Remote Sensing of Environment 113 (2009) 126–136

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Short-term assessment of burn severity using the inversion of PROSPECT and GeoSail models

Angela De Santis [a,*], Emilio Chuvieco [a], Patrick J. Vaughan [b]

[a] Department of Geography, University of Alcalá, Calle Colegios 2, 28801 Alcalá de Henares, Madrid, Spain
[b] Laboratorio de Espectro-radiometria y Teledetección Ambiental CCHS-CSIC Calle Albasanz 26-28, 28037 Madrid, Spain

ARTICLE INFO

Article history:
Received 27 March 2008
Received in revised form 1 August 2008
Accepted 30 August 2008

Keywords:
Forest fires
Burn Severity
RTM inversion
PROSPECT
GeoSail
GeoCBI
Landsat TM
SPOT-HRV
Local sensitivity analysis

ABSTRACT

Accurate estimations of burn severity and its distribution in post fire scenarios are critical for short-term mitigation and rehabilitation treatments. The use of remote sensing techniques, coupled with radiative transfer models (RTMs) can improve the accuracy, precision (in terms of number of classes) and cost-effectiveness of burn severity assessment. In this paper, an improved simulation model that combines PROSPECT and GeoSail to estimate burn severity from satellite data was tested in three Mediterranean forest fires. The determination of burn severity was based on a new version of the CBI index (named GeoCBI), that takes into account the vegetation fraction cover (FCOV) to compute burn severity of the total plot. Model inversion results showed accurate estimations of GeoCBI values (RMSE between 0.18 and 0.21) and a uniform performance in all three sites (107 field plots in total) throughout the full GeoCBI range (0–3).

1. Introduction

Forest fires are a major cause of environmental disturbance in Mediterranean ecosystems, causing biodiversity loss, soil degradation (Doerr et al., 2006), and greenhouse gas emissions (Andreae & Merlet, 2001).

Post-fire management is normally focused on minimizing post-fire erosion effects (mitigation) and shortening ecosystem recovery times (rehabilitation) (Miller & Yool, 2002). In large forest fires, both post-fire mitigation and rehabilitation treatments can be costly and cumbersome due to the extension of the area affected. In addition, summertime forest fires are generally followed by autumn rains, which are often torrential and cause erosion and soil degradation. Consequently, treatments must be completed within weeks after the fire. In this context, it is critical to target the efforts on high priority locations to reduce erosion risks in a cost effectively approach (Miller & Yool, 2002).

Both short and long-term post-fire effects on vegetation and soil can be estimated in terms of “burn severity” (Chuvieco et al., 2006; De Santis & Chuvieco, 2007; Key & Benson, 2005; van Wagtendonk et al., 2004; White et al., 1996). Detailed knowledge of the level of damage and its distribution throughout the burnt area (burn severity map) is a key factor to quantify the impact of fires on landscapes (van Wagtendonk et al., 2004), to select and prioritize treatments applied on site (Bobbe et al., 2001; Patterson & Yool, 1998), to plan and monitor restoration and recovery activities and, finally, to provide baseline information for future monitoring (Brewer et al., 2005). Different methods of burn severity estimation have been applied using post-fire field evaluation of soil and vegetation conditions (Moreno & Oechel, 1989; Pérez & Moreno, 1998). Since field surveys are costly and time consuming and do not provide a good spatial coverage, remote sensing imagery has been proposed as a sound alternative. For instance, Interagency Burned Area Emergency Rehabilitation (BAER) teams use a semi-automatic estimation of burn severity from satellite images on a nationwide scale, applying techniques developed by the Remote Sensing Applications Center - RSAC of the USDA Forest Service (Bobbe et al., 2001). The field assessment method used by BAER is based on the widely used Composite Burn Index (CBI) (Key & Benson, 2005), which takes continuous values ranging from 0 (unburned) to 3 (completely burned). However, in most studies dealing with burn severity estimation from satellite imagery, damage levels are normally grouped into only four severity classes: unburned, low, moderate and severe (Cocke et al., 2005; Epting et al., 2005; Hyde et al., 2007; Kokaly et al., 2007; Lentile et al., 2006; Miller & Thode, 2007;

* Corresponding author.
E-mail addresses: angela.desantis@uah.es (A. De Santis), emilio.chuvieco@uah.es (E. Chuvieco), pvaughan@ieg.csic.es (P.J. Vaughan).

0034-4257/$ – see front matter © 2008 Elsevier Inc. All rights reserved.
doi:10.1016/j.rse.2008.08.008

