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Minas de Riotinto (south Spain) forest fire: Burned area assessment and fire severity mapping using Landsat 5-TM, Envisat-MERIS, and Terra-MODIS postfire images

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[1] This analysis concerns an estimation of burned area and fire severity levels in an area affected by a large wildfire that took place in the south of Spain in July 2004. Fire severity is defined in this work as the impact of fire on the vegetation. The objective was to find an efficient method for quick fire severity mapping based on remote sensing techniques that can be useful for postfire forest management. Several methods for image analysis (Linear Spectral Unmixing, Matched Filtering and Normalized Burn Ratio Index) were applied to postfire Landsat 5-TM, Envisat-MERIS, and Terra-MODIS images. Maps depicting fire severity of three levels of an acceptable reliability were obtained using a small amount of field data and following a simple method of processing. Linear spectral unmixing produced the best classifications for MERIS and MODIS images, while the matched filtering technique produced the most accurate classification for the TM image. These preliminary results show that short-term fire severity maps can be obtained by means of high- to medium-resolution postfire remote sensing data, in order to evaluate the situation after a forest fire and plan forest restoration works.

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1. Introduction

[2] It is a well-established fact that wildfires are a major hazard in Mediterranean type ecosystems [*Chuvieco and Congalton*, 1998]. During the last few decades, large forest fires have spread at an unprecedented rate in Southern Europe [*Pausas and Vallejo*, 1999] due to changes in traditional land use patterns which have led to an unusual accumulation of forest fuels, notably increasing fire risk and fire severity [*Chuvieco*, 1999]. This has increased the need for information about burned areas both for resource management and global climatic change research.

[3] There is interest in finding a quick and affordable methodology for obtaining fire severity maps that can be made available only a few days after the fire, as this information could prove very valuable in the early stages of rehabilitation planning for large fires. These maps should be based on independent data sources, such as remote sensing, employ automatic or semiautomatic methods, and produce results of an acceptable reliability. This system would be useful for generating preliminary burn severity maps which can later be replaced by higher-resolution maps [*Miller and Renschler*, 2003].

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[4] The goal of the research presented in this paper was to evaluate approaches to generate maps from satellite remote sensing data showing different degrees of damage affecting vegetation after a large wildfire in an effective manner. These maps could then be combined with slope and soil type cartography, in order to locate priority intervention areas and plan forest restoration works.

2. Background

[5] Since forest fires are a major source of concern for European security [*Barbosa et al.*, 2002], reliable, quantitative information on forest fires should be readily available, rapidly accessible and well-coordinated to help fire fighting, restoration planning and the regular production of statistics. This information is often difficult to obtain, especially when fire size, remoteness, and rugged terrain impede direct observation of burned areas [*Van Wagtendonk et al.*, 2004]. In addition, the use of traditional, field-based methods to map forest fires is expensive and time consuming. In this context, remote sensing techniques can be considered as the most accurate way for burned area location, extent determination and level of damage assessment [*González-Alonso et al.*, 2006].

[6] There are different definitions for fire severity, depending on the user requirements. In this work, fire severity is defined as the impact of fire on the vegetation, which can be estimated by the amount of vegetation

surviving after the fire [*Ryan and Noste*, 1983]. Most medium and large-sized fires produce a wide range of fire severity levels. Consequently, the pattern of damage after a fire is usually very fragmented, owing to the different propagation patterns [*Díaz-Delgado and Pons*, 1999].

[7] Short-term information on the different fire severity levels within areas affected by wildfires is highly valuable for forest managers and authorities, particularly when vast areas have to be managed and decisions must be taken in a very short period of time. Fire severity maps are useful as a tool to evaluate the damage produced by the event, to locate priority intervention areas and to help authorities in the management of subsidies for affected regions when necessary. Obtaining information on fire severity as quickly, but as accurately as possible is of the utmost importance for forest managers, in order to protect life, property, water quality, and deteriorated ecosystems from further damage, and to plan restoration works so as to reestablish the lost vegetation cover in the shortest period of time. This is the objective of the USDA's (United States Department of Agriculture) BAER program (Burned Area Emergency Rehabilitation, 2006 release, available at http://www.fs.fed.us/biology/watershed/burnareas/index.html). BAER teams are assisted with fire severity maps based on satellite data and provided by the USDA Forest Service's Remote Sensing Applications Center (RSAC), that have proven very useful to assess the situation after the fire ("Satellites do it faster, cheaper," Rebecca Lindsey, 2002, Satellites aid burned area rehabilitation, available at http://earthobservatory.nasa.gov/Study/BAER/baer.html).

