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Applications of satellite remote sensing to forested ecosystems

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Abstract

Since the launch of the first civilian earth-observing satellite in **1972,** satellite remote sensing has provided increasingly sophisticated information on the structure and function of forested ecosystems. Forest classification and mapping, common uses of satellite data, have improved over the years as a result of more discriminating sensors, better classification algorithms, and the use of geographic information systems to incorporate additional spatially referenced data such as topography. Land-use change, including conversion of forests for urban or agricultural development, can now be detected and rates of change calculated by superimposing satellite images taken at different dates. Landscape ecological questions regarding landscape pattern and the variables controlling observed patterns can be addressed using satellite imagery as can forestry and ecological questions regarding spatial variations in physiological characteristics, productivity, successional patterns, forest structure, and forest decline.

Introduction

Since the launching of the first earth-observing civilian Landsat satellite in **1972,** satellite remote sensing has been used for gathering synoptic information on forests. In the early years, satellite data were used mostly by geographers to create maps of forest types. These early efforts relied almost entirely on satellite-collected digital spectral data with no integration of ground-based digital information such as topography. More recently, ecologists have joined the geographers in utilizing satellite technology for a variety of forest-related applications which will be reviewed in this paper: detecting landscape change over time, relating landscape patterns to biological or physical phenomena, evaluating physiological processes of forest canopies, and quantifying forest cover, biomass, or productivity over varying scales of spatial resolution.

The sophistication of applications evident in recent years has been made possible by **(1)** the use of more spectrally and/or spatially discriminating sensors; **(2)** the improvement of hardware and software systems designed to process spatially-referenced digital data, and **(3)** the increased availability, standardization, and compatibility of other spatially-referenced digital data sets such as digital topographic variables generated from digital elevation models. The most common sources of satellite data relevant to forests are the **U.S.** Landsat Thematic Mapper (TM), the **U.S.** Landsat Multispectral Scanner (MSS), the **U.S.** Advanced Very High Resolution Radiometer (AVHRR), and the French Système Probatoire d'Observation de la Terre (SPOT). The spectral characteristics and spatial resolution of data from these sensors are por-

