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Satellite remote sensing of forest resources: three decades of research development

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Abstract: Three decades have passed since the launch of the first international satellite sensor programme designed for monitoring Earth's resources. Over this period, forest resources have come under increasing pressure, thus their management and use should be underpinned by information on their properties at a number of levels. This paper provides a comprehensive review of how satellite remote sensing has been used in forest resource assessment since the launch of the first Earth resources satellite sensor (ERTS) in 1972. The use of remote sensing in forest resource assessment provides three levels of information; namely (1) the spatial extent of forest cover, which can be used to assess the spatial dynamics of forest cover; (2) forest type and (3) biophysical and biochemical properties of forests. The assessment of forest information over time enables the comprehensive monitoring of forest resources. This paper provides a comprehensive review of how satellite remote sensing has been used to date and, building on these experiences, the future potential of satellite remote sensing of forest resources is highlighted.

Key words: biophysical and biochemical properties, dynamics, extent, forest resources, forest type, satellite remote sensing.

I Introduction

An unmanned satellite was launched on 23 July 1972 as part of the Earth Resources Technology Satellite (ERTS) programme (later known as Landsat). The Multispectral Scanner (MSS) carried on board ERTS-1 was designed specifically for the collection of multispectral remote sensing data for the analysis and monitoring of the Earth's natural resources. One important natural resource base that has benefited from developments in satellite remote sensing in the three decades since the launch of ERTS-1 is that of forests. This paper reviews how the opportunities provided by satellite remote sensing have been exploited for the collection of

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information pertaining to forest resources and, building on these experiences, prospects for the future are highlighted.

Forests are an important natural resource base, requiring action for their informed utilization, management and protection at spatial scales from the local through to the global. Forests provide material goods, such as fuelwood, commercial timber and other nonwood products. They are a biodiversity and genetic resource, as well as providers of other environmental services, and a key player in poverty alleviation (Myers, 1996; Sellers *et al.*, 1997; Food and Agriculture Organization (FAO), 2003). Despite the vital essence of this resource base, forests remain under pressure, with the world's natural forests continuing to be felled and the land given over to other uses and types of cover. Furthermore, forests continue to be degraded, contributing further to the loss of forest resources (FAO, 2001).

The continuing pressures on the forest resource base has promoted much debate over how best to manage their future; Myers (1996) suggests that '…the accelerating decline of many of the world's forests represents one of the greatest problems and opportunities facing the global community'. An important component of this debate is the need for accurate information on the status of forests and, in particular, where and how they change over time (Franklin, 2001; Kleinn *et al.*, 2002). This information is required at a range of spatial and temporal scales, from local forest inventories used for economic resource management purposes and updated annually, through to global data on carbon, water and energy fluxes required for environmental management (e.g., the modelling and mitigation of climate change) over a number of decades (Cohen *et al.*, 2001). Remote sensing can play a crucial role in providing information across these scales (Franklin, 2001). It allows for the frequent measurement and monitoring of the world's forests on a continuous basis (Running *et al.*, 2000), thus informed judgements on their resources may be made at any given time. Accordingly, over the past three decades there has been a progressive evolution of remote sensing approaches for the collection of forest resource information. Satellite remote sensing has been the principal focus of attention (Sader *et al.*, 1990), which is used to enhance and increase confidence in field-based inventory and monitoring methodologies (Frankin, 2001; Mickler *et al.*, 2002). It is unlikely that it will replace aerial photograph interpretation at cartographic scales larger than 1:25,000 but, where information on forest resources is required over larger areas, the use of satellite data is cheaper and more consistent (Lunetta, 1999; Roller, 2000).

II Satellite remote sensing for forest resource assessment: framework

Despite the different generations and types of satellite sensors that have been launched over the past 30 years since ERTS-1 (Figure 1), no one sensor currently meets fully the requirements of a comprehensive forest resource assessment system (Malingreau *et al.*, 1992). From the resources perspective, satellite remote sensing may be used to provide three levels of information. The first level refers to information on the spatial extent of forest cover, which can be used to assess the spatial dynamics of that cover; the second level comprises information on forest type, and the third level provides information on the biophysical and biochemical properties of forests. The assessment of forest information over time enables the comprehensive monitoring of forest resources. With consideration given to the desired level of forest resource information, an appropriate sensor or combination of sensors may be commissioned for use.

Like all applications of remote sensing, the measurement of forest resources relies on the interaction of electromagnetic radiation with the target and analysis of the returned signal as recorded by a sensor. In broad terms the satellite platforms of the past 30 years have carried two broad types of sensor system; the optical and active Synthetic Aperture Radar

Year	Satellite *(Main sensors carried on board)*
1972	**ERTS-1** (later renamed as **Landsat-1**) *(MSS)*
1975	**Landsat-2** *(MSS)*
1978	**Landsat-3** *(MSS)*
1979	**NOAA-6** *(AVHRR)*
1981	**NOAA-7** *(AVHRR)*
1982	**Landsat-4** *(MSS, TM)*
1983	**NOAA-8** *(AVHRR)*
1985	**Landsat-5** *(MSS, TM);* **NOAA-9** *(AVHRR)*
1986	**SPOT-1** *(HRV);* **NOAA-10** *(AVHRR)*
1988	**NOAA-11** *(AVHRR);* **IRS-1A** *(LISS I, LISS II)*
1990	**SPOT-2** *(HRV)*
1991	**NOAA-12** *(AVHRR);* **ERS-1** *(ATSR, SAR);* **IRS-1B** *(LISS I, LISS II)*
1992	**JERS-1** *(SAR, OPS)*
1993	**SPOT-3** *(HRV)*
1994	**NOAA-14** *(AVHRR)*
1995	**ERS-2** *(ATSR, SAR);* **IRS-1C** *(LISS III);* **Radarsat** *(SAR)*
1997	**IRS-1D** *(LISS III);* **Seastar** *(SeaWiFS)*
1998	**SPOT-4** *(HRVIR, Vegetation);* **NOAA-15** *(AVHRR)*
1999	**Landsat-7** *(ETM+);* **IKONOS** *(High resolution sensors);* **Terra** *(MODIS, MISR, ASTER)*
2000	**NOAA-L** *(AVHRR);* **EO-1** *(Hyperion, ALI);* **EROS A1** *(EROS A1)*
2001	**Quickbird-2** *(High resolution sensors);* **PROBA** *(CHRIS)*
2002	**SPOT-5** *(HRG);* **Envisat** *(AATSR, ASAR, MERIS);* **AQUA** *(MODIS);* **NOAA-M** *(AVHRR)*
2003	**ICESat** *(GLAS)*
	Radarsat-2 *(SAR)*
	ALOS *(VSAR, AVNIR-2)*
	NASA *(VCL)*