[8] Fire severity has been widely related to variations in surface reflectance recorded by spaceborne multispectral systems [*González-Alonso et al.*, 2006; *Parra and Chuvieco*, 2005; *Miller and Renschler*, 2003; *Walz et al.*, 2005; *González-Alonso et al.*, 2004; *Chafer et al.*, 2004; *Key and Benson*, 2004; *Ruiz-Gallardo et al.*, 2004; *Van Wagtendonk et al.*, 2004; *Navarro et al.*, 2001, 1998; *Caetano et al.*, 1994], but reliable accuracy has yet to be gained using standard methods over different fire size and vegetation types [*Rogan*, 2005].

[9] In the present study, it was decided to employ only postfire images, as it is considered of great interest to find a mapping method which avoids the use of prefire images. In doing this, money and time could be saved in terms of obtaining, correcting and normalizing images. This might result in a standard nonexpensive methodology that could be easily applied by the forest teams of areas affected by large fires. These two conditions of being "standard" and "nonexpensive" are usually very important points when presenting a new method to forest managers who face a significant challenge in managing large amounts of information when these events occur, with limited human and economic resources. Among the different techniques used to estimate burned area by means of satellite images, three have been chosen to develop the current research: Linear Spectral Unmixing, its variation Matched Filtering, and the Normalized Burn Ratio Index.

[10] *Shimabukuro et al.* [1994] highlighted the Spectral Unmixing method to solve some of the limitations relating to the differentiating of two images from affected areas, acquired before, and after, the fire. This technique aims at estimating the surface abundance of a number of pure spectral components (or endmembers), together causing the observed mixed spectral signature of the pixel. The Spectral Unmixing technique was successfully applied by *Caetano et al.* [1994] to distinguish between burned areas, slightly burned areas and areas with a high risk of erosion. *Cochrane and Souza* [1998] applied this method to a Landsat–TM (Thematic Maper) postfire image in order to identify burned forests and quantify the level of damage [*Quintano Pastor et al.*, 2002]. The Matched Filtering technique [*Boardman et al.*, 1995] is a variation of the LSU method, where only one endmember is considered. As only postfire images were used in the present work, Linear Spectral Unmixing and Matched Filtering seem suitable methodologies.

[11] The Normalized Burn Ratio index (NBR) integrates the Near Infrared and Shortwave Infrared bands, which respond most, but in opposite ways, to burning. Employed with the Landsat TM and ETM+ (Enhanced Thematic Mapper) sensors, this technique has been demonstrated to produce accurate measurements of fire severity by looking at reflectance changes in vegetation before and after the fire, a process which is known as differenced NBR (dNBR) [*Key and Benson*, 1999]. Prefire and postfire images need to be reasonably paired by phenology and moisture in order to obtain reliable dNBR values [*Van Wagtendonk et al.*, 2004]. Currently, dNBR-derived fire severity maps are being used by the U.S. Forest Services for postfire landscape assessment. In the present research, only NBR from postfire images was obtained, in order to assess if it is feasible to use it as a measure of fire severity.

[12] Among the wide range of sensors available at the moment, Landsat TM is the most widely used to determine fire severity [*Key and Benson*, 2004; *Ruiz-Gallardo et al.*, 2004; *White et al.*, 1996; *Rogan and Franklin*, 2001; *Kushla and Ripple*, 1998; *Navarro et al.*, 1998; *Patterson and Yool*, 1998]. Nevertheless, promising results have been recently obtained when estimating fire severity with data from MODIS (MODerate Resolution Imaging Spectrometer) and MERIS (MEdium Resolution Imaging Spectrometer) sensors [*Walz et al.*, 2005; *González-Alonso et al.*, 2004; *Miller and Renschler*, 2003]. These last two sensors have the advantage of a more frequent coverage of the Earth's surface than Landsat 5-TM, and furthermore, MODIS data can be downloaded free of charge from the Internet.

[13] Postfire images from the three sensors (Landsat 5-TM, Envisat-MERIS and Terra-MODIS) were compared in this work, and the three aforementioned techniques were used for their analysis (Linear Spectral Unmixing, Matched Filtering and Normalized Burn Ratio Index), in order to facilitate the search of a reliable methodology for quick and effective fire severity mapping that can be useful for postfire forest management. The three techniques were tested on TM and MODIS images, while only the two first ones were tested on MERIS, due to its spectral characteristics, as explained in section 3.5.

3. Methods

[14] The focus of the research presented in this paper is a forest fire that started in Minas de Riotinto (Huelva-Andalucía; see Figure 1) on 27 July 2004, and lasted for four days. It was the most devastating wildfire in Spain in

Figure 1. Geographical location of the study area (in red).

the summer of 2004. The affected forest area was dominated by the following species: *Pinus pinea* L., *Quercus suber* L., *Quercus ilex* L. and *Eucaliptus* sp. The ecological and economic consequences were dramatic, as the fire was very severe, and the forest is one of the main resources for the population from the affected and surrounding areas.

