Improving satellite-based mapping of burnt areas in Mediterranean ecosystems by image segmentation

Part II: Digital Map PRE
(Order Form #EN 9705381)

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ATTACHMENTS (CD):

Map of pre-fire conditions:
  MAP_PRE10v.bmp
  MAP_PRE3v.bmp

Revised map of fire impact:
  RSIMPACT_RT.gif
  RSIMPACT_DIST.gif
  RSIMPACT-NLS.gif
ABSTRACT

We use LANDSTAT-TM imagery to estimate the impact of fire on a Mediterranean forest and shrubland. In our previous report, we described our segmentation-based approach to delimit the fire scar and presented a metric for fire impact, which was based on a distance in the plane defined by the first two Kauth-Thomas components.

In this report, we further deal with the assessment of fire impact by the joint analysis of pre- and post-fire images, taking the response of different landcover categories and the eventual phenologic change into account. After an atmospheric standardization, we conducted an stratified exploratory analysis of the change between both images, for which we first produced a segmentation-based classification of the pre-fire image. After studying the trajectories of burnt and not burnt regions, we defined an index of fire impact as the difference between the actual post-fire image and a model of a not-burnt image at the post-fire date. We used a simple median model and a regression tree model, with the median model producing a better discrimination of field-assessed degrees of fire impact. Finally, we produced three estimated images of fire impact by applying (i) a simple minimum absolute distance allocation rule, (ii) a regression tree, and (iii) an exponential model fitted to the data. Error, which was estimated by a jackknife procedure, was lowest for the first method.
1. INTRODUCTION

In our previous report, after a general background on the problem and the area of study, we described our segmentation-based approach to delimit the fire scar and presented a metric for fire impact. The metric was based on a distance in the plane defined by the first two Kauth-Thomas (Crist & Cicone 1984) components. We recall from our previous report that the fire that we are dealing with a fire occurred on May 30th, 1995 in a Mediterranean forest and shrubland in Aznalcollar (Sevilla, Spain, 37° 38’ N, 6° 26’ 12”W). Our area of study was a rectangle of 13.3 km² in the SW foothill of Sierra Morena (29N UTM zone from coordinates 737620, 4168723 to 726190, 4157053). We analyzed a pre-fire TM image of 20-7-1994 and a post-fire image of 5-6-1995.

We also recall that, in addition to the satellite imagery, we are using data from a field-based study on fire impact that was conducted shortly after fire was extinguished (Navarro et al. 1997). 158 sites were visited and fire impact was assessed by visual inspection according to a legend of five degrees (see table 1 in our first report).

In this report, we further deal with the assessment of fire impact by the joint analysis of pre- and post-fire images, taking the response of different landcover categories and the eventual phenologic change into account. As it is mandatory for any multi-temporal study, we first proceeded to an atmospheric standardization that rendered a formal comparison of pre-fire and post-fire images possible. We then conducted an stratified exploratory analysis of the change between both images, for which we first produced a segmentation-based classification of the pre-fire image. After studying the trajectories of burnt and not burnt regions, we defined three indexes of fire impact and compared their values to the field-assessed levels of fire impact. Finally, we produced an estimated image of fire impact by applying an empirical non-linear model fitted to the data.
2. ATMOSPHERIC STANDARDIZATION

After an standard georectification by means of second-order polynomials that rendered combined mean square errors of 0.829 and 0.852 pixels respectively for the pre- and the post-fire images. We transformed both subscenes from digital counts to radiance using the calibration coefficients (Table 1). Calibrated images were then transformed to at-sensor reflectance by applying:

\[
\varphi = \frac{n_t}{d^2 \cdot E_a \cdot \cos \phi} \]

\[
d = \left[ 1 - (0.016729 \cdot \cos(0.9856 \cdot (j - 4))) \right]^{-1} \]

\( \varphi \): reflectance.
\( L \): calibrated radiance.
\( d \): Sun - Earth distance.
\( \phi \): Sun zenithal angle.
\( E_a \): Exoatmospheric Irradiance.
\( j \): Day of the year.

