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Satellite remote sensing of biomass burning with optical and thermal sensors

Douglas O. Fuller

Department of Geography, 619 21st Street, NW, The George Washington University, Washington DC 20052, USA

Abstract: A major goal in satellite remote sensing of fire is to derive globally accurate measurements of the spatial and temporal distribution of burning. To date, the main sensor employed in fire and fire-scar detection has been the Advanced Very High Resolution Radiometer (AVHRR) on board NOAA polar-orbiting platforms. Other sources supporting fire observation over large areas include the Defense Meteorological Satellite Program – Optical Linescan (DMSP-OLS), the Geostationary Operational Environmental Satellite – 8 (GOES-8) and the Along Track Scanning Radiometer (ATSR). These sources have often been used in conjunction with high spatial-resolution imagery provided by the Landsat Thematic Mapper and SPOT to assess the accuracy of proposed fire and fire-scar retrieval algorithms.

Although a range of fire detection algorithms have been proposed based on more than a decade of research on the AVHRR data, it remains to be seen whether variations in land-cover type, surface temperature and fire regimes will permit application of global thresholds of temperature and reflectance. Moreover, the emerging set of satellite sensors with demonstrated utility in fire monitoring indicates substantial possibilities for greater synergy of current and future remote-sensing systems leading to improved monitoring of fire extent and frequency. As a more complete global picture of biomass burning emerges with the launch of new sensors for fire monitoring (e.g., MODIS), this information, combined with detailed data from field experiments, can help provide reliable budgets of trace gases and particulate species that affect global energy balance and climate.

Key words: active fires, AVHRR, earth-observation satellites, fire scars, trace-gas emissions.

I Introduction

Scientists have long recognized the role of fire in shaping the structure of vegetation communities and landscapes. Decades of ecological research have shown that fire regimes generally vary as a function of the vegetation type, weather and climate and

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land-management practices (e.g., Pyne, 1995; Whelan, 1995). Burning experiments based in tropical, temperate and boreal regions have also shown that fires each year produce a substantial flux of trace gases and aerosols from the biosphere to the atmosphere. Although considerable uncertainty remains about relative and absolute quantities of pollutants produced, evidence indicates that biomass burning accounts for about 40% of annual anthropogenic CO_2 emissions and about one-quarter of anthropogenic particulate matter, respectively (Levine, 1996). Studies of fire and its impacts have also increasingly emphasized biomass burning as a major driving force in anthropogenic land-cover change, especially in the tropics (Mueller-Dombois and Goldammer, 1990; Cochrane *et al.*, 1999). Recent episodes of biomass burning in the forests of southeast Asia, South America and the southern USA associated with the El Niño Southern Oscillation (ENSO) event of 1997–98 have underscored the need for more research on the environmental impacts of these and other vegetation fires (Goldammer, 1999).

One of the major obstacles to achieve greater understanding of global fire frequency and extent has been a lack of reliable observations of fire and its immediate signature, charred material, over large areas. Burned material deposited after fires, commonly referred to as 'fire scars' in the scientific literature, consists mainly of ash and black carbon or charcoal, which contains of a range of carbon-based molecules from polycyclic aromatics to elemental carbon or graphite (Kuhlbusch and Crutzen, 1996). Because of its inertness, charcoal may remain in the environment for centuries or millennia where it is often detected in sediment cores and in tree rings (Goldammer and Siebert, 1990; Firescan Team, 1996; Goldammer *et al.*, 1996). However, immediate surface deposition of ash and charred material following fire provides an opportunity for remote observation using space-based sensors.

Satellite remote sensing has played a growing role in fire detection and monitoring over the past two decades (Justice *et al.*, 1993). Whereas fire scars generally contrast strongly with unburned surfaces in the visible (0.4–0.7 μm), near infrared (0.7–1.5 μm) and middle infrared (1.5–4 μm or MIR) portions of the electromagnetic spectrum,[1] researchers often use thermal detectors operating from about 4 to 15 μm to identify active fires. Recently, however, sensors operating in the visible wavelengths have also been used in active fire detection (Elvidge *et al.*, 1996). The emerging set of satellite sensors with demonstrated utility in fire monitoring indicates substantial possibilities for greater synergy of current and future remote-sensing systems leading to improved monitoring of fire extent and frequency (Justice *et al.*, 1993; Barbosa *et al.*, 1998; Eva and Lambin, 1998a; 1998b). The goal of this article is to provide an overview of several recent advances and to describe the potentials and limitations of current optical and thermal remote-sensing systems (Table 1) for fire evaluation and mapping.

II Detection of active fires

1 General considerations

The use of satellite observations to detect fires poses a number of significant challenges. Although some wild fires may burn for days or weeks, fires generally occur as ephemeral events that may not coincide with the timing of the orbital overpass. Fires may also smoulder at or below ground level at low temperature then later reach high temperatures in the flaming stage if sufficient dry fuel and oxygen are available. Moreover, clouds and smoke from fires often obscure the surface and therefore cause many fires to be missed by satellite sensors. Thus low-overpass frequency combined

Table 1 Characteristics of some current and planned satellite sensors for fire and fire-scar detection