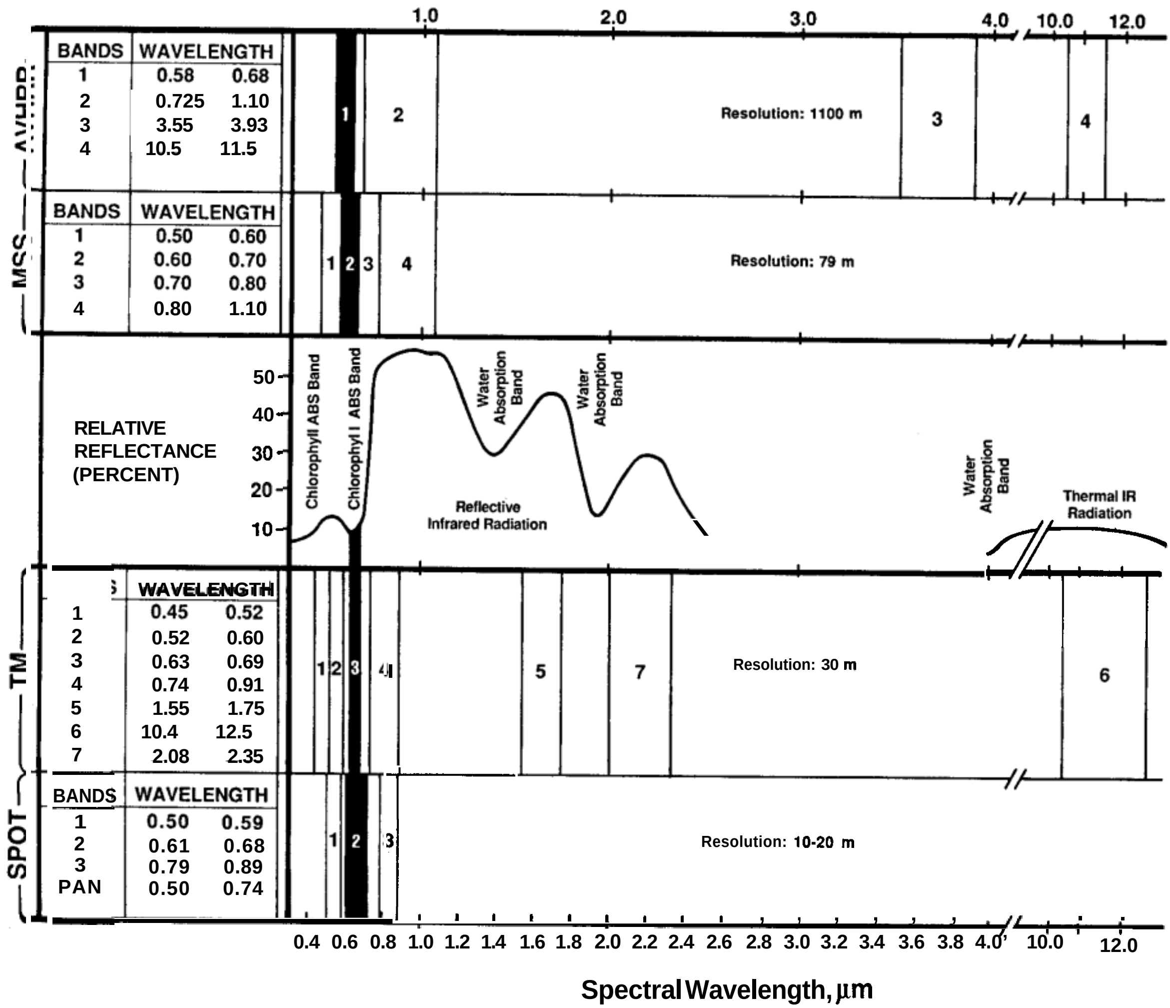

Fig. 1. Spectral and spatial resolution for four common satellite sensors: **AVHRR,** MSS, **TM** and SPOT. **Also** shown is a spectral response curve for typical green vegetation.

trayed in Fig. 1 and compared to the electromagnetic spectrum typically found in green vegetation. More details on each sensor's characteristics can be found elsewhere (*e.g.*, Billingsley **1984;** Greegor **1986).** Several other sensors have been used in forest-related applications but much less frequently; for example, the Scanning Multichannel Microwave Radiometer (SMMR) to monitor vegetation in semiarid regions (Choudhury and Tucker **1987)** or for assessing global primary productivity (Choudhury **1988)** and radar data for detecting forest change (Lee and Hoffer **1988;** Stone and Woodwell **1988).** Several sophisticated airborne sensors are capable of detecting a great deal of ecological information on forests, but are beyond the scope of this paper. Sensors on the recently launched Japanese satellite and the Russian satellite are also useful in forest applications although their full potential is untested.

Current trends in ecological studies have dictated the integration of remotely sensed digital spectral data into geographic information systems (GIS). This merger moves satellite spectral data beyond standard image processing and permits the use of remotely sensed spectral data in conjunction with such other spatially referenced digital data as elevation, slope aspect, vegetation type, and soils. In this way, information about a landscape can be enriched beyond what is possible by the separate systems (Logan and Bryant 1987). The integration of image processing systems and multilayered spectral data (as provided by satellite sensors) with GIS and digital geographic databases allows for the development of more sophisticated models of landscape-scale variables such as regional forest cover (Iverson *et al.* 1989).

The objective of this paper is to review ways in which satellite remote sensing can be useful in delineating structural and functional characteristics of forests at a variety of geographical scales. We focus on the following uses of satellite imagery: (1) classification and mapping of forest types; **(2)** detection of areal change in forestland due to clearing or reforestation; (3) determination of patch disappearance and compositional change during succession; (4) assessment of forest structure (basal area, biomass, leaf area index, density, crown closure); *(5)* determination of damage or forest decline; (6) assessment of physiological processes and (7) assessment of forest cover and productivity.

Applications of remotely-sensed data to forests

Mapping of forest types

Using satellite data to classify and map various forest and/or land-use types has historically been, and still is, the most frequent use of satellite data. Pixels are classified according to their ground reflectance values as measured by the satellites. The desired map is created by displaying the classified pixels in their appropriate geographic context. Two types of classification procedures may be followed to create a forest type map from a satellite image (Colwell 1983; Lillesand and Kiefer 1987). In *unsupervised* classification, computer algorithms are used to examine the spectral data of the entire scene and to clump pixels with like spectral properties into common classes according to the specific clustering algorithm used. The classes are independent of any *apriori* assumptions as to what ground cover they actually represent. After the classes are generated, the operator assigns meaning to the classes (*i.e.*, converts the classes to landcover types) on the basis of ground-based data and the spectral properties of the class (*e.g.*, water has unique reflectance characteristics so it can often be discerned directly from its spectral signature). In *supervised* classification, the operator assigns specific pixels (training sites) to particular landcover classes on the basis of ground-based data. Computer algorithms are used to analyze the spectral properties of those sets of pixels and to assign the remaining pixels to landcover classes on the basis of the statistical similarity of their spectral properties.

