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Remote sensing information for fire management and fire effects assessment

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[1] Over the past decade, much research has been carried out on the utilization of advanced geospatial technologies (remote sensing and geographic information systems) in the fire science and fire management disciplines. Recent advances in these technologies were the focus of a workshop sponsored by the EARSEL special interest group (SIG) on forest fires (FF-SIG) and the Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD) fire implementation team. Here we summarize the framework and the key findings of papers submitted from this meeting and presented in this special section. These papers focus on the latest advances for near real-time monitoring of active fires, prediction of fire hazards and danger, monitoring of fuel moisture, mapping of fuel types, and postfire assessment of the impacts from fires.

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1. Introduction

[2] Fire is a natural process in many ecosystems that have a long history of fire disturbance. Most developed countries have well-established procedures and the physical and human infrastructure to carry out fire suppression in order to protect lives and property [*Goldammer and Stocks*, 2000; *Grissom et al.*, 2000; *Keeley and Fotheringham*, 2001; *Ward and Mawdsley*, 2000]. As a result, the fire regime in many ecosystems has been altered. For example, the suppression of many small, low-intensity fires has led to a growing accumulation of fuel, which have resulted in larger and more intense fires over the long term. In this regard, a comparison between fire regimes in the United States and Mexican sides of California shows very distinct patterns [*Minnich*, 1983]: For similar ecosystems, the number of fires is much lower in the United States than in Mexico, but the total burned area is fairly similar.

[3] Results from similar studies have shown that fire policy needs to be reviewed and several countries are currently using prescribed burning to reduce fuel loads, or have adopted a “let them go” policy for fires that have natural causes [*Grissom et al.*, 2000; *Ward and Mawdsley*, 2000]. In other countries, such as most of Europe where forest fires have a great impact, fire is still considered harmful, and society demands additional means of fire suppression and fire risk estimation [*Vélez*, 2004]. On the other hand, as many developing countries have not developed the infrastructure for fire suppression, most fires are allowed to burn without intervention, even though they are mainly human caused.

[4] Any environmental policy requires the timely generation of reliable information to support decision making. For fire management, this information includes maps of (1) historical patterns of fire ignitions, sources, and burned area; (2) the location of buildings, homes, roads, railroads and utility corridors; (3) vegetation type and fuel loads; (4) fuel condition, in particular the moisture content of live and dead vegetation; (5) topography; (6) the potential damage to the landscape and human values resulting from fire (e.g., fire vulnerability); and (7) the impacts of the fire on vegetation regrowth, erosion, and other environmental characteristics (associated with burn severity). In addition to the data itself, methods are required to integrate data from multiple sources and provide information in a timely fashion. Managers require the means and approaches to integrate these information products into assessments of fire risk and probability.

[5] Fire statistics are rather poor in most fire-affected countries. Most fires are georeferenced very coarsely or not at all, although in recent years the growing use of global positioning system (GPS) technology has improved the situation in developed countries. Fire danger ratings are generated in many countries using meteorological data [*Stocks et al.*, 1989], which is very coarse in many areas of the tropical and boreal regions, the most affected globally by biomass burning.

[6] Information derived from satellite and airborne remote sensing systems provide a sound alternative to derive critical information for fire scientists and decision makers. This information is spatially comprehensive, provides the capability for periodical updating, and information can be directly derived from land-surface characteristics, instead from surrogates (like atmospheric conditions, as in the case of meteorological data). The most challenging issues for the

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operational use of remotely sensed data in fire-related research and management are associated with the current status of satellite sensor technology (including the generation and provision of information in a timely fashion), the present status of satellite missions that lack the spatial, spectral or temporal resolution required for operational needs, and further developing the geospatial technology and analytical approaches required for the delivery of information products.

