Chapter 6
Satellite Observation of Biomass Burning

Implications in Global Change Research

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Abstract Biomass burning, which involves wildland fires as well as agricultural and grassland burnings, plays a critical role in the environmental equilibrium of our planet, since it is a major driving force in land cover transformations and contributes significantly to greenhouse gas emissions. Several satellite missions provide critical information required to better understand the temporal and spatial distribution of biomass burning. Satellite images provide objective and comprehensive information on global patterns of fire occurrence, as well as data on factors affecting fire ignition and propagation. Recent improvements in spatial, temporal, and spectral resolution of satellite remote sensing systems reduce past uncertainties – systems can now be used to obtain a more precise evaluation of burned areas and post-fire effects on soils and plants. Greater efforts are required to operationally use Earth Observation data in fire prevention and early warning. Longer time series data are required to acquire a better understanding of fire regimes, and their mutual relationships with global warming.

6.1 The Role of Fire in Global Change Analysis

Fire is a natural process driving landscape transformation for many terrestrial ecosystems, which are adapted in one way or another to recurrent burning. Fire has positive and negative effects on soil, water, vegetation and the atmosphere, the review of which are outside the scope of this text. Figure 6.1 presents a general scheme on which aspects of biomass burning might be considered at global-scale, by identifying the uses of fire by human beings, the effects of fire on environment and society, and the main factors driving global fire activity.

Fire results in the transformation of dead or senescent vegetation into its mineral components, providing a short-term pulse of key nutrients that facilitate vegetation regrowth. Intentional setting of fire is a common practice in savanna areas of Africa or South America, where millions of hectares are burned annually to remove unpalatable grasses and to promote the growth of fresh grass for grazing (Van Wilgen 1997). In forested areas, fire aids in stand thinning, the clearing of understory vegetation, and promotes vertical stratification of the forest canopy. As a result of these

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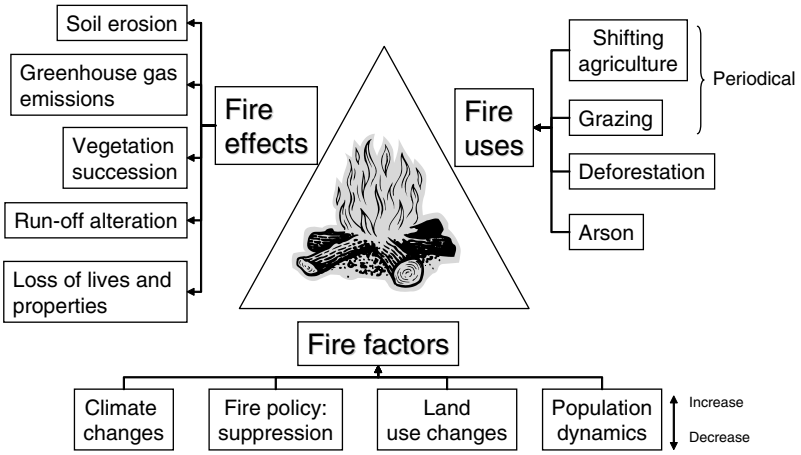

Fig. 6.1 Framework for analysis of biomass burning at global scale

positive feedbacks, natural fire regimes provide a common framework for species succession (Johnson and Miyanishi 2001; Omi 2005).

However, fire has also been used historically as a clearing tool for land use transformation, removing trees from forested areas for agricultural or grazing purposes. These transformations may be perennial or cyclical, depending on the type of agricultural practice in place. For most tropical countries, shifting cultivation has been the traditional form of farming (Spencer 1966). This regime is based on using fire to remove forest cover while fertilizing the land by providing N and other nutrients to mineral soils. After a few years, yields are reduced as a result of intense rainfall that results in leaching of nutrients from soils and soil erosion. As a result, farmers need to move to another forested area to start a new cycle, and from there on to another one, until they return to the original location in 30 to 40 years. In recent decades, these cycles have been shortened, as a result of a more intense land use, and therefore the crop production is increasingly degraded. Reduced agricultural yields, in turns, increases poverty and migration to urban regions.

The use of fire for permanent land cover change has been historically associated with movements of the agricultural frontier, as it was evident in the temperate forest of North America during the eighteenth and nineteenth centuries (Pyne 1995). Currently, the conversion of forested to agricultural or grazing areas is mainly occurring in tropical forests. Deforestation is one of the main factors to take into account in global carbon budgets, since they affect large areas (Houghton et al. 1985), and accounts for a significant proportion of total greenhouse emissions: 26% for carbon dioxide, 48% for methane and 33% for nitrous oxide has been estimated from deforestation processes (Houghton 2005). The relation between fire and deforestation, both complete clearing and selective logging, has been well documented (Cochrane et al. 1999; Skole and Tucker 1993; Souza et al. 2005).

For industrialized societies, the opposite trend has been observed, since land abandonment has occurred over the past century, as a result of changes in economic

policy and immigration to cities. As a result, in many areas, patterns of traditional human-ignited fire activities have been altered and long-established practices in rural areas (grazing, energy consumption from wood, etc) have also been discarded. These changes have resulted in a larger accumulation of fuels, which increase fire intensity and severity compared to natural conditions, altering landscape structure that was historically shaped by less severe fires (Vega-Garcia and Chuvieco 2006).

The effects of global warming on natural fire regimes have recently been observed lately, especially in boreal regions, where fire seasons tend to last longer and may be more severe (Kasischke and Turetsky 2006).

In summary, increased intensity during burning associated with deforestation in tropical regions and during natural fires in temperate and boreal forests, and increased fire occurrence in boreal forest as a result of climate change all emphasize the importance of improving our understanding of global biomass burning.

In spite of the importance of and interest in biomass burning, a significant amount of information is still required to better understand the spatial-temporal patterns of fire occurrence. In most regions, fire statistics are scarce and mainly focus on commercial forest plantations, leaving aside wildland, savanna and agricultural fires. Only few countries have maintained consistent statistics on fire occurrence, and even fewer generate a cartographic inventory of fire-affected areas. Consequently, only general information about the spatial-temporal distribution of fire is available, which prevents a better understanding of fire regimes and their relationship to human activities and global climatic changes.

6.2 Contributions of Earth Observation Data

Satellite remote sensing is an especially suitable tool for fire monitoring and research. The wide area coverage and high observation frequency provided by satellite-borne sensors, the potential rapid access to acquired data, as well as their collection of data using near and thermal IR data, make their data a very valuable resource for fire detection and mapping and management fire-prone areas.

From the first airborne sensor campaigns of the late sixties (Hirsch et al. 1971) until now, a great range of remotely sensed systems have been used for mapping and analysis of wildland fires. During the 1980s and 1990s, the primary sensors used for fire monitoring were the Thematic Mapper (TM) on board Landsat-4 and 5, and the Advanced Very High Resolution Radiometer (AVHRR) on board the NOAA satellites. The most extensive use of satellite data in this context was the detection of active fires and the mapping of burned areas. The former was based mainly on multiband thresholds and contextual techniques, while the latter was addressed by several techniques: statistical classification, logistic and multiple regressions, neural networks, decision trees, post-fire and multitemporal thresholding, etc., both using high and low spatial resolution sensors. Good summaries of satellite detection and mapping of fires can be found in several textbooks, such as Ahern et al. (2001) and Chuvieco (1999; 2003).

In recent years, new sensors have been added for analyzing global biomass burning, the most important being the Moderate-Resolution Imaging Spectroradiometer (MODIS) sensor on board the Terra and Aqua platforms. Other sensors have been used to derive operational burned area products, such as the VEGETATION, on board the French SPOT-4 and 5 satellites, and the Along Track Scanning Radiometer (ATSR-1 and 2) on board the European ERS satellites and the Advanced ATSR (AATSR) on the Envisat. Higher resolution sensors have been used to generate fire products as well, including the high resolution (1 to 4 m; Ikonos or Quickbird) to medium-high resolution sensors (20–60 m, such as ASTER, IRS-AWIFS or SPOT-HRV).