Satellite data of all resolutions have been used to generate forest type maps, from high resolution SPOT and TM land-use maps (*e.g.*, Hopkins *et al.* 1988; Buchheim *et al.* 1985; Nelson *et al.* 1984) to mid resolution MSS maps (*e.g.*, Beaubien 1979; Dodge and Bryant 1976) to coarse resolution AVHRR maps (*e.g.*, Tucker *et al.* 1985; Norwine and Greegor 1983; Townshend *et al.* 1987).

Comparisons of the various sensors for classification and mapping accuracy have shown the superiority of the finer resolution TM data over the MSS data (DeGloria 1984; Williams *et al.* 1984; Malila 1985; Toll 1985; Hopkins *et al.* 1988). Toll (1985) found that the improvement in classification of a scene of rapidly urbanizing Washington D.C. was due primarily to the better spectral discrimination of TM data (especially TM bands 1, 5, and 7; Fig. 1) and to a lesser degree to the increase in quantization of the spectral data within a band (a raw MSS band value can range from 1–128; a TM band value can range from 1–256). Interestingly, Toll found that the increased spatial resolution of TM reduced his ability to differentiate land-use classes of the first order such as urban, forest, agriculture, and water. This reduction occurred because the finer resolution TM data increased spectral variability within the pixels of first-order classes but the spatial context of the pixel was not incorporated into the classification algorithms (*e.g.*, forested urban areas such as yards and small parks were classified as forest rather than urban). However, Hopkins *et al.* (1988), examining forested areas of Wisconsin, USA, found the spatial detail of TM to be advantageous in classifying second- and third-order forest land-use types such as upland coniferous forests and central hardwoods. The difference in classification accuracy lies in the nature of the land-cover classes desired: for classification of a finer, higher order, the higher spatial resolution of TM is beneficial (Williams and Nelson 1986); for classification of a coarser, lower order, TM is disadvantageous unless the spatial context of a pixel is incorporated into the classification procedure.

The usefulness of SPOT data in classifying forest types has received mixed reviews. In an urban study in Athens, Georgia, SPOT data were found to increase the accuracy of all second- and third-order classifications by about 15 to 20% over that of TM (Welch 1985); further, these data were suitable for cartographic mapping at a scale of 1:24,000. However, SPOT data may be less helpful for mapping forest types (away from urban regions) because its reduced spectral resolution (fewer bands) relative to TM may obscure vegetation differences.

AVHRR classifications are useful for maps of large areas and can be verified with higher resolution images or map data (Schneider 1984). For example, multitemporal AVHRR data were used to develop a vegetation map of South America in which 16 vegetation classes were differentiated, several with accuracy greater than 90% (Townshend *et al.* 1987).

Much research has been conducted in an effort to enhance classification results. Raw spectral data may be pre-processed prior to classification. Various mean or median filters, in which pixels are reassigned the mean or median spectral value of their surrounding pixels, may be applied to reduce intra-class variance while retaining the boundary detail of classified areas (Atkinson *et al.* 1985; Cushnie and Atkinson 1985). Raw spectral values are also sometimes converted to their principal component values via principal components analysis of the entire scene. More sophisticated techniques for classification include stepwise discriminant analysis (Nelson *et al.* 1984) and per-field algorithms (Dean and Hoffer 1982) in which the classification of a pixel depends not only on its own spectral characteristics but also on those of adjacent pixels.

Recently, classification accuracies have been improved by using a GIS to integrate digital biogeographical data with satellite sensor data (*e.g.*, CERMA 1985). For example, topographic variables were integrated with TM data to increase the accuracy of classifications of vegetation communities in Rocky Mountain terrain (Frank 1988). By incorporating topographic variables, the shadowing effects created by the angle of the sun can be accounted for. Topo-climatic variables can also provide indirect information about vegetation cover which can be incorporated directly into classification algorithms. Other biogeographical variables – soil types, landforms, geology, or vegetation maps – can also be helpful in classifying by providing strata (*e.g.*, forest–non-forest, cultural–non-cultural, or wetland–non-wetland masks) that allow image classification to be focused on a particular area or resource of interest.

