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Status of Remote Sensing Algorithms for Estimation of Land Surface State Parameters

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Ecosystem process, biosphere-atmosphere transfer, and carbon exchange models all require parameterization of the land surface, including land vegetation cover and soil moisture. Although not yet a demonstrated global capability, the most feasible method for obtaining these parameters and updating them periodically, is satellite remote sensing. In this paper we will summarize our understanding of the desired land surface parameters, including soil moisture, and provide an assessment of the state of the art of surface state remote sensing algorithms to infer those parameters on a global basis.

First, we will consider a) modeling requirements for land cover parameters, including vegetation community composition and biophysical parameters, for example, leaf area index (LAI), biomass density, fraction of photosynthetically active radiation (Fpar) absorbed by the vegetated land surface, and b) modeling requirements for soil moisture.

We will then review the status of remote sensing algorithms for obtaining these parameters and examine a number of issues involved in the global implementation and testing of these algorithms. Finally, we will look at future needs to make global mapping of land cover parameters a reality.

INTRODUCTION

To define the land cover parameter requirements for modeling, both the parameter set as well as the temporal and spatial resolution requirements for these parameters must be specified. The spatial and temporal requirements for these parameters are not as well understood as are the parameters needs, because issues of scale invariance are involved. In this section, we will discuss both issues in turn.

Model Requirements; Land Cover

A number of assessments of the requirements for land cover information have been compiled, for example, Bolle (1991), Skole (1992), Sellers and Schimel (1993), Rasool (1992). More recently, a comprehensive assessment of required land cover parameters were developed at the International Satellite Land Surface Climatology Project (ISLSCP) meeting at Columbia, Maryland. At this meeting, involving over 200 participants, including the land-process modeling and the remote sensing communities, an integrated set of parameter requirements was developed for ecosystem process, biosphere-atmosphere transfer, and carbon exchange models. A summary of the proceedings can be found in Sellers (1992). The general categories of parametric inputs specified at that meeting are as follows: Community composition (see Table 1), vegetation structure such as leaf area index (LAI), biomass density, phenology, vegetation condition, net primary productivity, fraction of incident photosynthetically active radiation absorbed by the canopy (Fpar), canopy roughness.

These parameters are controlling variables in land-atmosphere carbon, energy and water exchange models characterizing the state of the land surface and represent the thermodynamic, chemical, and biological processes inherent in the interaction between the land surface and the lower atmosphere.

The process models utilize community composition information to partition the global landscape into functionally different strata. Each strata differs in terms of the biological, thermodynamic, or chemical pathways inherent to the different vegetation associations and incorporated into the process models. For example, coniferous and deciduous communities give rise to

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differences in biological processes affecting the relationship between incident solar radiation, photosynthesis, and evapotranspiration. Seasonal variations inherent to differences in these communities influence patterns of latent heat flux throughout the year by effecting differences in turbulent exchange parameters such as surface roughness, and radiation exchange variables such as albedo. See for example, Sellers et al. (1986), Sato et al. (1989). The way water is used varies within different ecosystems as a function of whole plant and xylem water potentials, leaf area and stomatal closure, rooting depth, and canopy structure across the soil–plant–atmosphere continuum.

Community composition differences also effect functional differences in biogeochemical cycling of carbon, nitrogen, and other elements at regional to global scales (Houghton and Skole, 1990; Houghton et al., 1987; Moore et al., 1981), thus are critical to understanding the dynamics of net ecosystem production and nutrient interactions.

In additional to the functional differences in process rates and pathways implied by community composition and structure, the release of several important atmospheric constituents such as CH_4 and N_2O are conditioned by community type and mode of disturbance (e.g., logging versus burning). For example, conversion of tropical forest to pasture appears to be important in trace gas dynamics for years after pasture formation Luizao et al. (1989), Matson et al. (1987), Goreau and de Mello (1988). The conversion of land in the tropics often occurs with biomass burning, which may be an important source of CH_4, CO, and other radiatively important trace gases. Uncertainties in current estimates of trace gas dynamics result from the lack of data on events such as the rate and distribution of biomass burning events, the type and condition of the biomass, and emission factors of trace gases. Detailed land cover assessments from satellites can contribute in the provision of all of these data sets. Thus land cover categorizations are needed in which the categories are defined by functional characteristics relating directly to properties such as energy, water, and nutrient cycling rather than by purely species characteristics.

Spatial and Temporal Requirements of Land Cover Parameters

Parametric inputs can be used by the process models at a variety of spatial scales ranging from 0.01 to 200 km. For example, general circulation models use input levels of 50 to 200 kilometers, whereas estimates of land cover change in the tropics for carbon modeling may require much finer resolution data from Landsat or similar systems (Skole and Tucker, 1993). Precisely how process model accuracies depend on the spatial scale of their inputs is a matter of ongoing investigation. At coarser resolutions, vegetation communities are mixed, but most of the physiological relationships on which land surface process models depend were developed from studies of homogeneous vegetation communities. Thus the quality of the process model predictions should improve with increasing spatial resolution of the parametric inputs, but at a cost of processing increasingly large quantities of data. Processing global data sets at scales as fine as 0.01 km may be prohibitive for some models and algorithms. There are two general approaches to dealing with this problem. One is to coarsen spatial resolution of the satellites producing the parameter maps; however, many of the remote sensing algorithms are also valid only for homogeneous community types. Thus coarsening resolution to include mixed community types could complicate, or in some cases seriously degrade the quality of the spectral-biophysical relationships. An alternate approach, is the use of statistical sampling of the satellite data with subsequent aggregation to the process model grid scale to reduce processing loads. Utilization of a small, well-designed statistical sample of 1 km or 30 m resolution data to estimate parameters within the larger modeling grid scales by aggregation, can produce parametric estimates at the larger scale with very small sampling error. With this latter sampling approach the remote sensing spatial resolution requirements are effectively decoupled from those of the process models and processing loads are defined entirely by the desired parameter input accuracies at the larger scales.

Temporal requirements for the parameter sets differ by parameter and application. Land cover changes on an annual basis may be sufficient, but for some land cover classes, biophysical parameters will be required on a much more frequent basis. The leaf are index for grasslands, for example, can change over the course of a few days (Hall et al., 1992a), whereas conifer communities are relatively stable throughout a season (Hall et al., 1992b). Of course, given a single satellite to observe all parameters, the acquisition frequency requirement is driven by the most frequently needed parameter. For grassland and crop land communities, changes of 5 days can reasonably be considered to define the maximum temporal frequency requirement.

The previous summary of requirements should make it clear that a single categorization of land cover type is unlikely to meet all modeling requirements. Nevertheless at the ISLSCP meeting at Columbia, Maryland (Sellers et al., 1992) it was apparent that a relatively simple scheme of cover types would satisfy many requirements (Table 1). Different needs will demand different land surface categorizations and will require data bases with different spatial and temporal resolutions.

Table 1. Simple Scheme of Functional Classes / Ecosystem Requirements for Global Land Cover Maps Proposed at the ISLSCP Workshop Report, June 23rd–26th 1992

1.	Coniferous forest
2.	Deciduous forest
3.	Broadleaf evergreen forest
4.	Tundra
5.	Woodland (discontinuous tree cover)
6.	Savanna
7.	Grassland
8.	Desert
9.	Shrubland
10.	Cultivated (with subdivisions of crops / grasslands / irrigated versus nonirrigated / tilled vs non-tilled)
11.	Wetlands
12.	Freshwater areas
13.	Ice cover
14.	Built areas

Modeling Requirements; Soil Moisture

Soil moisture is an environmental descriptor that integrates much of the land surface hydrology and plays a crucial role in the interface between the earth surface and the atmosphere. As important as this seems to our understanding of hydrology, the related ecosystem dynamics, and biogeochemical cycles, it is a descriptor that has not had widespread application in the modeling of these processes. There are two important reasons for this. First, soil moisture is a difficult variable to measure on a consistent and spatially comprehensive basis. The large spatial and temporal variability that soil moisture exhibits in the natural environment is precisely the characteristic that makes it difficult to measure and use in earth science applications. Second, our understanding of the role of soil moisture in hydrology, ecosystems processes, and biogeochemistry has been developed from point studies where the emphasis has been on the variability of soil moisture with depth. As a parallel consequence, most models have been designed around the available point data and do not reflect the spatial variability.

Point-Level Soil Moisture

At a point, moisture on the surface and within the root zone controls hydrologic processes and energy balance in three quite different modes depending on soil moisture levels.

1. Surface saturation. At surface saturation, and to some point below field capacity, soil pores are water filled; for moisture levels greater than this, free evaporation dominates the surface partitioning of radiation, heat, and evaporation.
2. Moisture stress onset: When the root zone dries sufficiently, soil moisture becomes the dominant control on evapotranspiration; for moisture levels below stress onset, stomatal conductance and thus evaporation is reduced precipitously.
3. Transition range: For moisture levels within the bounds of (1) and (2) surface and root-zone soil moisture does not play a dominant role in evapotranspiration; in this soil moisture range evapotranspiration is under stomatal control, which in turn is regulated by light, temperature, and humidity.

The sensitivity requirements for microwave sensing of these three soil moisture levels will depend on the soil type and associated physical properties. Volumetric moisture values at which moisture stress onset occurs can vary from 2% to 20% between coarse sandy soils, which hold water much less tightly than finer-grained loamy soils. Saturation levels vary somewhat less with soil type in the range of 30% to 40% volumetric.

Scaling from Point to Regional Level

In terms of regional moisture-energy balance relations, it is of crucial importance to know how the point-level relations scale. That is, are the regional-scale soil moisture-energy balance relations similar to the point-level ones? For these relations to be similar among all scales, it is sufficient that the relations are linear or that the spatial variability is small. In mode (1), the point level moisture-evapotranspiration relations should scale to the region because free evaporation dominates and spatial variability plays a very minor role. In mode (2) the point-level relations are nonlinear but soil moisture is not a dominant control on evapotranspiration; rather it is controlled primarily by spatial variations in light and humidity. However, as the region dries toward onset of moisture stress, mode (3), the relations become highly non-linear and spatial variability becomes extremely important. For example, with a regional average soil moisture slightly above moisture stress onset, the regional average can be a poor indicator of regional evapotranspiration because a substantial fraction of the point values can be below moisture stress onset, yielding evapotranspiration rates significantly different than the regional average would imply.

In the context of this general discussion of soil moisture requirements, a number of specific soil moisture parameter requirements emerge. The moisture algorithm must define whether the soil moisture level at each point in the region is at saturation, at moisture stress onset, or in the transition range. Within the transition range the moisture algorithm must specify a minimum of three soil moisture levels (high, medium, and low); five levels would be desirable. In a region following a large scale precipitation event, daily maps would be desirable, particularly for regions dominated by well-drained soils and relatively infrequent rainfall; however, given data processing volumes on a global scale, weekly or even monthly observations might be more practical. The minimum spatial resolution at which point soil moisture can be estimated to permit scale invariance of the remote sensing algorithms is still an open question.

STATUS OF COMMUNITY COMPOSITION ALGORITHMS

A number of factors determine the ability of remote sensing algorithms to distinguish between and permit the identification of different community composition classes: (1) the type and quality of the remote sensing and ancillary data sources, (2) the manner in which the remote sensing data are calibrated and corrected for atmospheric effects, and (3) the type of classification algorithm used. The remote sensing data source can consist of spectral information, view, and illumination (bidirectional) information, spatial information, temporal information, and polarization information. Most commonly, spectral information is the main source used to distinguish among and identify community composition classes, however, algorithms exist to utilize all aspects of the remote sensing images. In this section we will focus on the evaluation of classification algorithms as they have been variously applied to different types of remote sensing information.

A variety of pattern recognition methods have commonly been used for community composition mapping and monitoring, for example, Swain and Davis (1978), Mather (1987), Townshend et al. (1991). Many methods incorporate a supervised classification algorithm based on statistical maximum likelihood decision theory. This class of procedures uses training data, that is, remote sensing measurements acquired from ground-identified land cover classes, to optimize the likelihood of correctly classifying these land cover classes based on their multispectral reflectance characteristics. Alternative procedures based on unsupervised classification algorithms have been used. These algorithms cluster the multispectral remote sensing data. The user then generates a cluster map of a region and labels these clusters by comparison to areas of known land cover. Whether the procedure chosen is supervised, unsupervised, or hybrids of the two, ground observations of land cover are required to associate the remote sensing data with land cover classes. It is not possible at this point in time to use atmospheric and radiative transfer models to accurately enough compute which remote sensing data values correspond with which land cover classes. However, use of these models and atmospheric correction algorithms can reduce greatly the dependence on ground observations for classifier training.

Classification algorithms that rely on methods other than maximum likelihood have been used to improve on the use of spectral data. In addition these methods, including maximum likelihood, incorporate spatial and temporal data in an attempt to improve discrimination power. Some of these methods are summarized in Table 2. One approach for reducing the volume of training data is the use of neural network procedures (Hepner et al., 1990). An additional important approach has been to use decision-tree approaches in which rules are used successively. For example, Lloyd (1990) used a binary decision tree classifier based on summary indices derived from time series NDVI data. Mixture decomposition algorithms (Horowitz et al., 1975) are designed to infer the areal proportions of spectrally distinct elements composing the land cover in each pixel—for example, shadow, sunlit canopy, and sunlit background. The choice of these elements is driven by the particular application; however, they must be spectrally distinct from each other (so-called "end-members") and their number equal or less than the number of available spectral bands. Mixture decomposition algorithms have been used, for example, to measure the regional abundance of vegetation in deserts (Smith et al., 1990a, 1990b).

Table 2. Examples of Methods Used to Improve upon Per-Pixel Classifications of Remotely Sensed Data

Procedure Applied	*Example of Application*
Spatial filtering of spectral data prior to classification	Atkinson et al., 1985
Reclassification of data after application of a standard per-pixel classifier	Gurney and Townshend, 1983; Booth and Oldfield, 1989
Modelling the statistical areal variability of image data in terms of Markov models	Settle, 1989; Besag, 1986
Image segmentation and then classifying the images based on the "objects" which are extracted	Kettig and Landgrebe, 1976; Quegan et al., 1992; Beaudoin et al., 1990
Use of external data in the form of boundaries from digital topographic data	Wooding, 1985; Mason et al., 1988
Integrated use of remotely sensed data with digital terrain data	Strahler et al., 1978; Jones et al., 1988
Characterization of pixels as mixtures of basic components (end-members)	Smith et al., 1990a; Lennington et al., 1984; Quarmby et al., 1992; Hall et al., 1995
Use of neural networks	Benediktsson et al., 1990; Hepner et al., 1990; Kanellopoulos et al., 1992; Key et al., 1989

Other approaches have been developed to exploit the temporal variation in spectral properties of vegetation types through the growing season. This has mainly been applied to changes in the greenness, as measured by various indices and has been applied to multitemporal Landsat data, for example, Hall and Badhwar (1987), coarse resolution Advanced Very High Resolution Radiometer data, for example, Townshend et al. (1991) and to radar data, for example, Foody et al. (1989).

Algorithms to extend the use of Landsat data over years, or within a season have also been developed and tested (Hall et al., 1991b). The algorithms permit a Landsat data series, consisting of both MSS and TM data, to be radiometrically rectified to each other so that the series appears to have been taken by the same sensor, under the same atmospheric conditions and at the same phenological stage. Thus, training statistics acquired at one date, can be applied to Landsat scenes acquired earlier or later to infer change in land cover status with time. These algorithms have been tested using FIFE data (Hall et al., 1991b) and were shown to correct relative calibration and atmospheric differences to within 1% absolute reflectance.

In the case of microwave data, multiple frequencies look angles and polarizations have been used in similar ways to the use of spectral bands in optical remote sensing for the classification of land cover classes (Doktor and Kuhbauch, 1990; Paris, 1982; Hoogeboom, 1983), though most experience has been gained in distinguishing crop and forest types.

For classification procedures that rely solely on the spectral reflectance properties of each pixel, classification accuracies depend on the spectral differences between classes. Generally speaking, broad cover classes such as soils, vegetation, and water can be discriminated from each other with accuracies well above 90%. However, among vegetation types, classification accuracies using spectral data alone can be much lower. Spectral differences depend primarily on class differences in (1) canopy structure, that is, sunlit canopy fraction, shadow fraction, sunlit background fraction and (2) the spectral signatures of the structural elements. Precisely what accuracy levels are acceptable has not been established. Even with classification accuracies in the 80% range, classification maps generally agree visually with actual land cover. Misclassified pixels usually appear as spatially random noise in the image, preserving to a large degree the spatial integrity of the landscape information. In using the classified pixels to compute areal proportions of classes, canceling errors of omission and commission between classes can significantly reduce the bias in estimates of class proportions.

In the regional and global application of pattern recognition techniques, most work has been carried out using high resolution satellite data, such as those from Landsat and SPOT, relying primarily on the multispectral distinctiveness of different land cover types. Numerous studies show that a variety of land cover classes can be distinguished using satellite data, however, these studies are usually at relatively local scales and only infrequently at regional and continental scales (though see Hall and Badhwar, 1987; Skole and Tucker, 1993). Some indication of the success of the procedures has been already provided and numerous papers have appeared on this topic in this journal as well as *Photogrammetric Engineering and Remote Sensing* and the *International Journal of Remote Sensing*.

Coarse resolution satellite data such as those from the Advanced Very High Resolution Radiometer (AVHRR) have also been used in land cover classification at continental and global scales. Using multitemporal data sets, the seasonal variation in spectral vegetation indices has also been used to discriminate between vegetative cover types. Using the NOAA Global Vegetation Index product, with a resolution of approximately 15 km, maps of African land cover (Tucker et al., 1985), and South American land cover have been produced (Townshend et al., 1987). More detailed map products have been produced using a similar approach applied to AVHRR data, the most notable example of which is the land cover characterization of the conterminous United States at 1 km resolution (Loveland et al., 1991). A statistical estimate of global land cover was derived (Shimoda et al., 1986) and maps of global land cover have been generated at coarse resolutions, for example, Koomanoff (1989), Defries and Townshend (1994a, 1994b).

Certain inherent problems remain in distinguishing land cover types using existing data sources. Current procedures reliant on data from the visible and shortwave infrared depend on reflectance properties mainly related to leaf properties such as pigments, leaf structure, and foliar moisture. Hence discrimination of cover types on the basis of bulk properties will be indirect and may well be difficult. For example discrimination between shrub and tree cover types with similar proportional coverage is inherently problematic, unless the optical properties of their canopies are also different and this may not occur. To distinguish between such cover types two possibilities appear to have the most prospects, namely the use of radar and exploitation of the bidirectional properties of canopies that are related to vegetation structure. In terms of exploitation of bidirectional properties, their potential has been demonstrated in numerous aircraft experiments and modeling studies, but as yet we are unaware of any convincing demonstrations using satellite derived data; quite likely this stems from the absence of suitable multiple look data sets. In the case of radar data, encouraging experimental results have been reported. The previous methods described have largely been applied to visible and near infrared data. Various experiments have demonstrated the potential of single frequency, single polarization data (Paloscia and Pampaloni, 1987), multi-polarization observations (Le Toan et al., 1989), and multi-frequency multi-polarizing images (Foody et al., 1989), for distinguishing between different agricultural crops. Similarly the use of radar imagery in the recognition of forests and in distinguishing between different forest types has been established in several studies (e.g., Evans et al., 1989; Beaudoin et al, 1990; Hallikainen et al., 1990).

One of the challenges in the use of data from existing satellites, notably ERS-1 and some planned satellites, stems from the sensors having only a single frequency and polarization, since the discriminatory power of radar imagery has often been shown to depend on the use of multiple frequencies and polarizations. Achieving satisfactory discrimination will probably depend on the use of multitemporal remote sensing to exploit the information available in the phenological changes of vegetation, as well as producing improved signal-to-noise ratios (Beaudoin et al., 1990; Moreira, 1990). Also with current microwave frequencies, discrimination becomes difficult as woody biomass increases. The extremely accurate height estimates obtained from radar interferometry also suggest the possibility of either directly estimating canopy roughness or of incorporating such information into improved land cover classification (Hartl et al., 1994).

Consideration of the various evaluations that have been carried out shows that classification of land cover using remote sensing is very rarely likely to occur without error. Consequently to carry out thorough evaluations of the usefulness of satellite data, it is essential for the various modeling activities to state their requirements as precisely as possible in terms of accuracy and precision. Without this there can be no definitive statement of whether the use of remote sensing can match modeling needs.

STATUS OF LAND COVER BIOPHYSICAL PROPERTIES ALGORITHMS

Two general classes of approaches have been applied to infer biophysical properties of land cover: 1) Empirical approaches that rely primarily on curve-fitting to correlate various measures of surface reflectance, including vegetation indices, to the biophysical characteristics of interest and 2) Physical modeling approaches that attempt to forward model the relationship between leaf, canopy, and stand-level biophysical characteristics and reflected and emitted radiation. These models are referred to generally as canopy reflectance models. Once developed and tested, the understanding gained from the models can then be used to either develop algorithms to relate biophysical characteristics to reflectance or the reflectance models can be used directly in the so-called inverse model, that is, solved for the biophysical parameters given an input of reflectance. The empirical approaches have utilized "spectral vegetation indices (SVI)," that is, various linear and nonlinear combinations of spectral bands, that maximize sensitivity of the index to the canopy characteristic of interest (e.g., fraction of photosynthetically active radiation absorbed Fpar) while minimizing the sensitivity to the unknown and unwanted canopy characteristics (e.g., background reflectance). A popular index of this type is the Normalized Difference Vegetation Index (NDVI), which reduces the effects of canopy structural shadowing on reflectance.

The SVI have also been used to follow seasonal dynamics of vegetation. From analysis of the temporal shape of the NDVI, inferences can be made regarding phenology and condition of the vegetation. Parameters such as beginning of leaf flush, peak greenness, and width of the growing season have been estimated from the use of temporal profile analysis (Badhwar and Henderson, 1982; Henderson and Badhwar, 1984). The seasonally integrated SVI have also been used as a measure of accumulated photosynthetically active radiation absorbed by a canopy, and have been shown to be correlated with above-ground gross primary production on an annual basis (Goward and Dye, 1987).

In this section, we will review first, an empirical approach, which has been applied to a global $1° \times 1°$ AVHRR data set to estimate Fpar, LAI, and canopy roughness; then we will survey the status of the physically based modeling algorithms, none of which have been applied globally.

Empirical Algorithms

The potential of empirical algorithms can be illustrated by recent work in estimating surface vegetation properties for an atmosphere-biosphere model. Figure 1 presents a graphic overview of the components of FASIR (Sellers et al., 1994), a global algorithm to estimate a number of canopy biophysical parameters. FASIR relies on composited $1 \times 1°$ NDVI data set from the AVHRR and uses a stratified, global vegetation composition map with different NDVI-Fpar relationships between the different strata.

The primary value of NDVI is the reduction of sun-angle induced variations in structural shadowing within a canopy. Additional techniques are applied in FASIR to reduce other sources of variation such as atmospheric effects including clouds, and variations in background reflectance. As can be seen in Figure 1 an empirical temporal filtering is applied to remove residual cloud or snow contamination following compositing. In the boreal regions where snow contamination is a problem in establishing realistic winter values for NDVI, FASIR assigns a constant winter value as the NDVI observed in the brief period following snow melt but before spring leaf emergence has begun. In tropical

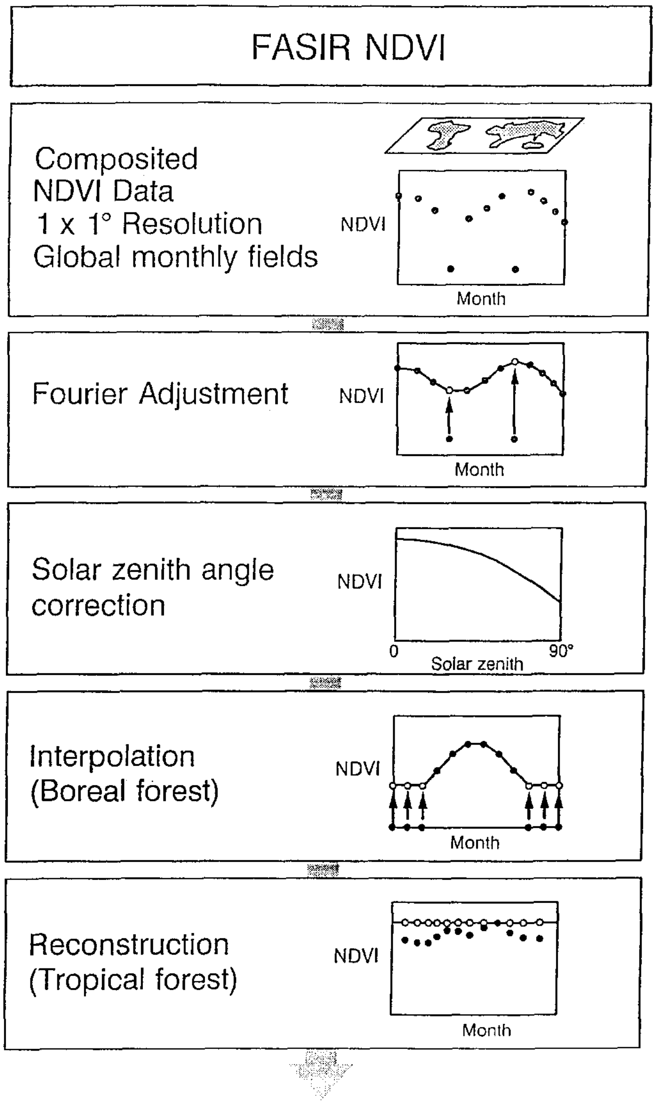

Figure 1. Graphic overview of the components of FASIR, a global algorithm to estimate a number of canopy biophysical parameters.

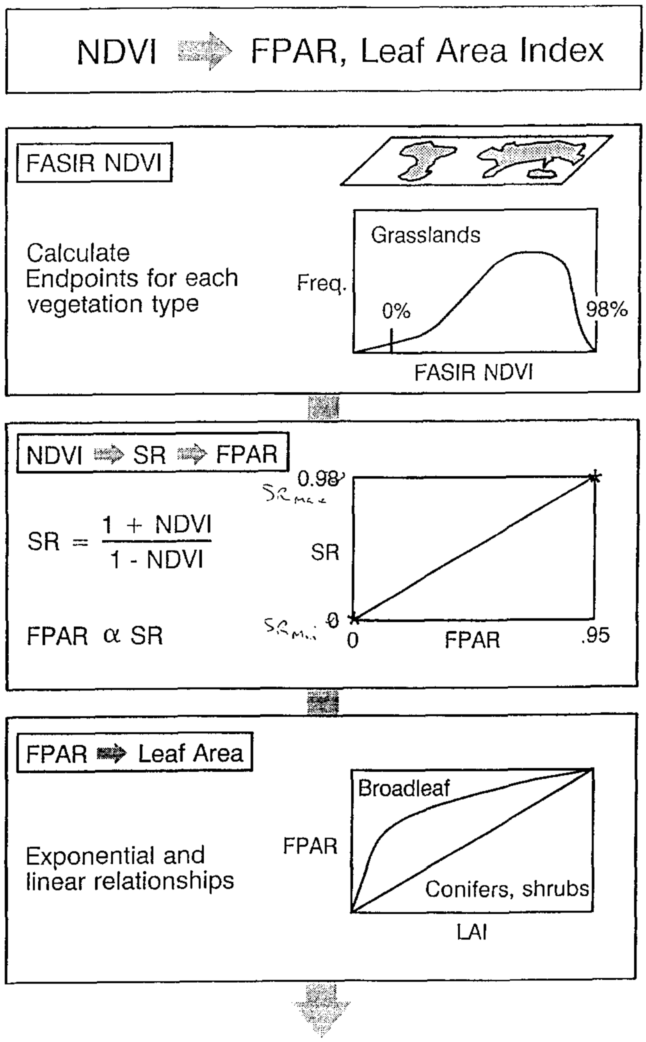

Figure 2.

environments, the FASIR algorithm simply assumes that tropical NDVI is constant over the season and adjusts "low" values of NDVI to a constant value for the reason.

Although NDVI reduces the effects of solar illumination angle, it is still somewhat sensitive. To further reduce this sensitivity, a number of nearly identical landscape elements are found along an orbital track. These are illuminated by the range of solar elevation angles encountered on an orbit, and thus the average dependence of NDVI on illumination angle can be computed. An empirical function is fit through the NDVI versus sun angle curve and used to correct each vegetation type separately.

The next steps shown in Figure 1 are to infer Fpar from NDVI. For horizontally homogeneous, closed canopies with small amounts of nonphotosynthetic biomass, both theory and measurements have confirmed that NDVI, as well as other vegetation indices, are monotonically increasing functions of canopy Fpar. FASIR assumes that simple ratio (SR) is linear in Fpar and uses a two-stream radiative transfer model to derive other biophysical variables of interest, for example, leaf area index and albedo from Fpar. FASIR also derives surface roughness from LAI based on canopy roughness models, and derives photosynthesis and transpiration from Fpar using canopy physiology models.

Although FASIR is the first attempt to produce global Fpar, LAI and surface roughness maps, it has not been quantitatively evaluated. A global data set of biophysical parameters simply does not exist to do so. There are such data from field experiments for local areas such as FIFE and HAPEX; however, these data have not been used yet in an evaluation.

It is clear, however, from an examination of the assumptions underlying FASIR, a number of improvements are possible. Among these are alternative vegetation indices, improved techniques for filtering the data for atmosphere and cloud effects, different compositing

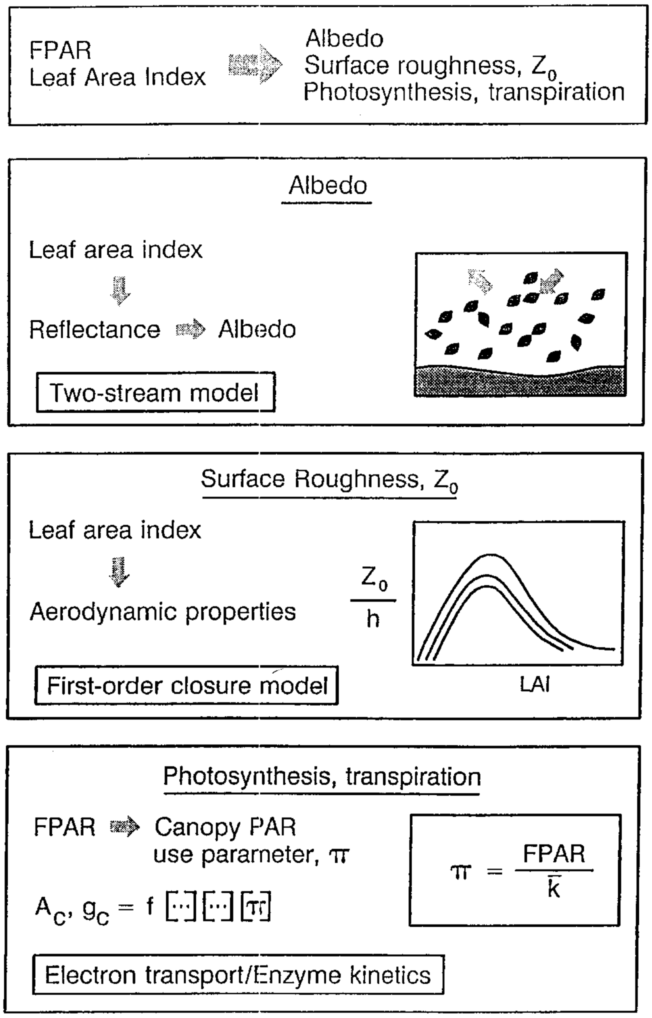

Figure 3.

approaches, and inversion of canopy reflectance models to infer biophysical properties from NDVI. But these would be more-or-less tune ups to FASIR. Even more radical approaches might be considered, particularly with the EOS AM platform, where data from MODIS and MISR will be available. Landsat and SPOT could provide useful synergy with the EOS sensors, associated with the improved spatial resolution.

It is proverbial that the better is the enemy of the good. In producing a second-generation Fpar product, we need to be guided by two principles: (a) How much improvement in the global Fpar estimates is needed and (b) What are the relative contributions to the total error for each of the algorithmic components of the existing approach. Regarding (a), no sensitivity analysis has been done that specifies the required accuracy of the Fpar products. It would be very helpful to conduct such an analysis to specify the acceptable tolerances from the pixel, the grid, the regional, and the global scales. For example, we know that the NDVI-Fpar relationship is sensitive to background (Huete et al., 1985; Goward and Huemmrich, 1992). However, where evaporation and photosynthesis are most important in heavily vegetated regions, the fraction of visible background is small, perhaps reducing greatly the impact of this error. Regarding (b) we do not at this time have a quantitative evaluation of the FASIR product at any scale. FASIR could be evaluated using in-situ collected data from a number of field experiments, such as FIFE, but this evaluation has not been carried out. Until it is, it will be more difficult to concentrate the research effort on those components most badly in need of improvement.