2. Summary and Context of the Papers of the Special Section

[7] In June of 2005 the 5th international workshop on remote sensing and GIS applications to forest fire management: fire effects assessment was hosted by the University of Zaragoza in Zaragoza, Spain. This workshop was coorganized by the EARSEL special interest group (SIG) on forest fires (FF-SIG) and the Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD) fire implementation team. This workshop focused on reviewing research on the uses of remotely sensed data for fire science and fire management, with a specific focus on the following topic areas: (1) global burned scar mapping projects; (2) atmospheric effects of fire; (3) environmental dynamics after fire (regeneration, fire soil effects, landscape patterns, etc.); (4) new sensors for fire detection (UAV, geostationary satellites, fire-dedicated satellites, etc.); and (5) modeling efforts for fire danger and risk estimation.

[8] In this special section, ten papers are presented that deal with using geospatial technologies (remote sensing and geographic information systems (GIS)) for fire science and management. In the following sections, we summarize the findings of these papers in the context of the current state-of-the-science.

2.1. Active Fire Detection From Space

[9] Satellite observation of active fires is based on two different physical principles. On the one hand, fire produces light, and therefore can be detected on nocturnal satellite imagery using the visible wavelengths of the electromagnetic spectrum [*Cahoon et al.*, 1992; *Elvidge*, 2001]. On the other, the high temperatures that fires generate greatly increases the radiance emitted in the middle infrared bands, with those centered on the 3.7 μm being most suitable for active fire detection.

[10] The detection of fire lights has been achieved using the optical landscan sensor (OLS) on board the Defense Meteorological Satellite Program satellite series. The spatial and temporal resolution of the OLS is rather coarse, but this system has provided accurate data on the spatial patterns of fire occurrence through differentiating between stable lights (cities, power stations) and dynamic lights (mostly fires) [*Elvidge*, 2001].

[11] The detection of active fires has been most commonly achieved from the analysis of middle infrared data. The first information products were based on data collected by the AVHRR (Advanced Very High Resolution Radiometer) on board the NOAA meteorological satellite, the first of which was launched in 1979. Although channel 3 (centered at 3.7 μm) of this sensor has low sensitivity (it saturates at 320 K), and therefore produces frequently false alarms [*Robinson*, 1991], the daily coverage of AVHRR has provided useful information on fire patterns in many regions of the world [*Flannigan and Vonder Haar*, 1986; *Kaufman et al.*, 1990; *Stroppiana et al.*, 2000] and has been used in an operational mode in several regions [*Fraser et al.*, 2000; *Sukhinin et al.*, 2004]. Fire discrimination from AVHRR data has been achieved through establishing global and regional thresholds from the middle and thermal infrared channels mainly, and it is more accurate at night time than at daytime, especially in semiarid regions with high soil temperatures [*Flasse and Ceccato*, 1996]. The Joint Research Center (JRC) of the European Commission supported a worldwide project to obtain active fires globally, by using a decentralized network of AVHRR receiving antennas with a common processing chain (the results of this project, named world fire web, are available on the Internet (http://www-tem.jrc.it//Disturbance_by_fire/products/fire_occurrence/global-fire-product1996-99.htm)).

[12] The European Space Agency's Data User Program created a similar project to map globally active fires from the ATSR (Along Track Scanning Radiometer), on board the ERS-1 and 2 and the Envisat (in this case an improved version of ATSR) satellites. The ESA World Fire Atlas detects fires in ATSR images using two algorithms based on simple thresholds of the 3.7 μm channel at nighttime acquisitions. The detected fires since 2000 are freely available in the web page of the project (http://dup.esrin.esa.it/ionia/wfa/index.asp).

[13] Since 2000, global fire detection has been greatly improved on the basis of data collected by MODIS (Moderate resolution Imaging Spectroradiometer). This sensor includes several bands in the thermal and middle infrared that were specifically defined for detecting fire anomalies, and therefore it provides higher accuracy than AVHRR data. Fire detection is based on a set of rules applied to different spectral bands, including contextual criteria [*Giglio et al.*, 2003, 2006]. Detected active fires are recorded daily and made freely accessible in the internet through the MODIS rapid response team web page (http://rapidfire.sci.gsfc.nasa.gov/firemaps/). Input data are based on both Terra and the Aqua satellites.