Using satellite imagery to classify forest types is still a subjective procedure and as much an art as a science. Nonetheless, the technique has proven very useful not only to researchers but also to agencies that manage land resources. Classifications tend to be more accurate in flatter terrain and when the vegetation types are sharply contrasting, for example, coniferous versus hardwood or forested versus agriculture. The use of multitemporal scenes to capture phenological differences in vegetation often improves accuracy. In inaccessible parts of the world such as the tropical and boreal regions, satellite imagery is invaluable in mapping forest-land because often no other current data are available.

Detection of forest change

Changes in forest cover over time are important because of the role forests play in the global carbon cycle, in global climatic trends, and in providing species habitat (Woodwell *et al.* 1984). Although understanding forest change is important worldwide, it is especially important in the tropics, where land-use transformation is occurring very rapidly and where timely ground data are scarce.

The basic methodology for detecting change is straightforward: two or more satellite images of the same area, preferably taken at the same phenological period but in different years, are overlaid to show geographically specific changes in landcover.

In some cases, raw satellite spectral data can be taken from the two scenes and merged to make a multiple band combination data set, which is then classified. Usually, however, the two images are classified separately prior to combining the data; this technique permits the use of varying data types such as MSS and TM or even historic ground-based maps.

By comparing digitized ground-based maps of Costa Rican forestland from 1940, 1950, and 1961 and MSS-derived forest cover maps of 1977 and 1983, Sader and Joyce (1988) found that forest cover had decreased from 67 to 17% between 1940 and 1983 with the most rapid rate of clearing between 1977 and 1983. Furthermore, four of the 11 Costa Rican life zones had disappeared completely: the dry tropical, the moist premontane, the moist lower montane, and the wet montane. They also demonstrated the close relationship between road building and deforestation by overlaying transportation network maps with forest cover maps.

Deforestation in the Amazon basin of Brazil has been quantified by using AVHRR band 3 thermal data which, unlike the visible bands, can penetrate the ubiquitous cloudcover of the region (Tucker *et al.* 1984; Malingreau and Tucker 1987). Estimates of deforestation were obtained by using band 3 to detect both the fires associated with lines of active deforestation and the devegetated areas, which are warmer. The studies of Rondonia, Brazil, indicate that the deforested area increased from 4200 km^2 in 1978 to 10,000 km^2 in 1982 to 27,000 km^2 in 1985 to over 35,000 km^2 in 1987 (Malingreau and Tucker 1987; Malingreau and Tucker 1988).

Deforestation rates in Rondonia, Brazil, have also been evaluated using AVHRR data in combination with selected cloudfree 1976, 1978, and 1981 MSS scenes of much smaller portions of the region (Nelson and Holben 1986; Nelson *et al.* 1987; Woodwell *et al.* 1987). The spatially precise MSS data revealed a doubling of deforestation rates between the 1976–1978 and 1978–1981 intervals (Woodwell *et al.* 1987). The MSS data were also used to check the accuracy of AVHRR band 3 estimates of cleared areas for the entire state of Rondonia. The estimates appeared reasonably accurate given the constraints on the satellite data and the lack of timely ground data. Radar data also holds good potential for assessing deforestation in the tropics since radar data are not constrained by cloud cover. For example, Stone and Woodwell (1988) found Shuttle Imaging Radar-A (SIR-A) data to have the brightest returns (the highest signal returns to the radar sensor result from smooth, deforested areas) on recently deforested regions in Amazonia.

Although most forest change studies using satellite data have focused on deforestation in the tropics, temperate forest changes have also been studied because of their importance with regard to soil protection, water retention during flooding, wildlife habitat, timber resources, and recreation sites. For example, loss of bottomland forest coincident with upland forest regeneration has been documented in southern Illinois, USA, using classified 1978 MSS and 1984 TM scenes (Iverson and Risser 1987), as has forest degeneration in the high-elevation forests in the Green Mountains of Vermont (Vogelmann 1988).

The accuracy of satellite-based studies of forest change in the tropics are difficult to determine, given the lack of ground-based data for verification. Nonetheless, the results are valuable because they are often the only source of timely, regionally consistent information on deforestation. In temperate regions where ground-based data are often available (*e.g.*, national forest inventories), satellite studies are nevertheless valuable because they can show the spatial pattern of change, which most inventories cannot, because they can look at shorter time intervals (two to three years versus 10 or more years for most ground-based surveys), and because the methodologies developed to assess forest cover (or change) over large regions can be validated with the independent inventory data sets (as in Iverson *et al.* 1989).