Sensor	Major applications	Spatial resolution	Swath width	Bands (μm range)	Major advantages	Major limitations
AVHRR	Active fires Fire scars	1.1 km	2400 km	0.58–0.68 0.72–1.10 3.55–3.93[1] 10.3–11.3 11.5–12.5	Widely available, low cost, high temporal frequency	325 K saturation in channel 3
DMSP-OLS	Active fires	0.56 km 2.07 km	3000 km	0.58–0.91 10.3–12.9	High sensitivity; high temporal frequency	Night-time use only during low lunar illumination
SPOT-4	Fire scars	10 m PAN from 0.61 to 0.68 μm 20 m MS[2]	60 km	0.50–0.59 0.61–0.68 0.79–0.89 1.58–1.75	High spatial resolution, MIR band	Low temporal frequency, low area coverage, high cost
SPOT vegetation	Fire scars	1 km	2000 km	0.43–0.47 0.61–0.68 0.78–0.89 1.58–1.75	MIR band, large areas covered, high temporal resolution	Unknown
Landsat TM and ETM+[3]	Fire scars	15 m PAN[4] 30 m MS	185 km	0.45–0.52 0.52–0.60 0.63–0.69 0.76–0.90 1.55–1.75 10.4–12.5[5] 2.08–2.35	MIR band, high spatial resolution, well-known data source	Low temporal resolution, high cost[6]
GOES-8	Active fires	1 km (visible) 4 km (infrared channels)	Hemisphere	0.52–0.72 3.78–4.03 6.47–7.02[7] 10.2–11.2 11.5–12.5	Very high temporal resolution	Coarse spatial resolution; 3.9 μm band saturates at 335 K
ATSR[8]	Fire scars	1 km	500 km	3.51–3.89 1.57–1.63 10.4–11.3 11.5–12.5	Good spectral configuration for fire-scar mapping	Unknown
MODIS	Active fires Fire scars	250 m 500 m 1 km	2330 km	36 bands including 3.9 and 11 μm	Saturation of 450 K at 4 μm and 400 K at 11 μm	Unknown

Notes:
[1]NOAA recently launched an AHVRR on NOAA-15 with a new channel 3a centred at 1.6 μm.
[2]PAN = panchromatic, MS = multispectral.
[3]Enhanced Thematic Mapper launched in early 1999 on Landsat-7.
[4]Only available on the ETM.
[5]120 m resolution.
[6]Landsat-7 data products will be supplied to the scientific community at greatly reduced costs.
[7]8 km spatial resolution.
[8]Only ATSR-1 is reviewed here, although ATSR-2 has similar potential in fire mapping.

with fire variability and high cloud cover often lead to serious underestimation of fire extent with remote sensing.

Furthermore, many current remote-sensing systems were not designed explicitly for fire monitoring, but mainly for vegetation, oceanic and atmospheric studies. Since these features normally possess temperatures below 300 K, high temperatures associated with most fires, which typically range from about 400 to 1200 K, produce saturation in the middle infrared and thermal channels of most sensors. The term 'saturation' is used widely to describe the problem in which a temperature greater than a certain amount receives a maximum value in the output range of the sensor. Some sensors saturate at such low temperatures that warm land surfaces and fires cannot be distinguished, and thus saturation may lead to overestimation of fire extent. Saturation also precludes accurate estimation of fire temperatures, which relate directly to emissions of particulates and trace gases (Albini, 1993).

2 The NOAA-AVHRR

Despite these challenges, satellite sensors such as the Advanced Very High Resolution Radiometer (AVHRR) on board polar-orbiting satellites of the US National Oceanic and Atmospheric Administration (NOAA) have provided a great deal of information on fires (Cracknell, 1997), especially in remote areas where fires are not normally monitored by other means. Although never intended for fire monitoring, the AVHRR has provided a source of information on biomass burning since 1981 (Justice *et al.*, 1993; Malingreau and Grégoire, 1996; Setzer and Malingreau, 1996). AVHRR data have been applied widely to study fires in the savannas of Africa (Belward *et al.*, 1994; Kennedy *et al.*, 1994; Razafimpanilo *et al.*, 1995; Justice *et al.*, 1996; Barbosa *et al.*, 1998; Eva and Lambin, 1998b), where one-third of all carbon emissions from biomass burning are thought to originate (Andreae, 1991). AVHRR data have also been applied extensively to South American forests and savannas to study both active fires and scars (Kaufman *et al.*, 1990; Setzer and Pereira, 1991; Pereira and Setzer, 1993b). Recent studies have also relied on the AVHRR for fire detection in the maquis of the Mediterranean (Chuvieco and Martín, 1994; Illera *et al.*, 1996; Fernandez *et al.*, 1997; Pozo *et al.*, 1997) and in boreal forests of Alaska and Russia (Kasischke *et al.*, 1993; Kasischke and French, 1995; Rauste *et al.*, 1997).

One of the most common AVHRR-based methods for active fire detection involves the application of single temperature thresholds to AVHRR channel 3 (Table 1) day and night passes (Justice *et al.*, 1993; Chuvieco and Martín, 1994; Setzer and Malingreau, 1996). The use of night-time passes generally eliminates the problem of low saturation (~ 322–325 K) in channel 3 daytime passes as well as the reflection of solar radiation, particularly sun glint off water surfaces and bright soils. However, several studies (Malingreau, 1990; Prins and Menzel, 1994) have shown that fire occurrence and spread tend to be greatest near solar noon (Figure 1) when winds and low relative humidity favour fire spread. Therefore, the use of night-time AVHRR passes may underestimate the extent and number of fires substantially. Moreover, for the single threshold algorithm to operate effectively, different thresholds may need to be developed for a given region and season of interest.