Physically Based Algorithms

An important problem in using remotely sensed measures of surface reflectance to infer canopy level structural and biophysical characteristics is the problem of scaling. That is, transferring reflectance and biophysical property relationships from the leaf level, where they can be easily measured and related to leaf composition and structure, to the pixel level, where leaf optics interact with canopy structure, under story characteristics, view and illumination geometry to produce a complicated relationship among pixel-level reflectance, stand structural, biophysical and leaf optical properties. In general, when extrapolating leaf-level optical properties to the stand level, the physical assumptions used for horizontal layers of leaves (Allen and Richardson, 1968) do not hold, yielding unrealistic solutions. Modeling efforts that have addressed this problem are numerous, and can be placed into four general classes of models (Goel, 1988): (i) turbid medium models, for example (Suits, 1972; Verhoef, 1984), (ii) geometric models (Li and Strahler, 1985), (iii) hybrid combinations of (i) and (ii) (Rosema et al., 1972), and (iv) complex computer, simulation models, for example (Goel, 1991). These models compute canopy and pixel-level reflectance in terms of not only leaf optical properties, but other biophysical parameters such as over story and under story leaf area index, leaf angle distribution, bark area index, crown shape and spacing, etc. The models have been used to infer biophysical characteristics, from pixel-level measures of reflectance by numerical iteration and convergence, that is, matching reflectance values to parameter sets, a process referred to as "inversion" (Goel, 1989). The problems with inversion are that: (i) the dimensionality of the remote sensing measurement space must equal or exceed the number of parameters being estimated, and (ii) in the more complex models, the number of parameters that must be estimated is large, and the dimensionality requirements for their "inversion" often exceeds the intrinsic dimensionality of the remotely sensed data. The intrinsic dimensionality of the remotely sensed data for a single viewing angle and date is determined by the number of physically independent (uncorrelated) wave bands, generally no more than three to four. At the leaf level, the visible wave band reflectances all respond to the same physical absorption and scattering process by plant pigments, thus these reflectances are highly correlated and do not form a linearly independent set. The near-infrared bands are generally uncorrelated with the visible wavelengths, but near infrared reflectance is largely driven by leaf cell structure and thus different near infrared bands are correlated with each other. Exceptions are the near and middle infrared regions where protein, lignin, and starch molecules absorb strongly at certain frequencies. These regions have been investigated for their ability to provide information on canopy chemical composition (Wessman et al., 1988, 1989). Thermal infrared bands are sensitive primarily to canopy radiative temperature and thus are independent of the visible, near and mid-infrared bands, however, their use adds additional parameters to be estimated, parameters related to turbulent heat and long-wave radiative transfer within the canopy. Finally, mid-infrared reflective bands, which respond to plant water content are, in live vegetation, highly correlated to plant chlorophyll (Hall, 1994). At the canopy and stand level, all bands are sensitive to shadowing and canopy background that can induce correlation among them providing information on canopy structural variables and morphology. Thus, at most, three to four independent bands are available to estimate the many biophysical parameters that populate complex canopy reflectance models, and two of these, the visible and near infrared, seem to provide most of the information about canopy structure and leaf properties.

These complications have necessitated the investigation of approaches that hold some of the unknown parameters fixed, estimating them from nonremote sensing data, or approaches that attempt to reduce the influence on reflectance of canopy biophysical parameters that are of little interest to a particular application, for example, leaf-angle distribution. Three frequently cited indices in this vein are the Normalized Difference Vegetation Index (NDVI), or its closely related index, Simple Ratio (SR), and the Kauth-Thomas (KT) greenness index (Kauth and Thomas, 1976). A number of studies have shown that these indices are sensitive to biomass, LAI, and Fpar (Tucker et al., 1983; Hatfield et al., 1984; Sellers, 1985), but relatively insensitive to shadowing effects, and thus view and illumination angles. However, they are also sensitive to under story reflectance (Huete et al., 1985; Goward and Huemmrich, 1992), canopy structure and atmospheric absorption and scattering. More recently, other vegetation indices have been proposed to deal with variations induced by atmospheric aerosols (Kaufman and Tanre, 1992) and variations in background reflectance (Hall et al., 1990; Huete et al., 1994).

What is known, is that stand-level reflectance for canopies exhibiting distinct geometric features, such as conifers, is strongly related to shadow fraction, sunlit canopy fraction and sunlit background fraction and their reflectance (Li and Strahler, 1985; Jasinski, 1990). Li and Strahler performed Monte-Carlo simulations, randomly placing cones within a pixel, over a snow background, to examine the relationships between pixel-level KT greenness and brightness and the fraction of illuminated cone area, fraction of illuminated background area and shadow area. They showed that as canopies were randomly added to the pixel field of view, the KT greenness-brightness followed a 2-dimensional trajectory, originating in the illuminated bare snow point and terminating at a different point in the KT space, whose greenness-brightness value was defined by the average reflectance of sunlit and shadowed canopy. The shape of this trajectory, and the position along it, were uniquely determined by the height:width ratio of the canopy, the number of canopies and the reflectance of the sunlit canopy, shadows and the sunlit background. Thus they were able to "invert" or solve their geometric model using as input, multispectral measures of KT greenness and brightness for (i) the number of canopies within a pixel, (ii) the average height of the canopies, and (iii) the average cone angle for the canopies. They applied this inversion technique to KT greenness and brightness data collected from red fir canopies, but found that the errors in determining the canopy parameters were large, ranging up to $\pm 100\%$.

Jasinski (1990) examined the dependence of NDVI on canopy fraction using a simple geometric shadowing model consisting of randomly placed opaque blocks within a pixel. He assigned arbitrary reflectance values to the blocks, the background, and the shadows and showed that NDVI is a monotonically increasing function of the fraction of sunlit canopy cover within the pixel, and was strongly sensitive to background reflectance. He compared the NDVI predictions from his simple model to actual NDVI measurements taken over a pecan orchard and juniper forests, and showed that indeed, the predicted NDVI increase with increasing canopy cover was observed.

Thus we see that physically based algorithms have not been widely used to estimate biophysical parameters from satellite multispectral data. However, a number of field studies have been conducted to investigate the feasibility of inverting canopy radiative transfer models to estimate such parameters.

In theory the values of N parameters that characterize the canopy reflectance models can be inferred from a set of N independent reflectance measurements over the canopy. In practice, such measures are difficult to obtain. As was mentioned earlier in this paper, only three or four spectral bands are sufficiently independent for canopy parameter inference, therefore, these must be augmented by multi-angle measurements. From satellite measurements from Landsat TM and NOAA AVHRR independent measures of canopy reflectance can only be obtained using multiple satellite acquisitions. Given the cloud cover frequencies in most vegetated regions of the earth, even three cloud free looks are unlikely within a 10-day period when the canopy can be considered relatively unchanged (Hall et al., 1992a). These practical difficulties usually require that most of the free parameters in the radiative transfer model must be known (e.g., leaf optical properties, canopy structure parameters, etc.), with only one parameter subject to estimation. At any rate, field studies over homogeneous crop canopies using these inversion techniques, where only leaf area index was the free parameter, resulted in errors varying between $\pm 10\%$ and $\pm 20\%$, where at least four observation angles were available (Goel and Thompson, 1985). More work needs to be done in this area, including testing using actual satellite data, where atmospheric effects are important, and with heterogeneous canopies, where structural parameters are important.

STATUS OF SOIL MOISTURE ALGORITHMS

Recent advances in remote sensing technology have shown that soil moisture can be measured by a variety of techniques using all parts of the electromagnetic spectrum. However, only those using microwave technology have demonstrated the ability to quantitatively measure soil moisture under a variety of topographic and vegetation cover conditions. The depth of the surface moisture layer to which the microwave signal responds is a function of the frequency of the sensor, and the moisture content. (Newton et al., 1982) found that for L-band (21-cm wavelength) the sampling depth was about two-tenths of the wavelength. A number of experiments using truck mounted sensors, aircraft, and spaceborne sensors have shown that a thin layer, on the order of 5 cm, of the soil can be accurately measured.