[15] The general structure of the applied methodology can be summarized as follows: (1) a preliminary fire severity map was obtained from a Landsat-TM image, (2) a field assessment was carried out with the help of the previous fire severity map, (3) remotely-sensed images from different sensors were analyzed applying several processing techniques and using information collected on the ground, (4) maps depicting three levels of fire severity were obtained and (5) their accuracy was analyzed using ground data. The different phases of the work will be further analyzed in sections 3.4 and 3.5, while section 3.1 provides a description of the employed material, section 3.2 provides the definition for the considered levels of fire severity, and section 3.3 provides an explanation of the processing techniques applied to the images.

3.1. Material

[16] The present work is based on the use of three types of data: (1) postfire satellite images, (2) forest cartography and (3) postfire field data.

[17] Three postfire images were employed. They were each acquired by different sensors, with different temporal and spatial resolutions, and different radiometric properties. The goal is to compare results obtained with these images, so as to decide which would be the most adequate to fulfill the stated requirements. A full description of the images is given below.

[18] The Landsat 5-TM (Thematic Mapper) image was acquired on 31 July 2004 and delivered by NASA. TM images have six spectral bands in the visible, near and middle infrared (bands 1–5 and 7, with 30 m spatial resolution) and one band in the thermal infrared (band 6, 120 m spatial resolution). Bands 1–5 and 7 were used in this work. TM allows global coverage of the Earth every 16 days.

[19] The Full Resolution Level-2 Envisat-MERIS (Medium Resolution Imaging Spectrometer) image was acquired on 14 August 2004 and delivered by ESA (European Space Agency). MERIS images have 300 m spatial resolution and 15 spectral bands: 13 bands containing reflectance values in the visible and near-infrared plus two bands containing vegetation indexes TOAVI (Top Of Atmosphere Vegetation Index) and BOAVI (Bottom Of Atmosphere Vegetation Index). MERIS allows global coverage of the Earth every 3 days.

[20] The Terra MODIS (MODerate Resolution Imaging Spectrometer) was acquired on 30 July 2004 and downloaded from NASA Earth Observing System Data Gateway. The MOD09GHK product (MODIS Surface Reflectance Daily L2G Global 500m SIN Grid) was employed. It provides daily information with 500m spatial resolution and 7 spectral bands in the visible, near and middle infrared (bands 1–7 from MODIS). Terra MODIS achieves a daily global coverage of the Earth.

[21] Forest cartography was extracted from the European land use database CORINE Land Cover 2000 (CLC2000) (2006 release, available from European Environment Agency, Instituto Geográfico Nacional, at http://www.mfom.es/ign), which classifies the territory in 44 categories. Land use classes in the affected area were reclassified in four forest types (coniferous, broadleaved, eucalyptus and mixed forest) plus one agricultural and one pasture land classes, in order to have a vegetation map easy to use and suitable for the proposed objective. A thematic vegetation cover map of the study area is presented in Figure 2.

[22] Postfire field data were collected within the affected area in October 2004, and they were employed to define training areas for the image analysis techniques and to verify the obtained classifications. Further explanation about the field assessment will be provided in section 3.4.

[23] Software used for processing and analyzing data involved digital image processing packages (BEAM 2.2, ENVI 4.1, ERDAS Imagine 8.7), geographic information systems (ArcView 3.2) and statistical software (Statgraphics Plus 4.1).

3.2. Definition of Three Levels of Fire Severity

[24] The degree of damage caused in vegetation by a wildfire is complex to evaluate and can be affected by a high degree of subjectivity, which makes it necessary to define and characterize the different fire severity levels very precisely in order to obtain comparable measurements and avoid confusions during the process. In the present work, three levels of fire severity were established: high, moderate and low, as well as an unburned class. These three levels are considered suitable for forest management purposes, and they are also adequate for mapping fire severity by means of remote sensing data [*González-Alonso et al.*, 2006; *Walz et al.*, 2005; *Rogan*, 2005; *Ruiz-Gallardo et al.*, 2004; *Key and Benson*, 2004; *Navarro et al.*, 1998].