During the last decade, the range of applications for fire monitoring and management has significantly increased, making satellite remote sensing the main input data source for generating critical information on biomass burning, especially for global applications. A review of current developments will follow, preceded by a presentation of the spectral and temporal requirements for the analysis of global fire activity.

6.3 Physical Basis for Satellite Observation of Biomass Burning

The use of remotely sensed data in fire applications can be grouped into three categories, depending on whether the need for improved information is the determination of fire danger conditions (pre-fire), the detection of hot-spots (active fires), or the analysis of fire effects (post-fire) (Chuvieco and Martín 1994; Jain et al. 2004). These three information needs have different spatial and temporal requirements depending on whether they are implemented by local, regional or national managers (Fig. 6.2). At local scale, the spatial resolution is most critical, while at national scale, frequent coverage is often the highest priority. For fire danger estimation, the main required for a regional manager is to detect changes in vegetation water content, one of the leading factors controlling fire ignition and propagation, while the local manager is mainly interested in fuel loads and horizontal and vertical

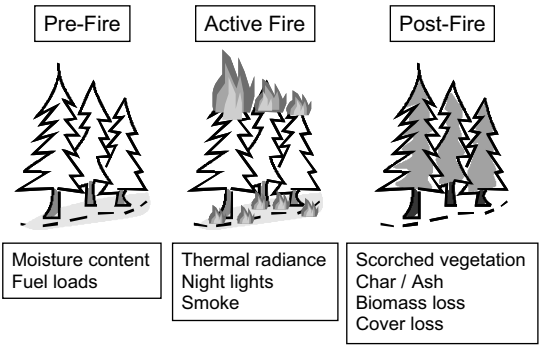

Fig. 6.2 Temporal stages in fire management and main physical variables that can be remotely observed

distribution of fire fuels. Active fire detection requires a high observation frequency (hourly), combined with a fine radiometric sensitivity to avoid false alarms. In contrast, post-fire assessment of burning impacts is not constrained by temporal resolution, since most burn severity evaluation can be carried out weeks or even months after the fire is over. In this case, the spectral and spatial resolution will be the main requirements.

The physical basis to remotely detect fire information varies according to the information required. When the requirement is to estimate fuel moisture content, the contrast between reflectance in the short-wave infrared (SWIR: 1–2.5 μm) and the near infrared (NIR: 0.7 to 1 μm) is most commonly used (Ceccato et al. 2001; Hunt et al. 1987; Sims and Gamon 2003)., although some authors have proposed the use of two narrow bands in the NIR (Peñuelas et al. 1997). Most spectral indices are sensitive to the amount of water per leaf area (named, equivalent water thickness, EWT), while fuel moisture content (FMC) is a measure of the amount of water per dry matter (DM). Therefore, an accurate estimation of FMC requires both the variations of water and DM contents (Danson and Bowyer 2004; Fourty and Baret 1997; Riaño et al. 2005). The use of thermal IR 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 (ET) from plants, which uses part of the incoming radiation to convert liquid to gaseous water (latent heat) as a mechanism of thermal regulation. Water stress implies a reduction in ET, and therefore an increase in surface temperature when compared to non-stressed plants (Moran et al. 1994).

For fuel loads and fuel type mapping, the main target variable is the vertical and horizontal arrangement of the vegetation components. This application has been pursued with different sensors, with the most accurate results obtained using sensors that measure heights, instead of reflectance, using mainly airborne sensors, such as the interferometric RADAR and LIDAR (Riaño et al. 2004).

Active fire detection is commonly based on the middle infrared (MIR) spectral region (3–5 μm), where following the Wien displacement law, the peak sensitivity to spectral radiance is at the temperature of a vegetation burning (500 to 1,000 K). The contrast between radiance in this region and the thermal infrared (TIR) band (10–12 microns) offers a straightforward discrimination of active fires over average Earth temperatures (300 K), providing the sensor has enough radiometric sensitivity and the fire is large enough relative to the sensor target pixel size. Active fires can also be discriminated by the light they display in nocturnal images, if the sensor offers high sensitivity to low radiances and that stable lights (cities, industries) can be properly discriminated from intermittent ones (fires, volcano eruptions). Detection of fires has been achieved through the analysis of smoke plumes, as well.

Finally, post-fire effects are discriminated by analyzed the changes in leaf color, leaf area index and soil substratum after the fire has been extinguished. The short-term signal is dominated by charcoal, ash, and scorched leaves, while the medium to long-term signal is associated with lost of vegetation abundance or changes in species composition (Pereira et al. 1999; Roy and Landmann 2005).

6.4 Satellite Information for Assessing Fire Risk

Following a terminology that is generally accepted in natural hazard literature, the term risk refers to the combination of the physical probability that an undesired event occurs and the degree of potential damages caused by that event (Jones 1992). Within this framework, the assessment of fire risk should consider both the likelihood that a fire affects a particular area (danger), as well as the values at stake within that area (vulnerability) (Allgöwer et al. 2003). The former should consider the probability that a fire ignites and propagates, while the latter should take into account socio-economic values (properties, recreation resources, wood value, etc.), as well as the potential environmental damage (vegetation degradation, soil erosion potential, lost of endemic species, landscape quality, etc.) that may result from a fire.

The role of remote sensing data in fire risk assessment can also be grouped into these two categories: (1) generation of critical variables for fire ignition or propagation (Chuvieco et al. 2003b); and (2) assessment of resource values at risk. Most studies using satellite data for fire risk assessment have focused on the former, especially in the estimation of fuel moisture content and distribution of fuel types. Little effort has yet been dedicated to estimate vulnerability, although in recent years some analysis have been conducted with high-resolution images and census data to assess the risk potentials in the urban wildland interface (Radeloff et al. 2005). Additionally, a global analysis of population distribution has been performed within the context of natural hazards prevention (Dobson et al. 2000), which may have potential for global analysis of human-caused wildland fires.

6.4.1 Fuel Type Mapping

Description of fuel properties is critical in all phases of fire management and fire research (Chuvieco et al. 2003c): prevention (for fire danger estimation); suppression (fire behaviour modelling), and fire effects assessment (trace gas emissions, vegetation recovery after fire). Since the combination of fuel properties of different vegetation species is almost infinite, the most relevant fuel properties are simplified by generating broad categories that are named fuel types. Depending on the specific information requirement, approaches for fuel type classification may be very different, since they will consider some fuel properties or others. The most well-known fuel classification systems were developed for fire behaviour modelling. In this context, fuel types can be defined as "an identifiable association of fuel elements of distinctive species, form, size, arrangement, and continuity that will exhibit characteristic fire behaviour under defined burning conditions" (Merrill and Alexander 1987). Commonly, a fuel type has a range of quantitative parameters associated to each category, such as average fuel load, density, compactness, distribution of fuel beds by size, etc.

Several fuel type classification schemes have been proposed, the best known being the U.S. Forest Service's Northern Forest Fire Laboratory (NFFL) of Missoula

(Montana), which was developed within the Behave fire propagation model (Burgan and Rothermel 1984). This scheme was developed for surface fires propagation studies and has 13 fuel types, where the groups are based on the primary nature of the surface fuel: herbaceous, shrubs, and dead leaves, slash residues and basal accumulation material.

Other fuel type classification systems include the National Fire Danger Rating System (NFDRS) fuel type classification, which used 20 models and it was intended for general fire danger estimation (Deeming et al. 1978), and the Canadian Forest Fire Behaviour Prediction (FBP) System, with 16 fuel types (Hirsch 1996).

Mapping surface fuel types from remotely sensed data presents two main challenges. On one hand, in many cases surface fuels are hidden below a dense overstory canopy, and are therefore difficult to retrieve from satellite observations. The second problem is associated with estimating of fuel heights and biomass loads, which are required to differentiate several categories, since those parameters are critical in fire propagation.