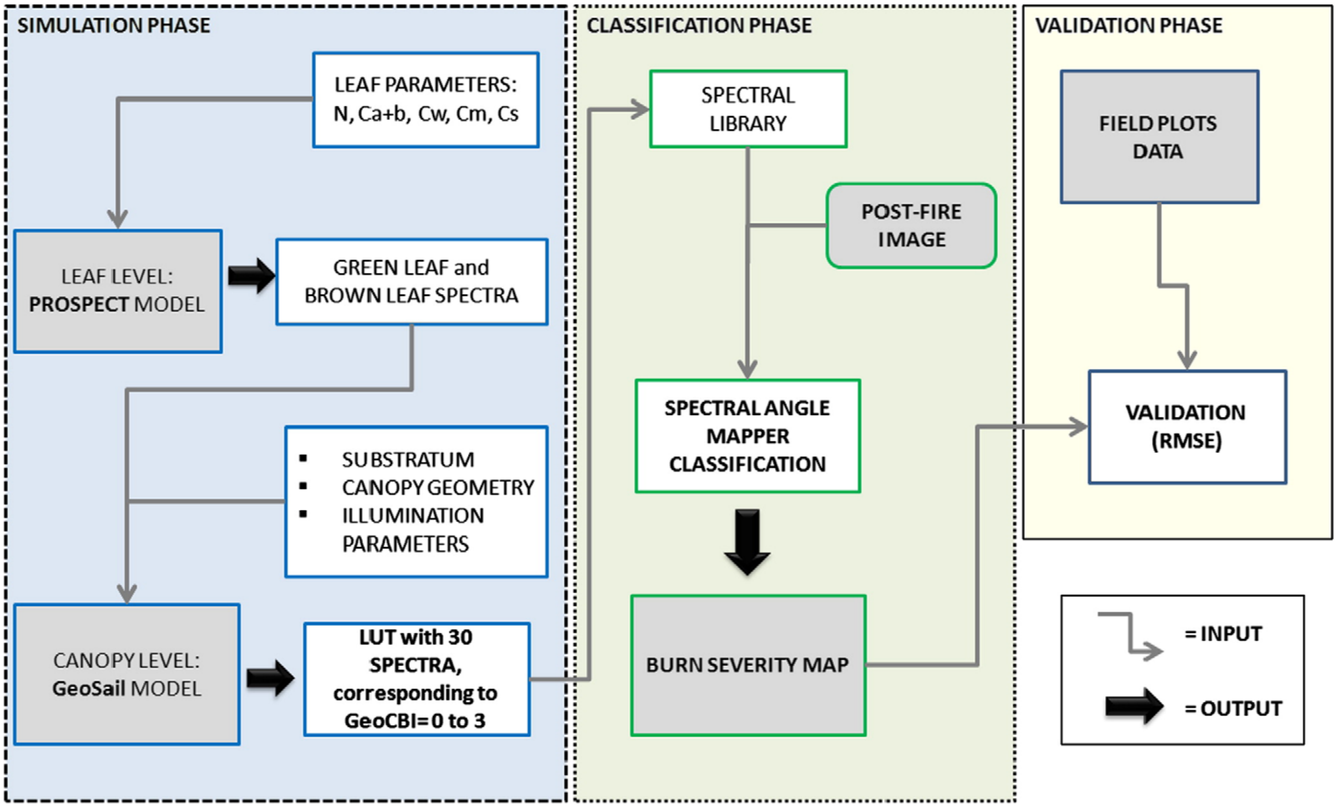

Fig. 1. Methodological workflow used in this study.

Patterson & Yool, 1998; van Wagtendonk et al., 2004; Wang, 2002). Moreover, Rogan & Franklin (2001), having analyzed 71 different publications, observed that, as the number of burn severity classes considered increases, the accuracy of burn severity estimation decreases from 80% (for two classes: burned/not burned) to only 35% (for five classes).

To solve this limitation in accuracy and precision, recent studies have proposed the use of Radiative Transfer Models (RTMs) to simulate the continuum interval of burn severity levels measured in CBI (Chuvieco et al., 2006, 2007; De Santis & Chuvieco, 2007). RTMs simulate spectral signatures from a set of input parameters at both leaf and canopy level. In the forward simulation mode, RTMs are used to analyze the effects of such plant parameters on spectral reflectance, whereas, in the inverse mode, spectra (from remotely sensed data) are used as an input to estimate some of those plant parameters (output). The use of RTMs in forward mode to simulate burn severity scenarios (in terms of CBI) was proposed by Chuvieco et al. (2006). De Santis and Chuvieco (2007) used the same simulation scenario in the inverse mode to estimate CBI values from a large forest fire using Landsat-TM images. RTMs used in both studies performed better than the traditional empirical fitting (De Santis & Chuvieco, 2007) especially in the extreme values of burn severity. However, in the intermediate range, burn severity was not correctly estimated, due to the high *vertical* contrast between the understory, which was highly affected by the fire, and the less affected overstory (Chuvieco et al., 2007; De Santis & Chuvieco, 2007). In these studies, the simulation was carried out linking two models: PROSPECT (Jacquemoud, 1990), a widely used leaf level model, and a canopy model developed by Kuusk (Kuusk, 2001), which considers each vegetation stratum as a homogeneous layer composed of a turbid medium. These models are simple to compute and fit well into the structure of the field index used. However the assumption of a uniform turbid medium composition is not often the case in many forested areas, composed of non homogeneous vegetation layers that are unevenly distributed. An alternative to solve these problems is using geometric RTMs, which take into account the canopy structure and the illuminated/shadowed elements in the plot.

Therefore, the main objective of this paper is to test the performance of a geometric RTM in order to improve the estimation of burn severity from satellite images. New study sites were considered to test the generalizing power of the model, although the scenarios always refer to the evaluation of short-term effects of fire within Mediterranean ecosystems. Burn severity was defined in terms of GeoCBI, a new version of the original CBI field index that is better adapted to the use of remotely sensed data (De Santis and Chuvieco, submitted for publication).

2. Materials and methods

2.1. Methodological workflow

Three consecutive phases were carried out to perform this study: simulation, classification and validation (Fig. 1).

Simulation of burn severity values was accomplished by linking PROSPECT and GeoSail RTMs, two well known leaf and canopy models, respectively. At leaf level, PROSPECT model estimated leaf reflectance and transmittance from biophysical input parameters. Both reflectance and transmittance, together with a series of canopy parameters

Table 1
Hierarchical structure of the GeoCBI and its adaptation to the GeoSail simulation model

Field estimation				GeoSail simulation
GeoCBI of total plot	Understory	A: Substratum	⇨	Substratum
		B: Herbs, low shrubs and trees <1 m	⇨	Understory
		C: Tall shrubs and trees = 1 to 5 m		
	Overstory	D: Intermediate trees = 5 to 20 m	⇨	Overstory
		E: Large trees >20 m		