Conversion of at-satellite radiance values to surface temperature depends upon a

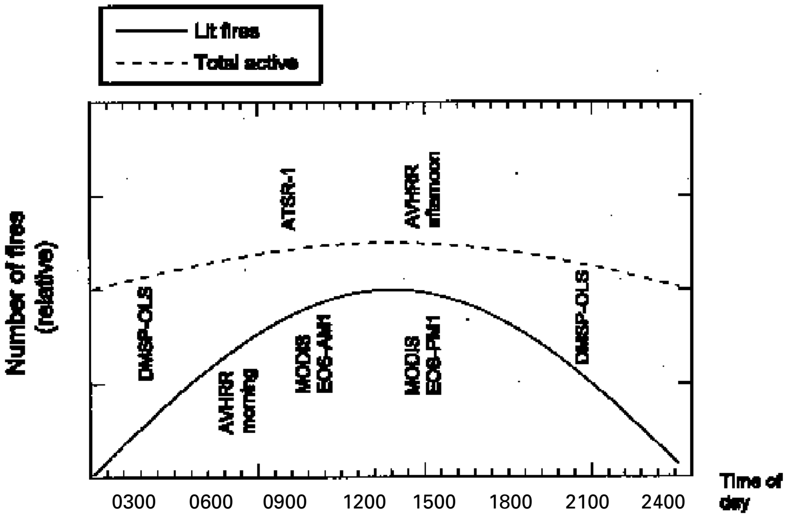

Figure 1 Schematic diagram depicting the diurnal cycle of fire in relation to the timing of overpass of orbital platforms that provide broad-area coverage
Source: Adapted from Malingreau and Grégoire, 1996

number of factors including the emissivity of the objects in the satellite field of view, the atmospheric attenuation caused by gases and aerosols and other sources of thermal radiance originating from the upwelling atmospheric radiant flux, and the satellite itself (Qin and Karnieli, 1999). Although the total atmospheric attenuation may be estimated, this is rarely done for remote areas where *in situ* measurements of aerosol optical depth, water vapour, CO_2, CO and other absorbing gases are often not available. Another important problem is that vegetation fires themselves generate a large flux of absorbing species (particularly CO_2, CO and ozone) and these gases are likely to be spatially heterogeneous within a satellite image. Further, calibration of the AVHRR thermal channels 3–5 relies on a certain set of assumptions (Kidwell, 1991) that may not be valid, especially for channel 3 (Setzer and Malingreau, 1996). Thus, given the uncertainty over these factors it is difficult to ascertain the errors involved in the estimation of channel 3 temperature.

The number of fires detected using the single-threshold method also appears to vary greatly depending on the value applied. Figure 2 provides an example of detected fires in three maps covering Kalimantan on 6 August 1997 in which thresholds of 310 K, 315 K and 321 K were applied to a channel 3 daytime image. This example shows that the number of detected fires may range over an order of magnitude with a change of only 6 K in the threshold, with many fire pixels probably misclassified owing to saturation below 315 K. In response to the saturation problem, Flasse and Ceccato (1996) developed a contextual or neighbourhood approach based on channel 3. Their algorithm selects fire pixels if sufficient contrast exists between a high-temperature pixel and its neighbours, provided the temperature of the central pixel is above a certain minimum.

Other algorithms rely on a set of thresholds involving multiple AVHRR channels. For

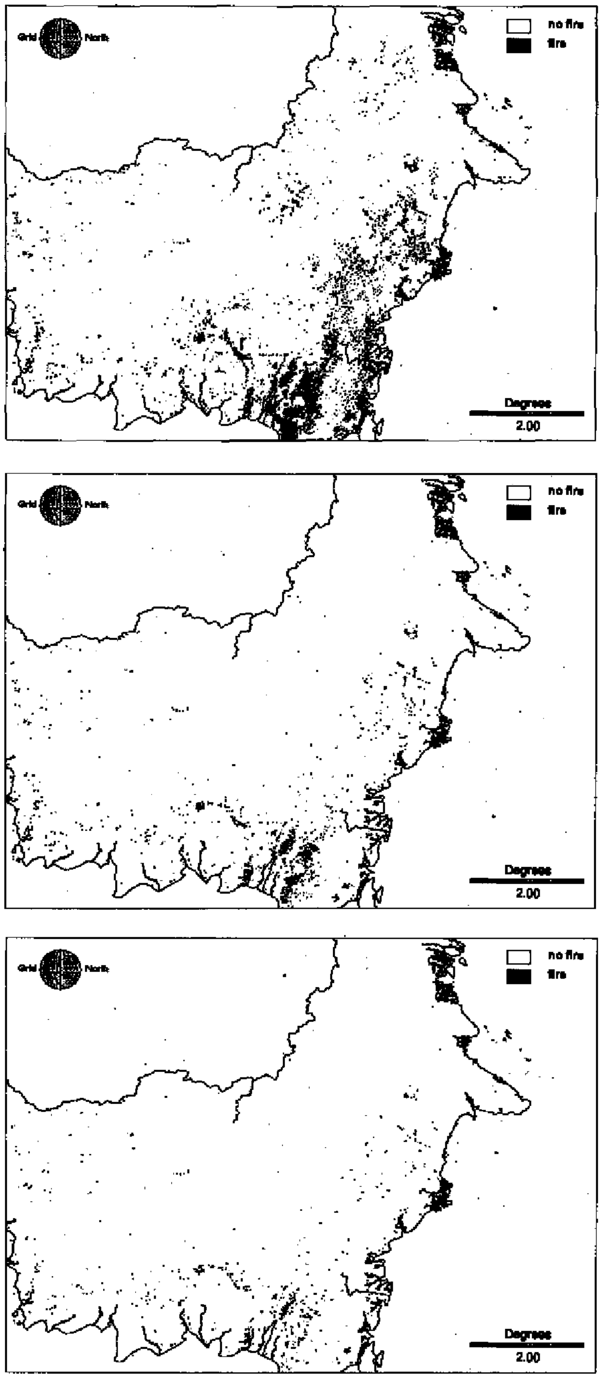

Figure 2 Active fires detected in Kalimantan, western Indonesia with three different temperature thresholds applied to AVHRR channel 3 daytime images, 6 August 1997. Each dot represents an active fire: (a) 310 K; (b) 315 K; (c) 321 K

example, Kaufman *et al.* (1990) developed an algorithm for Amazonian forest fires that applied three thresholds to AVHRR channels 3 and 4. In their algorithm, a pixel is classified as containing a fire if channel 3 ≥ 316 K, channel 3 minus channel 4 ≥ 10 K and channel 5 ≥ 250 K (Kaufman *et al.*, 1990). Kennedy *et al.* (1994) showed that thresholds such as these developed for a humid environment produced extensive saturation in dry savannas of west Africa. They tested and refined Kaufman's method for savanna fires by increasing the threshold values and adding a fourth criterion that channel 2 reflectance ≤ 16%. This final criterion helped eliminate areas associated with sun glint and reduced saturation effects substantially.