Figure 1 Timeline depicting launch date of major satellites and platforms operating in the optical and radar spectrum affording the collection of forest resources information

(SAR) systems. The former measure reflected radiation in one or more discrete wavebands located in the spectral range 400–3000 nm, whereas the latter measure backscattered microwave radiation at wavelengths between 1 cm and 1000 cm. Optical wavelengths are several orders of magnitude smaller than the leaves, needles and branches that make up a forest canopy and, consequently, radiation may be both absorbed and scattered by these components. In the case of the longer microwave wavelengths, scattering from leaves, branches, trunks and the ground is the dominant mechanism (Figure 2). It follows that optical remote sensing systems may provide information on the amount of foliage and its biochemical properties whereas microwave systems provide information on

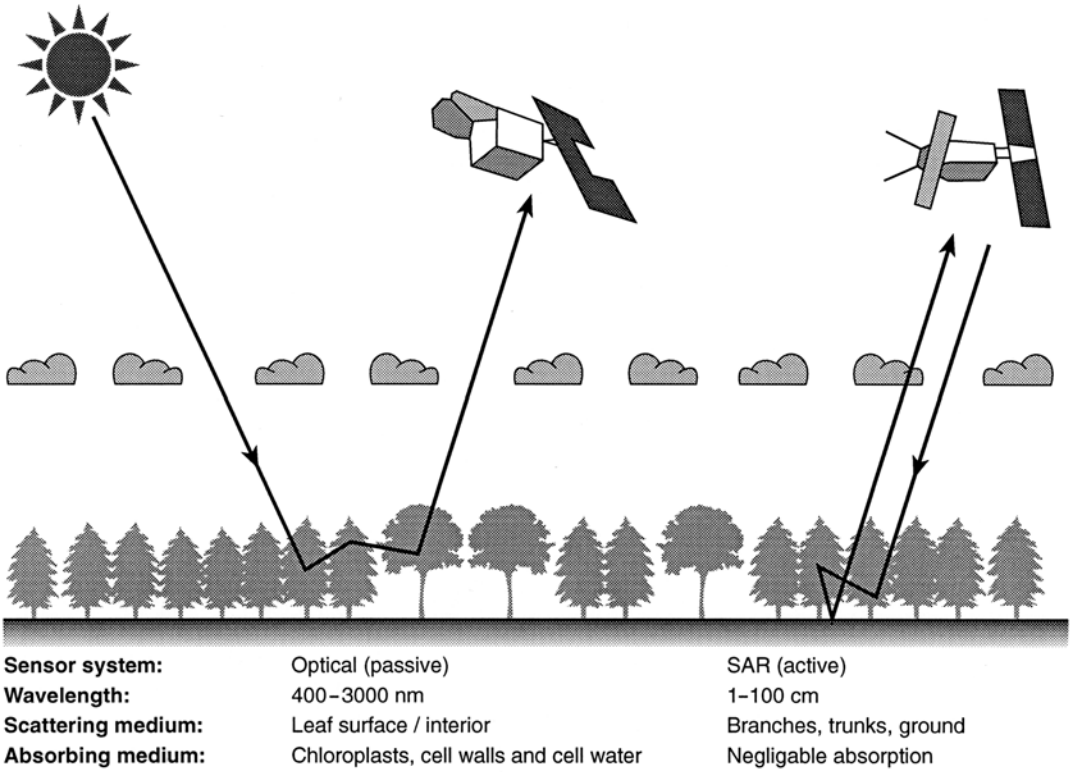

Figure 2 Interaction mechanisms for forest canopies

woody biomass and forest structure. Additionally, some systems also measure emitted radiation (between 3000 nm and 15000 nm) to provide important measures of surface energy fluxes and temperatures (Quattrochi and Luvall, 1999). Moreover, remote sensing instruments are imaging devices that may provide additional spatial information related to the three-dimensional structure of the canopy and the spatial resolution of the imaging sensor (Marceau *et al.*, 1994). Extracting information on forest resources therefore depends on developing techniques to infer the desired resource information from the remotely sensed data acquired by the various satellite systems that have been in operation (Danson *et al.*, 1995). Accordingly, different satellite remote sensing systems and techniques have been developed for different forest ecosystem and resource requirements (Lambin, 1999).

III Level 1 forest resource information: forest extent and change dynamics

Techniques for measuring forest extent and their change have evolved rapidly. Much of this work has focused on tropical forests, as they constitute the fastest land use change at this spatial scale in human history (Myers, 1992) and, moreover, the full extent of this change still poorly known (Achard *et al.*, 2002). The remote sensing of forest extent and change dynamics has developed along two strands. One strand relies on the delineation of forest from nonforest and the calculation of the areal extent of forest cover. The other uses the occurrence of forest fires as an indicator of active areas of forest burning used to estimate forest loss. Both these strands enable a comprehensive evaluation of how much forest remains, where forested areas are and where they are being lost (Mayaux *et al.*, 1998).

1 Delineating forest cover from nonforest cover

The utility of a particular satellite remote sensing system for the task of mapping forest and nonforest is dependent upon the sizes of the deforested areas under study, their spatial arrangement and the spectral contrast between the deforested areas and the original forest (Townshend and Justice, 1988). However, the choice of sensor in a particular study may be determined by practicalities such as availability of funds, processing capabilities and time constraints, rather than theoretical knowledge. Thus, coarse spatial resolution imagery are often used in large area studies. These produce estimates of nonforest/forest that may be inaccurate locally because of spatial aggregation errors but acceptable over a very large area (Mayaux *et al.*, 1998). Fine spatial resolution imagery, on the other hand, used in local area studies, produce accurate estimates for the local area covered by the imagery; however, the extrapolation of results to other areas, where the imagery are unavailable, may be inaccurate because of spatial variability in forest cover.

Pioneering studies illustrated the potential of fine spatial resolution optical sensors for the delineation of forest cover from nonforest cover, prompting the use of sensors such as those carried on the Landsat and SPOT series of satellites for forest cover estimation at the local and national levels (Woodwell *et al.*, 1987; Green and Sussman, 1990; Houghton *et al.*, 2000). The FAO's *Forest resources assessment* (2001) has noted the advantages of using these data in their Pan-tropical remote sensing survey. However, the use of data acquired by fine spatial resolution optical sensors, particularly at regional and global levels, can be compromised by their relatively high cost, large data volumes and low frequency of data acquisition, compounded further in tropical regions particularly by cloud cover and smoke from forest fires (Malingreau and Tucker, 1988).

