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A Remote Sensing Based Vegetation Classification Logic for Global Land Cover Analysis

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This article proposes a simple new logic for classifying global vegetation. The critical features of this classification are that 1) it is based on simple, observable, unambiguous characteristics of vegetation structure that are important to ecosystem biogeochemistry and can be measured in the field for validation, 2) the structural characteristics are remotely sensible so that repeatable and efficient global reclassifications of existing vegetation will be possible, and 3) the defined vegetation classes directly translate into the biophysical parameters of interest by global climate and biogeochemical models. A first test of this logic for the continental United States is presented based on an existing 1 km AVHRR normalized difference vegetation index database. Procedures for solving critical remote sensing problems needed to implement the classification are discussed. Also, some inferences from this classification to advanced vegetation biophysical variables such as specific leaf area and photosynthetic capacity useful to global biogeochemical modeling are suggested.

INTRODUCTION

The accurate representation of terrestrial vegetation in Earth Systems models has been a continuing challenge, due to the incredible diversity found at global scales. Vegetation responds to the range of climates, geomorphic substrates, natural disturbances, and human encroachments occurring globally with an incredible array of different species, growth habits, and even basic lifeforms. Global scientists have been faced with 1) developing a logic for simplifying vegetation into a smaller array of critical attributes and 2) developing a means of measuring vegetation globally. First attempts at developing a global vegetation database illuminated a variety of problems of raw data availability, inconsistency of historical vegetation definitions, and difficulty in translating taxonomic nomenclature to global modeling requirements (Matthews, 1983).

Global vegetation databases have been developed from published maps, atlases, and national databases that attempt to represent existing vegetation (Matthews, 1983). These databases provide global models with a generally realistic estimate of current landcover at coarse spatial resolution. However, these databases suffer from lack of consistency in vegetation classification used, variable measurement techniques, and a variety of spatial sampling resolutions. Not infrequently, 10,000 km^2 may be sampled and represented by one 1 ha plot, and the possibility of repeating the measurement may be nil.

Historically, global vegetation classifications have been derived from bioclimatic analyses, virtually the only global database available, the two best known being by Holdridge and Koppen [recently reviewed by K. C. Prentice (1990)]. These and similar classifications use simple temperature and water indices to define potential vegetation types, and global distribution is inferred from the global climate dataset. Recently, more ecologically mechanistic logics have been derived (Woodward, 1987; Prentice et al., 1992; Neilson et al., 1992; Neilson, 1993) that define the geographic distributions of biomes based on specific physiological responses of different plant types to cold tolerance, growing season heat sums, and drought stress. Because climate is an integral part of

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their classification schemes, a number of classes of equivalent vegetation type, such as forests, are defined separately as boreal / temperate / tropical forest, to provide geographic specificity. These new biome models are improving the ecological basis for global classification of vegetation, but they produce maps of *potential* vegetation only.

Consequently, Townshend et al. (1991) argued that the most essential new global vegetation classification must be remote sensing driven, to provide a realistic measure of *existing* landcover. Use of a consistent, remote sensing based measurement regime could also eliminate the ambiguities currently extant in global vegetation maps derived from varying methodologies and definitions. However, current remote sensing capabilities cannot produce the large number of landcover classes usually defined, particularly because climate classes are usually part of the definition (Loveland et al., 1991). Townshend et al. (1991) also found that because there is no clearly defined set of vegetation characteristics used for these classifications, there is significant disagreement among authors of the existing global extent of different biome classes. A simpler logic based only on clearly observable plant physiognomic characteristics is needed.

If a comparable map of existing global vegetation cover could be derived, a very useful evaluation of global change could be done by comparing the climate defined potential maps with the remote sensing defined existing biome maps. Estimates of the amount of the global land surface perturbed from its original vegetation range between 10% and 20%, and the amount is increasing annually at unknown rates, a critical dynamic factor to monitor in global change research (Townshend et al., 1991).

The development of realistic global models of climate, carbon cycles, hydrology, etc. all rely on an unambiguous, repeatable definition of the existing terrestrial vegetation. Each cell of a global model is defined with a certain landcover, and from that definition a number of biophysical parameters are derived for use in the energy and mass flux calculations of the model. Most global climate and biogeochemical models immediately translate the landcover classes into biophysical parameters, such as leaf area index, roughness length, and surface conductance (Dickinson et al., 1986; