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Burn severity estimation from remotely sensed data: Performance of simulation versus empirical models

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Abstract

Burn severity is a key factor in post-fire assessment and its estimation is traditionally restricted to field work and empirical fitting from remotely sensed data. However, the first method is limited in terms of spatial coverage and cost effectiveness and the second is site- and data-specific. Since alternative approaches based on radiative transfer models (RTM) have been usefully applied in retrieving several biophysical plant parameters (leaf area index, water and dry matter content, chlorophyll), this paper has applied the inversion of a simulation model to estimate burn severity in terms of the Composite Burn Index (CBI). The performance of the model inversion method was compared to standard empirical techniques. The study area chosen was a large forest fire in central Spain which occurred in July 2005. The model inversion showed the most accurate estimation for high severity levels (for CBI > 2.7, RMSE = 0.30) and for unburned areas (CBI < 0.5, RMSE = 0). In both methodologies, the error associated to CBI from 0.5 to 2.7 was not acceptable (RMSE > 0.7), because it is higher than 25% of the total range of the index. Finally, burn severity maps from both methods were compared.

Keywords: Forest Fires; Burn Severity; Kuusk Model; RTM Inversion; Landsat TM; Spectral Indices; NBR; CBI

1. Introduction

Forest fires are a critical factor of disturbance in worldwide ecosystems. Their effects on soil and plants depend on frequency, fire intensity, and fire residence time, as well as on plant resilience and resistance (Pérez & Moreno, 1998). Moreover, the main consequences of fire on plants and atmospheric emissions depend largely on fire/burn severity. The term "fire severity", which has a long tradition within the forest fire research community, refers to the combination of soil and overstory effects caused by fire (Brewer et al., 2005; Chappell & Agee, 1996; Doerr et al., 2006; Ryan & Noste, 1985; Turner et al., 1994; Wang, 2002; White et al., 1996). More recently, other authors have used the term "burn severity" to address the same concept (Chuvieco et al., 2005; Chuvieco et al., 2006; Key, 2005; Key & Benson, 2004, 2005; Parra & Chuvieco, 2005; Patterson & Yool, 1998). This discrepancy of terminology makes comparing map products potentially ambiguous (Miller & Yool, 2002). To clarify these concepts, the analysis of fire effects can be better classified in the context of the fire disturbance continuum (Jain & Graham, 2004), which addresses three different temporal phases: before the fire, during the fire and after the fire. Within this framework, the term fire severity indicates the direct effects of the combustion process and refers to the active fire (direct effects of fire process). In contrast, burn severity identifies the impact of fire on soil and plants when the fire is extinguished, and it is related to the post-fire phase (what is left). The latter definition will be used in this paper.

Burn severity is generally estimated using post-fire field data (Moreno & Oechel, 1989; Pérez & Moreno, 1998), which consider several variables as: depth of char, percentage of tree basal area mortality (Chappell & Agee, 1996), decrease in plant cover (Jain & Graham, 2004; Rogan & Yool, 2001), volatilization or transformation of soil components to soluble mineral forms (Turner et al., 1994; Wang, 2002; Wells & Campbell, 1979), proportion of fine branches remaining on the canopy (Moreno & Oechel, 1989), and degree of canopy consumption and mortality (Doerr et al., 2006; Key & Benson, 2002; Patterson & Yool, 1998;

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Rogan & Franklin, 2001; Ryan & Noste, 1985; van Wagtendonk et al., 2004). The poor spatial representation associated with field methods and the cost of these approaches make it advisable to use alternative methods.

Remote sensing can be potentially a sound choice to map burn severity, since vegetation removal, soil exposure, changes in soil and vegetation moisture content imply changes in reflectance (Jakubauskas et al., 1990). Indeed, fire-related decreases in chlorophyll content and vegetation moisture lead to decreases in the visible and near-infrared (NIR) reflectance and increases in the mid-infrared (SWIR) reflectance (White et al., 1996).

Since the amount of green biomass destroyed by fires depends upon the burn severity, several authors have found good correlations between vegetation indices, computed from post-fire remotely sensed data, and burn severity (Díaz-Delgado et al., 2003; Doerr et al., 2006; García-Haro et al., 2001; Hammill & Bradstock, 2006; Ruiz-Gallardo et al., 2004; Sunar & Özkan, 2001). The Normalized Difference Vegetation Index (NDVI) has been related to field measurements of burn severity (Chafer et al., 2004; Hammill & Bradstock, 2006; Sunar & Özkan, 2001). NDVI is defined as:

$$\mathrm{NDVI} = \frac{(\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}})}{(\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}})} \tag{1}$$