<table>
<thead>
<tr>
<th>Table 1. Calibration coefficients.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Offset (mW/cm²•sr•μm)</strong></td>
</tr>
<tr>
<td>-------------------------------</td>
</tr>
<tr>
<td>0.08024</td>
</tr>
<tr>
<td>Gain (-)</td>
</tr>
<tr>
<td><strong>E_a (mW/cm²•sr•μm)</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2. Parameters for the calculation of Top-Of-the-Airplane reflectance.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
</tr>
<tr>
<td>---------------------------</td>
</tr>
<tr>
<td>Date</td>
</tr>
<tr>
<td>Day of the year</td>
</tr>
<tr>
<td>Elevation angle</td>
</tr>
<tr>
<td>Sun-Earth distance</td>
</tr>
</tbody>
</table>

A formal atmospheric correction, either based on the formulation of Tanré et al. (1990) or in a simplified version (i.e., SMAC, Rahman and Dedieu, 1994), would have required reliable measurements of atmospheric optics or, at least, vertical profiles of temperature (radio-soundings) from which to estimate the optical properties of the atmosphere through an appropriate model (i.e., LOWTRAN or MODTRAN). As
neither measurements were available for any date, we standardized both atmospheric conditions by linear regression. Caselles and López-García (1989) show that a close-to-linear relationship between at-sensor reflectance of the same TM band at different dates is to be expected if images for both dates are acquired under clear-sky conditions, which is a normal requirement for purchasing Landsat-TM imagery.

We thus calculated a robust regression line between the pixel at-sensor reflectance at both dates for each spectral band and also identified a number of sites which were supposed to be spectrally invariant between both dates as recorded by the TM sensor. We then plotted the values of the invariant targets on the regression plots (Fig. 1, Table 3).

Robust regression was performed using Least-Trimmed Squares regression (Rousseeuw 1984), a method in which only the \( q \) smallest squared differences are used for the fit instead of using all. Typically, \( q \) is set to be slightly larger than \( n/2 \) for \( n \) pairs of observations.

As some of the supposedly "invariant" targets were actually departing from the linearity (mostly the ones selected on narrow roads and fire barriers), once we compared the transformations suggested by both methods (Table 3), we selected the robust linear regression equation as the most reliable. We applied the equation to the pre-fire image, thus rendering both images of at-sensor reflectance spectrally comparable.

Table 3. Statistics of the ordinary and Least-Trimmed-Squares linear regressions.

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th></th>
<th>Robust LTS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope</td>
<td>Intercept</td>
<td>( R^2 )</td>
<td>Slope</td>
</tr>
<tr>
<td>TM-1</td>
<td>0.9427</td>
<td>0.0039</td>
<td>0.652</td>
<td>1.0236</td>
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<tr>
<td>TM-2</td>
<td>0.9515</td>
<td>0.0040</td>
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<td>0.702</td>
<td>1.1259</td>
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<td>0.637</td>
<td>0.9980</td>
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<td>0.0097</td>
<td>0.677</td>
<td>1.1267</td>
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<tr>
<td>TM-7</td>
<td>1.0030</td>
<td>0.0050</td>
<td>0.691</td>
<td>1.1448</td>
</tr>
</tbody>
</table>
Figure 1. Regression lines for each TM spectral band. Points, pixel values used for the computations. Numbers, invariant targets: 1, roads; 2, water; 3, fire barriers; 4, bare soil.
3. SEGMENT-BASED CLASSIFICATION.

Although fire has a notorious effect on surface reflectance and fire scars use to be prominent features in TM imagery, the assessment of the degree of fire impact is more subtle and requires a detailed analysis to consider the differential response of land cover categories. Also, it is desirable that the assessment of fire impact involve the comparison of pre- and post-fire images, and these image often are separated by a significant length of time. Such a phenologic change is, typically, dependent on the vegetation type, for which differences in phenologic change among land cover types also must be considered. In our study, with pre- and post-fire images separated by more than 10 months, while the positions of burnt pixels in the TC-1 - TC-2 plane was very distinct (see next section), phenologic change was also evident for the not-burnt part of the image, as it will be shown in the following sections.

In order to perform an analysis that could consider the eventual differential response of land cover categories, we conducted an stratified exploratory analysis of the change between the pre- and the post-fire image. We defined statistical strates by means of land cover classification, applying methods based on image segmentation, hierarchical clustering and discriminant analysis.