To overcome some of the problems of using remotely sensed data acquired by the fine spatial resolution optical sensors, data from coarse spatial resolution optical sensors and SAR sensors have been used. In the case of the former, much consideration has been given to the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) series of sensors. By virtue of its moderate spatial resolution (1.1 km) and high temporal resolution (providing near-daily coverage), the AVHRR sensor provides an invaluable data source for large-area land cover studies and has been proposed as the foundation of a global monitoring system (Mayaux *et al.*, 1998; Franklin and Wulder, 2002). The continuation of optical remotely sensed data collection at these spatial and temporal resolutions was assured through the launch of Envisat Medium Resolution Imaging Spectrometer (MERIS) (Verstraete *et al.*, 1999) and Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) (Townshend and Justice, 2002).

The use of SAR systems affords the certainty of cloud-free data. The increasing proliferation of spaceborne SAR sensors is a result of recommendation by studies that report them to be well-suited to mapping forest cover, particularly, through the acquisition of multitemporal datasets (Suzuki and Shimada, 1992; de Groof *et al.*, 1992; Kuntz and Siegert, 1999; Quegan *et al.*, 2000; Rosenqvist *et al.*, 2000; Balzter *et al.*, 2002; Sgrenzaroli *et al.*, 2002).

As opposed to using remotely sensed data from a single satellite sensor, the synergy of remotely sensed data from multiple sensors has been shown to provide improved delineation of forest from nonforest. Synergy allows for the exploitation of exclusive information on the forest and nonforest provided by the different spectral data collected by different sensors. A particularly attractive approach is to combine data acquired by SAR systems with those acquired by optical sensors (Nezry *et al.*, 1993; Kuplich *et al.*, 2000; Mayaux *et al.*, 2000) (Figure 2). In addition to the spectral synergy afforded, the cloud-penetrating capability of microwave sensors allows areas that have missing optical data to be included in analyses, particularly if multi-temporal methods are being employed (Asner, 2001; Salas *et al.*, 2002). There is also benefit in using multiple spatial resolution sensor data (Jeanjean and Achard, 1997; Trichon *et al.*, 1999; Salajanu and Olson, 2001; Wu and North, 2001).

Over the past 30 years a number of techniques using the remotely sensed data acquired by both optical and SAR satellite sensors have been employed to delineate forest cover from nonforest cover. Early studies focused on visual image interpretation conducted by trained people with knowledge of the forested area under study. The interpreter relies on spectral and spatial pattern recognition to define areas of forest. The shape, size and pattern characteristics of pixels having similar spectral responses in a single channel or a combination of channels may provide insight to the arrangement of forested and nonforested areas (Tucker *et al.*, 1984). Others have taken advantage of image texture. Texture is particularly evident in fine spatial resolution imagery. It refers to the variance of pixel values associated with a particular object and is prevalent in images of forests. Canopy complexity and the relative sizes of crowns and pixels mean that forest cover has a different texture to a nonforested area (Riou and Seyler, 1997; Saura and Miguel-Ayanz, 2002). Human interpretation of images allows the influence of different satellite viewing angles and bi-directional reflectance of different surfaces to be accounted for. However, the approach can be time-consuming, difficult and subjective. Furthermore, it may be wasteful of information, being based on an image representation of, at most, three spectral bands combined into a colour composite at any one time. With the advent of more sophisticated digital image processing methods, the visual interpretation approach is more often used in the preliminary inspection of imagery or in combination with other approaches (D'Souza *et al.*, 1995). It is these digital image processing methods that have received most attention for the estimation of forest cover and will continue to do so, incorporating the capabilities afforded by the launch of new satellite sensors (see Section IV).

The binary classification of remotely sensed data into a forest or nonforest class allows the application of a radiance threshold to remotely sensed data, whereby those areas having a spectral response either side of the threshold are allocated to a different class (Malingreau and Tucker, 1988; Laporte *et al.*, 1995; Grover *et al.*, 1999). A greater utilization of the spectral information acquired by a sensor for the delineation of forests from nonforests can be achieved using other image classification methods. There are many examples of successful unsupervised and supervised classification of forest and nonforested areas (Brown *et al.*, 1993; Saatchi and Rignot, 1997; Steininger *et al.*, 2001). The quality of the classification output is evaluated by comparison with some ground or other ancillary reference data from which quantitative measures of accuracy may be derived (Foody, 2002).

Studying the intra-annual response of remotely sensed imagery acquired over the same area at different times of year, enables a considerable amount of useful information to be obtained for the delineation of forests from nonforests. The general change in spectral response from areas of forest and nonforest can be characterized and utilized (Malingreau *et al.*, 1995; Roy and Joshi, 2002; Liu *et al.*, 2002). However, it must be remembered that the availability of imagery may be restricted by cloud cover (for optical systems) and cost. Moreover, pre-processing requirements are demanding, since the comparison of images requires the time-consuming task of radiometric, geometric and atmospheric correction of the remotely sensed data (Song *et al.*, 2001; Franklin and Wulder, 2002). Nonetheless, the attractiveness of this approach has been advocated for a number of forested ecosystems (Achard and Blasco, 1990; Conway, 1997; Gemmell *et al.*, 2001).

The growth in the use of remotely sensed data for forest resource assessment has focused attention on the inherent shortcomings of using satellite imagery. In particular, on the coarse spatial resolution remotely sensed data that are the most useful for forest cover delineation for large areas (Grainger, 1993; Downton, 1995; Achard *et al.*, 2001). Generally, as the spatial resolution of an image coarsens, a greater proportion of pixels will have a partial forest cover and so the accuracy of a forest/nonforest classification decreases. The pixels of current coarse spatial resolution sensors typically represent a ground area of 1 km^2 and so the vast majority of pixels will cover a ground area with two or more land cover classes (Holben and Shimabukuro, 1993). These mixed pixels cannot be accommodated or appropriately represented in the conventional 'hard' techniques used widely in remote sensing, where each pixel is only associated with one class, in this case forest or nonforest. Consequently, this results in a classification error of up to 50% (Cross *et al.*, 1991; Skole and Tucker, 1993), with the extent of forest cover often underestimated, resulting in an overestimation of deforestation rate.