Forest succession

The spatial and temporal patterns of forest succession can be studied using spatially referenced vegetation data from two or more dates. Transition probabilities of forest succession pathways in northern Minnesota, USA, were calculated using classified MSS scenes from **1973** and **1983** (Hall *et al.* **1987).** Transition probabilities of the managed areas differed from those of the wilderness areas primarily because of the influence of logging, which altered not only the rates of transition but also the possible types of transition. In a second type, Walker *et al.* **(1986)** successfully used Landsat MSS data in Australian semi-arid eucalypt woodlands to detect stage of seccession based on structural differences in *0* to 50 year old clearings.

In another forest succession study, which utilized both image processing and GIS technology, the stability and fate of abandoned pasture patches in a mosaic of mountainous forest were found to be significantly related to original patch size and elevation (Graham *et al.* **1987).** This study used **1934** vegetation maps depicting the abandoned pastures and **1984** TM imagery. The fate of the pastures patches was determined by comparing the **1984** spectral signature of pixels within the historic boundaries of the abandoned patches with the spectral signature of pixels just outside the patch boundaries.

Satellite imagery holds considerable promise for determining the rate and spatial context of succession; however, this use is still experimental and not without problems. The accuracy of transition probabilities will depend in large part on the accuracy of the original classifications. Furthermore, there are theoretical problems in calculating transition probabilities with data that have a time interval equal to or greater than that of the change phenomena.

Assessment of stand structure

Satellite data have been used with varying degrees of success to quantify spatially such forest structure characteristics as crown cover, tree density, tree diameter, basal area, tree height, tree age, biomass, and leaf area index. In general, the technique is to collect spatially-referenced ground data on the forest structure variable of interest and then to determine the statistical relationship between the ground-obtained data and the spectral data for the same location. Thus far, most studies have used spectral data generated from airborne sensors such as the thematic mapper simulator (TMS), which has bands identical to TM, rather than satellite-borne sensors. The resolution of airborne spectral data is often finer than that of satellite data. Virtually all studies have focused on coniferous forests, which tend to be more uniform and more distinguishable from other vegetation types than are deciduous forests. Whether the techniques used to relate satellite data to forest structure in coniferous forests will also be appropriate for non-coniferous forests is yet to be determined.

Canopy closure in montane, coniferous forests of California, USA, correlated well with the spectral intensity of several TMS bands ($r = 0.62$ to $0.69, n = 103$) irrespective of forest type (Peterson *et al.* **1986).** Total stand basal area, however, was poorly related to the spectral data ($r < 0.33$). Stratification by forest type improved the spectral relationship with basal area. The data suggested that the relationship between total basal area and spectral signature will be strongest in young, low density, even-age stands. In another study of Californian coniferous forests, TMS bands **1, 2** and **3** (analogous to TM bands 1, **2** and **3)** were most strongly related to stand basal area and leaf biomass (Franklin **1986).**

A relatively high relationship between TMS spectral band intensity and canopy closure ($r = 0.80, n = 32$ for band **5)** was found for the pine-aspen forest of Colorado, USA (Butera **1985).** By applying a regression model of this relationship to the raw band 5 value of every pixel in the mountainous scene, Butera generated a map of forest canopy closure. The accuracy of the map was **71%, 74%,** and **54%** for canopy closures of 0–25%, 25–75%, and **75–100%** respectively.

Spanner *et al.* **(1984)** used a classification approach to study the ability of TMS imagery to differentiate crown closure and tree size classes in a fir-dominated forest in Idaho, USA. They found > 60% accuracy in classifying crown closure classes of > 70%, 40–69%, and 10–39%, with less accuracy on sites of very low (< 10%) crown closure. Sawtimber and pole size classes were also classified with **72–87%** accuracy. The optimal bands in these analyses were, in order, **4, 7,** 5, and **3.**

Again using TMS imagery, researchers have related leaf area index (LAI) of coniferous forests to spectral band intensity (Running *et al.* **1986;** Peterson *et al.* **1987).** In these studies, LAI of coniferous forest stands along a transect across the mountains of Oregon, USA, was strongly related to the ratio of band 4 to band **3** ($r^2 = .82$, $n = 18$). LAI of these stands ranged from < 1 to > 16.