We proceed to classify the pre-fire image according to the methods detailed in Lobo (1997) and also used in our previous report. We just remind here that this method is based on (i) a segmentation of the image with the IMORM algorithm, (ii) a hierarchical clustering of a random subset of the image, (iii) a sub-optimal definition of the number of classes, (iv) a refinement of centroids (vectors averages and dispersion matrices) through an iterative linear canonical discriminant process, and, finally, (v) the classification of the entire image by allocating each segment to its closest centroid.
Figure 2. Color composite of the Kauth-Thomas transform of the pre-fire TM image. Brightness presented as red, greenness as green and "wetness" as blue.

Figure 3. Vectorized edges of the segments produced by IMORM overlaid on the color composite of the Kauth-Thomas transform of the pre-fire TM image.

Figure 4. Final segment-based classification of the pre-fire TM image.

Figure 5. Vectorized edges of the final segment-based classification overlaid on the color composite of the Kauth-Thomas transform of the pre-fire TM image.
The segmentation processing rendered a partition into 4423 segments (Figs. 2 and 3). All segments larger than 50 pixels (1216 segments) were used to create a multivariate table with the values of the per-segment means of the first three Principal Components, and this table was submitted to a model-based hierarchical clustering (Banfield and Raftery 1993) that can be represented by its dendrogram (Fig. 6). The optimal partition was defined by calculating the approximate Bayes factor for all consecutive number of classes, that is, the ratios of posterior to prior odds for \( r \) and \( r+1 \) classes given the data (Fig. 7). Unfortunately, such an optimal partition implies too high a number of classes for them to be interpreted from field information. Therefore, we searched a sub-optimal number of classes from a plot of the number of classes as a function of dissimilarity level (Fig. 8), which indicated that 7 classes was a good compromise as this number implied a relatively large decrease in dissimilarity.

The seven classes were used to define a training set for a Linear Canonical Discriminant Analysis (LCDA). The goal of this LCDA is to define an ad-hoc transformation where hierarchical a clustering defines the final classes. This second hierarchical clustering was performed in the canonical space (Fig. 8), which rendered a classification with 10 classes (Figs. 9 and 10). All segments were then classified by minimum Euclidean distance to the centroids defined by these 10 classes in the canonical space (Figs. 4 and 5).

A plot of the training segments in the plane defined by the first two canonical components (Fig. 10), as well as a plot in the Kauth-Thomas space, along with the inspection of high-resolution digitized color aerial photography, was sufficient for a summary interpretation of the 10 classes. This interpretation was thereafter confirmed by considering changes between pre-fire and post-fire TC values.
Figure 6. Dendrogram of the model-based hierarchical clustering of the 1216 segments larger than 50 pixels.

Figure 7. Plot of the approximate weight of evidence (based on an approximation to the Bayes factor) versus the number of clusters for the model-based clustering of the segments of the pre-fire image.

Figure 8. Hierarchical clustering in the canonical plane.

Figure 9. Plot of the dissimilarity versus number of classes for the hierarchical clustering in the canonical plane.

Figure 10. Plot of the 1216 segments larger than 50 pixels in the canonical space. Numbers refer to the final 10 classes.
4. TRAJECTORIES IN THE KAUTH-THOMAS SPACE.

We plotted a random sample of 1000 pixels of both dates in the space defined by the first two Kauth-Thomas components (Crist and Cicone 1984), including the robust regression line between both components for the pre-fire conditions (Fig. 11). In a similar way as observed with the regression line for the unaffected region of the post-fire image in our previous report, the burnt pixels clearly clustered in the lower-left part of the plot.

![TC-1 vs TC-2 plane](image)

**Figure 11.** Scatter plot of a random sample of 1000 pixels in the plane defined by the first two Kauth-Thomas components. Points in red, burnt pixels; blue, unburnt pixels in the post-fire TM image; green, values in the pre-fire TM image. The line of the robust (least-trimmed) regression for the prefire image is also shown.