It is possible to compensate for misclassification bias by focusing on the validation and correction of regional estimates of deforestation, although the spatial distribution of deforestation will still be erroneous. Forest/nonforest classifications based on coarse spatial resolution data are compared with classifications of a sample of co-registered finer spatial resolution data (Laporte *et al.*, 1995). Corrections may take the form of a simple regression between the classifications at the two spatial resolutions by obtaining the relationship between the two sets of data. This provides an indication of the extent to which the coarse spatial resolution data represent the areally integrated spectral response of the ground surface at the pixel resolution of the sensors (Cracknell, 1998). Others have stratified the coarse resolution classification according to the degree of forest fragmentation across the area of study prior to regression formulation (Mayaux and Lambin, 1995). Misclassifications occurring as a result of image quality, atmospheric variations, topographic and bi-directional reflectance effects, a particular problem with studies using image mosaics, may also be addressed using this approach. Another approach to increasing the classification accuracy of coarse spatial resolution imagery is to unmix the land cover composition of each pixel. Thus, rather than derive a conventional 'hard' image classification, whereby each pixel is classified as either forest or nonforest, estimates of the class composition of each pixel may be derived. These may be used to derive fraction images, which display the proportional coverage of a particular class (in this case either forest or nonforest) in each pixel (Foody *et al.*, 1997a). Although such techniques fail to provide information on the exact location of the sub-pixel compositions, the accuracy of forest cover estimation is often increased. Techniques that have received attention are mixture modelling (Cross *et al.*, 1991; Settle and Drake, 1993; de Moraes *et al.*, 1998), artificial neural networks (Hepner *et al.*, 1990; Peddle *et al.*, 1994; Foody *et al.*, 1997a; Ardö *et al.*, 1998) and sub-pixel calibration (DeFries *et al.*, 1997). These techniques, which afford sub-pixel resolving capabilities coupled with the growing availability of global-scale sets of remotely sensed data (e.g., the AVHRR 8-km Pathfinder data (James and Kalluri, 1994) and the AVHRR 1-km global land dataset (Eidenshink and Faudeen, 1994)), mean that the operational production of forest cover and related statistics at global scales is now an emerging reality. Recent outputs include maps of global percentage tree cover and associated proportions of trees with different leaf longevity and type at the relatively fine spatial resolution of 1 km (DeFries *et al.*, 2000) and pan-European maps of forest cover and a database distinguishing the proportions of coniferous forest, broadleaved forest and mixed woodland at 1 km^2 spatial resolution for France (Kennedy and Bertolo, 2002).

2 Fire occurrence

Remotely sensed data may be used to provide information on biomass burning, which can indicate the magnitude and temporal dynamics of forest cover change through deforestation by burning events (Eva and Lambin, 2000). As with forest cover delineation, much research has focused on the tropical forest environment. The occurrence of biomass burning is indicated by the presence of active fires, burn scars and smoke plumes, all of which are detectable *via* satellite remote sensing. There are many examples of the use of remote sensing for the observation of smoke plumes over forests (e.g., Helfert and Lulla, 1990; Li *et al.*, 2001), however, in terms of measuring changes in forest cover it is important to be able to detect when, where and how much of an area of forest has been burnt. These variables are most accurately estimated through active fire detection algorithms which provide the temporal and locational information and burn area estimation that allow the quantification of change in forest cover through burning (Eva and Lambin, 1998). Inferences about type of fire activity may also be made from such information, which in turn is indicative of the mechanisms promoting forest change. For example, in tropical regions, regular patterns of fire activity are indicative of organized clearance, linear fire patterns may suggest the movement of the fire front or road construction, and multitemporal analysis detecting small, scattered and repeated fire occurrences in one particular area may indicate the rotation cycles for shifting cultivation (Lambin and Ehrlich, 1997).

Theoretically, active fires may be detected by any remote sensor with a middle (1.5–5.0 μm) or thermal (8.0–15.0 μm) infrared spectral channel (e.g., Malingreau *et al.*, 1985; Matson and Holben, 1987; Eva and Flasse, 1996; Wooster *et al.*, 1998; Fuller, 2000; Stroppiana *et al.*, 2003). Active fires emit radiation strongly at these wavelengths, providing a signal that appears widely divergent from its surroundings. The peak spectral emission associated with forest fires vary from between 8 and 12 μm for a cool forest fire (at 500K), 2.9 μm for a moderate forest fire (at 1000K) to 1.6 μm for an intense fire (1800K), thus indicating that at these wavelengths the largest contrast between a fire pixel and a nonfire pixel will be obtained (Robinson, 1991). The choice of wavelength used to detect a fire can affect the accuracy with which the temperature and size of the fire are estimated (Giglio and Justice, 2003), thus the sensor used requires careful selection.

The high temporal resolution of satellite sensors, such as the NOAA AVHRR and Earth Resource System (ERS) Along Track Scanning Radiometer-2 (ATSR-2), makes satellite remote sensing an attractive proposition for measuring active fires; the daily revisit cycle increases the likelihood of new fires being recorded. There are problems however, with using such data. For instance, the NOAA AVHRR sensor has a 1.1 km spatial resolution and a threshold temperature that leads to the saturation of the pixel by small intense fires, medium to large fires of moderate intensity and by many sorts of fires if the background temperature is sufficiently high. This may lead to an imprecise location of burning activity within the ground area represented by a pixel and little indication of the impact of fire on the forest environment. Small fires may not be detected, which also leads to incorrect estimation of remaining forest cover (Kaufman *et al.*, 1990). Despite these problems it has been suggested that remote sensing is at least as effective as ground-based observations of fire and will be a favoured approach in the future (Li *et al.*, 1997).

Burn scars provide a spectrally distinct response from the surrounding vegetation that can be measured using satellite remote sensing with both optical and microwave sensors (Eva and Lambin, 1998; Barbosa *et al.*, 1999; Liew *et al.*, 1999; Fraser and Li, 2002; Bourgeau-Chavez *et al.*, 2002). The success of spatially delimiting burn scars as a prerequisite to estimating change in forest cover by fire events is highly dependent on the spatial resolution of the sensor used (Vazquez *et al.*, 2001). Fine resolution sensors (between 20 m and 80 m) are generally sufficient to capture the spatial pattern of burn scars; however, at coarser spatial resolutions, the burn scars are unlikely to be satisfactorily detected. There is the additional consideration that over time the spectral discrimination of burn scars diminishes, with vegetation growth and removal of the ash layer by wind. This has led to the suggestion that a multisensor approach, in which regional burnt area estimates from coarse spatial resolution data are calibrated on the basis of a sample of fine spatial resolution estimates of burnt areas, should be adopted (Eva and Lambin, 1998).

IV Level 2 forest resource information: forest type

Different forest types lend themselves to different economic uses and have differing conservational value. Satellite remotely sensed data have been used to enhance resource information and provide a resource assessment that relies on knowledge of forest type. There are many examples of forest type identification and mapping using remotely sensed data acquired by both optical and SAR sensors in temperate regions (e.g., Wu and Linders, 2000; Salajanu and Olson, 2001). However, the heterogeneity of forest cover types, particularly in the tropics, and the highly complex spectral response from them, may limit the number of forest types identifiable by satellite remote sensing. An increase in spatial, spectral and radiometric resolution of satellite sensors will enhance the potential information to be exploited. As such the discrimination between forest species as demonstrated by spectroradiometric analysis will become a reality (Van Aardt and Wynne, 2001). However, it must be recognized that while the total information content of remotely sensed data is determined by such prefixed sensor attributes, thematic details derived from the data depend on the analytical techniques used for information extraction (Saxena *et al.*, 1992). These are in development, with a few studies demonstrating their use for the identification of tree species (Foody and Cutler, 2003), assisting the realization of satellite remote sensing for forest biodiversity assessment (Innes and Koch, 1998; Fuller *et al.*, 1998; Turner *et al.*, 2003).