In spite of these difficulties, researchers have carried out fuel type mapping from medium and high-resolution sensors, using primarily Landsat-TM and MSS data (Anderson et al. 1993; Fazakas et al. 1999; Riaño et al. 2002). The results show accuracies above 80% 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, for instance) or those that were under the canopy layer (model 7 of NFFL). Recent studies have shown the potential improvements in fuel type mapping from very-high resolution data, when several categories of spatial aggregation are considered (Arroyo et al. 2006).

RADAR and LIDAR systems have been used to overcome limitations of passive optical systems for mapping fuel types. The retrieval of understory information has been attempted by several studies based on L band RADAR data (Hyyppa et al. 2000; Ranson et al. 2001), but unfortunately L-band RADAR missions have been very brief, and therefore little experience is available from these data at global scales. On the other hand, active microwave data do not yet provide sufficiently accurate estimation of canopy height, with uncertainties greater than 5 m (Hyyppa et al. 2000; Toutin and Amaral 2000), and therefore the discrimination of shrub fuel types becomes unfeasible. Additionally, microwave signal has shown to have limited sensitivity to high biomass levels (Kasischke et al. 1997).

Airborne LIDAR sensors have proven more successful in the estimation of those geometrical properties that are required for fuel type mapping (Morsdorf et al. 2004; Riaño et al. 2004; Riaño et al. 2003), such as crown base height or crown bulk density (Fig. 6.3). The main drawbacks of this technology are its high costs and highly localized coverage, since most high-resolution sensors are airborne and with narrow fields of view. Accuracy is generally good enough for retrieval of critical fuel parameters although in shrubs fuels, the estimations are more controversial. In a recent study by Riaño et al. (2007a), standard LIDAR processing did not provide enough accuracy for height estimations of shrub species, and it was necessary to rely on passive optical sensors to improve detection of base heights.

Consequently, it is not possible with current sensors to generate a global fuel type maps, since biomass loads and geometrical properties are difficult to retrieve

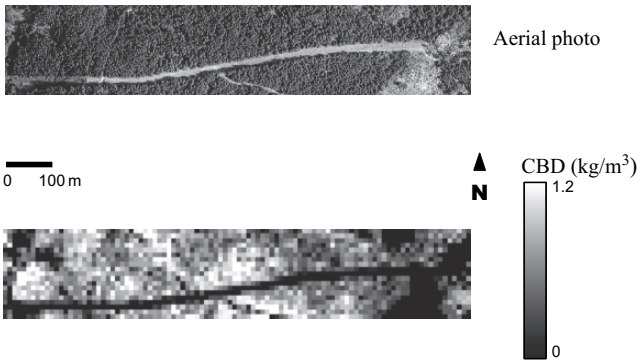

Fig. 6.3 Crown Bulk Density estimated from airborne LIDAR data in the Canencia Forest (north of Madrid). Data processed by D. Riaño (see Riaño et al., 2004)

from optical sensors. Unfortunately, the only orbiting LIDAR system, on board the Icesat satellite, was not designed for vegetation studies and it is not well suited for global retrieval or fuel properties. The coarse footprint (60–70 m) and the footprint cross track separation between orbits (up to 15 km) create severe difficulties for retrieval biomass loads, especially in rough terrain (Harding and Carabajal 2005; Lefsky et al. 2005). A global airborne LIDAR database is being put together (http://www.lidarxchange.com/) that could be used for calibration and validation of fuel classes estimates from optical sensors. At least for general fuel categories, optical sensor data can provide enough accuracy, integrated with other ancillary data or ecological modelling (Rollins et al. 2004), but additional effort is required to improve parameterization of those fuel classes. Meanwhile, the closest available products are vegetation or land cover maps, which provide global information on the spatial distribution of vegetation classes (Friedl et al. 2002; Price 2003; Zhu and Evans 1994), but do not offer quantitative information on their characteristics (biomass loads, heights, density, etc.), and therefore can only be used as a simple-generalized approach to fuel type mapping.

6.4.2 Mapping Temporal Patterns of Fuel Moisture

Fuel moisture content (FMC) is a critical variable for fire ignition and fire propagation studies, since the amount of water on plants is inversely associated to its flammability and fire rate of spread (Dimitrakopoulos and Papaioannou 2001; Nelson 2001). It also affects greenhouse emissions derived from fires, as a result of the impact of FMC on burning efficiency (Korontzi et al. 2004).

FMC has been traditionally based on field observations and meteorological fire danger indices. The former are more reliable and provide a direct measurement, but only offers estimation of local study areas. While meteorological indices provide a wider spatial perspective, they are only indirect estimations since they are based on atmospheric conditions (temperature, humidity, wind, etc.), which in turn affect

plant moisture, but in a different way depending on species physiology. For this reason, they are mainly oriented towards estimating FMC of dead fuels, which are more directly related to changes in atmospheric characteristics.

The spatial and temporal coverage provided by remote sensing systems offers a reasonable alternative for estimating FMC of live fuels at regular time intervals. Unlike meteorological indices, which depend on 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 are based on physical characteristics related to vegetation condition (reflectance or temperature) at the time of imaging, whereas meteorological indices measure live 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; Ceccato et al. 2003; Fourty and Baret 1997; Zarco-Tejada et al. 2003), and empirical approaches (Chuvieco et al. 2004b; Chuvieco et al. 2002b; Peters et al. 2002; Sims and Gamon 2003; Tian et al. 2001). FMC studies have used a wide variety of sensors, including laboratory spectroradiometric measurements, and medium and coarse resolution sensors. Laboratory studies provide important information for understating the effects of external factors, such as illumination angle, density and leaf area index (De Santis et al. 2006; Gillon et al. 2004).

Medium-resolution sensors have been used experimentally to test the sensitivity of spectral reflectance spatial-temporal variations in vegetation moisture, but they are not useful for operational estimation of FMC in fire danger applications because they lack enough temporal resolution. Successful estimation of FMC have been reported with Landsat-TM/ETM images, using empirical approaches on agricultural plots (Chen 2005; Holben et al. 1983; Thompson and Wehmanen 1979), as well as for natural vegetation, grasslands and shrublands, in fire danger estimation (Chuvieco et al. 2002b). RADAR C-band data have also been used for this purpose (Beaudoin et al. 1995; Couturier et al. 2001), but results are more uncertain since the texture components tend to veil the moisture variability of the backscatter signal(Bourgeau-Chavez et al. 1999; Leblon et al. 2002)

The estimation of FMC from satellite data in operational fire danger assessment can only be approached from coarse-spatial resolution sensors, which have the required revisiting frequency to account for short-term variations in plant moisture conditions. Until the launch of the MODIS sensor, the available high temporal resolution sensors did not provide sufficient spectral sensitivity for confident retrieval of FMC. Analyses based on AVHRR images relied in Normalized Difference Vegetation Index (NDVI) time series analysis. While the NDVI is a sound indicator of chlorophyll content and leaf area index, it does not provide a direct estimation of water content (Ceccato et al. 2003). Only when changes in moisture content affect directly the greenness of plants, the NDVI is suitable to monitor FMC, which mainly occurs with herbaceous species (Chuvieco et al. 2004a). For this reason, experiences of retrieving FMC from NDVI data in grasslands have been generally successful (Chladil and Nunez 1995; Chuvieco et al. 2002b; Hardy and Burgan 1999; Paltridge

and Barber 1988). However, the estimations are more erratic with shrub species (Alonso et al. 1996; Chuvieco et al. 2004a; Everitt and Nixon 1986). For this reason, the combined use of surface temperate and NDVI has also been recommended for FMC retrieval from AVHRR images (Chuvieco et al. 2003a; Chuvieco et al. 2004b; Moran et al. 1994), as well as the analysis of the differences between surface and air temperature, as a surrogate of evapotranspiration (Sandholt et al. 2002; Vidal et al. 1994).