where ρ_{NIR} and ρ_{RED} are the reflectance of near infrared (NIR) and RED bands respectively. However, according to White et al. (1996), a single post-fire band 7 (SWIR) of Landsat Thematic Mapper (TM) showed stronger correlations than NDVI. Likewise, Jakubauskas et al. (1990) used the 7/5 ratio of Landsat Multi Spectral Scanner (MSS) to map the burn area and extract degrees of burn severity. Other authors have found stronger correlations for spectral indices using the NIR and short wave infrared (SWIR) bands rather than the NDVI. Although, these NIR-SWIR indices were originally designed to estimate plant water content (De Santis et al., 2006; Fraser et al., 2000; Gao, 1996; Hunt & Rock, 1989), they have also proved useful to map burnt areas (López García & Caselles, 1991) since burning implies a severe decrease in plant and soil moisture contents. The most effective NIR-SWIR index for burn severity available in the literature is the Normalized Burn Ratio (NBR) proposed by Key and Benson (2002):

$$\mathrm{NBR} = \frac{(\rho 4 - \rho 7)}{(\rho 4 + \rho 7)} \tag{2}$$

where $\rho 4$ and $\rho 7$ are the reflectance of band 4 (NIR) and 7 (SWIR) of Landsat TM respectively. Since burn severity is dependent on the pre-fire vegetation conditions, these authors suggest the use of the temporal difference between pre- and post-fire NBR (ΔNBR) values (Key & Benson, 2002):

$$\Delta\mathrm{NBR} = \mathrm{NBR}_{\mathrm{PRE-FIRE}} - \mathrm{NBR}_{\mathrm{POST-FIRE}} \tag{3}$$

This variable has been proposed as an operational index to estimate burn severity from satellite data.

The post-burn approach (simple NBR) is less expensive than the multi-temporal approach, and reduces the errors caused by differences in geometric correction, in sensor calibration, in sun-sensor geometry, in atmospheric effects and in plant phenology. However, the use of a single post-image, without the pre-burn reference image, leads to difficulties in mapping spectrally similar areas such water and recent burns, or senescent vegetation and older burns (Epting et al., 2005; Garcia & Chuvieco, 2004; Pereira, 1999; Pereira & Setzer, 1993).

The ΔNBR index calculated from Landsat TM and ETM+ images have shown very strong correlation with burn severity values estimated in the field in several study cases (Cocke et al., 2005; Epting et al., 2005; Miller & Yool, 2002). A comparison between ΔNBR calculated from Landsat-TM and Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) data, showed very similar results (van Wagtendonk et al., 2004).

Other indices that include the mid-infrared spectral region have also shown high correlations, according to Rogan and Yool (2001) and van Wagtendonk et al. (2004), but generally did not perform as consistently as the NBR index. Similarly, the evaluation of six different approaches for classifying and mapping fire severity using multi-temporal Landsat TM data, performed by Brewer et al. (2005), confirms that the NBR provides a flexible, robust and analytically simple approach.

As well as spectral indices, linear transformation techniques have been used for the multi-temporal mapping of burn severity. Patterson and Yool (1998) compared two linear transformation techniques, the Kauth–Thomas (KT) and principal components (PC) transforms, for mapping fire severity. The KT or "Tasselled Cap" transform is sensitive to fire-induced changes in the moisture content of soil and vegetation and, in this study, produced betters result than the PC transform. Chuvieco (2002) and Caetano et al. (1994) concluded that spectral mixture analysis (SMA) proved to be efficient in detecting the charcoal signal even in lightly burnt areas that kept a strong vegetation signal, a situation that is typically considered to be problematic. SMA was considered advantageous over vegetation index-based methods, due to its improved capability to distinguish burns from other bare or sparsely vegetated areas (Caetano et al., 1996; Díaz-Delgado et al., 2001). This technique was also successful applied by Díaz-Delgado and Pons (1999) and Rogan and Franklin (2001) to carry out the burn severity classification.

The studies previously referred to are based on empirical approaches, which are relatively easy to compute, when a good set of field data is available. However, empirical approaches have also limitations due to the lack of physics introduced in the retrieval technique which reduces their generalization power (Weiss et al., 2000). Alternative approaches are based on radiative transfer model (RTM) techniques. In the forward mode, RTM help understand how the changes in plant biophysical parameters modify the spectral response at both leaf and canopy level, whereas inverse modelling uses spectral signatures as inputs to quantify plant parameters. The latter mode has been extensively used to estimate: leaf area index (LAI) (Fang & Liang, 2003; Koetz et al., 2005), water and dry matter content (Riaño et al., 2005; Zarco-Tejada et al., 2003), and chlorophyll content (Zarco-Tejada et al., 2001). The results of these studies are generally very precise, but the performance of RTM greatly depends on whether the assumptions of the