To date, the majority of studies have used satellite remote sensing to map forest types defined on the basis of structural and bioclimatic attributes related to the degree of canopy closure. Roy *et al.* (1991) and Saxena *et al.* (1992) explored forest type identification using remotely sensed data by both visual interpretation and supervised classification techniques. An analysis of the cost effectiveness of these techniques revealed the latter to be more economical. Other studies have concentrated on purely digital classification techniques with refinements to increase the accuracy of classifications (e.g., Sudhakar *et al.*, 1996). Classification accuracy may also be increased through the use of contextual and ancillary information, such as historical land use information, site characteristics (i.e., topography) and geobotanical relationships (Paradella *et al.*, 1994; Tuomisto *et al.*, 1994; Brondizio *et al.*, 1996).

The accuracy with which forest types are mapped using remotely sensed data is also enhanced using inter-annual multitemporal data. Classification of inter-annual multitemporal data sets exploit the temporal change in spectral response from different forest types as a result of phenological activity (e.g., leaf shedding, canopy greeness and senescence) and enable this to be exploited within a classification procedure. This relies primarily on the characterization of the seasonal dynamics of different forest types and their biophysical properties (Spanner *et al.*, 1990; Duchemin *et al.*, 1999). Forest types such as dense evergreen, dense seasonal and tropical deciduous have been distinguished in this way (Achard and Estreguil, 1995), as well as coniferous, mixed and deciduous temperate forest types (Schriever and Congalton, 1995).

V Level 3 forest resource information: forest biophysical and biochemical properties

Measurement of forest biophysical and biochemical properties provide an indication of resource quality, as well as resource management strategy information. In regions of southeast Asia and Africa, shifting cultivation and selective logging have resulted in structural alteration of the forest rather than wholesale clearance (Green and Sussman, 1990; Gilruth *et al.*, 1990) and these would be optimally detected through biophysical property estimation. Additionally, variables such as leaf area index (LAI), the one-sided area of leaves per unit ground area, and leaf biochemistry, affect forest function in terms of light interception and absorption, nutrient cycling and productivity (Bonan, 1993). They vary both spatially and temporally across forest areas and are difficult and expensive to measure. They are, however, the key spatial variables required to drive forest ecosystem simulation models at a range of spatial scales and so considerable effort has been expended in developing remote sensing techniques to map these variables over extensive forest areas (Running *et al.*, 1989; Cropper and Gholz, 1993; Liu *et al.*, 1997; Lucas *et al.*, 2000; Song and Woodcock, 2002).

Forest stand properties, such as age and timber volume, for example, can also be inferred from biophysical properties. Commercial forest managers may require local data on variables such as stand age, average tree height, basal area or timber volume (Poso *et al.*, 1987; Ardö, 1992). Moreover, the accurate measurement of forest regeneration age is pertinent for the development of regional and global carbon budgets (Brown *et al.*, 1993) and the provision of information on forest recovery after loss. Furthermore, it has been noted that, in tropical environments in particular, forest age may be used to infer biophysical properties such as biomass and basal area (Saldarriaga *et al.*, 1988; Brown and Lugo, 1990), as well as other variables such as canopy structure and roughness, and species composition (Swaine and Hall, 1983; Uhl 1987). Thus, forest stand property measurement is also important for forest resource quality assessment.

The past 30 years has seen the adoption of two approaches to relate remotely sensed data to biophysical variables. In physical modelling, canopy radiative transfer processes are simulated mathematically with valuable insights into the fundamental factors driving the relationships between remotely sensed data and vegetation biophysical and biochemical properties (Chen and Cihlar, 1996; Danson *et al.*, 2001). However, their widespread use for forest resource assessment is presently hindered by factors such as the heterogeneity of the canopy, the dynamic characteristics of the canopy optical properties and external effects, such as atmospheric scattering and absorption, all of which are difficult to model. An alternative, and more operational, approach is empirical modelling, whereby the quantitative relationship between remotely sensed data and various derivatives (e.g., vegetation indices) and ground-based biophysical and biochemical property data is calibrated by interrelating known coincident observations of the remotely sensed and ground data. Often, statistical regression procedures are used. The use of radiometically and atmospherically corrected remotely sensed data to develop an empirical model allows its application at other spatial and temporal resolutions. Despite the attractiveness of using the latter approach, a fundamental problem often faced by researchers studying forests is the lack of appropriate ground data that can be brought together with the remotely sensed data (Curran and Foody, 1994). This may account for the limited number of studies conducted to date focusing on the estimation of biophysical and biochemical properties of forest using remotely sensed data. Studies conducted in temperate and boreal forests are more common than those in tropical forests and are used here to indicate the potential of using remote sensing for the assessment of Level 3 forest resource information.

1 Optical remote sensing

Of the many types of biophysical property that influence the radiation at optical wavelengths from forests, LAI is the most important (Danson, 1995). Optical remote sensing for the estimation of forest LAI or its related biomass (leaf and wood) has built on earlier successful work to estimate these variables for agricultural crops and grassland canopies (Curran, 1983; Asrar *et al.*, 1985). In visible wavelengths light absorption is the dominant process and, in general, as LAI or biomass increase, visible reflectance decreases so that a negative asymptotic relationship between red reflectance (R) (0.6–0.7 μm) and LAI is expected. In near infrared wavelengths (NIR) (0.7–0.9 μm) leaf absorption is low and leaf reflectance and transmittance is high. A positive asymptotic relationship is therefore expected between NIR reflectance and LAI or biomass (Danson, 1995). The spectral contrast between red and NIR reflectance has been used to develop 'vegetation indices', which are linear or nonlinear combinations of the reflectance in two or more wavebands (Boyd, 2001) and a number of studies have attempted to correlate vegetation indices with forest LAI.