The use of MODIS data for water estimation has been successfully tested in several biomes (Cheng et al. 2006; Dennison et al. 2005; Roberts et al. 2006; Stow et al. 2005; Yebra et al. 2007; Zarco-Tejada et al. 2003), providing a sound alternative for FMC retrieval. MODIS offers much higher spectral sensitivity than AVHRR for estimation of water content, since includes several spectral bands in the SWIR and NIR as well as the transition between the NIR and red bands, which has also proven susceptible to water content (Stow et al. 2005). With these foundations, NASA, under a project directed by Susan L. Ustin (www.cstars.ucdavis.edu), is studying the addition of a MODIS global vegetation canopy water content product.

SPOT-Vegetation images have also been used for water content estimation. While providing less spatial resolution than MODIS (1000 versus 500 m), for bands with similar spectral coverage, this sensor offers higher geometric and radiometric accuracy than AVHRR, and it includes a band in the SWIR. Initial results on the retrieval of FMC from SPOT Vegetation have been successful (Chuvieco et al. 2004a; Cocero et al. 2001).

6.5 Active Fires Products from Space Observations

Detection of active fires from space has been used extensively to analyze spatio-temporal patterns of fire occurrence (Dwyer et al. 2000), to account for emissions derived from fires (Randerson et al. 2005) and to relate deviations from fire regimes to major climatic events (van der Werf et al. 2004). Consequently, active fire detection is very relevant for global change studies.

At more local scales, identification of fire outbreaks is also required for fire managers for planning first attack, and subsequently for monitoring fire behavior. A typical target for a fire manager is to detect a new fire within less than 30 minutes after ignition occurs. Once the fire starts, and considering its dynamics, information on fire growth needs to be updated very frequently as well. Therefore, the use of satellite data for operational identification of new fire outbreaks or for fire monitoring requires a high observation frequency, which it is currently provided only by geostationary satellites (15 to 30 minutes revisiting time). The utility of these data for fire monitoring was first demonstrated for fires in South America (Prins and Menzel 1992), and then it has been used for routine retrieval of active fires since 1998 (Prins et al. 1998). However, the coarse resolution of these sensors precludes their use in operational fire detection, since the detectable burning area commonly exceeds the optimal threshold for fire initial attack. The improvements in spatial

and spectral resolution of second-generation of geostationary satellites may provide a semi-operational scenario in the next future (Calle et al. 2006).

Meanwhile, the use of medium to coarse spatial resolution sensors deployed on board polar orbiting platforms has provided the alternative for global analysis of active fires over the past 25 years. These sensors offer one or two images per day, which it is not enough frequency for early detection, but it does provide critical information on fire activity. Obviously, those fires starting after image acquisition will not be detected until the next image, or missed if they are extinguished prior to the acquisition of the next one. In addition, those fires under thick cloud coverage will not be detected, but at least a global view of spatio temporal patterns of fire occurrence can be obtained.

The AVHRR sensor has been the most widely used for active fire detection since 1979. Its use started at the beginning of the eighties, when the first studies for monitoring fire activities in tropical and boreal regions were published (Flannigan and Vonder Haar 1986; Matson et al. 1984). The proposal of a simple mixing method for detection of sub-pixel fire spots (Dozier 1981) was also widely used, with reasonable accuracies in densely vegetated areas. However, it should be pointed out that the AVHRR was not designed for active fire detection, and therefore the thermal sensitivity of its MIR channel (band 3, 3.55–3.93 μm) was not very suitable for this task, with a low saturation threshold at $\approx 47\,^{\circ}$C. This low threshold can eventually lead to confusion with other hot targets (exposed soils, for instance), or with highly reflective zones. Consequently, a simple threshold in this channel does not provide a sufficiently accurate discrimination of fires. Confusion with other surfaces is very common in semiarid areas, where forests are often mixed with croplands or bare soil (Martín et al. 1999). In areas with dense vegetation cover, surface temperatures tend to be cooler, and therefore the potential confusions with fires are lower. Nocturnal images can also reduce false alarms (Langaas 1992), but they increase the risk of biasing fire detection, since much biomass burning is conducted during the central hours of the day (Giglio et al. 2003b; Kennedy et al. 1994). Some other hot targets, such as certain industries and gas flares linked to oil extraction or energy production, may also saturate the MIR channel. Confusion with highly reflective surfaces such as clouds and cloud edges is also possible, since they can be very reflective and saturate the MIR channel. False alarms related with the saturation of the MIR channel may occur with lakes, reservoirs, rivers and other water bodies, as a result of specular reflection (Martín et al. 1999). This phenomenon, known as Sun glint, only occurs within a certain geometry of illumination and observation. In spite of these problems, since AVHRR was operationally operated and a long time series of images were available, it provided the input data for a number of global scale fire detection projects.

The first global effort to obtain a world wide active fire coverage was undertaken by the International Geosphere Biosphere Program (IGBP) Data and Information System (DIS) core project. The project was aimed to develop a Global Fire Product (GFP), from a consistent series of AVHRR images at full spatial resolution (1.1 km at nadir). Daily AVHRR data were collected for the period April 1992 to December 1993 by the IGBP-DIS 1 km AVHRR Global Land Project (Eidenshink and Faundeen 1994). Fires were identified using a multiband threshold and contextual

algorithm developed by Flasse and Ceccato (1996). A cloud-masking algorithm was also performed, based on the criteria proposed by Saunders and Kriebel (1988). Data processing was done at the Joint Research Centre (JRC) in 1996 and 1997 (Stroppiana et al. 2000b). This product was the basis of several global analysis of fire occurrence patterns, which identified those regions with more recurrent an extensive fires, the main world fire regimes with the most active periods of the year, and the differences between latitude belts, especially between African and Central American fires (Dwyer et al. 2000).

Following this experience, the JRC undertook another global project to obtain global coverage of fire activities. The project was named "world fire web", and it was based on a common processing chain for a decentralized network of receiving stations that covered most of the Earth land surface (Pinnock and Grégoire 1999). The detection algorithm was also based on Flasse and Ceccato's work, and it was systematically applied to AVHRR afternoon images. Unfortunately, this project only lasted a few years (Grégoire et al. 2001)

Regional projects to detect active fires in AVHRR images were developed in South East Asia (Malingreau et al. 1985), Canada (Flannigan and Vonder Haar 1986; Li et al. 2000), the U.S.A. (Matson et al. 1987), Russia (Sukhinin et al. 2004), Africa (Kennedy et al. 1994; Langaas 1992), Brazil (França and Setzer 2001; Matson and Holben 1987; Setzer and Pereira 1991) and many other regions of the world.

During the last decade, the European Space Agency (ESA) proposed the use of the ATSR on board the ERS-1 and 2 to monitor active fires globally. The project was named World Fire Atlas and has been working since 1995 to the present (http://dup.esrin.esa.int/ionia/wfa/index.asp). After 2003, the project relies on data from the Advanced ATSR, on board the Envisat satellite. The discrimination of active fires is based on two single thresholds applied to the night images of the 3.7 μm channel: one at 312 K and the other, less conservative, at 308 K, which generate two different products (Piccolini and Arino 2000). These products are offered every 2 days at 1 km spatial resolution. The discrimination of active fires from ATSR should be less noisy than with day time AVHRR images, since it avoids solar contamination, and it is claimed to have less bidirectional reflectance problems. However, the product is potentially less complete than AVHRR detections, since fires lasting a diurnal cycle are not detected.