[14] New sensors are being planned to more readily fulfill the specific needs of operational fire detection and fire growth monitoring. The most innovative projects in this regard are the BIRD program of the German DLR [*Briess et al.*, 2001] and the Fuegosat of the Spanish company Insa [*Martínez et al.*, 2000].

[15] While existing and planned orbiting satellite systems provide valuable information on the location and extent of active fires, the temporal frequency of sampling from these systems (at best 2 times per day) is low for many fire management activities. To overcome this limitation, data from the Geostationary Operational Environmental Satellite (GOES) system can be used. The utility of these data for fire monitoring was first demonstrated for fires in South America by *Prins and Menzel* [1992]. The GOES satellite systems can detect fires within their field of view every 30 minutes, and have proven to be useful for monitoring active fires [*Prins et al.*, 1998]. Recently, scientists have begun to explore the utility of GOES data from other regions for fire monitoring. In this special section, the paper

by *Calle et al.* [2006] evaluated the utility of data collected by the SEVIRI (Spinning Enhanced Visible and Infrared Imager) instrument onboard the European MSG (Meteosat Second Generation) satellite for fire detection. *Calle et al.* [2006] not only validated that SEVIRI could detect fires as small as 0.7 ha in size, but showed that the radiant energy detected by SEVIRI was proportional to the energy being emitted by individual fire events. This demonstration is an important step for implementing the operational use of data collected by the GOES system on an operational basis.

2.2. Mapping Fuel Types and Fuel Conditions and Assessing Fire Risk

[16] The term "fire danger" is widely used in forest fire literature and refers to the "process of systematically evaluating and integrating the individual and combined factors that determine the ease of a fire starting and spreading, difficulty of control and some immediately evident fire impacts (e.g., crown scorch, depth of burn) based on an assessment of ignition risk, the fire environment (i.e., fuels, weather, topography) and values-at-risk" (*Countryman* [1966], as quoted by *Lee et al.* [2002]). Following a broader definition taken from the natural disasters literature, the prefire assessment should also consider the potential effects of fire once it occurs (the likelihood of damage) [*Jones*, 1992; *Jain*, 2004]. Within this context, fire risk should consider both fire danger and fire vulnerability. The former should consider the probability of fire ignition and fire propagation, while the latter should take into account the values at stake, both human (properties, recreation, wood value, etc.) and ecological (soil erosion potential, damage to endemic species, plant resilience, and so on).

[17] Fire danger estimation requires constant updating of climate and fuel moisture information that is spatially distributed. The role of remote sensing focuses on generating some of the required input variables for fire ignition and fire propagation estimation [*Chuvieco et al.*, 2003b]. The most relevant variables in this context are the estimation of fuel moisture content (FMC) and fuel loads and distribution.

2.2.1. Fuel Type Mapping

[18] Description of fuel properties is critical in all phases of fire management and fire science: prevention, fire danger estimation; suppression: fire behavior modeling; fire effects assessment: trace gas emissions; and vegetation recovery after fire [*Chuvieco et al.*, 2003c]. Several fuel characteristics are critical for fire propagation studies: crown bulk density, crown base height, canopy height, canopy closure, surface area to volume ratio, vertical and horizontal continuity, dead and live fuel loads, live woody loads, and size of particles in reference to vegetation geometry. In addition, fuel moisture (see Section 2.2.2 below) is related to vegetation physiology and variations in climate. Since the combination of fuel properties of vegetation species are almost infinite, the description of those properties relevant to fire danger estimation and fire propagation studies is based on fuel types, defined as "an identifiable association of fuel elements of distinctive species, form, size, arrangement, and continuity that will exhibit characteristic fire behavior under defined burning conditions" [*Merrill and Alexander*, 1987]. Vegetation type can provide a clue type the morphology, dead woody debris, and surface litter properties [*Keane et al.*, 2001], but are not necessarily a determinant for fire management, since the same vegetation type may present completely different fire propagation rates if their fuel load, density, vertical continuity, compactness, or surface area to volume ratio characteristics, among others, change over time [*Anderson*, 1982; *Andrews*, 1986; *Deeming et al.*, 1978].