A hybrid approach developed by Justice *et al.* (1996) involves both multiple thresholds and neighbourhood analysis. Although applied to savanna fires in southern Africa, their approach is intended to have wider application. Like other algorithms, it involves thresholds to channels 3 and 4 with the addition of the following test: $\Delta T_{34} > \Delta T_{b34} + 2\,\sigma_{\Delta Tb34}$ where ΔT_{34} is the difference in the brightness temperature between channels 3 and 4 and ΔT_{b34} is the average difference between the response in channels 3 and 4 in a neighbourhood around the pixel being tested and $\sigma_{\Delta Tb34}$ is the standard deviation of ΔT_{b34}.

Although the use of neighbourhood statistics represents a significant advance that should lead to wider applicability, Setzer and Malingreau (1996) have questioned the use of channel 4 in AVHRR-based fire algorithms because its sensitivity to smoke plumes may produce inconsistent results. Moreover, uncertainties over the calibration of channel 3 have also been raised by Setzer and Malingreau (1996), who recommend application of thresholds to raw channel 3 digital counts in areas with low channel 1 reflectance and which have mapped fires consisting of less than 20 contiguous pixels.

A recent modelling study conducted by Giglio *et al.* (1999) suggests that three different algorithms (Arino *et al.*, 1993; Flasse and Ceccato, 1996; Justice *et al.*, 1996) will produce similar results in different biomes for large fires (> 1000 m^2). However, for small fires the authors also found these algorithms will perform differently depending on smoke, neighbouring fires and biome type. Because the methods proposed and developed by Justice *et al.* (1993), Setzer and Malingreau (1996), Flasse and Ceccato (1996) and others (e.g., Randriambelo *et al.*, 1998) have yet to be compared systematically and validated with field observations over a range of different land-cover types, it remains to be seen which will become the most widely accepted. Moreover, inherent environmental variability may necessitate the adjustment of different AVHRR-based thresholds among different biomes and seasons.

3 DMSP-OLS and GOES-8

The Defense Meteorological Satellite Program – Optical Linescan System (DMSP-OLS) provides another remotely sensed data source for fire mapping (Cahoon *et al.*, 1992; Elvidge *et al.*, 1996). The DMSP-OLS on board US Air Force orbital platforms possesses a wide swath (and hence high overpass frequency) and high sensitivity to night-time fire observations in its visible to NIR waveband (0.58–0.91 μm). This high sensitivity to light sources is achieved via a photomultiplier tube that allows improved detection of active fires relative to current thermal sensors (Elvidge *et al.*, 1996). Its use in conjunction with AVHRR, for example, may provide a way to reduce potential uncertainty over AVHRR temperature thresholds as suggested by Fuller and Fulk (2000).

The NOAA National Geophysical Data Center serves as the archive for DMSP-OLS data. The NGDC has developed a fire algorithm that uses a database of stable light sources associated with urban areas to distinguish ephemeral light sources (e.g., fires and gas flares) on the land surface (Elvidge *et al.*, 1996). However, the DMSP-OLS is likely to overestimate the number of active fires substantially because the data are generally collected at a spatial resolution of 2.7 km. Overlap between adjacent pixels means that a single fire may be counted in up to six DMSP-OLS pixels (Elvidge *et al.*, 1996). Fortunately, DMSP-OLS data are now being collected and archived at 0.56-km resolution, which will increase its utility substantially in night-time fire monitoring (Elvidge, pers. comm.).

As mentioned above, estimation of fire extent may depend strongly on the time of satellite overpass (Figure 1). However, geostationary satellites such as the Geostationary Operational Environmental Satellite (GOES) and Meteosat, which possess middle and thermal-infrared bands, may reveal the relative magnitude of diurnal effects by providing observations every 30 minutes. While the sensor on board Meteosat may be used for detection of smoke plumes, the 3.9 μm channel of GOES-8 permits detection of active fires as well as smoke. Although much coarser than the AVHRR at 16 km spatial resolution, previous GOES instruments (GOES-4 and GOES-7) have also been used to show a strong diurnal signature in biomass burning over South America. Prins and Menzel (1994), for example, showed that the area burning in South America was two to five times greater in the early afternoon than at other periods. Moreover, Menzel and Prins (1996) demonstrated that GOES-8 (launched in 1994) provides improved fire detection relative to previous GOES instruments since the 3.9 μm channel saturates at a minimum of 335 K and has a spatial resolution of 4 km. GOES-8 fire observations have been validated in Colorado, USA (Weaver *et al.*, 1995) and in Costa Rica (Alfaro *et al.*, 1999). Although, like AVHRR channel 3, the 3.9 μm channel on GOES-8 may be adversely affected by sun glint from water bodies and bright soil surfaces, it is surprising that it has not been used more for fire detection given its high temporal resolution, high temperature saturation relative to the AVHRR and large spatial coverage (Table 1).