Early studies by Peterson *et al.* (1987) and Spanner *et al.* (1990) examined the relationships between the LAI and reflectance of temperate forest sites across the western USA and found a significant negative relationship with R reflectance, a significant positive relationship with the simple ratio (SR) vegetation index (NIR/R) or normalized difference vegetation index (NDVI), but no significant relationship with NIR reflectance. Other studies, however, have found only weak correlations between forest LAI and the NDVI (Danson and Plummer, 1995; Hall *et al.*, 1995) and it has been suggested that the spatially variable contribution of soil or understorey to the scene reflectance, coupled with variations in canopy structure and leaf optical properties, may confound the application of vegetation indices for estimating forest LAI (Hall *et al.*, 1996). Moreover, the influences of extraneous factors vary seasonally (Badwhar *et al.*, 1986; Curran *et al.*, 1992; Chen *et al.*, 1997; Miller *et al.*, 1997). These studies indicate that the strength of the relationships between forest LAI and vegetation indices, such as the NDVI, may be site-, time- and species-specific and that above an LAI of about 5 or 6 the NDVI may not be sensitive to LAI variation (Turner *et al.*, 1999). These observations may help explain reported weak relationships between the NDVI and tropical forest biophysical properties, since these forests reach high LAI (Sader *et al.*, 1989; Boyd *et al.*, 1999; Foody *et al.*, 2001). Other factors are also significant (Boyd and Curran, 1998) and include the attenuation of reflected radiation by the large atmospheric water and aerosol load above tropical forests, the low reflectance in red and NIR wavelengths that are observed from tropical forest canopies, and the ecological and physical complexity of tropical forest environments.

Recent research has sought to increase the accuracy of estimation of forest LAI using optical remote sensing via several approaches. One has been to use remotely sensed data acquired at middle infrared (MIR) wavelengths (1.5–5.0 μm). Nemani *et al.* (1993) found that incorporating a MIR infrared waveband from the Landsat TM sensor with R and NIR normalized the effect of variable canopy cover on the relationship with LAI. An exploratory study by Boyd *et al.* (1999) revealed that correcting the MIR radiation acquired by the NOAA AVHRR sensor for thermal emission to derive MIR reflectance, increased the strength of the relationship between radiation acquired in MIR wavelengths and total forest biomass of west African tropical forests over that obtained using the NDVI. The use of MIR reflectance, either alone or within the vegetation index VI3 (NIR−MIR reflectance/NIR+MIR reflectance), provided the strongest relationship with total forest biomass. This success was replicated for the estimation of the LAI of the boreal forest of Canada (Boyd *et al.*, 2000). This suggests that MIR reflectance may be more sensitive to changes in forest biophysical properties than the reflectance in visible and NIR wavelengths and should be considered when estimating the biomass of forests.

The second approach to increasing the estimation of forest LAI using optical remote sensing has focused on high-spectral resolution data, where measurements of surface radiance are made in several hundred narrow wavebands. Several experiments have shown that calculation of first or second derivatives of the canopy reflectance may suppress the effects of variation in understorey reflectance and allow more accurate estimation of LAI (Gong *et al.*, 1992; Johnson *et al.*, 1994). High-spectral resolution data may also be used to calculate the position of the 'red-edge', the point of inflexion in the reflectance spectrum around 720 nm. Correlations between the red-edge position and forest LAI have been found to be stronger than those with single wavebands or vegetation indices based on broad wavebands (Danson and Plummer, 1995; Shaw *et al.*, 1998). The application of these techniques is currently limited by the availability of high-spectral resolution data from satellite platforms. However, the recent launch of the MODIS, MERIS and EO-1 Hyperion sensors provides new opportunities to apply the techniques based on high-spectral resolution data to estimate forest biophysical properties (Van Der Meer *et al.*, 2001; Pu *et al.*, 2003).

The significant advances made in estimating forest LAI and related biomass from remotely sensed data have been partly facilitated by the use of new techniques and instruments for measuring the LAI of forest stands using light interception. This has allowed the traditional and expensive destructive sampling techniques to be complemented by techniques that allow rapid measurement of LAI at a large number of sites (Chen *et al.*, 1997). Furthermore, large multidisciplinary experiments such as the Oregon Transect Ecosystem Research Project (OTTER) and the Boreal Ecosystem and Atmosphere Study (BOREAS) have provided comprehensive ground and remotely sensed data sets with which to develop and test LAI estimation techniques (Peterson and Waring, 1994; Sellers *et al.*, 1997). Further developments are likely to involve a greater emphasis on the application of radiative transfer models of forest canopy reflectance, to investigate how differences in leaf optical properties and forest structure and composition affect the relationships between forest LAI and spectral reflectance (Dawson *et al.*, 1999). Other developments will include the use of off-nadir viewing, which increases the performance of vegetation indices for the estimation of LAI when compared with nadir viewing data (Gemmell and McDonald, 2000) and the use of artificial neural networks (ANN), which yield stronger correlations with biophysical properties of forest in both tropical and non-tropical environments than vegetation indices (Jensen *et al.*, 1999; Foody *et al.*, 2001).

Forest stand properties have no direct physical relationship with the remotely sensed signal, but they may be co-correlated through indirect relationships with LAI, biomass or canopy cover (Danson and Curran, 1993). For example, a large number of studies have sought relationships between forest stand variables and a range of remotely sensed data with mixed success. Strong negative relationships have been found between red and NIR satellite sensor data and wood volume or basal area in a range of forest environments (Danson, 1987; Ripple *et al.*, 1991; Cohen and Spies, 1992; Baulies and Pons, 1995), while other studies have found strong correlations with forest stand age and tree density (DeWulf *et al.*, 1990; Brockhaus and Khorram, 1992; Danson and Curran, 1993). Relationships established by correlation and regression techniques depend mainly on the existence of a consistent monotonic change in reflectance as the stand develops. Such a relationship may exist up to a point where the forest stand reaches full canopy cover but not thereafter (Nilson and Peterson, 1994; Puhr and Donaghue, 2000). Furthermore, additional factors are likely to influence the empirical relationship between spectral response and stand age (Cohen *et al.*, 2001), for example spatial variations in canopy cover or differences in terrain slope (Gemmell, 1995).

The ability to estimate forest stand age has assumed much importance in the drive to understand carbon budgets of forests, particularly in tropical regions. Forest age is linked to the amount of carbon sequestered by an area of the Earth's surface from the atmosphere (Houghton, 1996). Studies exploring the remotely sensed response from tropical forests of different ages have demonstrated the capabilities of remote sensing for deriving regeneration age class maps of tropical forests, at least up to the point where the primary and secondary forest spectral responses 'blend' (Kimes *et al.*, 1998). Age class maps of tropical forest via remote sensing have been derived using one of three approaches. One has utilized the resolved relationships between remotely sensed response and age (Mausel *et al.*, 1993; McWilliam *et al.*, 1993; Steininger, 1996; Boyd *et al.*, 1996). Another approach to deriving age class maps has been to classify remotely sensed images of forests into age classes via a supervised classification (Foody *et al.*, 1996; de Moraes *et al.*, 1998; Helmer *et al.*, 2000). The last approach uses a time series of coregistered, multispectral images (Lucas *et al.*, 1993; Alves and Skole, 1996; Frohn *et al.*, 1996). These image sequences, however, often have gaps because of the difficulties of obtaining cloud-free scenes, costs and temporal discontinuities between satellite sensors and this missed information could introduce unknown errors into the mapping of forest age (Kimes *et al.*, 1998).