Microwave techniques for measuring soil moisture include both the passive and active microwave approaches, with each having distinct advantages. The theoretical basis for measuring soil by microwave techniques is based on the large contrast between the dielectric properties of liquid water and of dry soil. The large dielectric constant for water is the result of the water molecule's alignment of the electric dipole in response to an applied electromagnetic field. For example, at L-band frequency the dielectric constant of water is approximately 80 compared to that of dry soils, which is on the order of 3–5. Thus, as the soil moisture increases, the dielectric constant can increase to a value of 20, or greater (Schmugge, 1983).

For passive microwave remote sensing of soil moisture from a bare surface, a radiometer measures the intensity of emission from the soil surface. This emission is proportional to the product of the surface temperature and the surface emissivity, which is commonly referred to as the microwave brightness temperature, which is given approximately by,

$$T_B = (1 - r)T\text{soil} = \varepsilon T\text{soil} \qquad (1)$$

where r is the reflectivity and $\varepsilon = (1 - r)$ is the emissivity, which is dependent on dielectric constant of the soil and the surface roughness. Thus over the normal range of soil moisture, a decrease in the emissivity from about 0.95 to 0.60 or lower can be expected. This translates to a change in brightness temperature on the order of 50 degrees K or more. The theoretical relationship between emissivity and brightness temperature is approximately linear even though the empirical relationships show that dielectric constant has a nonlinear dependence on soil moisture. Thus, though the brightness temperature–soil moisture relation has a strong theoretical basis, most algorithms are empirical in that they depend on ground data for the relationship.

For the active microwave approach over a bare soil, the measured radar back scatter, σ_s can be related directly to soil moisture by

$$\sigma_s = f(\mathcal{R}a, M_v) \qquad (2)$$

where $\mathcal{R}$ is a surface roughness term, a is a soil moisture sensitivity term, and M_v is the volumetric soil moisture. Although $\mathcal{R}$ and a are known to vary with wavelength, polarization, and incidence angle, there is no satisfactory theoretical model suitable for estimating these terms independently. Thus, as is the case for the passive microwave approach, the relationship between measured back scatter and soil moisture requires an empirical relationship with ground data, even for bare soils.

To use the microwave signal to infer surface soil moisture, a number of other surface-related effects must be taken into account. The major effects are surface roughness, and vegetation cover. The effect of a rough surface is to increase the surface emissivity and thus to decrease the sensitivity to soil moisture (Newton and Rouse, 1988). Theis et al. (1984) have demonstrated the possibility of using a multisensor approach for improving the estimates of soil moisture under field conditions. In this case, the effects of surface roughness were accounted for with scatterometer measurements. These were then used in a soil moisture equation that included terms related to the emissivity measured by the radiometer and to the scatterometer roughness term. Inclusion of the roughness term improved the r^2 values from 0.22 to 0.65 for C-band and from 0.69 to 0.95 for L-band. Although roughness may not be a serious limitation for passive sensors, at least for most natural surfaces, it is a major factor for radar. In many cases the effects of roughness may be equal or greater than the effects of soil moisture on the back scatter. Thus the soil moisture problem becomes one of determining the roughness effect independently so that a model can be inverted to yield a measure of soil moisture. A number of investigations are underway to sort out these separate effects. For example, (Oh et al., 1992) have developed an empirical model in terms of the rms roughness height, the wave number, and the relative dielectric constant. By using this model with multipolarized radar data, the soil moisture content and the surface roughness can be determined. The key to this approach is that the copolarization ratios (hh / vv) and cross-polarization ratios (hv / vv) are given explicitly in the terms of the roughness and the soil dielectric constant. Results from this model look very good and if further testing proves this approach as valid, it will be a major step forward in determining soil moisture from radar back scatter. Furthermore, this model appears to work well in the roughness domains that the more classical methods have failed in the past.

The effect of vegetation is to attenuate the microwave emission from the soil; it also adds to the total radiative flux with its own emission. The degree to which vegetation affects the determination of soil moisture depends on the mass of vegetation and the wavelength. Barton (1978) used an aircraft mounted 2.8 cm radiometer to measure soil moisture over bare soils and uniform grass cover. Although he demonstrated a strong relationship between brightness temperature and moisture for the bare fields, no relationship for the grass sites could be perceived. In studies over bare soil and sorghum, Newton and Rouse (1988) found no sensitivity to soil moisture with the 2.8 cm measurements over the sorghum, but with the 21 cm data the radiometer was sensitive to soil moisture even under the tallest sorghum. Basharinov and Shutko (1975) and Kirdiashev et al. (1979) studied a variety of crops in the USSR with wavelengths varying from 3 cm to 30 cm, which confirmed theoretical predictions that longer wavelengths are less sensitive to vegetation cover. For wavelengths greater than 10 cm, their results indicate that one can expect a decrease in sensitivity to soil moisture of about 10%–20% for vegetation cover consisting of small grains. With broad leaf crops such as corn, the sensitivity could decrease by as much as 80% for wavelengths shorter than 10 cm, and 40% for a 30 cm wavelength. However, models that treat the vegetation cover as an absorbing layer, for example, Jackson et al. (1982), permit the vegetation moisture contribution to the surface signal to be removed given estimates of vegetation biomass and thus water content. Wang et al. (1992) investigated the passive L-band remote sensing of surface soil moisture in FIFE. Their studies showed a linear decrease in brightness temperature across the full range of volumetric soil moisture (20%–40%) observed in FIFE, except for unburned portions where a surface thatch layer had accumulated. They hypothesized that moisture held in the thatch layer is highly absorptive at L-band frequencies, thus increasing microwave surface emissivity and brightness temperature, thus obscuring the subsurface soil moisture signal.

To account for the influence of vegetation cover on passive microwave soil moisture measurements, remote sensing estimates of surface biomass can be used to quantify the cover amount and correct for its effect. Theis et al. (1984) demonstrated the use of visible and infrared data to calculate a perpendicular vegetation index (PVI), which in turn was used to correct the L-band emissivity determined with a passive microwave radiometer. They found as long as the PVI was less than 4.3, good results could be obtained. More recently, Jackson and Schmugge (1991) have analyzed a large amount of published data to verify previous findings. In addition, they have defined a vegetation parameter that is based on the optical depth of the canopy. This parameter appears to be inversely related to the wave length and can represent four types of vegetation classes (leaf dominated, stem dominated, grasses and trees and shrubs). However, at longer wavelengths, a single value of the parameter might be used for any cover type. Furthermore they speculate on how this parameter could be estimated using visible and near infrared satellite data in an operational sense. These studies point up the possibility of a total satellite remote sensing approach for soil moisture without any ground sampling.

With radar, both canopy structure and canopy water content affect the back scatter, thus adding more complexity to the problem of soil moisture estimation. A number of theoretical models have been developed to account separately for these effects. Most models represent the vegetation as a random medium whose statistical characteristics are related to physical quantities of the vegetation layer. Of these types of models, two types of parametric representations are generally used: continuous and discrete. In the continuous case, the vegetation layer is modeled by assuming that its dielectric constant or permittivity is a random process whose moments such as the mean and correlation function, are known. The continuous models were introduced to treat the problems in turbulence (Tatarskii, 1971), but later on they have been employed for vegetation modeling (Fung and Fung, 1977; Tsang and Kong, 1979). In the discrete case vegetation is represented as a collection of dielectric scatterers whose position and orientation statistics are given, for example, the individual leaves and stems and the total scattering cross-section of the canopy is expressed in terms of the scattering cross-sections of the individual scatterers. The advantage of discrete approach is that the results are expressed in terms of quantities (plant geometry and orientation statistics) that are easily related to the biophysical properties of individual plants. The discrete model approach for a random layer of vegetation was first used by Du and Peake (1969) to compute the attenuation through a layer of leaves. Later, Lang (1981); Karam and Fung (1983); Ulaby et al. (1990) have used them to develop more rigorous theoretical models for back scattering from a layer of vegetation over soil surface.

Over the years, the discrete scatter approach seems to have gained favor as a preferred approach for vegetation modeling.