4 MODIS

Numerous field experiments (e.g., Levine, 1996) have shown that the concentration of trace gases such as CO, CO_2, NH_4 and volatile organic compounds in smoke plumes varies as a function of fire temperature and fuel type. Therefore, remote measurements of fire temperature may be used to draw qualitative inferences about gaseous emissions. The need for more information on fire temperatures from remote sensing has led to the inclusion of two fire channels in the Moderate Resolution Imaging Spectrometer (MODIS) to be launched by NASAon the EOS-AM1 and PM1 platforms. MODIS fire channels are centred at 3.9 μm and 11 μm, which are designed to saturate at 450 K and 400 K, respectively (Justice *et al.*, 1998). Since smouldering fires tend to produce more emissions than flaming fires and also tend to be cooler than 600 K, it is expected that MODIS-based algorithms will be able to distinguish fires in their flaming and smouldering stages. Prototype fire-detection algorithms using the MODIS fire channels are based largely on research using the AVHRR sensor and will involve a range of multiple thresholds and neighbourhood characterization (Justice *et al.*, 1998; Kaufman *et al.*, 1998). Moreover, the overpass frequency of MODIS-carrying platforms will enable better estimation of the diurnal fire cycle. NASAintends to launch two such platforms, the first of which will have local overpass times of 10.30 am/pm and the second will possess overpass times of 14.30 (Figure 1).

III Detection and mapping of fire scars

1 Rationale for study

Several studies have shown that very small fires (~ 10^{-4}–10^{-3} km^2) may produce the same sensor response in the thermal infrared as large fires that potentially burn large areas (Matson and Dozier, 1987; Kaufman *et al.*, 1990). Therefore, satellite-based maps depicting active fires generally do not provide a good representation of burned area unless checked carefully against high-resolution imagery (Scholes *et al.*, 1996a). However, through fire-scar detection and mapping, remote sensing provides a way to improve scaling of carbon flux from the biosphere to the atmosphere. Prior to the use of satellite data, calculation of carbon emissions at regional to global scales involved classifying vegetation into broad types and estimating the fuel load, frequency of burning and fraction of biomass consumed within each type. Data on vegetation characteristics have often been obtained from small-area studies that may not have represented the fuel and fire situations over large areas. The total emissions from burning were then calculated as the product of the area of each type and its emission summed over all vegetation types (Kendall *et al.*, 1996; Scholes *et al.*, 1996a). Since satellite data provide reliable information on burned area and the functional characteristics of vegetation (e.g., canopy cover, above-ground biomass and foliar moisture content), assumptions of spatial homogeneity per vegetation class are no longer needed.

Another advantage to using fire scars in emissions modelling is that they are less ephemeral than fires themselves (Eva and Lambin, 1998b; Roy *et al.*, 1999). Furthermore, interest in mapping of burned area has recently increased in the wake of the catastrophic fires of 1997–98 in southeast Asia and Amazonia, which may have destroyed large areas of forest (Goldammer, 1999). In particular, environmental scientists and policy-makers are interested to know how much area burned in different land-cover types during these events, the amount of area burned relative to past ENSO-related fires as well as the economic consequences of fires in tropical forests (Anon, 1997; Schweithelm and Glover, 1999).

The literature on fire scar reflectance and duration remains very limited (e.g., Frederiksen *et al.*, 1990) and more studies of these properties are clearly needed. As several authors have noted (e.g., Kendall *et al.*, 1996; Roy *et al.*, 1999), blackened, carbonized material deposited on the surface after fires may also be transported by wind and water or covered quickly by canopy litter or regenerating canopies over a matter of days or weeks. The rate at which these features change is likely to vary widely from biome to biome and season to season. In addition, fire-scar duration relates to the frequency of cloud cover, since high cloud cover will reduce the number of possible observations of a given fire scar or set of scars.

High-spatial resolution data provided by the Landsat Thematic Mapper (TM) and SPOT XS have enabled limited study of the spectral and spatial properties of burns, although their temporal frequency and spatial coverage are very low (Table 1). High spatial-resolution images also provide an important intermediate scale to link broad-scale observations (e.g., AVHRR) with field data. Systems such as SPOT and Landsat also possess spectral bands that are more appropriate for fire-scar detection than systems designed primarily for ocean and atmospheric applications (e.g., GOES and AVHRR). Figure 3 provides an example of the response of channels 4 and 5 of Landsat TM across a range of burned and unburned cover types in South Kalimantan, Indonesia, acquired after major burning in December 1997. Contrasting reflectance of fire scars in the NIR and MIR suggests that new MIR-based indices may be created (e.g., Pereira and Setzer, 1993a; Pereira, 1999) that may relate to chemical contents of burned material or the mass of char deposited at the surface. Unlike vegetation indices (VIs), however, fire-scar indices have yet to be examined in light of biochemical and physical properties of burned surfaces.

2 Time-series of vegetation indices

One widely used approach for fire-scar detection involves analysis of time-series of vegetation indices, the most common of which is the normalized difference (NDVI).