[25] A visual classification of fire severity, which had already been adapted to Mediterranean vegetation characteristics by *Ruiz-Gallardo et al.* [2004], was chosen for the field assessment. This classification was found suitable according to the objectives of the work, as it is based in evaluating the damage caused by a fire to the vegetation cover, and does not require an extensive field campaign. The different fire severity classes are defined as follows [*Ruiz-Gallardo et al.*, 2004]: Class (0) is unburned: Effects

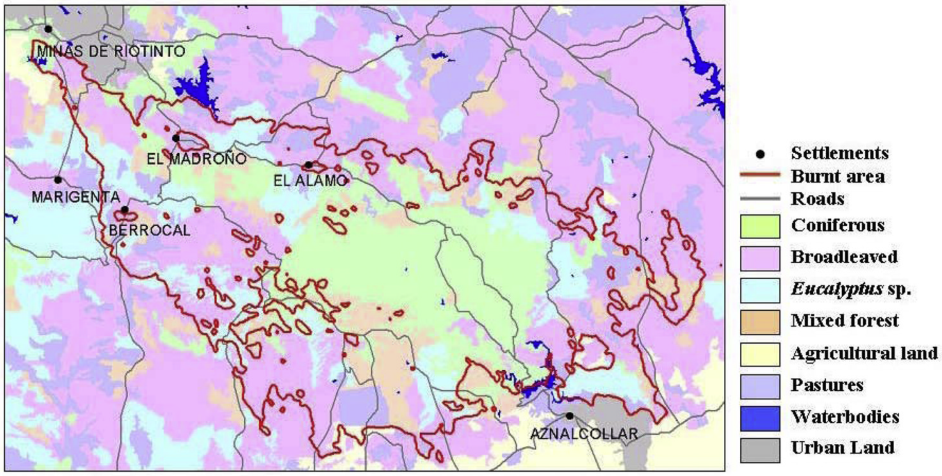

Figure 2. Thematic map of the study area.

of fire on vegetation cannot be observed. Class (1) is low: Less than 50% of vegetation cover affected. Ground fuel and low shrubs are the most affected. Less than 30% of trees appear completely burned. Some of the affected trees have only been scorched in the bottom part of their stems and crowns. Unburned spots can be found. Class (2) is moderate: Between 50 and 90% of vegetation cover affected. Ground fuels and the branches of shrubs completely consumed, even though some of them may retain the capacity to sprout. Less than 75% of trees completely burned. Most of smaller trees dead, dominant trees less affected although their crowns can be scorched up to a 60%. Class (3) is high: More than 90% of vegetation cover completely burned and apparently dead, even though some plants may still be able to sprout. Many stems of shrubs consumed by fire, with only the lower stems remaining.

3.3. Methods Employed for Image Classification

[26] Coregistration was performed on the images and the CLC2000 data layers. Landsat 5-TM digital numbers were transformed into Top of Atmosphere reflectance data [*Chuvieco*, 2000; *Ruiz-Gallardo et al.*, 2004], but no atmospheric or topographic corrections were applied, as this step would have required a significant amount of processing, and we wanted to evaluate how well the analysis methods performed when these corrections were not applied. Both MODIS and MERIS products were already corrected, as they provide “surface reflectance” values.

3.3.1. Linear Spectral Unmixing (LSU)

[27] Spectral Unmixing [*Smith et al.*, 1985; *Settle and Drake*, 1993] aims at estimating the surface abundance of a number of pure spectral components (or endmembers), together causing the observed mixed spectral signature of the pixel. A linear combination of spectral endmembers is chosen to decompose the mixed reflectance spectrum of each pixel into fractions of its endmembers [*Van der Meer and de Jong*, 2000].

[28] The crucial, and most difficult, part of the LSU is the actual process of selecting the endmembers [*Reithmaier et al.*, 2005]. A set of endmembers should allow the definition of all spectral variability for all pixels, produce unique results, and be of significance to the underlying scientific objectives. The selection of endmembers can be achieved in two ways: (1) selecting them from spectral libraries (reference endmembers) or (2) deriving them from the purest pixels in the image (image endmembers) [*Van der Meer and de Jong*, 2000]. *Kerdiles and Grondona* [1995] affirms that it is not advisable to use spectral libraries with vegetation endmembers, because of spectral properties variation with climatology, atmosphere and year, factors which are not usually considered in spectral libraries. Because of all these considerations, image endmembers were used in the present study. Two sets of endmembers were considered:

[29] 1. Set1 is based on fire severity field data. Endmembers were extracted from pixels where “Ground points” were located (during the field survey, see section 3.4). There are three endmembers, where each one represents one of the three levels of fire severity. It is assumed that every burned pixel can be decomposed into fractions of high, moderate and low fire severity. Linear Spectral Unmixing performed using this set of endmembers will be referred to as LSU1. The unburned state is not considered, as the LSU1 was applied on images where unburned pixels had already been masked. Further explanation on this point will be given in section 3.5.

[30] 2. Set2 is based on landscape components. Three endmembers were extracted from areas in the image representing “green vegetation,” “bare soil” and “burned surface.” Linear Spectral Unmixing performed using this set of endmembers will be referred to as LSU2.