These models, using iterative inversion methods, can form the basis for soil moisture algorithms. The algorithms use the measured scattering cross-sections or brightness temperatures as input and attempt to invert the models for the vegetation and soil parameters. The relationship between the vegetation and soil parameters and model parameters is complicated, which makes the problem ill-posed. In such problems, a small error in the data can produce a large error in the solution. A number of techniques based on either increasing the information contents of the system, for example, statistical inversion (Njoku and Kong, 1977), neural networks (Benediktsson et al., 1990), or restricting the solution space of the problem, for example, Twomey-Phillips method (Chauhan et al., 1993), Twomey-Tikhonov method (Twomey, 1963), have been proposed. All of the above methods have achieved limited success due to numerical instabilities to the solution of retrieved parameter obtained from active or passive data sets.

Change detection is an alternate approach for using soil moisture data derived with microwave measurements that minimize the problems discussed directly above. Change detection can be used for either passive and active microwave data. This method minimizes the impact of target variables such as soil texture, roughness, and vegetation because these tend to change slowly, if at all, with time.

GOING GLOBAL: SATELLITE, REFERENCE DATA AND IMPLEMENTATION ISSUES

Satellite and Reference Data

Enormous volumes of satellite data have been suitable for land cover discrimination. Their use has been inhibited by a number of factors:

1. Lack of continuity of data sets. Data are often not generated in spatially or temporally consistent forms. For example, following commercialization of Landsat, the spatial coverage declined substantially (Justice and Townshend, 1994) and for many parts of the world many years may pass without a single acquisition. Data sets may be processed in different ways at different times hindering longitudinal studies of land cover change. For example NOAA's widely used Global Vegetation Index product has been altered a number of times (Kidwell, 1990).
2. User overhead. Considerable effort may be needed by the user to process the data for actual application. Such preprocessing can include geometric registration and resampling, and even calibration of the DN values.
3. Unwanted signal distortion. Many effects cause the received signal at the sensor to have confusing distortions. One set of effects relates to those induced by the atmosphere, primarily as a result of water vapor and aerosols, which are the most variable components. Even well-understood effects such as Rayleigh scattering may not be corrected that vary spatially with topographic elevation. A further problem is related to view and sun angle effects. Images of large areas are normally created by compositing procedures whereby images are generated from several days selecting the pixel, which seems least affected by clouds and other atmospheric effects. Although generating visually acceptable images, embedded in the data are problems associated with the fact that pixels are derived from very different look angles, and hence the same canopy may be represented by different DN values as a result of bidirectional effects.
4. Large volume of data sets. The large volume of many satellite data sets makes substantial demands on computing systems. This problem is being enhanced rather than reduced by the new data sets that are starting to become available (see below).
5. Cost of data. High-resolution data such as those obtained from Landsat and SPOT is expensive especially when large areas are being investigated. These problems may diminish in the future. For example, recently the Committee of Earth Observation Satellites and IGBP-DIS have been coordinating efforts to supply the scientific community with lower cost data for research purposes.
6. Expense and difficulty of collecting reference data. All classificatory procedures require some ground reference data either for training of classifiers in supervised classification or for labeling of classes derived from unsupervised approaches. Moreover reference data are also needed for validation. Unfortunately collecting reference data is a costly time-consuming process especially when large areas are being considered. Consequently there is an absence of sufficiently comprehensive testing, and there is often uncertainty about the regional or global applicability of the procedures. In relation to validation of data sets at continental and global scales there are obvious logistical constraints in acquiring sufficient data for testing the results. Current efforts to create global series of test sites by a number of groups including the MODIS Science Team as part of the EOS project, the IGBP Global Change and Terrestrial Ecology core project, and the Global Terrestrial Observing System (Heal et al., 1993), is expected to provide data sets suitable for much-improved

validation and improvement of the procedures. Creation of data sets in which there has been some atmospheric correction and standardization of the processing over large areas should do much to reduce the need for reference data.

In response to the problems of acquiring data sets in forms suitable for use for many global studies, major efforts have been made to reprocess existing data sets into forms more suitable for scientific use. The Pathfinder projects of the EOSDIS version 0 include the generation of long term data sets from NOAA's AVHRR (James and Kalluri, 1994). These will include calibrated, georegistered, partially atmospherically corrected data sets of the NDVI and the individual spectral bands at a spatial resolution of 8 km from 1982 to the present (Table 3).

A global data set of the AVHRR data is also being assembled at the basic resolution of 1.1 km by the EROS Data Center, largely part in response to the scientific needs of the IGBP (Townshend, 1992) using data collected at several ground-receiving stations throughout the world (Eidenshink and Faundeen, 1994). This will be processed in a similar way to the Pathfinder data sets. Because there has never been a global archive at this resolution the global data sets will only be available from March 1992.

Globally comprehensive collections of finer resolution data sets have not been systematically created. Nevertheless it has proved possible to carry out regional analyses of large areas using high-resolution data. For example, large volumes of Landsat data are being acquired through the Landsat Pathfinder project (Lawrence and Chomentowski, 1992). Especially in recent years there has been little attempt to collect globally comprehensive data sets from high-resolution sensors such as the Thematic Mapper of Landsat. Coverage of microwave data from satellites such as ERS-1 and JERS-1 is not global and many acquired data remain to be processed. Various ancillary data sets needed for land cover discrimination are also not in forms suitable for use. These include global topographic data and fields of atmospheric constituents, especially water and aerosols, needed for atmospheric correction.

Data from a number of new systems will prove of considerable value for land cover classification. These include the coarse resolution instrument of SPOT 4 (Achard et al., 1992), the ATSR-2 (Along Track Scanning Radiometer) of ERS-2, the Moderate Resolution Imaging Spectrometer (Running et al., 1994) and several other EOS instruments including ASTER and MISR. It needs to be stressed though that existing high-resolution optical sensors, on board the Landsat and SPOT platforms already provide high quality land cover information suitable for investigation of many aspects of global change: ensuring continuity of these data, though with much more spatially comprehensive coverage is of the highest importance for observations of land cover.

As promising as microwave remote sensing for soil moisture appears to be, the future for using microwave data for operational use is somewhat uncertain. For the next few years, researchers will be limited by the lack of suitable data. Currently the ERS-1 SAR from the European Space Agency and the JERS-1 SAR from the Japanese are the only operational microwave satellites with frequencies suitable for soil moisture. Although these instruments should be valuable data sources for extending our knowledge of SAR for measuring soil moisture, to date very little data have been available for this purpose. Fortunately there have been some

Table 3. Characteristics of the AVHRR Land Pathfinder Data Set

Band	*Units*	*Valid Range*	*Quantization*
1. NDVI		−1.0 to 1.0	8 bit
2. CLAVR[a] flag[b]			8 bit
3. QC flag[b]			8 bit
4. Scan angle	radians	−1.04719–+1.04719 (±54°)	16 bit
5. Solar Z	radians	0–1.3962 (0–0 90°)	16 bit
6. Relative azimuth	radians	0–6.2832 (0–0 360°)	16 bit
7. Ch1 reflectance[c]	% reflectance	0–100%	16 bit
8. Ch2 reflectance[c]	% reflectance	0–100%	16 bit
9. Ch3 btemp[d]	degrees K	160–340 degrees K	16 bit
10. Ch4 btemp[d]	degrees K	160–340 degrees K	16 bit
11. Ch5 btemp[d]	degrees K	160–340 degrees K	16 bit
12. Day of year	DDD.HH	0–366.23	16 bit

[a] Cloud flag (Stowe et al., 1991).
[b] Numeric values from lookup tables.
[c] Using calibration from Rao, 1993.
[d] Using calibration from Rao, 1993.
From (James and Kalluri, 1994). Data are available as 10-day composites derived by maximum value compositing (Holben 1986) and also as daily products. A similar 1-km data set is also being created but without QC and CLAVR flags (Eidenshink and Faundeen 1994).

intensive and science-driven aircraft experiments conducted in the last several years and these data are beginning to become available to the scientific community. These should be invaluable for providing sample data for developing and testing algorithms as well as answering some of the target-sensor questions.