[19] Several fuel type classification schemes have been proposed. The best-known classification system was developed by the U.S. Forest Service's Northern Forest Fire Laboratory (NFFL) of Missoula for the development of the Behave fire propagation model [*Albini*, 1976; *Anderson*, 1982]. This scheme was based on the type of vegetation covering the forest understory: herbaceous, shrub, dead leaves, slash residues and basal accumulation material. The main difficulty in classifying these fuel types from remotely sensed data is in the estimation of fuel height (which is critical in fuel load assessment) since passive optical sensors only provide 2-D information. An additional problem relies on the emphasis of the NFFL classification on surface fuels. Surface vegetation may be covered by the forest canopy, and therefore will not be directly sensed from satellite images.

[20] In spite of these difficulties, researchers have carried out fuel type mapping from medium and high-resolution sensors, primarily using Landsat-TM and MSS data [*Anderson et al.*, 1993; *Fazakas et al.*, 1999; *Riaño et al.*, 2002]. The results were good (above 80% accuracy) for some categories (grasses, dense forest, dense shrub), but failed for those that require height estimations for discrimination (models 4, 5 and 6 of the NFFL system) or were under the canopy layer (model 7).

[21] Radar and Lidar sensors provide a possible alternative to the two difficulties previously stated. On one hand, L or C-band radar data may provide additional information on the forest understory, thanks to their canopy penetration capability. Numerous studies based on ERS-1, JER-1 and Radarsat data have been undertaken to predict forest attributes that are critical for fuel type mapping, such as foliar biomass, tree volume, tree height and canopy closure [*Hyyppa et al.*, 2000; *Ranson et al.*, 1997; *Toutin and Amaral*, 2000]. However, current limitations of active microwave data preclude their use for accurate estimation of canopy height, since the uncertainty in the estimation is greater than 5 m [*Hyyppa et al.*, 2000; *Toutin and Amaral*, 2000]. Another limitation is that radar is insensitive to high biomass levels [*Kasischke et al.*, 1997]. The estimation of 3D attributes that are required for fuel type discrimination may be achievable from active optical sensors (Lidar), which are able to measure distances in the vertical spatial domain [*Peterson et al.*, 2003]. From Lidar measurements, researchers have generated critical parameters for fuel parameterization, such as crown height and crown bulk density [*Naesset and Okland*, 2002; *Peterson et al.*, 2003; *Riaño et al.*, 2003; *Riaño et al.*, 2004]. Unfortunately, this technology is still very expensive and covers small areas, since only airborne systems are available.

[22] In this special section, several papers explore the use of satellite remote sensing data for mapping of vegetation cover for use in wildfire danger assessment. *Cheret and Denux* [2007] developed an approach for assessing wildfire danger using maps of vegetation cover derived from an

analysis of coarse resolution SPOT-Vegetation data. These data were combined with information on topography, fire ignitions, and climatic indices, derived from analysis of time series SPOT-Vegetation data (see section 2.2.2 below). These parameters were combined within a model to estimate spatially explicit estimates of fire severity. Often, fire managers require finer-resolution maps of fuel types for decision making, in particular in making decisions with respect to deployment of resources during actual suppression events. *Arroyo et al.* [2006] explored the utility of high-resolution (4 m) satellite imagery for the production of fuel type maps. In this study, *Arroyo et al.* [2006] explored a new data processing approach, object-oriented classification, which allows for considering spatial context of adjacent pixels in the eventual generation of the fuels map. It was concluded that this approach produced higher accuracies than would have been generated using traditional maximum likelihood classifiers. Finally, the paper by *Perez-Cabello et al.* [2006] explores the use of satellite imagery for identifying erosion-sensitive areas following wildfires. They found that the most important variables for predicting erosion potential were site aspect and the prefire vegetation greenness (NDVI) derived from satellite imagery.