Another sensor that has been used for active fire detection is the Visible and Infrared Scanner (VIRS) on board the Tropical Rainfall Measuring Mission (TRMM). The satellite was launched in 1997 into a circular orbit inclined at 35° at 350 km initially, and 402.5 km after 2001. Being an Equatorial orbit, the sensor acquires information at different times of the day, which provides a better understanding of fire regimes, at the cost of non observing areas above or below 38 degrees. The VIRS has five bands covering the visible, NIR, MIR and TIR regions of the spectrum. Channel 3 has a similar spectral resolution as AVHRR, with a nominal spatial resolution of 2.1 km Its saturation threshold is also similar to AVHRR: 321.2 K. The algorithm to detect active fires in VIRS images was similar to the one applied to MODIS and AVHRR images, with multiple band thresholds and contextual criteria (Giglio et al. 2003b). Using this algorithm, monthly series of active fire products have been generated since 1998 to present, using a 0.5° resolution cell. This information has

been used for estimations of biomass burning emissions associated to El Niño events (Randerson et al. 2005).

The development of the Earth Observing System (EOS) missions during the nineties was built upon the experiences of working sensors, and therefore new systems were developed to solve or mitigate identified problems of previous missions. MODIS characteristics are a clear example of this progress, since the sensor was explicitly design to improve retrieval reliability of several key variables (Justice et al. 2002b). Specifically for detecting the active fires, MODIS includes two MIR bands, one with high thermal sensitivity (up to 500 K) and the other with a lower one (saturation at 331 K), as well as high-sensitivity TIR bands (saturation at 400 K). These improvements reduce the potential of false alarms found in AVHRR data analysis, while preserving temporal resolution. The algorithm for fire identification is based on thresholds over the MIR channel and on the difference between the MIR and TIR channels. Additionally, contextual rules (deviation from background signal) are applied for candidate pixels (Justice et al. 2002a). Improvements were made in a second revision of the algorithm (Giglio et al. 2003a). The validation efforts conducted have found a good relationship with fires detected in higher resolution images, although problems still remain with the presence of dense smoke and understory fires (Csiszar et al. 2006; Morisette et al. 2005).

Global processing with this algorithm produces several active fire products: daytime, nightime and daily fire product (MOD14G, D and A1, respectively), 8 day summary fire product at full resolution and 8 day summary at coarse-spatial resolution for global climate modelling (http://modis-fire.umd.edu/). The products are generated from data obtained from both Terra and Aqua satellites, providing two complete, daily coverages of the world. A quick summary of fire outbreaks is offered daily by the rapid response system (http://rapidfire.sci.gsfc.nasa.gov/). Additionally, 10 day composites of detected fires are available by the same system, and monthly and year summaries within the Web Fire Mapper of the University of Maryland (http://maps.geog.umd.edu/firms/default.asp: Fig. 6.4). These active fire products have been the basis for a large number of analysis associated to global gas emissions (Randerson et al. 2006; Venkataraman et al. 2006), analysis of fire regimes (Csiszar et al. 2005; Giglio et al. 2006a), studies on factors associated with fire occurrence (Mollicone et al. 2006), and relations of fire with tropical deforestation (Morton et al. 2006).

Global analysis of fire activity has also been generated from the Operational Linescan System (OLS) on board the DMSP (Defense Meteorological Satellite Program). In this case, the fires are detected from the visible part of the spectrum (light instead of heat, as other reviewed sensors) during night acquisitions (Elvidge 2001; Fuller and Fulk 2000). At local scales, airborne detection and monitoring of fires has also been carried out (Ambrosia and Brass 1988), using MIR and TIR sensor systems. More recently the use of unmanned systems have also been successfully tested (Ambrosia et al. 2003).

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 promoted by the Spanish company Insa (Martínez et al. 2000).

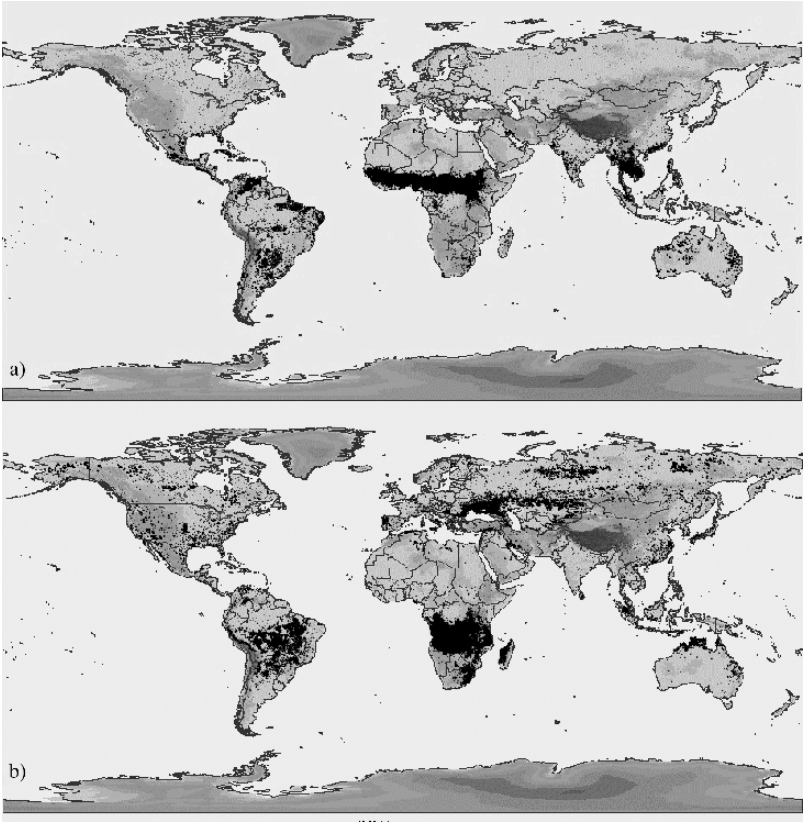

Fig. 6.4 Global fire spots detected by the MODIS sensor in 2005: January (a), July (b). Maps taken from the Fire Information for Resource Management Systems at U. Maryland (http://maps.geog.umd.edu/firms/maps. asp)

6.6 Analysis of Fire Effects

The assessment of fire effects accounts for the different impacts of fire on biophysical and socio-economic values. Most commonly, they refer to the analysis of post-fire changes in soil, water, vegetation and atmosphere in relation to pre-fire conditions.

In spite of the importance of detecting active fires, these products do not provide a complete evaluation of fire-affected areas, since several factors (fire length, temporal resolution of satellite overpass, cloud obscuration, etc.) may preclude the detection of an important number of fire events. Several attempts have been made to relate active fires to burned area (Giglio et al. 2006b), which emphasise the spatial differences between these two parameters.

Consequently, the evaluation of fire effects have mainly focused on mapping burned areas at different spatial and temporal resolutions. The discrimination of burn severity (levels of post-fire affects on vegetation communities) has received

less attention, although a growing interest in this topic is reflected in the scientific literature as discussed below. Finally, the effects of fire on water, soil, fauna and atmosphere have not been widely analyzed using satellite data, with the exception of the estimations of gas emissions derived from biomass burnings. These estimations are based on approximating the amount of biomass burned and the emission coefficients for each biomass type.

All these post-fire analysis tend to highlight the short-term effects of fire, but medium to long-term effects are also critical on understanding vegetation and landscape composition changes.

6.6.1 Burn Area Mapping

The most common use of remotely sensed data for burned land mapping has concentrated at local scales, using medium to high-resolution sensors, such as Landsat-TM/ETM+, SPOT-HRV, IRS-WIFS/AWIFS and SAC_C-MMMRS (Chuvieco and Congalton 1988; Chuvieco et al. 2002a; García-Haro et al. 2001; Garcia and Chuvieco, 2004; Jakubauskas et al. 1990; Koutsias et al. 1999; López García and Caselles 1991; Salvador et al. 2000; Siljeström and Moreno 1995; Vázquez et al. 2001). The accuracies for burned area mapping are regularly above 80% for discriminating the fire perimeter, especially when medium to large fires (>100 hectares) are considered.

