J.RSE.2004.06.006

Graham R (2003) 'Hayman fire case study.' USDA Forest Service, Rocky Mountain Research Station General Technical Report RMRS-GTR-114. (Ogden, UT)

Hadjimitsis D, Clayton C, Hope V (2004) An assessment of the effectiveness of atmospheric correction algorithms through the remote sensing of some reservoirs. *International Journal of Remote Sensing* **25**, 3651–3674. doi:10.1080/01431160310001647993

Jakubauskas M, Lulla K, Mausel P (1990) Assessment of vegetation change in a fire-altered forest landscape. *Photogrammetric Engineering and Remote Sensing* **56**, 371–377.

Karteris M (1995) Burned land mapping and post-fire effects. In 'Remote sensing and GIS applications to forest fire management'. (Ed. E Chuvieco) pp. 35–44. (University of Alcala: Alcala de Henares, Spain)

Milne A (1986) The use of remote sensing in mapping and monitoring vegetational change associated with bushfire events in Eastern Australia. *Geocarto International* **1**, 25–35.

Mitri G, Gitas I (2004*a*) A semi-automated object-oriented model for burned area mapping in the Mediterranean region using Landsat-TM imagery. *International Journal of Wildland Fire* **13**, 367–376. doi:10.1071/WF03079

Mitri G, Gitas I (2004*b*) A performance evaluation of a burned area object-based classification model when applied to topographically and non-topographically corrected TM imagery. *International Journal of Remote Sensing* **25**, 2863–2870. doi:10.1080/01431160410001688321

Patterson MW, Yool SR (1998) Mapping fire-induced vegetation mortality using Landsat TM data: a comparison of linear transformation techniques. *Remote Sensing of Environment* **65**, 132–142. doi:10.1016/S0034-4257(98)00018-2

Pausas J, Vallejo V (1999) The role of fire in European Mediterranean ecosystems. In 'Remote Sensing of Large Wildfires'. (Ed. E Chuvieco) pp. 3–16. (Springer-Verlag: Berlin)

Pollet J, Omi P (2002) Effect of thinning and prescribed burning on crown fire severity in ponderosa pine forests. *International Journal of Wildland Fire* **11**, 1–10. doi:10.1071/WF01045

Rogan J, Yool S (2001) Mapping fire-induced vegetation depletion in the Peloncillo Mountains, Arizona and New Mexico. *International Journal of Remote Sensing* **22**, 3101–3121. doi:10.1080/01431160152558279

Scott J, Reinhardt E (2001) 'Assessing crown fire potential by linking models of surface and crown fire behaviour.' USDA Forest Service, Rocky Mountain Research Station Research Paper RMRS-RP-29. (Fort Collins, CO)

Smith R, Woodgate P (1985) Appraisal of fire damage and inventory for timber salvage by remote sensing in mountain ash forests in Victoria. *Australian Journal of Forestry* **48**, 252–263.

Stephens S (1998) Evaluation of the effects of silvicultural and fuels treatments on potential fire behaviour in Sierra Nevada mixed conifer forests. *Ecology and Management* **105**, 21–35. doi:10.1016/S0378-1127(97)00293-4

Tanaka S, Sugimura T (2001) Cover: a new frontier of remote sensing from IKONOS images. *International Journal of Remote Sensing* **22**, 1–5. doi:10.1080/014311601750038802

Tsatsoulis C (1993) Expert systems in remote sensing applications. *IEEE Geoscience and Remote Sensing Newsletter* **June**, 7–15.

White J, Ryan K, Key C, Running S (1996) Remote sensing of forest fire severity and vegetation recovery. *International Journal of Remote Sensing* **6**, 125–136.