Pioneering work in the late 1980s began to explore the use of remote sensing for determining the relationships between forest canopy biochemicals and rates and patterns of biogeochemical cycling. Ecologists had established the importance of foliar nitrogen content of forest vegetation that, in conjunction with LAI, is closely related to photosynthetic capacity and nitrogen uptake (Gholz, 1982). In addition, the ratio of leaf lignin to leaf nitrogen has been shown to be related to rates of litter decomposition (Melillo *et al.*, 1982). Measurement of these and other biochemicals over large areas of forest was therefore seen as a key step toward mapping the spatial characteristics of forest nutrient cycles (Peterson *et al.*, 1988). This became a possibility with the new generation of field spectroradiometers and imaging spectrometers, which allowed measurement of surface reflectance in a large number of narrow wavebands.

Experiments on dried ground samples confirmed that leaf nitrogen and lignin content could be estimated using laboratory instruments (Card *et al.*, 1988; Peterson *et al.*, 1988; Wessman *et al.*, 1988) but the challenge for ecological remote sensing was to extend the laboratory techniques from analysis of dried ground samples to fresh leaves, whole branches and complete canopies. Work on fresh foliage further indicated the potential of the technique for estimating the biochemistry of intact leaves (Peterson *et al.*, 1988). Although the presence of water in the leaves may suppress the biochemical signal because of water absorption in the short-wave infrared (SWIR), several studies have shown that leaf nitrogen, protein, cellulose, lignin, chlorophyll and starch content may be estimated from reflectance measurements (McLellan *et al.*, 1991; Jacquemoud *et al.*, 1995; Johnson and Billow, 1996). It does appear, however, that the wavebands selected in step-wise regression for fresh leaves are not always clearly related to known absorption features for the biochemicals (Grossman *et al.*, 1996).

The results of the work on estimating leaf biochemistry stimulated the first experiments on estimating the biochemistry of complete forest canopies using data from imaging spectrometers (Vane and Goetz, 1993; Wessman *et al.*, 1988). Further work using imaging spectrometers has been conducted in two major experiments, the OTTER project (Peterson and Waring, 1994) and the NASA-funded Accelerated Canopy Chemistry Program (ACCP) (Aber, 1994). These involved the use of the Airborne Visible Infrared Imaging Spectrometer (AVIRIS). In the OTTER project AVIRIS data were acquired in 1990 and 1991 over six study sites along a 250 km east–west transect representing forest vegetation zones from coastal rainforest to semi-arid scrub (Johnson *et al.*, 1994; Matson *et al.*, 1994). Strong correlations were found between the AVIRIS first difference spectra and total nitrogen, chlorophyll and lignin measured both as canopy biochemical content (kg ha^{-1}) and foliar concentration (mg g^{-1}). Correlations for starch were weaker for both concentration and content. In the ACCP, AVIRIS data were acquired over a number of forest test sites in 1992 and 1993. Martin and Aber (1997) used data for Blackhawk Island, Wisconsin and Harvard Forest, Massachusetts to examine spatial and temporal variation in canopy lignin and nitrogen concentrations for a total of 40 stands. They found strong correlations between first difference spectra and biochemical concentrations for both sites separately and for data combined from both sites. However, when the calibration equation derived for one site was used to predict biochemical concentrations at the other, the relationships were insignificant. Errors in atmospheric correction and low signal to noise ratio were suggested as possible causes for the inconsistency. Curran and Kupiec (1995) and Curran *et al.* (1997) also used AVIRIS data to estimate the biochemical composition of a slash pine canopy in Florida. They found very strong correlations between the remotely sensed data and chlorophyll, nitrogen, lignin and cellulose measured both as concentration and content.

Remote sensing is the only technique available for estimating forest biochemical properties over large areas and shows great potential for providing biochemical information related to forest productivity and health and for input into process-based ecosystem models. The recent availability of data from the spaceborne MODIS, MERIS and Hyperion sensors, and advances in radiative transfer modelling of leaf and canopy reflectance, should ensure further progress (Curran and Kupiec, 1995; Gastellu-Etchegorry and Bruniquel-Pinel, 2001; Dawson *et al.*, 2003).

2 Microwave remote sensing

There has been growing interest in the capabilities of microwave remote sensing, particularly in the form of SAR instruments, for the estimation of forest biophysical properties. This research on the microwave response of forest canopies has benefited from the availability of data from space-borne instruments, in particular the C-band (3 cm) Active Microwave Instrument (AMI) on ERS-1 and ERS-2, the L-band (23 cm) SAR on JERS-1, and data from the Shuttle Imaging Radar (SIR-C) flown on the Space Shuttle Endeavour in 1994 (C and L band). In addition, sophisticated airborne SAR instruments such as the C-, L- and P-band (50 cm) AirSAR and E-SAR have provided an opportunity to test the application of multifrequency polarimetric data (Paloscia *et al.*, 1999; Hoekman and Quinones, 2000).

Microwave signals, in contrast to optical wavelengths, are unaffected by atmospheric conditions, including clouds, because the wavelength of the radiation is several orders of magnitude larger than the atmospheric particles (Baker *et al.*, 1994; Quegan, 1995). This means that SAR instruments have an all-weather day/night imaging capability, which is a major advantage for imaging the cloudy regions of the Earth, where forests are present. The processing and analysis of SAR data is relatively complex with the magnitude of the backscattered radiation dependent on both wavelength and polarization. However, it has been shown both experimentally and by theoretical modelling that the penetration of microwaves into the forest is dependent primarily upon wavelength. Short wavelength (e.g., X band ≈ 3 cm) microwaves interact with the surface of the canopy causing scattering from leaves, twigs or branches; medium wavelength (e.g., C band ≈ 6 cm) microwaves interact with the volume of the canopy/trunk volume; and longer wavelength (e.g., L band ≈ 22 cm) microwaves penetrate the canopy, interacting with the ground/trunk (Curran and Foody, 1994). The depth of microwave penetration is further dependent on the angle of incidence of the sensor, canopy closure (Ulaby *et al.*, 1982; Churchill and Sieber, 1991) and on the polarization of the sensor (Elachi, 1988). Many SAR can both transmit and receive microwaves at two different polarizations and this enhances the information provided, particularly on surface roughness and geometric regularities in the forest stand (Carver, 1988).