Generation of global analyses of burn areas was initiated from AVHRR images during the nineties. 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 was also used (Fraser et al. 2000; Roy et al. 1999). Extensive regions have been mapped from AVHRR temporal series, especially in the boreal forest, where burned land maps derived from this sensor are proving the effects of global warming on fire regimes (Sukhinin et al. 2004). Similarly to other fire applications, AVHRR data provided reasonable estimations when the spectral signal show enough contrast with the background, which in post-fire conditions happened for large burn scars (>1000 hectares), when the images were acquired close enough to fire extinction. AVHRR lacked radiometric and geometrical temporal consistency to provide more accurate results (Maggi and Stroppiana 2002).

Global burned scars products from full resolution AVHRR data have not been developed so far, but temporal series of burn scar maps have been created from the Pathfinder AVHRR Land (PAL) program (http://daac.gsfc.nasa.gov/interdisc/readmes/pal_ftp.shtml), which included a global archive AVHRR data at a degraded resolution (8×8 km) since 1982. The discrimination of burned areas using coarse resolution AVHRR was carried out using the algorithm developed by Barbosa et al (1999a). This product was used to show that burned area was significantly related to climatic fluctuations associated to El Niño events (Carmona-Moreno et al. 2005; Riaño et al. 2007b).

More recently, other sensors with greater sensitivity for mapping burned scars have been used to create global inventories of burned areas. In 2000, two world-wide projects were developed at 1 sq km spatial resolution. The first project, named GBA2000, was coordinated by the JRC, and based on SPOT-Vegetation data. Daily images were acquired, mosaicked and composited in 10 day periods using a variation of the minimum albedo rule (Sousa et al. 2003). Burn scar areas were discriminated using a set of global algorithms, developed by different expert groups. The final results are available online (http://www-tem.jrc.it/Disturbance_by_fire/products/burnt_areas/global2000/global2000.htm), and in the process of being validated (Tansey et al. 2004).

The second world-wide project was named GLOBSCAR and was an initiative of the European Space Agency. The project was based on daily ATSR-2 images, on board the ERS-2 satellite, acquired during 2004. Two algorithms to discriminate burned areas were proposed (named K1 and E1), based on different thresholds on the NIR and TIR spectral bands, the K1 algorithm (Piccolini and Arino 2000), and on red, NIR, TIR and several vegetation indices, the E1 algorithm (Simon et al. 2004). These two algorithms created two different burned area products, which are available online at http://dup.esrin.esa.it/ionia/projects/summaryp24.asp.

The spectral and spatial enhancements of the MODIS sensors over other global-scale instruments, such as AVHRR, Vegetation and ATSR, should facilitate the generation of global maps of burned areas from this sensor data. Several studies have already shown an improved discrimination of MODIS over other sensors in regional

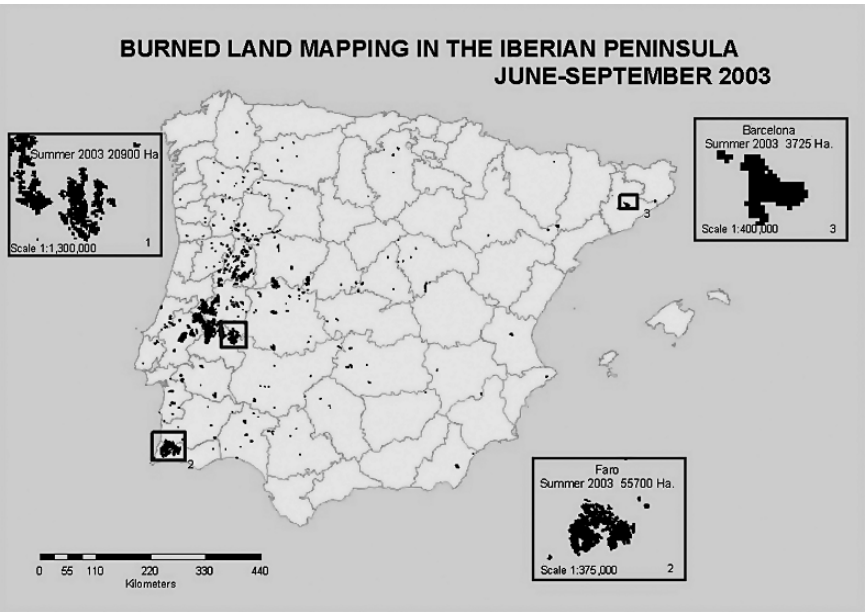

Fig. 6.5 Burn scar areas in the Iberian Peninsula from MODIS data. Images processed by Pilar Martin for the European Project Spread. Used with permission

studies (Chuvieco et al. 2005; Li et al. 2004; Martín et al. 2002; Sá et al. 2001): Figure 6.5. The next collection of MODIS land variables (which are to be released soon) will include a new standard product with global burned land areas at 500 m spatial resolution. The algorithm to generate this product is based on a multitemporal change detection approach that labels the pixels according to the differences found between modeled and actual reflectance, taking into account bidirectional reflectance corrections (Roy et al. 2005b; Roy et al. 2002).

Finally, other global-scale burn scar projects are being developed by the European Space Agency, using AATSR, VEGETATION, and the new MERIS hyperspectral sensor on board the Envisat satellite. The generic term for this undertaking is GLOBCARBON, and it involves the development fully calibrated estimates of several land products, such as Burnt Area Estimates (location, timing, area affected), leaf area index and active photosynthetic radiation, and vegetation growth cycle (timing, duration, spatial and temporal variability). The GLOBCARBON Burnt Area Estimate products (BAE) are global maps of monthly difference products representing the new burnt areas detected in the last month with a minimum confidence ratio index of 80% (http://dup.esrin.esa.it/ionia/projects/summaryp43.asp).

6.6.2 Determination of Burn Severity

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. Burn severity, defined as the amount of ecosystem transformation as a result of fire, has a significant effect on gas emission estimates derived from biomass burning, since it is related to the amount of biomass consumed by the fire (commonly named burned efficiency, which is currently one of the most uncertain components of global estimations of biomass burning emissions) (Chuvieco et al. 2004a). Additionally, it is closely linked to vegetation recovery after a fire (Pérez and Moreno 1998; Wheatherspoon and Skiner 1995). The longer and more intense a fire is, the more severe are the effects of the fire and the slower the vegetation recovers. Fire intensity and duration depend on fire behavior, which is controlled by different variables related to the fuel properties (load, moisture content, chemical properties), fire weather, and to the surrounding environment (slope, aspect, wind, rainfall, etc.).

The evaluation of burn severity can be undertaken using different approaches (Lentile et al. 2006). The methods are closely linked to the objectives of the evaluation which may include an assessment of vegetation recovery, soil erosion potential, or landscape fragmentation (Key and Benson 2002). Traditionally, burn severity assessment has been undertaken using field methods, mainly considering the changes in soil color and condition, depth of the affected organic layer, amount of scorched leaves or remaining branches (Key and Benson 2004; Moreno and Oechel 1989; Pérez and Moreno 1998). The cost of this approach, as well as the lack of spatial representation associated with field methods, have led to the use of remotely sensed images, since they provide relatively cheap and spatially comprehensive coverage of an area of interest.

Several authors have used remotely sensed data for discriminating burn severity levels using empirical approaches (Caetano et al. 1994; Cocke et al. 2005; Díaz-Delgado et al. 2001; Epting et al. 2005; Miller and Yool 2002; Parra and Chuvieco 2005; Rogan and Franklin 2001; van Wagtendonk et al. 2004; White et al. 1996).

Most studies have been conducted with Landsat TM/ETM+ images, since they provide appropriate spectral and spatial resolution for burn severity discrimination at landscape level. However, post-fire reflectance is greatly affected by spatial and temporal variability of burn severity (Key 2005), as well as other environmental factors. Fully burned or undisturbed areas generally have a distinctive spectral reflectance, but most studies have found it problematic to discriminate intermediate severity values (Jakubauskas et al. 1990; Miller and Yool 2002; Minick and Shain 1981). Hyperspectral sensors, such as AVIRIS and Hyperion, may offer greater spectral sensitivity to these intermediate values of burn severity (Parra and Chuvieco 2005; van Wagtendonk et al. 2004), but additional efforts are required to better understand the signal derived from different burning conditions, especially when several vertical strata need to be assessed. As a future research topic, building an improved severity index should incorporate improved knowledge of how fires of different severity displace the position of prefire vegetation in multispectral space (Roy et al. 2006).