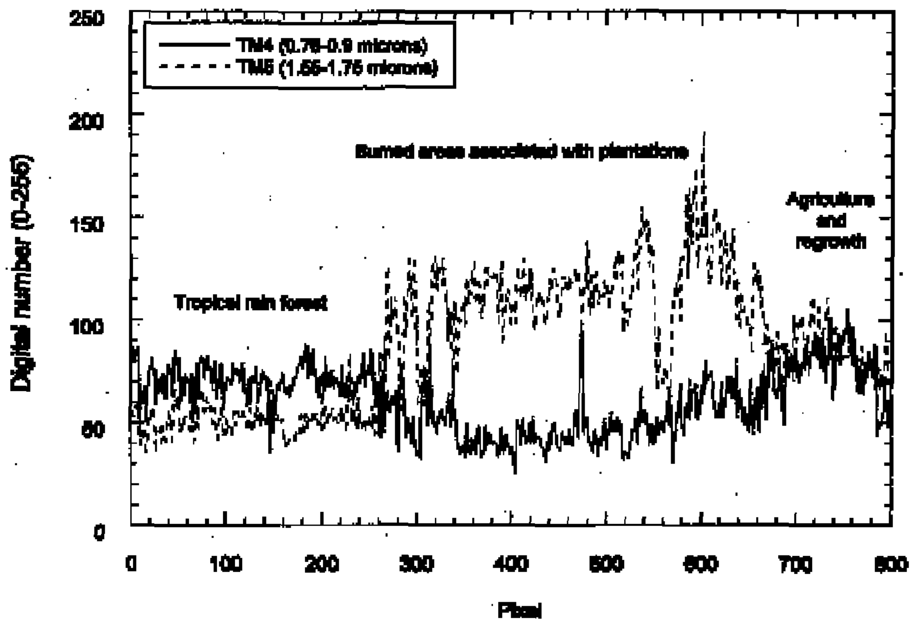

Figure 3 Behaviour of Landsat TM channels 4 and 5 across a transect of 800 pixels which cover a range of cover types in South Kalimantan, Indonesia, after major ENSO-related burning episodes (16 December 1997). Channel 5 is the MIR band and clearly shows elevated values over fire scars relative to channel 4

NDVI is strongly correlated with green vegetation cover, photosynthetic activity and primary production (Prince, 1991; Goward and Huemmrich, 1992) and is calculated from the expression (NIR – red)/(NIR + red), where NIR and red are reflected radiance or reflectance values in the near infrared and red portions of the electromagnetic spectrum. NDVI ranges from about –0.2 for certain exposed soil surfaces to approximately 0.7 for closed vegetation canopies, although it is highly sensitive to atmospheric water vapour and aerosol optical depth when derived from AVHRR channels 1 and 2 (Holben, 1986; Justice *et al.*, 1991). It also shows substantial sensitivity to soil background effects where canopy cover is sparse as in some savannas and steppes (Huete, 1988). Notwithstanding atmospheric and background effects, NDVI time-series data have found many uses in land-cover change studies (Eastman and Fulk, 1993; Lambin and Erlich, 1997; Fuller, 1998) and their application in fire studies is consistent with damage to green vegetation canopies that occurs as a result of burning.

Theory suggests that change in NDVI is inversely related to the area burned (Figure 4) provided there is high contrast between burned and unburned surfaces and that at least 20% of the pixel has been burned (Razafimpanilo *et al.*, 1995). Razafimpanilo *et al.* (1995) modelled NDVI changes due to burning over a range of water vapour concentrations, solar elevation angles and view angles. The authors also found that for NDVI calculated from top-of-atmospheric (TOA) reflectances, a decrease of about 0.65 NDVI units may be expected if the pixel was entirely green before the fire and entirely burned after. The results from this study are encouraging for a number of reasons. First, forest vegetation is largely green before fires and the amount of change in NDVI (ΔNDVI) expected from high aerosol optical depths and precipitable water vapour will be substantially less than a complete burn. Model simulations also suggest that threshold application does not require detailed atmospheric correction and that the relationship between area burned within a pixel and NDVI is not substantially affected by view angle, solar elevation, or atmospheric water vapour content. Finally, it may be possible to retrieve subpixel burned area by making certain assumptions about the VI of unburned canopies and soil background reflectance prior to fire events. These results all suggest that reasonable thresholds using channels 1 and 2 of the AVHRR may be

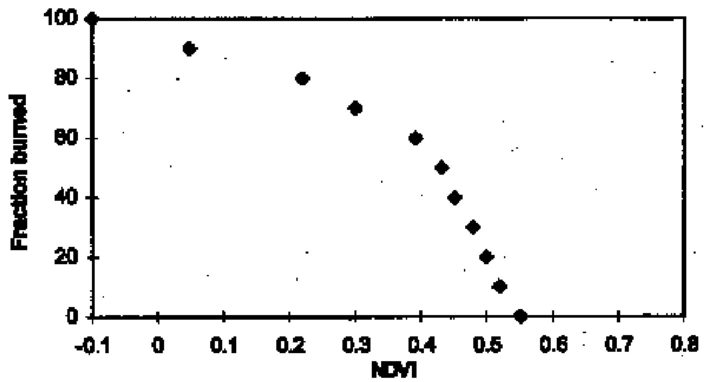

Figure 4 Theoretical relationship between the fraction (expressed as percentage) of an AVHRR pixel burned and NDVI for a pixel covered by green vegetation
Source: Adapted from Razafimpanilo *et al.*, 1995

established to distinguish burned and unburned pixels in forested regions.

Several empirical studies support the theoretical work by Razafimpanilo *et al.* (1995). For example, Kasischke and French (1995) showed that ΔNDVI selected over key periods in Alaskan taiga allowed for detection of 96% of large burns over 20 000 ha in size (i.e., approximately equivalent to a contiguous block of 200 AVHRR HRPT pixels) and 83% of all burns less than 20 000 ha. Fernandez *et al.* (1997) also used an NDVI differencing approach to detect medium-sized (> 400 ha) burns in Spain. They found that a regression approach, which establishes a relationship between pre- and postburn NDVI within 100 km × 100 km windows, produced slightly better results than a simple difference threshold. Overall, the authors found that both techniques provided adequate estimation of burned area in Mediterranean vegetation.