Many studies have found positive nonlinear relationships between microwave backscatter and forest above-ground biomass, with saturation of the signal occurring at different levels depending on the wavelength measured (Imhoff, 1995; Fransson and Israelsson, 1999), microwave polarization and sensor viewing geometry (Le Toan *et al.*, 1992; Baker *et al.*, 1994). Estimation accuracy is also dependent on forest structure and ground conditions (Baker and Luckman, 1999; Ranson and Sun 2000). Ranson *et al.* (1997) showed that SIR-C data could be used to map above-ground woody biomass of boreal forests to within 16 t ha^{-1} with sensitivity to a limit of 150 t ha^{-1}. Tropical forests, in general, reach higher biomass levels than other forests and have shown different relationships. L-band microwaves can be used to discriminate between different levels of regenerating forest biomass (up to approximately 20 years old, 60 t ha^{-1}) and cross-polarized backscatter is more sensitive to changes in biomass density than monopolarized backscatter. The use of C-band SAR imagery is limited to differentiating between very low biomass or clear cut areas and those with some vegetation when it is dry (Yanasse *et al.*, 1997; Luckman *et al.*, 1997, 1998). Increases in the strength of the relationship between microwave data and biomass have been attained using backscatter ratios (e.g., LHV/LHH) and moreover by stratifying the biomass data by forest type (Foody *et al.*, 1997b).

In addition to the work on estimating forest biomass there has been some success in the use of SAR for mapping forest stand properties. Unlike the classification of data from optical remote sensing systems, the classification of forest cover types from SAR data exploits differences in the macro structure between stands of different species, age or density (Ranson and Sun, 1994; Saatchi and Rignot, 1997; Castel *et al.*, 2002). Specific stand information, such as stem volume, tree trunk diameter and, through the use of interferometric coherence, forest height, has been estimated using SAR (Castel *et al.*, 2000; Balzter, 2001; Tetuko *et al.*, 2001). However, despite the potential shown by SAR for the provision of Level 3 resource information, currently it is the optical remote sensing approach that is more useful (Hyyppä *et al.*, 2000).

VI Future developments in forest resource assessment by remote sensing

As forest resources face increasing pressure so the need to acquire more accurate, timely information about their current status grows. As this review demonstrates, satellite remote sensing is well placed to provide this information, forming a significant part of any forest resources information system (Franklin, 2001). Indeed, to date there have been numerous major programmes that have used remotely sensed data to inventory and monitor forests (e.g., UN Food and Agriculture Organisation Forest Resources Assessment (FRA; Zhu and Waller, 2003) and Global Observations of Forest Cover–Global Observations of Landcover Dynamics (GOFC/GOLD; Townshend and Justice, 2002); UNEP Global Resource Information Database (GRID; Jaakkola, 1990); EC TREES (Malingreau *et al.*, 1995) and SIBERIA (Balzter *et al.*, 2002)).

Future developments in forest resource assessment by remote sensing will feature a number of strands. Critically, the success of these strands will be judged on their operationalization in forest management (Franklin, 2001). One strand results from the recent and imminent launch of new spaceborne sensors. The improved spectral, spatial, temporal, radiometric and angular resolutions of these sensors should serve to improve current capabilities of remote sensing for forest resource assessment (Kaufman *et al.*, 1998; Stibig *et al.*, 2001; Brown, 2002). It is hoped that the capabilities demonstrated by current airborne sensors such as the Scanning Lidar Imager of Canopies by Echo Recovery (SLICER) (Means *et al.*, 1999) and the European digital airborne imaging spectrometer (DAIS) (De Jong *et al.*, 2003), will be replicated by those in space. Hyperspectral sensors, such as EO-1 Hyperion (Martin *et al.*, 1998; Treuhaft *et al.*, 2003), along with hyperspatial sensors, such as IKONOS and EROS A1 Pan with its 1.5 m spatial resolution (St-Onge and Cavayas, 1995, 1997; Wulder, 1998; Franklin *et al.*, 2001) promise to increase the accuracy of forest resources inventories. Another highlight includes the ability to inventory forests in the *z*-dimension through the use of laser scanning (Drake *et al.*, 2002; McCombs *et al.*, 2003) and SAR interferometry (Varekamp and Hoekman, 2002).

There will be increased access to remotely sensed data and products targeted at forest resource assessment (Running *et al.*, 2000). Different data sources will enable users to choose products at a particular processing level, enabling them to work at coarse spatial resolutions to study global resources or at fine resolutions to study resources at targeted regions. Other developments will focus on improvements in remotely sensed data analysis. Assessment of forest resources by remote sensing depends on the existence of relationships between the forest spectral signature and the variable of interest, for example canopy nitrogen concentration. Much of the work done to date has sought statistical relationships between the spectral variables and the forest variables, often with some success. A problem arises, however, when the statistical relationships are dependent on the sensor used, the canopy type or the measurement condition. Recent work has begun to address this problem by developing radiative transfer models that describe the interaction of electromagnetic radiation with the leaves, branches and canopies of forests (Li *et al.*, 1995; North, 1996; Chen and Leblanc, 1997). These models can be used to simulate the reflectance of forest canopies by running them in the 'forward' mode, where data on the forest canopy variables are the inputs and the spectral signature is the output. They also have been used to estimate forest biophysical properties by applying them in the 'inverse' mode, where the spectral signature is the input and estimates of the forest biophysical variables are the outputs (Woodcock *et al.*, 1994; Gong *et al.*, 1999; Gemmell *et al.*, 2002). Although this work is in the early stages of development, the approach is potentially more robust and more accurate than the statistical techniques currently used.

Developments along each one of these strands will be mutually beneficial to the future of forest resource assessment using remote sensing. This will be coupled with the availability of ancillary data and the increasing length of the remote sensing record (Figure 1) that will provide a reliable historical record of forest resource change of benefit to those requiring improved understanding of agents and forces of forest change (Myneni *et al.*, 1998).

VII Conclusions

Forest resource assessment by remote sensing began in the first part of the twentieth century with local-scale forest mapping from aerial photography. Since 1972, with the launch of the first satellite sensor for monitoring Earth resources (ERTS), there have been significant advances in remote sensing technology that have allowed forest resources to be assessed over much larger areas through the use of spaceborne sensors. Sensors record remotely sensed data from forests and these are processed and interpreted to extract resource information, of which there are three levels of detail. The first level refers to information on the spatial extent of forest cover, which can be used to assess forest dynamics; the second level comprises species information within encompassing forested areas, and the third level provides information on the biophysical properties of forests. The assessment of such forest information over time allows the comprehensive monitoring of forest resources. The combination of new remote sensing technology and new data analysis techniques, with advances in remote sensing science and ecosystem modelling, have assured a critical role for remote sensing in mapping, monitoring and managing forest resources. However, the true success of remote sensing will come when the results of research are transferred to organizations that have the power to use this information in deciding policy with which to sustainably manage and use the Earth's forest resources (Franklin, 2001; Hayes and Sader, 2001).

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