In order to perform an analysis that could consider the eventual differential phenolgy of land cover categories, we conducted an stratified exploratory analysis of the change between the pre- and the post-fire image. We used the classification that was described in the preceding section for a more in depth analysis of the trajectories in the Kauth-Thomas space. We draw segments from the pre-fire to the post-fire positions of the classes (Fig. 12). We plotted the median of each class for the following regions: (i) the pre-fire and subsequently not burnt part of the image, (ii) the pre-fire and subsequently burnt part of the image, (iii) the post-fire but not-burnt, and, (iv) the post-fire and burnt part of the image. Segments linked (i) to (iii) and (ii) to (iv).
Figure 12. Trajectories in the Kauth-Thomas space. Numbers represent median values for the 16 classes. Green, values in the pre-fire TM image; red, values in the burnt part of the post-fire image; blue, values in the not-burnt part of the post-fire image.
Fig. 12 offers the possibility of several interesting observations. Lines linking (i) and (iii) medians describe the change of the not burnt surface between pre- and post-fire dates. This change is consistent with the nature of the different land cover categories. Land cover dominated by bare soil (classes 1, 8 and 10) decrease brightness but increase greenness and wetness. On the other extreme, closed forest (classes 4, 7 and 9) increase brightness while decrease greenness and, slightly, wetness. Open forest classes (2, 3 and 6) decrease in all three components. These dynamics imply that vegetation was drier at the post-fire date, while differences in bare soil reflectance are probably due to the change in solar incidence angle.

Lines linking (ii) and (iv) describe change due to fire. This change also shows differences according to land cover. Classes 1, 8, 10 and 5 (dominated by bare soil) did not get burnt, and actually acted as barrier to fire propagation. Closed canopy forest (classes 4, 7, and 9) severely decreased greenness and wetness with slight or no change in brightness, while open canopy forest (classes 2, 3 and 6) slightly decrease brightness in addition to a severe decrease in greenness. The decrease in brightness is more severe as the percent of openness is higher, as in class 6. These responses indicate that green vegetation loses the near-infrared - red contrast and that short, dry understorey becomes darker. Class 6, the most open of the three open canopy forest classes, has a different response to fire in terms of wetness: while all other classes slightly or moderately decrease wetness, wetness increases in burnt surfaces classified as 6.
5. INDICES OF FIRE IMPACT.

The analysis described in the preceding section suggests that the decrease in Kauth-Thomas greenness is a good measurement to assess the degree of fire impact, at least for closed canopies. Nevertheless, such a decrease cannot be measured as the difference between the values in the pre-fire image and the values in the post-fire image, as we have seen that there are important differences in the reflectance of both dates in the not-burnt region.

Therefore, we have empirically modeled the value of the TC components as if the region had not been burnt. We have used two approximations. The first one simply uses the classification of the pre-fire image and calculates the median values of the TC components for each land cover class in the not-burnt part of the post-fire image. Each pixel in the modeled image takes then the value of the median of its class. We will refer to this model as the "Median" model.

The second model uses more information. We calculated a regression tree (Breiman et al. 1984) using the not-burnt part of both pre- and post-fire images. Regression trees estimate the means of a response variable by intervals of a set of predictor variables. A hierarchical tree is built so that each split of a predictor variable minimizes the variance of the response variable in each of the two subsets. Regression trees are appropriate to predict the non-linear and abrupt response of a variable to a set of predictors. In our case, the regression tree uses the post-fire TC component as the variable to be predicted and all three pre-fire Kauth-Thomas components plus the classified image and terrain variables as predictors. The terrain variables were height, slope and cosine of the aspect, calculated from a digital elevation model. Fig. 12 represents the tree and Table 4 provides statistical summary information. We will refer to this model as the "RT" model.

<table>
<thead>
<tr>
<th>Table 4. Summary information of the regression tree.</th>
</tr>
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<tbody>
<tr>
<td>Number of terminal nodes: 110</td>
</tr>
<tr>
<td>Residual mean deviance: 0.0001122 = 1.34 / 11940</td>
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</table>