Further, Barbosa *et al.* (1998) also tested a number of different compositing methods in addition to the maximum value of NDVI, which is so widely used to screen pixels with off-nadir views, clouds and other atmospheric effects (Holben, 1986). They found that seven-day minimum value composites of albedo and NIR (i.e., from AVHRR channel 2) produced better images than NDVI composites for discriminating burned from unburned areas in four humid savanna regions of Africa. The results are interesting since the authors used coarse-resolution, 5 km global-area coverage (GAC) data and validated their results with high spatial resolution data with Landsat TM imagery.

3 Observations in the middle infrared

Despite encouraging results obtained with NDVI time series, Pereira (1999) recently compared NDVI against a set of other vegetation indices and found that it was less suited for burned-area evaluation than the Global Environmental Monitoring Index (GEMI) or two new MIR-based indices. His work suggests that further improvements in fire-scar detection and mapping can be realized by including MIR data, which are becoming increasingly available from a range of sources. As indicated in Table 1, MIR observations are currently produced by high spatial-resolution systems like Landsat TM as well as the coarse-resolution systems such as Vegetation Instrument on SPOT-4 and the Along Track Scanning Radiometer (ATSR). Two recent studies using the ATSR-1 by Eva and Lambin (1998a; 1998b) confirmed the fire-scar mapping utility of the 1.6 μm waveband from this instrument through comparison with other remotely sensed data from Landsat TM and NOAA-AVHRR. In another study, Eastwood *et al.* (1998) utilized TM data covering boreal forest stands to simulate the SPOT-Vegetation MIR waveband for fire-scar detection. The results of their study were compared against fire maps produced by the Canadian Forest Service and showed that the MIR waveband gave a more reliable indication of fire scars than approaches based on vegetation indices. Moreover, MIR reflectance over boreal fire scars changed at a slower rate than changes in the visible and NIR wavebands, which suggests that tracking changes in MIR reflectance may lead to improved monitoring of postfire recovery. Further study of the physical basis of MIR reflectance from fire scars (e.g., bidirectional effects, chemical contents and refractive indices) should help advance general understanding on how MIR observations relate to postfire recovery of plant communities.

IV The spatial nature of biomass burning

Fire monitoring from space is playing a growing role in assessment of fire spread, form and shape as they relate to different landscapes (Chuvieco and Martín, 1994; Chuvieco, 1999). Through spatial analysis of burning patterns, understanding of the relative importance of variables controlling fire risk and spread (e.g., vegetation type, fuel moisture, topography and weather) may be improved (Chuvieco and Congalton, 1989). In areas where flammable fuels are common such as the western USA, the Mediterranean Basin and Australia (Whelan, 1995), concerns about rapid spread of fire have led to the development and application of fire-spread models such as FARSITE (Finney and Ryan, 1995) and BEHAVE (Burgan and Rothermel, 1984). Remotely sensed images or maps can be used either as model inputs or to assess the performance of simulation model outputs (Clarke *et al.*, 1994). For example, fire spread over several weeks may be followed over broad areas using single AVHRR thresholds as done by Chuvieco and Martín (1994) in Spain. However, since fire-spread and hazard models are most often developed for application to relatively small regions (e.g., 1:1 000 000 or greater), model validation is generally carried out using high-resolution imagery such as Landsat or SPOT data rather than AVHRR data.

Remote-sensing studies have also emphasized the mapping of burned area as a means to derive improved scaling and estimation of gaseous emissions and aerosols. Several such studies suggest that the amount of area burned may not correspond well to figures extrapolated from field studies (Scholes *et al.*, 1996b; Eva and Lambin, 1998a). For example, using the ATSR-1 data, Eva and Lambin (1998a) showed that the proportional area burned in central Africa during the dry season of 1994–95 ranged from about 52% in Guinea–Congolian vegetation (subhumid to moist) to slightly more than 1% in the Sahelian zone. These values are substantially less than earlier figures for African savannas (~ 75% cited in Belward *et al.*, 1994), which were based on one particular study area of west Africa (Crutzen and Andreae, 1990).

Empirically based modelling work by Scholes *et al.* (1996a; 1996b) represents one attempt to link satellite observations of active fires, consumption of biomass, emissions of particulates and emissions of trace gases CH_4, CO and NO_x. The authors used a combination of Landsat MSS and AVHRR imagery to relate active fires observed over southern Africa to the area burned. To accomplish this they derived a calibration factor that accounted for the ratio of the scene fraction burned (from MSS image observations) to the cumulative proportion of pixels in which active fires were detected by the AVHRR. The calibration factor was not constant over southern Africa but varied as an exponentially decreasing function of mean annual precipitation, with large fires found in arid areas and small, numerous fires found in more humid locations. Scholes *et al.* (1996b) then used the output from their biomass consumption model to estimate total emissions of a given trace gas ($M_{\mathrm{gas},i,j}$) from

$$M_{\mathrm{gas},i,j} = \sum F_{i,j,k}\, E_{\mathrm{gas},i,j}$$

where $F_{i,j,k}$ is the total amount of biomass burned per grid cell per month and $E_{\mathrm{gas},i,j}$ is the emission factor for the gas, based on *in situ* measurements of gaseous fluxes.

In Africa and other areas of variable precipitation (e.g., the Mediterranean) interannual variability of fuel production may explain discrepancies in estimates of burned area. For example, Eva and Lambin (1998a) surmised that interannual variation in biomass burning in Africa is probably low. However, since most ecological and remote-sensing studies generally track vegetation conditions over one year or less, studies of interannual fire variability are rare. An exception is the study by Kendall *et al.* (1996), who used AVHRR 1 km imagery covering southern Africa and found substantial differences in fire extent between 1989 (relatively wet year) and 1992 (a drought year). Although rainfall explained some of the variation in fire numbers, the authors noted much unexplained variation, with an increase between 1989 and 1992 in some dry savannas of Zambia, Mozambique and Tanzania and a decrease in wet savannas of eastern Congo, Zimbabwe and the Okavango Delta of Botswana.