To address this problem, reflectance simulation models may be used to simulate the spectral variation caused by different burn severities. The use of radiative transfer models (RTM) in fire effects assessment was first achieved within the framework of evaluating the potential of satellite data to discriminate understory fires in tropical regions (Pereira et al. 2004). Specifically for burn severity discrimination, Chuvieco et al (2006) have recently proposed the application of the Kuusk two-layer RTM for simulating different burn severity conditions in short-term and medium-term temporal scenarios. The main factors considered were the changes in soil substrate color (from soil to carbon), the changes in leaf properties (from wet to dry), and the changes in leaf area index (Fig. 6.6). The inversion of this model was successfully tested in the retrieval of burn severity for a large forest fire in Mediterranean conditions using Landsat-TM/ETM data (De Santis and Chuvieco 2007). The simulations could also be applicable to other sensors, but additional simulations need to be done to reduce errors for intermediate values of severity (Chuvieco et al. 2007).

All those studies on burn severity rely on medium to high spatial resolution images. Few experiences are available on the potential application of coarse resolution images to burn severity, and therefore the generation of global products for this goal would probably still require several years.

6.6.3 Use of Satellite Data for Emission Estimations

Several authors have proven that biomass burning is a significant source of carbon to the atmosphere (Andreae 1991), hence is an essential factor to consider when evaluating climate changes at the global level. Great inter-annual and intra-annual variability of biomass burning (Hoffa et al. 1999; van der Werf et al. 2006) requires that monitoring emissions is done at frequent temporal scale, and therefore remote

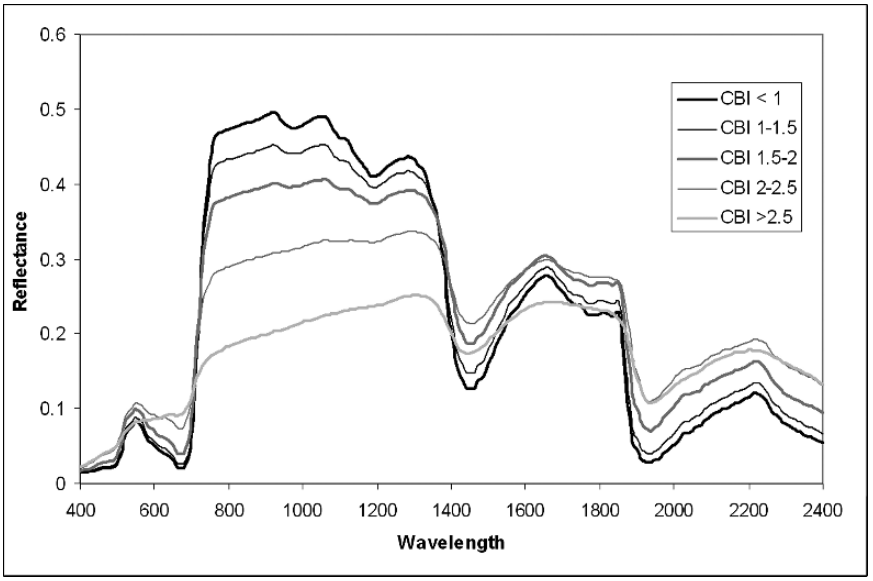

Fig. 6.6 Simulated reflectance for different burn severity values. CBI is a composite burn index, which ranges from 0 (none) to 3 (high) severity. From Chuvieco et al., 2006. Use of a radiative transfer model to simulate the postfire spectral response to burn severity, Journal of Geophysical Research, vol. 111, G04S09, doi:10.1029/2005JG000143. Copyright 2006 American Geophysical Union. Reproduced by permission of AGU

sensing of active fires and/or burned areas are a critical input to global fire emissions models (Palacios-Orueta et al. 2005).

Two main approaches for estimating biomass burning emissions have been proposed in the literature. The first one is based on direct measurements of trace gas released during a fire. This approach has been implemented from field measurements (Ferek et al. 1998; Hao et al. 1996), as well as from remote sensing analysis of smoke components (Ferrare et al. 1990; Kaufman et al. 1992; Randriambelo et al. 1998). Both, field and remote sensing gas emissions measurements require simultaneity with active fires, either experimental or actual ones. This is difficult due to operational difficulties to synchronize measurements campaigns with fire activity.

The second approach to estimate gas emissions derived from fire is based on accounting for the main factors associated to the emission process, mainly biomass loss and gas emission coefficients. The most widely used model was formulated by Seiler and Crutzen (1980):

$$M_{i,j,k} = BL_{i,j,m} \times BE_{i,j,m} \times BS_{i,j} \times E_k \times 10^{-15}$$

where, $M_{i,j,k}$ is the amount of gas **k** released for a specific area (with i,j coordinates) in Tg, $BL_{i,j,m}$ is the biomass load (dry matter) for the same area in gr m^{-2} (assuming the area has a homogenous cover of fuel/vegetation type **m**); $BE_{i,j,m}$ is the burning efficiency (i.e. proportion of biomass consumed, 0–1) of fuel/vegetation type **m**;

$BS_{i,j}$ is burned surface of the same area (m^2); and, E_k is the amount of trace gas **k** released per dry matter unit (gr Kg^{-1} of biomass).

Remote sensing is an excellent source of information to derive some of those input parameters (Ahern et al. 2001; Barbosa et al. 1999b; Palacios-Orueta et al. 2005; Stroppiana et al. 2000a).

The most common use of satellite data in the estimation of biomass emissions have been the retrieval of burned areas, either from active fires or from actual burn scars. The former approach has been more extended, because of the greater availability of fire detection over burned land mapping. As previously commented active firest may not provide an accurate estimation of actual burned area and therefore the estimations from available active fire products may underestimate actual emissions (Giglio et al. 2006b; Liousse et al. 2004).

The second critical variable to estimate gas emissions is the assessment of biomass loads. This has been traditionally undertaken in remote sensing literature from indirect inferences of net productivity or vegetation density. However, there is always a great uncertainty in measuring biomass loads when vertical measurements are not available. As explained above, at present only LIDAR sensors provide a sound estimation on vertical distribution of vegetation, but this is confined to local scales until satellite borne LIDAR systems are launched. Surrogates of this information may be obtained through the analysis of multiseasonal trends of spectral vegetation indices, providing a base biomass load is available (Palacios-Orueta et al. 2004). Recent years efforts to estimate Net Primary Productivy of Vegetation may also help the estimation of biomass loads (Zheng et al. 2001).

Finally, the burning efficiency, that is the amount of biomass actually consumed by the fire, has been estimated from field measurements (Fearnside et al. 2001), and by analyzing pre-fire moisture content (Levine 2000), since the amount of water is inversely related to fire intensity and duration. Some studies have proposed the use of relative variation of NDVI (greenness indices), as a surrogate of fuel moisture content to estimate burning efficiency (Barbosa et al. 1999b). However, as said before, greenness indices only facilitate good estimations of water content for herbaceous vegetation, and therefore the method needs to be adapted to shrubs and forested areas (Chuvieco et al. 2004a).

In any case, satellite data have a great potential for estimating critical variables in fire emissions. The use of different spatial-resolution sensors may be used to upscale field or local scale measurements to regional or global scenarios (Fig. 6.7), and therefore spatial heterogeneity of biomass loads and burning efficiency can be better considered. Additionally, the temporal frequency of remote sensing observations may greatly improve time-domain estimations of gas emissions (Palacios-Orueta et al. 2005).