<table>
<thead>
<tr>
<th>Distribution of residuals:</th>
</tr>
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<tbody>
<tr>
<td>Min</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>0.08245</td>
</tr>
</tbody>
</table>
Figure 12. Regression tree calculated between the pre-fire values of the TC components (az1tc1, az1tc2 and az1tc3) and the terrain variables (height, aspect and slope) as predicting variables, and the post-fire but not-burnt TC-2 (greenness) values as fitted variable. (a) Representation of the tree, where the vertical axis is proportional to the reduction in total variance. In order to facilitate reading, (b) and (c) are the left and right branches of the tree, with uniformed spacing in the vertical axes. In (c), the bolded value 0.05639 is fitted from values lower than 0.09 but higher than 0.08 in pre-fire greenness ("az1tc2"), AND lower than 344.5 m in height ("dem"), AND lower than -0.45 in cosine of aspect, AND higher than 328.5 m in height ("dem"). The bolded value 0.07721 is fitted from values larger than 0.09 but lower than 0.11 in pre-fire greenness ("az1tc2"), higher than 208.5 m in height ("dem"), AND do not belong to classes c, f or j, AND are lower to 0.2 in pre-fire brightness ("az1tc1").
Improving satellite-based mapping of burnt areas in Mediterranean ecosystems (2nd part)
Figure 13. Empirical models of the post-fire greenness (2nd Kauth-Thomas component) as if the region had not been affected by fire. Top, observed (a) pre- and (b) post-fire greenness images. Bottom, modeled images of undisturbed conditions at the post-fire date: (c) medians model; (d) regression tree model.
An index of fire impact was defined as the difference between the actual post-fire greenness (TC-2) and the modeled pre-fire date greenness, and we calculated this index with both the median and the RT models of pre-fire greenness. We analyzed the values of these indices compared to the field observations of fire impact. We calculated summary statistics of the index for each level of fire impact as observed in the field and present results by means of boxplots and Multiple Comparisons (Hsu 1996). As a reference, we also include a similar analysis using the actual post-fire TC-2 and NDVI images, and the difference between the actual post- and pre-fire TC-2 images.
Figure 14. Boxplots of the values of the four indexes of fire impact stratified by the field-observed levels of fire impact. White bands indicate the medians; square brackets, the range; notches, 95% confidence intervals of the medians.

Figs. 14 and 15 collect all boxplots, in which non-overlapping notches imply significant differences at the 95% level. Values of the TC-2 of the post-fire image are significantly different among levels of fire impact as estimated in the field, and almost all levels also significantly differ in terms of the values of the post-fire NDVI. Nevertheless, it must be noted that the predictive power of the plain post-fire TC-2 and NDVI is very poor as there are many points with a "natural" low greenness that have not been affected by fire. Instead, the index based on the difference to the models cancels out all parts of the image which decrease in greenness is not due to fire. Such distinction cannot be made in the boxplots because field sampling intentionally discarded the not-burnt part of the image and was directed to assess the impact on trees.

Despite the visual impact of the TC composite of the RT models (Fig. MODEL-RT), the index calculated with the modeled Median TC-2 performs better in terms of statistical significance than the same difference calculated with the RT model.
Statistical significance is similar between the plain post-fire TC-2 and the difference to the Median model. It is important to note that values of the difference between post-fire and pre-fire TC-2 do not differ among fire impact levels.

Another important result is that statistical significance increases when only those field observations that lay in the closed canopy classes (4, 7 and 9) are considered (Fig. 15). The explanation is simply deduced by recalling Fig. 12: fire impact is almost exclusively tracked by a reduction of TC-2: in the closed-canopy classes, while the response in the open-canopy classes (2, 3 and 6) is a result of the combined response of the canopy and the understorey.

![Diagram](image)

**Figure 15.** Top, boxplots of the values of the index of fire impact (defined by the difference post-fire TC2 – Medians Model of TC2) stratified by the field-observed levels of fire impact. Note that the relationship is far more consistent for those observations lying in the closed-canopy classes. Bottom, boxplots calculated with the post-fire NDVI and with the Euclidean distance in the Kauth-Thomas space.

An index of impact defined as the Euclidean distance in the TC space between the actual post-fire and the modeled TC components performs worse than the mentioned index defined by the simple difference between both TC-2 (Fig. 15). This
was to be expected, as Fig. 12 shows that the impact of fire concentrates on the TC-2, while change not related to fire is also notorious in TC-1 and TC-3.

6. ESTIMATED IMAGES OF FIRE IMPACT.

Once the relationship between the index of fire impact and the field observations had been established, we decided to keep the index calculated as the difference (post-fire TC-2 – Medians Modeled TC2) and proceeded to calculate the images of fire impact as estimated from the index. We produced two different estimates. In the first one we just calculated the medium values ($\bar{x}_j$) and standard deviations ($s_j$) for the index in each level of fire impact, and then labeled each pixel $x_i$ to the level $j$ with the minimum reduced difference $d_{i,j}$:

$$d_{i,j} = \frac{|x_i - \bar{x}_j|}{s_j}$$

A second estimate was done by calculating a regression tree using the index of fire impact as predictor and the field-observed level of fire impact as predicted variable, and then applying the regression tree to the entire image of the index. This method has the advantage of producing a continuous estimate of the level of fire impact.