Looking ahead to when there may be more microwave sensors on orbiting platforms, one confronts the basic differences between passive and active instruments and the intended use of the data. Comparing the instruments simplistically, the active sensors have the capability to provide high spatial resolution data (on the order of tens of meters) but their sensitivity to soil moisture may be confused more by roughness, topographic features, and vegetation than the passive systems. On the other hand, the passive systems, although less sensitive to target features, can provide spatial resolutions only on the order of tens of kilometers. One then must consider how the data will be used. Meteorological and climate models currently use computational cells on the order of 10–100 km, which may be well within the capacity of future passive systems. However, if one is interested in more detailed hydrologic process studies and partial area hydrology, the passive data would appear to be of little use. It is in this context that the active systems appear promising. For example, existing and planned SARs can provide at least 20–30 m resolution over a swath width of 100 km. Some SARs also have the capability of a scanning mode (SCANSAR) to cover a much wider swath (300–500 km) at a reduced resolution (250 m). Future space launch manifests include several SARs but no passive systems other than the MIMR have frequencies low enough to be useful for soil moisture.

Scale Invariance of Models and Algorithms: Implementation Issues

To produce a timely, affordable regional or global parameter map requires the acquisition, preprocessing, and application of land cover inference algorithms and process models to large volumes of data. Many models that use these parameter sets do not require them at the same spatial resolution at which the remote sensing algorithms are required to operate. For example, general circulation models and the associated subprocess models, are implemented at a spatial resolution of 100×100 km, and could not currently use land cover parameters below that resolution. Some remote sensing algorithms, particularly those producing atmospheric radiation parameters, can operate at similarly coarse grid scales. However, as we have discussed, many of the land cover remote sensing algorithms are a function of the type of vegetation being observed. In many regions, vegetated landscapes have patch sizes of a few hundred meters or less; for such landscapes the algorithms must be applied at spatial resolutions much finer than the models to which they supply the parameters. Because roughly 133 million, 1 km AVHRR pixels are required to cover the earth's land surface, global application of remote sensing algorithms requiring spatial resolutions of 1 km or smaller could involve uncomfortably large data processing and storage rates.

This fact represents one of two opportunities to reduce data processing volumes:

1. Spatial averaging—Where remote sensing algorithms are valid at coarse spatial resolutions the satellite radiance data can be spatially averaged before applying the algorithm to reduce processing throughput.
2. Spatial sampling—Where remote sensing algorithms are valid only for homogeneous vegetation types, the grid cell can be sampled to reduce processing throughput and the finer resolution data processed.

To utilize option (1), spatial averaging, the algorithms must be scale invariant, that is, the algorithm applied to a spatial average of the satellite pixels must produce parameters equivalent to those produced when that algorithm is applied to the individual pixels. The effect of spatial resolution on satellite parameter estimates and energy balance process model relationships has been investigated to some extent by Mahrt (1987), Hall et al. (1992a), and Desjardins et al. (1992). Generally, these studies demonstrate that the algorithms relating satellite data to evaporation can be scale invariant under a wide range of conditions; However, the theoretical analysis of Hall et al. (1992a) shows that situations can arise when the algorithms will not be scale invariant and must be applied pixel by pixel. The importance and frequency of occurrence of these situations is unknown operationally and needs further investigation.

Where algorithms or subprocess models are not scale-invariant, spatial sampling may present an option to greatly reduce data processing loads. As a cautionary note, spatial sampling may not be applicable to all parameters and process models, particularly those that require keeping track of spatially contiguous interactions between adjacent landscape units such as is the case with certain hydrological models. But for model inputs that require only the average value of a parameter over a grid cell, and for which the remote sensing algorithm is applicable only at a much smaller spatial resolutions, sampling can greatly reduce satellite data and model processing loads. Yet the sampling approach can still produce "wall-to-wall" parameter estimates for each model grid cell.

To remind ourselves of the kinds of processing load reductions that may be achieved, we recall a well-known result from statistical sampling theory. The theorem states that to obtain an estimate of a normally distributed parameter, to within ± C% of its true value for the cell, with a confidence of 95%, requires n sample units where n is given by (Hansen et al., 1953),

$$n = 4\sigma^2 / C^2 \qquad (3)$$

and σ is the between sample unit coefficient of variation in the parameter within the grid cell due to both natural variation and random error from the processing algorithm. Thus, for example, if σ is ±50% within a 100 × 100 km grid cell, and the accuracy requirement C, is that the estimated parameter mean for that grid cell lies within ± 5% of the true value, then from (3) only 400, 1 km sample units are required within the 100 × 100 km grid cell to achieve this result. This amounts to processing only 4% of the total data within the grid cell. Of course, the processing algorithm can itself add random error which will inflate σ in equation (3) requiring additional sample units to achieve the same accuracy. In other words, processing the remainder of the AVHRR data within the cell can reduce sampling error by at most only 5%. Because some of the algorithms will require manual intervention, processing the huge volumes of data can actually lead to higher error rates, not to mention costs, thus reducing the accuracy of the estimates. Of course, as can be seen from equation (3), the achievable data load reduction for a given accuracy depends on the variability of the parameter within the sampling strata or grid cell, thus a stratified sampling design will be required to achieve the kinds of efficiencies illustrated above.

Again, sampling may not be useful for all parameters and processes. However, where it is appropriate, other advantages accrue. For example, one can use a technique referred to as double sampling, in which a small fraction of the sample units are measured for biophysical parameters using in-situ methods, then regression used to correct the satellite algorithm estimates for bias introduced by classification and other types of errors. Another advantage of a sampling approach would be reducing errors arising from missing data; primarily data lost to cloud cover or poor data quality. Suspect samples could be eliminated, and the parameter for that sample estimated using statistical inference techniques in which the parameter of the missing sample is inferred from relationships to adjacent cloud-free samples, established on the basis of previous surveys. The design of such a sampling strategy would require careful consideration, keeping in mind the requirements of the model that would use the parameter maps. Primary issues would be the size and number of the sampling units, the stratification approach and its congruence with grid cells, and the sample allocation strategy and required sample frequency. However, the design issues are relatively straightforward and could be addressed given adequate resources and expertise.

FUTURE NEEDS

Several important requirements for improving the quality of land cover data have been identified in the previous sections. Of these the most are important as follows:

1. Improved validation using well-characterized test areas from a wide variety of areas throughout the world.
2. Continued efforts in improving the algorithms: the potential of such work is clearly demonstrated by the fact that for many applications visual analysis still produces better results than automated methods.
3. Improved data sets: in particular there is a major requirement for data sets based on the visible and near infrared in which atmospheric effects due to water vapor and aerosols are much reduced; also microwave data sets need to be much more readily available.
4. Improvements in the capacity of computer systems available to environmental scientists to process the very large global data sets currently being generated. On line storage needs of c. 50 gigabytes are already required: improvements in computing power will almost certainly need the application of parallel computer processing.
5. Continued acquisition of high spatial resolution data especially from the Landsat and SPOT satellites with their known high capabilities, though with more spatially comprehensive coverage is of the highest importance for observations of land cover.

Most importantly, none of these can happen without a coordinated, focused, intensive effort. The coordination should involve the simultaneous development and testing of processing strategies (sampling versus averaging), algorithms, and the production and use of the regional and global parameter data sets. Development cannot proceed in the dark, divorced from the production problems, use of parameters in the models, and continuous feedback to the developers. The focus should be the sequential deliveries of improved regional and global data sets to users. Initially, this can involve the intelligent, combined use of conventional Landsat, SPOT and AVHRR. As the EOS AM platform comes on line, Modis and MISR can be added and should greatly improve the quality of the data sets. In terms of intensity of the effort, few, if any, additional resources will likely be required to develop and test the algorithms; perhaps additional resources will be required to actually push the data through.

Finally, to insure coordination between the algorithm developers and the modelers, a functional, information system must be in place. It must be able to anticipate the data sets, be prepared to document them fully, and able to organize and distribute them. CD

ROMS are an excellent vehicle for this purpose. For example, the FIFE information system (Strebel et al., 1990) captured over 120 gigabytes of electronic data, including meteorological, biophysical, topographic, and satellite images, as well as a soft-copy library consisting of photo images, and data documentation and published articles. The "best" of the FIFE data, as deemed by the FIFE science team, was organized and published on a five-volume set of CD ROMS. The five-volume FIFE CD ROM user interface software prompts the user with menus that permits them to find material about the overall design of the FIFE experiment and data set, search and view common format data files, read documentation on how each data set was prepared, photo documentation on the scientific instruments, and the theory behind the individual measurements. In the future, electronic versions of scientific papers that derive from the data can be presented on the CD ROM volumes.

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