6.7 Validation of Global Fire Products

The main challenge for using global products, either fire or any other critical variable, is obtaining a quantitative estimate of the accuracy of the results. When assessment is not properly done, the estimations derived from these products carry along

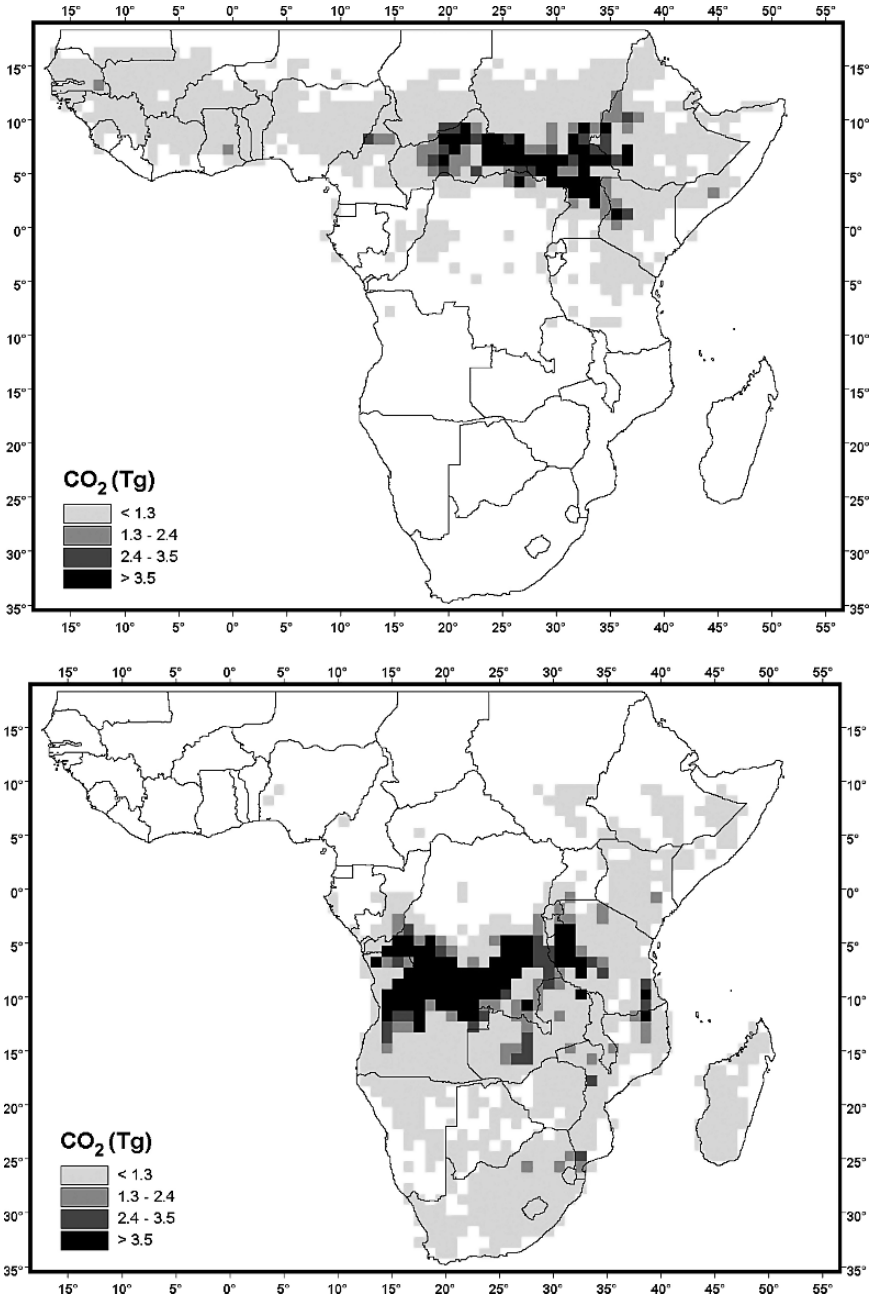

Fig. 6.7 Estimations of CO_2 emissions from African biomass burning. Upper January, Lower, July. From Palacios-Orueta et al., 2004. Remote sensing and geographic information system methods for global spatiotemporal modelling of biomass burning emissions: Assessment in the African continent", Journal of Geophysical Research, 109, D14S07, doi:10.1029/2004JD004734. Copyright 2004 American Geophysical Union. Reproduced by permission of AGU

a great level of uncertainty, and cross-checking with other products do not reveal which is more accurate (Boschetti et al. 2004; Korontzi et al. 2004).

Validation efforts of world-wide coverage products are obviously very costly and time consuming, and there is always a practical limit on the potential of being spatially representative. Within the MODIS Land science team, researchers have been working on validation of MODIS standard products (Morisette et al. 2002). Other global scale projects, such as GBA2000 and Globscar included some assessment, with a rough estimation of accuracy. However, the discrepancies between these products are surprisingly high (Boschetti et al. 2004).

The most common strategy to validate coarse spatial resolution products uses higher spatial resolution images, acquired simultaneously with the coarser one, or at least close enough as to derive a similar estimation. A common example is the use of ASTER images to validate active fire detection from MODIS, since they are carried out in the same satellite (Csiszar et al. 2006). This is especially critical for active fire detection, since the comparison images need to be acquired almost simultaneously. However, the comparison between these two sensors is not trivial, since they have very different spatial resolutions (60×60 m, ASTER versus 1 sq km for MODIS), which makes complex to compute the proportions that actual burns of such diverse areas.

For burn scars assessment, the temporal issue is not as critical as in active fire assessment, since the burn scars have a longer permanence. Therefore, non-simultaneous images can be used, or even from different dates. For this goal, the use of Landsat-TM/ETM+, CBERS or SPOT-HRV data, have been the most common. Burn scars delineated with these high resolution images are then cross-tabulated with those extracted from coarse resolution images to obtain confusion matrices and to compute omission and commission errors. Considering the great differences in spatial resolution between the two sources, an alternative to cross-tabulation is to obtain a scatter graph of burned land proportions identified by the two sensor sources, using a defined grid size (5×5 km, for instance). The correlation between the two data sources provides a measure of consistency, and the regression parameters, an estimation of the quality of area estimations (Roy et al. 2005a).

Other authors have suggested a validation strategy based on comparing discriminated burn scars with active fires, at least to evaluate spatial agreements patterns (Roy et al. 2005b). Obviously, these two products refer to the same phenomenon but with a very different perspective, since active fires only register a particular momentum in fire behavior, while burn scars refer to a more stable signal and affect a different territory. However, their comparison would at least serve to address omission errors, providing the active fire detections are correct.

6.8 Current Challenges for Global Observation of Biomass Burning

As reviewed in this chapter, satellite Earth Observation offers a wide variety of critical information for prevention and assessment of biomass burning impacts. At global scale, the most extended products are those associated with active fire

detection, which have been developed for the last 25 years, mainly from AVHRR, but also from ATSR, MODIS and geostationary satellites. Within the last five years, a growing interest on deriving global burned land products have implied the availability of two covers (GBA2000 and Globscar) and the development on new ones that soon will be released (MODIS Burned Product, Globcarbon), then enhancing our capacity of monitoring changes in fire regimes and atmospheric emissions derived from biomass burning. Burn severity products should be added to the wishing list, but the current interest is focused on high spatial and spectral resolution sensors, and global products are not yet fully envisaged.

Finally, the use of satellite data for early warning is still far from completion. The estimation of moisture conditions would require a global system of meteorological observations at proper spatial resolutions and a more detail monitoring of subtle changes in surface reflectance and temperature as a result of plant drying. The former may be based on forecasted data using global climate models, the latter requires the development of water content maps, which will hopefully be included in the next generation of MODIS standard products. Vertical profile sensors, such as LIDAR or long-wave RADAR systems, providing a global survey of biomass loads are strongly required to improve fuel management operations that would eventually lead to less catastrophic fires, as well as to better monitor regeneration trends after fire and get better account for gas emissions.

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