3.3.2. Matched Filtering (MF)

[31] The Matched Filtering technique [*Boardman et al.*, 1995] is a variation of the LSU method, where only one endmember is considered. MF partially unmixes the spectral data quantifying the abundance of the defined endmember [*Vázquez et al.*, 2001].

[32] The endmember was extracted from the pixels where “Ground points” affected by high fire severity were located (during the field survey; see section 3.4).

3.3.3. Normalized Burn Ratio Index (NBR)

[33] This index integrates the two bands that respond most, but in opposite ways, to burning (Near Infrared NIR,

Table 1. MF Class Limits for the Classification of Three Levels of Fire Severity

MF Value	Classes of Fire Severity
MF minimum relative < MF $\leq$ 0.5	1
0.5 < MF $\leq$ 0.9	2
MF > 0.9	3

and Shortwave Infrared SWIR) in order to provide an optimum measure for fire-effects:

$$\mathrm{NBR} = (\mathrm{NIR} - \mathrm{SWIR})/(\mathrm{NIR} + \mathrm{SWIR}).$$

It was defined for reflectance values from TM bands 4 (R4) and 7 (R7) [*Key and Benson*, 1999]. In this study, the NBR was performed with the postfire TM image, and it will also be calculated from MODIS data, using the MODIS NIR band 2 and the SWIR band 7.

[34] After applying the former techniques to the images, files containing a continuous range of values are obtained. As the final goal is to obtain maps with three levels of fire severity useful for forest management, the obtained files have to be (1) reclassified in three classes and (2) filtered so as to avoid the "salt and pepper" effect.

3.3.4. Image Reclassification

[35] Different methods were used to obtain three-class maps from the files obtained by applying the image processing techniques formerly explained.

[36] 1. Files obtained from LSU1 contain three bands (one for each endmember, corresponding to one fire severity class: low, moderate and high). They were reclassified by assigning to each pixel the fire severity class associated with the band registering a higher value.

[37] 2. Files obtained from LSU2 also contain three bands (one for each endmember corresponding to one landscape component: "green vegetation," "bare soil" and "burned surface"). The band corresponding to the "burned surface" endmember was stratified applying three-class Unsupervised Classification using the ISODATA algorithm [*Tou and González*, 1974].

[38] 3. Files obtained from MF contain only one band. They were stratified using two different methods. The first is performance of thresholds (see Table 1). These thresholds were obtained by the INIA Remote Sensing Laboratory in preliminary works, and produced good results when mapping fire severity in similar areas. The second method is applying three-class Unsupervised Classification using the ISODATA algorithm.

[39] 4. Files obtained from NBR index performance contain one band. Three-class Unsupervised Classification (ISODATA) was applied to them.

[40] The automatic methods employed for segmentation purposes (reclassification and ISODATA Unsupervised Classification) avoid the problem of extrapolating numeric thresholds to different study areas and situations. Classes obtained by applying these methods are considered representative of the different levels of fire severity, as the files used as input for the classifications have been obtained with processing methods applied in order to evaluate fire severity in burned areas.

3.3.5. Image Filtering

[41] As the objective is to obtain cartography useful for postfire forest management, it is important to have homogeneous patches, as isolated pixels will not be considered when planning forest works. That is why classifications obtained from Landsat-TM were filtered using Median filters to remove the "salt and pepper" effect. Different kernels were tried for the Landsat-TM image (3 $\times$ 3, 5 $\times$ 5 and 7 $\times$ 7), while no filtering was applied to the MERIS and MODIS images, owing to their coarse spatial resolution.

3.4. Field Survey

[42] In order to design the field campaign, a Matched Filtering analysis was applied to the TM image so as to obtain a first estimation of burned area, and preliminary fire severity cartography. The endmember was extracted from areas that could be visually identified as completely burned (high fire severity) in the image. A "burned area mask" was made from the resulting MF file, by choosing burned pixels using a criteria of an MF value over 0.134 (this value was the relative minimum in the histogram corresponding to the MF file). Those burned pixels were classified into three classes of fire severity: low (class 1), moderate (class 2) and high (class 3). MF class limits (Table 1) were obtained in previous preliminary works related to fire severity assessment. A 7 $\times$ 7 Median filter was applied to the classified image, and this produced a preliminary fire severity map. This classification will be referred to as "MF prefield."

[43] The considered forest types within the affected area are: coniferous, broadleaved, eucalyptus and mixed forest. A land-use map containing these forest types plus one agricultural and one pasture land classes was obtained by reclassifying land use classes from CLC2000.

[44] The fire severity map and the land-use map were combined, and a new map combining fire severity and forest types was obtained. This map was employed to design the field survey.