Danson **(1987)** correlated SPOT data with structural characteristics of pine forests in England and found highly significant correlations of SPOT band **3** (near infrared) to tree density, diameter at breast height, and tree age but not to canopy cover. Wu and Sader **(1987)** showed that airborne Multipolarization Synthetic Aperture Radar (SAR) also may be used with some success to estimate basal area, tree height, and total tree biomass.

An airborne, pulsed laser system, called the Light Detection and Ranging (LIDAR) system was also used to predict total tree volume and green weight biomass of pine plantations in Georgia (Nelson *et al.* **1988).** They were able to predict overall tree volume to within **2.6%** and mean biomass to within 2.0%, but were not successful at predicting volume or biomass on a site by site basis.

Results from these studies are encouraging in that statistically significant relationships between spectral data and forest structure data generally do exist. The results are also frustrating, however, because the relationships are not consistent across studies and are generally too weak to offer predictive accuracy at a per pixel scale. As a consequence of the latter weakness, the relationships cannot be used to examine the spatial patterns of structural attributes. Nonetheless, in some cases the relationships can be used to accurately determine the mean value of a structural attribute over a landscape (Iverson *et al.* **1989).** New approaches such as the incorporation of biogeographical data, along with additional research and probable technology development will be necessary before satellite imagery – forest structure relationships are sufficiently accurate and robust to be truly useful in large scale inventories or to detect spatial changes in stand structure.

Assessment of forest damage

The assessment of forest damage is an important use of remote sensing data. Many of the changes in tree or foliage morphology resulting from stress can be detected with remote sensors (Jackson **1986).** Furthermore, the spectral signature of stressed trees may indicate not only the degree of stress but also the type of stress. For example, TMS imagery of damaged red spruce (*Picea rubens*) stands in Vermont shows a large reduction in the near and shortwave-infrared reflectance (bands 4 and **5** respectively) (Rock *et al.* **1986).** The location of highly damaged stands was readily apparent in the scene if the ratio of these bands was displayed. Field verification of the image revealed that the foliage of the highly damaged spruce stands was drier and less dense than that of undamaged stands (Rock *et al.* **1986;** Vogelmann and Rock **1986).** These authors have continued their work with the TM sensor and have been successful in assessing forest damage in Vermont and New Hampshire (Vogelmann and Rock **1988).**

Damage produced by insect defoliation has also been successfully assessed from remotely sensed imagery. This type of damage is easily perceived by examining scenes of an area before and after defoliation. For example, areas of heavy gypsy moth defoliation in Pennsylvania, USA, were quite evident in a foliage difference map created from June **1976** and July **1977** MSS data (Williams and Stauffer **1979).** The key to successful defoliation assessment is to use scenes that capture the period of heaviest defoliation (Dottavio and Williams **1983).**

Spectral imagery is used routinely by forest managers to detect and measure insect defoliation, although the data often come from airborne rather than satellite sensors. Stress detection of forests is still in the research stage, but results thus far are promising.

Assessment of physiological parameters

Many physiological attributes – such as photosynthesis, evapotranspiration, plant maintenance respiration, turnover of organic carbon, and moisture retention – are related to the interaction of solar radiation and vegetation (Knipling **1970).** As such, satellite sensors, which measure the light reflectance of the earth's surface, should potentially be able to indirectly measure changes in these radiation-mediated physiological processes. Reflectance measurements should be useful in inferring spatial and/or temporal variations in photosynthesis and evapotranspiration rates because the structural and functional properties of leaves determine the radiation/interception characteristics of tree canopies (Sellers **1985;** Tucker and Sellers **1986).** Spectral data can provide information on the amount of chlorophyll pigment (visible wavelengths), the projected green leaf density (near infrared), and the leaf water content of the canopy (shortwave infrared). The first two can be used to infer potential photosynthesis although actual photosynthesis will be determined by solar flux, moisture availability, and other environmental factors operating on the system at the time (Tucker and Sellers **1986).**

Spectral reflectance data should also be useful in identifying many important biochemical features of forest canopies because many biochemical compounds possess unique spectral absorption properties (Waring *et al.* **1986).** Determination of leaf starch, nitrogen, protein, and lignin content should be feasible from spectral data, although probably not with current satellite technology (Waring *et al.* **1986).** For example, Spanner *et al.* **(1985)** were able to relate canopy nitrogen content to spectral data taken with the Airborne Imaging Spectrophotometer (AIS). Peterson *et al.* **(1988)** have extended this work over several sites to find relationships between nitrogen, lignin, and total water content with the AIS spectral signatures. The infrared region of the electromagnetic spectrum has been shown to be especially rich in information about canopy biochemical characteristics.