2.2.2. Mapping of Fuel Moisture

[23] The estimation of FMC has been based on several methods, including field sampling, meteorological indices, and remote sensing techniques. Field sampling is the most direct method, but it is also the most difficult and costly. Most operational fire danger rating systems base their estimation of fuel moisture conditions on meteorological data [*Stocks et al.*, 1989]. Most commonly, those meteorological danger indices try to estimate fuel water content of dead materials present in the forest understory or lying on the forest floor, which are the driest and most likely to ignite. In spite of the relevance of also estimating the FMC of live fuels, few models explicitly include such estimation.

[24] The spatial and temporal coverage provided by remote sensing systems makes this data source a useful alternative to estimate FMC for a whole area at regular time intervals. Unlike meteorological indices, which refer to the specific conditions where the weather stations are located, remote sensing data are spatially comprehensive, covering the whole territory at various spatial resolutions, from few meters to few kilometers, depending on the sensor. Moreover, remote sensing data result from the vegetation conditions (reflectance or temperature) at the time of imaging, whereas meteorological indices measure FMC indirectly, through the analysis of atmospheric characteristics from which vegetation water status is estimated. Several authors have shown the potentials of remote sensing data to estimate water content of plants, both using simulation models [*Ceccato et al.*, 2001, 2003; *Fourty and Baret*, 1997; *Zarco-Tejada et al.*, 2003], and empirical data [*Chuvieco et al.*, 2002, 2003a, 2004; *Peters et al.*, 2002; *Sims and Gamon*, 2003; *Tian et al.*, 2001].

[25] Most authors working on radiometric measurements and simulations based on radiative transfer models (RTM) have shown that reflectance in the SWIR (1000–2500 nm) is greatly affected by the amount of water content, especially at the leaf level [*Ceccato et al.*, 2001; *Hunt et al.*, 1987; *Sims and Gamon*, 2003]. However, at the canopy and plot levels, other variables such as leaf area index or fraction of vegetation cover may prevail over the water signal, thus creating severe difficulties for retrieval of water content, especially in cases where these variables cannot be estimated from other sources [*Zarco-Tejada et al.*, 2003]. Most simulation studies have been based in the equivalent water thickness (EWT), defined as the amount of water per leaf area. However, in forest fire danger estimation, EWT has never been considered, and the key water variable related to fire ignition (ignition delay, ignition potential) or fire behavior is the amount of water per dry mass unit (named fuel moisture content, FMC). The conversion between EWT and FMC may be based on the specific leaf weight, which implies that the estimation of FMC from reflectance measurements is required to estimate the effect of dry matter variations on reflectance, which is species dependent.

[26] The use of thermal data to estimate water content has also been tested by several authors [*Jackson et al.*, 1981; *Vidal et al.*, 1994]. The relations between water and temperature are governed by the rate of evapotranspiration from plants, which use part of the incoming radiation to convert liquid to gaseous water (latent heat), as a mechanism of thermal regulation.

[27] Several authors have shown good empirical relations between FMC and satellite derived variables in several ecosystems. FMC for grasslands was more efficiently estimated than for other fuels [*Chladil and Nunez*, 1995; *Chuvieco et al.*, 2002; *Hardy and Burgan*, 1999; *Paltridge and Barber*, 1988], because water variations in grasslands have a greater effect on other variables that critically affect plant reflectance (such as chlorophyll content or leaf area index), and are more sensitive to seasonal variations than shrubs or trees. Experiences with ecosystems that contain shrubs have been less successful, with diverse trends regarding the different species analyzed [*Alonso et al.*, 1996]. Satellite variables most commonly used are the Normalized Difference Vegetation Index (NDVI) and Surface Temperature (ST) or a combination of the two [*Leblon*, 2001; *Chuvieco et al.*, 2004]. Most of the referred studies were based on NOAA-AVHRR data, which provides a long-time series and a proper spatial and temporal resolution for regional studies. Recent sensors, such as SPOT-Vegetation and Terra-MODIS provide an alternative for FMC estimation, since they provide data in the SWIR and therefore direct estimation of EWT may be achievable [*Ceccato et al.*, 2003]. Finally, several researchers have demonstrated a relationship between fuel moisture and variations in radar backscatter recorded by the ERS-1 SAR satellite [*Bourgeau-Chavez et al.*, 1999; *Leblon et al.*, 2002].