Finally, a third estimate was calculated by fitting the following model to the data by non-linear least squares:

$$y = b_1 \cdot e^{b_2 \cdot x}$$

where $x$ is the index of fire impact defined as the difference of the observed post-fire greenness minus the modeled pre-fire greenness and $b_1$ and $b_2$ are the fitted coefficients.

As this study has been conducted two years after the fire, a conventional validation in the field was not possible. Instead, we have used the method of “jack-knifing” (Shao and Tu 1995), in which all observation minus one are used to calculate the estimate and the remaining one is used for validation. The method is repeated n
times for the n pairs of observations, which implies a considerable computing effort. We then calculated a regression line between observed and estimated values and used the Pearson correlation index as a measure of accuracy (table 5).

Table 5. Summary statistics of the linear regressions between observed and predicted levels of fire impact for the different estimation methods using the difference index (post-fire TC2 – Medians Model TC2)

<table>
<thead>
<tr>
<th></th>
<th>Regression Tree</th>
<th>Non-linear regression</th>
<th>Minimum absolute distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spearman's coefficient</td>
<td>0.758</td>
<td>0.805</td>
<td>0.806</td>
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<tr>
<td>N</td>
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<td>180</td>
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<tr>
<td>p-value</td>
<td>0.000</td>
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Table 6. Average errors for the three estimation methods

<table>
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<th>Degree of Fire Impact</th>
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</thead>
<tbody>
<tr>
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<td>0</td>
</tr>
<tr>
<td>Regression tree</td>
<td>-0.154</td>
</tr>
<tr>
<td>Non-linear regression</td>
<td>0.851</td>
</tr>
<tr>
<td>Minimum absolute distance</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Results of the regressions (tables 5 and 6) indicated that, overall, all three methods performed similarly, actually with the simplest (the minimum absolute difference) being the best. Nevertheless, inspection of the estimated images of fire impact (Fig. 16) reveals that only the regression tree method was able to label as 0 impact most of the not-burnt area. The asynthetic character of the exponential fit made that impact were systematically overestimated at the lowest values. In all three methods the riparian area in the SE of the scene is wrongly indicated as burnt. This error arises from the fact that greenness values of the water pixels are higher in the pre-fire image than in the post-fire one, either as a consequence of a change on sediment charge or as a consequence of the presence of more green vegetation mixed with the water in the same pixels. In any case, the decrease in greenness is wrongly measured as a fire impact. Most likely, this problem would be solved by identifying a water class in the pre-fire classification.
Figure 16. Estimated images of the degree of fire impact according to the three methods.

7. DISCUSSION AND CONCLUSIONS.

The results presented in sections 4 to 6 let us conclude that:

- A hierarchical classification of the segmented pre-fire image produces a land cover map that is consistent in terms of the fire response, indicating a differential response of the land cover categories to both phenologic change and fire impact.
- An study of the trajectories of the centroids in the Kauth-Thomas space from the pre- to the post-fire conditions indicates that fire impact is essentially reflected by the greenness component ("Tasseled Cap 2", TC-2), and that the proportional change on TC-2 increases with canopy closure.

- A simple difference between the atmospherically-standardized post and pre-fire greenness (TC-2) images shows a weak relation to field estimates of fire impact.

- A simple index of fire impact defined as the difference of the post-fire Kauth-Thomas greenness (TC-2) minus a modeled image of unaffected greenness at the post-fire date shows statistically significant (95%) differences among field estimates of fire impact. Although a regression tree provided the best model of unaffected greenness at post-fire date, the use of a more simple median model (based on the median values of the land cover classes) in the difference image results into a higher discrimination among field estimates of fire impact.

- Finally, a simple allocation rule by minimum absolute distance between the difference index of fire impact and the observed degrees of fire impact provided the least error to produce an image of estimated degree of fire impact, as measured by a jackknife procedure. Nevertheless, the jackknife procedure does not take the error of the field estimates into account.
REFERENCES