Leaf water content and consequently forest stand water relations should also be able to be inferred from canopy spectral reflectance properties in the shortwave infrared bands (*e.g.*, TM bands **5** and **7)** (Tucker **1980).** In the field, the higher values of the ratio of the percent reflectance at **1.65** pm to the reflectance at **1.26** pm corresponded to highly water-stressed vegetation (Rock *et al.* **1986).** Handheld spectral sensors have been used to detect water stress in buffelgrass in Texas, USA (Richardson and Everitt **1987).** To our knowledge, current satellite data have not yet been used to satisfactorily evaluate moisture availability of forested canopies.

Mounting evidence suggests that remotely sensed spectral data may become as successful, if not more successful, at estimating forest function (*e.g.*, photosynthesis or evapotranspiration) than forest structure (*e.g.*, biomass or leaf area) because of the dynamic nature of the reflectance-physiological interface (Tucker and Sellers **1986;** Kimes *et al.* **1987).** In the future, remote sensing may be able to detect portending ecosystem shifts by detecting changes in rates of key physiological processes that reflect basic ecosystem parameters (*e.g.*, photosynthesis and productivity) (Waring *et al.* **1986).** Evidence also suggests that some of these physiological parameters such as photosynthesis can be estimated without knowledge of species (Aber and Fownes **1985).** Detection of ecosystem parameters without identification of species is necessary to integrate data across landscapes and eventually the globe.

However, examples of satellite detection of physiological processes of forested ecosystems are relatively scarce at the present time. Running and Nemani **(1988)** found a high relationship between photosynthesis, transpiration, and aboveground primary productivity as ascertained by an ecosystem simulation model and the annual integrated normalized difference vegetation index (NDVI, (near infrared – red)/(near infrared + red) from the AVHRR sensor, Fig. 1) over seven sites in the U.S. They found the relationship to be especially rigorous on sites located at high latitudes with little seasonal water stress. Serafini **(1987)** used diurnal and seasonal variations in the difference between satellite-derived earth surface temperature (based on AVHRR data) and air temperature near the surface (as measured by ground-based, shelter-height sensors). Spatial variation of evapotranspiration could account for the variation in the derived differences. Tucker *et al.* **(1986)** and Fung *et al.* **(1987)** found a high correlation over a **3**½ year period between globally averaged NDVI and globally-averaged monthly atmospheric CO_2 concentrations. This relationship suggests that satellite data can be used to estimate terrestrial photosynthesis and productivity, since atmospheric CO, varies seasonally according to the amount of drawdown occurring via photosynthesis. The intensive studies of the First ISLSCP Field Experiment (FIFE), performed during 1987 and 1988 on the Konza Prairie, Kansas, used a large number of ground, airborne, and satellite sensors to assess the potential to understand the physiological characteristics of vegetation (especially with regard to the effect on climate) via remote sensing (Sellers *et* al. 1988). Most research, however, that relates spectral data to forest physiological features has been done using various airborne sensors (Sader 1987) or portable sensors mounted on platforms or low flying helicopters. Furthermore, often the sensors have been quite different from the sensors currently employed on satellites. More refined satellite sensors and much research will be needed before satellite spectral data will truly promote a better quantitative understanding of the temporal and spatial pattern of physiological properties of the earth's vegetation.

Assessment of forest productivity

If satellite sensors could accurately detect forest productivity, they would provide obvious cost and effort advantages over traditional field survey methods. Productivity estimates based on satellite data have been produced with some success for agronomic ecosystems (Olang 1983), wetlands (Butera *et* al. 1984; Hardisky *et al.* 1984), and shrublands (Strong *et al.* 1985). Productivity assessments of forests using satellite data are rare. Forest productivity classes in northwestern California, USA, were predicted with moderate success using a GIS with classified MSS data, topographic data, and ecological zone data (Fox *et* al. 1985).