[28] Several papers in this special section explore the use of remotely sensed data for the estimation of fuel moisture. To assess the potential use of satellite data for this purpose, *De Santis et al.* [2006] used laboratory-based studies, which included manipulations of the moisture of a single tree species (Holm oak) and measurements by two spectral radiometer systems. These studies identified suitable channels for discrimination between effects caused by moisture variations and those caused by variations in canopy background conditions, and provided insights for scaling up from ground to airborne/spaceborne observations. *Roberts et al.* [2006] carried out field-based observations of fuel moisture in a California shrubland ecosystem in order to assess the potential of AVIRIS hyperspectral and MODIS

multispectral imagery for assessing fuel moisture. They were able to find significant correlations between live fuel moisture and indices derived from both remotely sensed data sets. Finally, *Cheret and Denux* [2007] used seasonal vegetation greenness indices (NDVI) derived from SPOT – Vegetation data to produce meteorological index of drought potential for predicting wildfire danger.

2.2.3. Assessing Long-Term Fire Risk

[29] The generation of new and more accurate information layers as well as the availability of geographic information makes it possible for fire scientists and managers to have access to and utilize new data sources not previously available. However, challenges still remain in the effective utilization of these data, in particular in integrating these data within models and decisions support systems. In this special section, *Amatulli et al.* [2006] explore these challenges in the context of predicting long-term fire risk at a local scale. They utilize an approach that incorporates classification and regression tree analyses in order to be able to use different classes of independent variables (e.g., categorical and continuous).

2.3. Mapping of Burned Area and Fire Effects

[30] The use of remote sensing methods in fire effects assessment has grown notably in the last decade, using both high and low-resolution satellite sensors [*Ahern et al.*, 2001]. For global applications, the use of NOAA-AVHRR data was extensively tested in the 1990s. Most commonly, burn scar areas were discriminated from a multitemporal comparison of NDVI or other spectral indices [*Kasischke and French*, 1995; *Martín and Chuvieco*, 1995; *Pereira*, 1999], although some combination of thermal and optical channels have also been undertaken [*Fraser et al.*, 2000; *Sukhinin et al.*, 2004].

[31] More recently, other sensors with greater sensitivity for mapping burned scars have been used to create a global inventory of burned areas. In 2000, two worldwide projects were developed, one based on SPOT-Vegetation data, named GBA2000 and the other one based on ATSR-2 images, named Globscar. The former was coordinated by the Joint Research Center and created a global product of burn scars from several regional algorithms that intended to be better adapted to ecosystem variability. The final product has not been fully assessed, but first results show good agreement with expected trends [*Tansey et al.*, 2004]. The Globscar project is an initiative of the ESA, and it is based on ERS-2 ATSR images, using two global algorithms based on multiple thresholds [*Simon et al.*, 2004]. The bottle neck of these global approaches is the assessment of results, which is very complex and costly. However, the importance of undertaking a proper assessment of global products is becoming increasingly important in order to reduce uncertainties when using them as an input to other estimation models. The example on using burned land maps in the estimations of gaseous emissions derived from biomass burning in a clear example. Finally, the MODIS program plans to release soon a standard product on burned land areas at global scale, which will be based on a multitemporal change detection approach to analyze differences between modeled and actual reflectance, and to take into account BRDF corrections [*Roy et al.*, 2002, 2005].