[45] A rapid field assessment was undertaken in order to ascertain damage and assess areas that had been burned to a variable degree. Routes along vehicular tracks were designed through the affected area, based on the developed cartography, as every combination of fire severity and forest type was to be considered. Sample sites were located along the routes, walking 100–200 m perpendicular to the track. The following information was collected in each one of them: (1) GPS coordinates, (2) digital photographs, and (3) visual assessment of fire severity in the area, by observing the surrounding 20 m and assigning the site to one of the classes established in section 3.2.

[46] Fifty-two sample points were collected during the field survey. Thirty-four of them were called "Ground points," as they were located within forested areas, and detailed information was collected in them. The remaining 18 points were called "Road points," as information for them was less detailed and collected from the vehicle (Table 2). The whole set of 52 points was divided in two independent sets: (1) The "training set" contains 18 "Ground points," and was used to extract the endmembers for the LSU and MF methods. (2) The "verification set" contains the remaining "Ground points" (16) plus all the "Road points" (18), and was used for verification purposes.

Table 2. "Ground Points" and "Road Points" Collected in the Field Survey

	High Fire Severity	Moderate Fire Severity	Low Fire Severity	Total
Ground points	18	13	3	34
Road points	11	5	2	18
Total	29	18	5	52

[47] As can be observed in Table 2, most points are located in areas of high fire severity, and there are only a few points affected by low fire severity. This is a consequence of the real situation after the fire, with most areas sustaining high damage. It is worth pointing out that the visual classification employed for fire severity evaluation was found very practical, as the different classes could be identified on the field quite clearly.

3.5. Image Classification Process

[48] Once the field data had been collected, the image classification process was carried out. This process can be divided in three phases.

[49] 1. First of all, a MF file was obtained from the TM image using high fire severity "Ground points" to define the endmember. A new "burned area mask" was made from the resulting MF file, by choosing burned pixels according to those with an MF value of over the minimum relative of the MF histogram (the same process as followed in the field survey design, see section 3.4). This mask was applied to the three images in order to filter unburned pixels for the classification process. The mask also provided a second estimation of burned area based on field data.

[50] 2. The techniques for image processing explained in section 3.3 were applied to the masked images. The three methods (LSU, MF and NBR) were applied to the masked TM and MODIS images. Only MF and LSU were applied to the masked MERIS image, as its spectral range does not include bands in the SWIR, which are necessary to perform the NBR index. Fire severity information from "Ground points" was used to define the endmembers for the LSU and MF techniques.

[51] 3. In the postprocessing phase, maps depicting fire severity of three levels were obtained by: (1) applying the reclassification techniques explained in section 3.3, and (2) filtering the resulting classifications obtained from the TM image with Median filters so as to avoid the "salt and pepper" effect. No filter was applied to the MERIS and MODIS images, owing to their coarse spatial resolution. A summary of the different classifications with three levels of fire severity obtained during the process is shown in Table 3.

[52] 4. Information from the "verification set" (34 points, see section 3.4) was used to verify the resulting fire severity maps. Contingency tables were obtained in order to compare classification results with ground truth information. The Chi-square test was performed to check that both data sets were not independent, and the Overall Accuracy, the Kappa coefficient and the Kendall's (τ_c) correlation coefficient were obtained to analyze the degree of association between the two sets of data. Kappa varies between 0 and +1, where +1 means that the variables match perfectly. τ_c ranges from -1 (complete disagreement) to +1 (perfect agreement). For both indexes, 0 value means that the variables are independent.

4. Results

[53] Estimations of burned area were obtained applying the MF method to the TM image, and classifications of fire severity were performed by applying the LSU, MF and NBR techniques to the TM, MERIS and MODIS images (see section 3.3). Results for both burned area and fire severity estimations are described in this section.

4.1. Burned Area Estimation

[54] Two estimations of burned area were performed applying the MF method to the TM image. The first one was obtained during the field survey design (see section 3.4). The resulting affected area was 34473 ha. A second estimation was made following the same process, but using field information to define the endmember (see section 3.5). The obtained affected area was 32058 ha.

4.2. Fire Severity Estimation

[55] Only the best classifications obtained from the analyzed images are described below (see also Table 3).