Whereas interannual variability of burned area may be considered low in African savannas the same is probably not true of moist tropical forests. For example, Cochrane *et al.* (1999) showed that 90% of forest burning in eastern Amazonia occurred during ENSO-related drought events of 1983, 1992 and 1997. Using multitemporal Landsat TM data, they found that between 23 and 45% of their study areas burned during the ENSO years of 1992 and 1997, which is generally less than the reported proportional area of savanna burning in Africa. However, gaps in the Landsat TM data apparently did not permit the authors to make any firm conclusions about whether Amazonian fires are growing more extensive with successive ENSO events (Cochrane *et al.*, 1999).

In contrast to some savannas, studies of boreal forest fires with satellite sensors suggest that the areas burned may be much larger than previously thought (Kasischke and French, 1995; Kasischke *et al.*, 1999). In particular, AVHRR data have detected a number of very large fire scars (> 30 000 ha) in Alaska and in Siberia, which were previously unobserved owing to their remote locations. By comparing their results from the AVHRR with historical records, Kasischke and French (1995) have also indicated that fire extent has tended to increase in Alaska over the past three decades, a result which may be linked to the increased occurrence of warmer, dryer summers. The continued addition of greenhouse gases from biomass burning and industrial and transportation sources is therefore expected to create a positive feedback with greater warming at the higher latitudes, longer growing seasons, more fuel production and hence more intense and extensive fires in boreal forests. Remote sensing using current and future satellite platforms will continue to play an important role in identification of areas affected in the boreal zone and should enable improved assessment of burning trends there.

V Conclusions: towards global fire monitoring with satellite remote sensing

The spatial variability and ephemeral nature of fires make it difficult to generalize about their extent and frequency and thus their impact on the biosphere and atmosphere. In the past, the most common method to estimate the magnitude of the flux of trace gases from biosphere to atmosphere involved extrapolation of small-area measurements to entire communities and biomes. However, errors can propagate quickly in global calculations of emissions from fires that may move across landscapes unpredictably and often consume heterogeneous fuels. As Malingreau *et al.* (1993) have outlined, the basic requirements to derive improved global estimates emissions from fire include spatially referenced and temporally continuous data on vegetation conditions, occurrence and type of fire and the amount of burned biomass. Of all available technologies, satellite remote sensing has the greatest potential to meet these information needs.

High-resolution systems such as SPOT and Landsat may present some of the same problems posed by spatial extrapolation of results from field investigations owing to their limited extent and low temporal resolution (Cochrane *et al.*, 1999). Coarse-resolution, multitemporal systems such as the AVHRR, DMSP-OLS, SPOT Vegetation and MODIS must therefore be used to derive global estimates of burning. Attempts to develop a global system based largely on AVHRR observations have been made under the auspices of the International Geosphere–Biosphere Programme (IGBP). Since 1992, IGBP has convened a Fire Working Group (FWG) that has been working to develop a community consensus on fire algorithms and data inputs. Following recommendation from the FWG, a global fire product has been developed using 18 months of daily AVHRR data, which is currently undergoing evaluation (Dwyer *et al.*, 1997; Grégoire *et al.*, 1997). In addition, new algorithms and thresholds are being developed in the context of MODIS implementation (Kaufman *et al.*, 1998). However, few studies (Setzer and Pereira, 1991) have attempted detailed field validation of their results, which again is made difficult by the transitory nature of fire. One potential, but underutilized source for validation on fire temperatures and emissions is gas flares from oil refineries (Kaufman *et al.*, 1998). Other sources are needed to validate current and future fire mapping algorithms in a range of environments.

Large-scale field experiments such as SAFARI-92 (Southern Africa Fire-Atmosphere Research Initiative – 1992) and SCAR-C (Smoke, Clouds and Radiation – California), which emphasized the integration of emissions data and remote sensing (Levine, 1996), are also expected to help advance validation efforts. The SAFARI-2000 field campaign, which began in 1999 year, will replicate and expand upon the sites and measurements made in the previous SAFARI-92 experiment. Such field experiments, however, are costly and difficult to implement in remote areas with poor infrastructure and communications and therefore only a limited number can be performed. Nevertheless, continued integration of data from new sensors with well studied sources such as the AVHRR (e.g., Barbosa *et al.*, 1998; Eva and Lambin, 1998b; Fuller and Fulk, 2000) will permit validation in areas where detailed field observations are unavailable.

As more sensors are launched with MIR bands the potential for global mapping of fire scars will continue to increase. For example, NOAA has recently launched another AVHRR sensor that contains a MIR band (channel 3a) centred at 1.6 μm, although according to a recent report data transmission problems have plagued this particular satellite. Given the difficulties of remote measurement of fire temperatures and the likelihood that the next generation of sensors will be affected by saturation, fire-scar detection and mapping provide the best way to improve scaling of carbon flux and study of interannual variation. While much current research has emphasized remote sensing of fires and fire scars using optical and thermal sensors it is also important to acknowledge the emergence of synthetic aperture radar (French *et al.*, 1999) as a means to map fire scars. When used in conjunction with validated fire maps and high-resolution sources of optical data, radar has considerable potential to reveal burned area in places where cloud cover is persistent, particularly in the lowland tropics, an area of increasing interest in biomass burning and emissions studies.

Note

1. The division of the electromagnetic spectrum into discrete portions is somewhat arbitrary, and different authorities in remote sensing recognize different boundaries, particularly in the infrared portions of the spectrum.

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