[32] At local scale, a great number of papers have been published, mainly based in Landsat-TM/ETM data [*Koutsias et al.*, 1999]. The range of techniques used for discriminating burn scars is very wide, covering simple ratios and vegetation indices [*Chuvieco and Congalton*, 1988; *López García and Caselles*, 1991], to linear transformations (tasselled cap, principal component analysis [*Siljeström and Moreno*, 1995]), spectral unmixing [*Caetano et al.*, 1996], and a whole range of classification systems [*Gitas et al.*, 2004; *Kushla and Ripple*, 1998; *Sunar and Özkan*, 2001].

[33] While the discrimination of burned/unburned areas has been achieved with reasonable good results, even from low-resolution satellite data, burn severity estimation remains a challenge, although several studies have explored this issue in the recent literature [*Epting et al.*, 2005; *Key and Benson*, 2005; *van Wagtendonk et al.*, 2004]. Burn severity is a critical parameter for fire assessment, both from an ecological and atmospheric point of view, since the amount and distribution of biomass burned has a direct impact on gas emission estimation and is critical for projecting fire recovery after fire. Burn severity is rarely evaluated, even from field data. Considering the large field effort that burn severity requires, several papers in this special section further explore this potential.

[34] In this special section, *Chuvieco et al.* [2006] provide a theoretical assessment of the potential of using visible, near IR, and SWIR data assessing fire effects. They use a radiative transfer model to predict how damage from fires will alter the spectral reflection from a vegetated surface, and used the composite burn index (CBI) as a basis to estimate fire effects. This study showed that fire alters different regions of the electromagnetic spectrum, with the greatest impact occurring in the near IR region, followed by the SWIR and red regions. The study demonstrated that there are multiple wavelength regions where spectral indices produce correlations with CBI.

[35] Field-based assessments of satellite data sets were carried out in two papers. *Walz et al.* [2007] evaluated the differenced normalized burn index (dNBR) using both Landsat TM and MODIS imagery in a subtropical forest in southwest Australia. They concluded that in this region, burn severity derived from MODIS provided a good first-order assessment of fire severity. In contrast, *Roldan-Zamarron et al.* [2006] evaluated a number of different techniques for analysis of burn severity using Landsat TM, MERIS, and MODIS imagery in a Mediterranean ecosystem in Spain. They found that the NBR was the least accurate method for mapping burn severity, following matched filtering and linear spectral unmixing approaches.

[36] Finally, while *Perez-Cabello et al.* [2006] considered using post fire burn severity measures (NBR and dNBR) to assess potential for postfire erosion, the most accurate model they developed included neither of these parameters.

3. Discussion and Conclusions

[37] In spite of the recent increase of scientific dealing with remote sensing and fire-related topics as a result of important of research in this direction, there are still few operational systems that use routinely remotely sensed data in any of the three phases of fire management: estimation of fire danger conditions, detecting active fires and assessing

postfire effects. This fact may be caused by the lack of satellite missions oriented toward the fire community or the immaturity of some estimation approaches. The former is evident in the fire suppression phase, because none of the current Earth observing systems provides enough spatial and temporal resolution for operational fire detection. The latter is clear in some critical fire products, such as fuel type maps that require additional efforts to provide accurate estimations of fuel spatial variability.

[38] Recent advances in image processing of medium and low-resolution satellite data makes it possible to foresee the operational use of those data very close. This is the case, for instance of the burn scar mapping, which is already undertaken in some countries. Discrimination of burn severity requires more research, to tackle the different effects of fire damages on postfire reflectance, especially when forest is stratified in different vertical layers. Water content of fuels is also close to being operationally estimated, although more problems are expected when water needs to be computed as a function of dry weight and not of leaf area. The growing availability of data from new sensors, such as Lidar or interferometric radar may also solve the current problems with fuel type maps.

[39] Most fire scientists recognize the need of more updated and more accurate spatial information to improve current decisions for prefire planning and postfire mitigation. Most environmental decision makers acknowledge the importance of fire for atmospheric, hydrological, edaphological and vegetation management. New Earth Observation missions should tackle current technical limitations of available sensors if we intend to use remotely sensed data operationally. Additionally, we should maintain the effort of providing validated products that are properly integrated with other sources of information for comprehensive fire risk and fire effects assessment.

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