[56] 1. The best results obtained from the Landsat 5-TM were for the classification LanTM1, which is the result of

Table 3. Summary of the Classifications Obtained During the Process[a]

Image	Analysis Method	Reclassification Method	Median Filter	Classifications Produced
Landsat 5-TM	LSU1	reclassification	no / 3 × 3 / 5 × 5 / 7 × 7	4
	LSU2	3-class UC	no / 3 × 3 / 5 × 5 / 7 × 7	4
	MF	3-class UC	no / 3 × 3 / 5 × 5 / **7 × 7**	4 (LanTM1)
	MF prefield	thresholds	**7 × 7**	4 (LanTM3)
	NBR	3-class UC	no / 3 × 3 / 5 × 5 / **7 × 7**	4 (LanTM2)
Envisat-MERIS	LSU1	reclassification	no	1
	LSU2	3-class UC	no	MER1
	MF	3-class UC	no	1
Terra-MODIS	LSU1	reclassification	no	1
	LSU2	3-class UC	no	MOD1
	MF	3-class UC	no	1
	NBR	3-class UC	no	1

[a]The acronyms used for the best classifications appear in the last column. LSU, Linear Spectral Unmixing; MF, Matched Filtering; NBR, Normalized Burn Ratio Index; 3-class UC, three-class Unsupervised Classification.

Table 4. Verification Results for the Best Classifications Obtained From the Images

Satellite-Sensor	Classification	Overall Accuracy	Kappa Coefficient	τ_c Coefficient	Confidence Level, %
Landsat 5-TM	LanTM1	73.53	0.58	0.66	5.0
	LanTM2	61.11	0.30	0.31	5.0
	LanTM3	57.41	0.31	0.38	1.0
Envisat-MERIS	MER1	59.46	0.36	0.45	5.0
Terra-MODIS	MOD1	57.89	0.34	0.37	5.0

performing a Matched Filtering analysis (endmember obtained from high fire severity "Ground points," see section 3.3), a three-class Unsupervised Classification and applying a 7 × 7 Median filter to the resulting file. Other classifications obtained from the TM image which produced good results are: (1) LanTM2, obtained by calculating the NBR index, performing a three-class Unsupervised Classification on the resulting file and applying a 7 × 7 Median filter; (2) LanTM3 is the result of performing a MF analysis ("MF prefield," endmember extracted from the TM image with no field data, see section 3.4), performing previously obtained numeric thresholds for the segmentation of the MF file (see section 3.3) and applying a 7 × 7 Median filter.

[57] 2. The best results from the Envisat-MERIS image were for the classification MER1, obtained by performing a Linear Spectral Unmixing analysis using the Set2 of endmembers (landscape components; see section 3.3). The band corresponding to the "burned surface endmember" was segmented by applying a three-class Unsupervised Classification (see section 3.3).

[58] 3. The best results from the Terra-MODIS image were for MOD1, obtained by following the same process described for MER1.

[59] Table 4 shows verification results for the five classifications described above. The confidence level for the τ_c coefficient is also provided. Figure 3 shows classifications LanTM1, MER1 and MOD1.

[60] Table 5 shows the percentage of burned area related to each class of fire severity for the classifications: LanTM1, LanTM2, LanTM3, MER1 and MOD1. As can be seen in Table 5, the fire was very severe, since most of the affected area corresponds to either high or moderate fire severity levels. The spatial pattern is similar for the classifications LanTM1, MER1 and MOD1 (Figure 3), and there are only slight differences between surfaces percentages from the different sensors. Concerning the three classifications obtained from the TM image, there are larger differences between surfaces percentages for the different fire severity levels. These differences will be analyzed in future work.

5. Discussion

[61] Concerning burned area, it is remarkable that the estimation obtained during the field survey design, with no field data (34473 ha) is quite similar to the one obtained using data collected on the ground (32058 ha). The one based on field data is considered more accurate.

[62] Concerning fire severity estimation (Table 4), results obtained for the classification LanTM1 are in line with those from similar studies [*Ruiz-Gallardo et al.*, 2004; *Navarro et al.*, 1998]. It is necessary to remark that the consulted studies usually (1) employ prefire and postfire images [*Ruiz-Gallardo et al.*, 2004; *Navarro et al.*, 1998; *Key and Benson*, 2004; *Chafer et al.*, 2004], (2) perform an extensive field assessment [*Ruiz-Gallardo et al.*, 2004; *Navarro et al.*, 2001] and/or (3) use only two levels of fire severity [*Navarro et al.*, 2001; *Escuin et al.*, 2002]. Accuracies from classifications LanTM2 and LanTM3, although lower than those from some of the former studies, are considered acceptable taking into account that only one postfire image and little field data were used to produce them. In the same way, classifications MER1 and MOD1 are considered of an acceptable reliability, with the added value of using medium spatial resolution data, which are acquired with a higher frequency and have a lower price.

[63] Referring to the different image processing techniques, obtained results show the importance of spectral purity in the training phase (endmember extraction). Matched Filtering seems to produce good results if the endmember is "spectrally pure" enough (as can be assumed in the case of TM images, 30 m spatial resolution). As "spectral purity" decreases for MERIS and MODIS due to their coarser spatial resolution (300 m and 500 m), it is necessary to consider a larger amount of information to obtain acceptable results. Consequently, Linear Spectral Unmixing (with an endmember for each landscape component) seems more suitable for estimating fire severity using medium resolution images than Matched Filtering.