In another study, predictive models of wood mean annual increment of volume in three regions of the United States (southern Illinois, eastern Tennessee, and northeast New York) were developed using GIS, TM data, and digital biogeographical data on forest productivity and soils, slope, solar radiation, and/or vegetation type (Cook *et al.* 1987; Cook *et* al. 1989). In general, forest productivity was more accurately predicted with a combination of TM and biogeographical variables than with either data type alone. The best regression models in each of the three study regions were highly significant ($p < 0.002$) but left a considerable amount of the spatial variance in forest productivity unexplained. Because of the extreme heterogeneity of forests stands at the 30-m² resolution of TM and because of the many abiotic and biotic variables involved, it may not be reasonable to expect a high degree of predictability on small, site-specific areas (Franklin 1986; Peterson *et* al. 1986). Predictability may be improved by changing the scale of reference to cover larger areas or by pooling and/or stratifying data (Cook *et al.* 1989; Franklin 1986).

As a means to scale up to regional levels, Iverson *et* al. (1988) used the TM-derived models mentioned previously for the Illinois and Tennessee sites in combination with TM and AVHRR scenes of the same areas to develop predictive relationships between the much coarser but more extensive AVHRR data and forest productivity. Multiple regression was used to develop the models relating AVHRR spectral data to TM-derived estimates of forest productivity. The resulting models were then applied to each AVHRR pixel in the region to develop regional maps of forest productivity. The validity of these maps was tested by aggregating the AVHRR pixel productivity into county-level productivity estimates and then comparing these county-level estimates with independently derived county-level forest productivity estimates from the U.S. Forest Service.

For the 428 counties centered on the southern Illinois region, the correlation coefficient of the two productivity estimates was 0.72 P ($p < 0.0001$). For the 168 counties centered on the eastern Tennessee region, the coefficient was 0.52 ($p < 0.0001$). The lower success in the eastern Tennessee region was attributed to the more variable landscapes of counties > 100 km from the original TM-AVHRR-forest productivity calibration center. Closer to the calibration center (within 100 km), the correlation coefficient was 0.86. To extend this methodology of using nested TM and AVHRR scenes to scale up relationships between spectral values and productivity to continental or global scales will probably require stratification of the initial calibration sites by ecological regions such as Küchler's (1964) potential vegetation type or Bailey's (1980) ecoregions (Logan 1985).

The above methodology for developing regional estimates of productivity differs from most regional-scale remote sensing studies of productivity which generally rely solely on AVHRR data. A more common approach is to use multiple scenes of AVHRR data to capture the change in a spectral greenness index over the growing season (Goward ***et al.*** 1985, 1987; Tucker ***et al.*** 1985; Shimoda ***et al.*** 1986; Townshend and Justice 1986). The most successful index has been the normalized difference vegetation index (NDVI). For example, Goward ***et al.*** (1987) found a high correlation between seasonal changes in NDVI values and literature estimates of biome productivity across 24 North and South American biomes. Choudhury (1988) also found Nimbus-7 37 GHz SMMR data highly correlated with estimates of global net primary productivity. Generally, though, valid satellite-based estimates of productivity or other ecological parameters across a large area are difficult to obtain because of the problems with securing ground observations over such large regions (Curran and Williamson 1986).

Conclusions

The use of satellite data as an aid in understanding the ecological nature of forests is a very recent and rapidly evolving phenomenon. Although most forest applications are still in the experimental stage, research suggests that satellite data will prove extremely useful in extracting spatial information on forest ecosystem attributes. Because satellite sensor data integrate optically over the pixels, they are not as useful as finer resolution data if information on site specific ecological parameters is desired. However, satellite sensors are indispensible if one wishes to evaluate or monitor large areas. The synoptic quality of satellite data is just beginning to be exploited; most research has understandably focused on parameter identification rather than on spatial relations of ecological parameters. Satellite data provide two main applications to forest ecology: (1) the ability to monitor ecological attributes in inaccessible regions and/or spatially extensive regions, and (2) the capacity to detect the spatial ecosystem patterns and processes of forests. Much progress has been made toward the first application although much is left to be done. The second application has just begun to be explored.

Forests are fundamental to the healthy functioning of the biosphere. With the current global climate warming, loss of biodiversity, environmental degradation, and increased need for forest products (all problems that rely on forests as a key in the process or mitigation of the process), it is imperative that we monitor and understand the forests of this globe. Synoptic, timely information, which can be provided only with satellite data, is needed to support local, national, and global decision-makers in the crucial planning efforts designed to preserve the habitability of this planet for generations to come.

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