[64] The Linear Spectral Unmixing technique produces better results when endmembers are extracted from landscape components than when they are extracted from fire severity data collected in the field. This corroborates the importance of spectral purity in the training phase. Land-

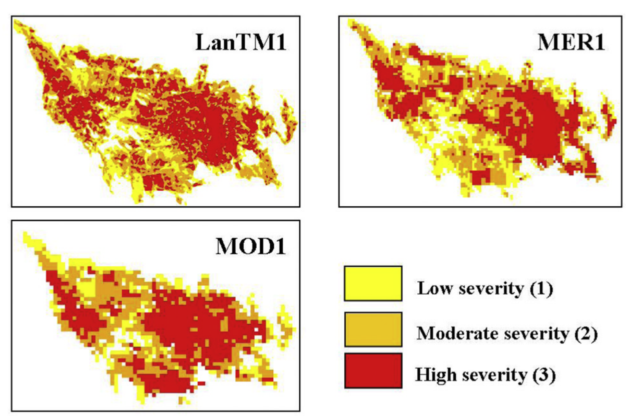

Figure 3. Classifications LanTM1, MER1 and MOD1 with three classes of fire severity.

Table 5. Percentage of Burned Area for Each Class of Fire Severity for LanTM1, LanTM2, LanTM3, MER1, and MOD1 Classifications

Classification	Percent Surface Low Fire Severity	Percent Surface Moderate Fire Severity	Percent Surface High Fire Severity
LanTM1	20.0	41.0	39.0
LanTM2	6.1	27.9	66.0
LanTM3	14.5	36.3	49.2
MER1	24.8	37.8	37.4
MOD1	18.7	37.4	43.9

scape components (''green vegetation,'' ''bare soil'' and ''burned surface'') can be assumed to be ''spectrally pure,'' but this assumption is less clear in the case of fire severity levels (''high,'' ''moderate'' and ''low'').

6. Conclusions and Implications

[65] The analysis of postfire images (high and medium spatial resolution) has produced fire severity maps of an acceptable reliability for short-term forest management in burned areas, in order to locate priority intervention areas and plan forest restoration works. Avoiding the use of prefire images considerably reduces the necessary cost and effort to produce fire severity maps, which is a very important point when presenting a new methodology to the forest services that have to face a hard work and manage a large amount of information when these events occur.

[66] Results obtained using medium resolution images (MERIS and MODIS) do not differ much from those obtained with high spatial resolution data (Landsat-TM). This implies that affordable, reliable maps can be produced in a very short period, as the required images are free (MODIS) or have a moderate price (MERIS) and MODIS covers the entire globe twice a day (on board Terra and Aqua satellites) while MERIS allows global coverage of the Earth in 3 days.

[67] Linear Spectral Unmixing based on ''landscape components'' produced the best classifications for MERIS and MODIS images. For the TM image, the Matched Filtering method produced the most accurate classification, and reliable results were also obtained with the NBR technique (no field data are needed to perform this index). This implies that, if the reliability of the methodology could be assured, fire severity maps of an acceptable quality could be obtained from TM, MERIS and MODIS images with no necessary field assessment.

[68] Unsupervised classification and reclassification seem to be valid techniques to obtain fire severity classes from files containing a continuous range of values indicative of fire severity, such as those resulting from Linear Spectral Unmixing, Matched Filtering or index performance (NBR). These classification methods avoid the problem of establishing numeric thresholds that depend on the area of study and time of acquisition of the images, and which cannot generally be extrapolated to different situations.

[69] A standardized methodology could be established for obtaining fire severity maps quickly after the event of a big wildfire. Ground plots for the verification process (GPS coordinates and fire severity levels) could be collected by the rangers that supervise the affected areas once the fire is extinguished, and sent to the corresponding Laboratory. In this way, a rapid nonexpensive estimation of fire severity levels could be performed, as well as the verification process of the obtained cartography.

[70] The proposed methodology produced promising results in terms of quickly evaluating the situation after a large forest fire. With this system, only one postfire image (high or medium spatial resolution) would be needed, the image processing is easy to perform, little effort for field assessment is required and results are of an acceptable reliability. This would provide users interested in fire severity information with a rapid, accessible and nonexpensive methodology for obtaining fire severity maps. The speed of this system should be useful in the creation of preliminary burn severity maps for the early stages of rehabilitation planning for large fires. Nevertheless, a rigorous use, and revision of the methodology is considered necessary in order to improve and check results, and also to contrast conclusions.

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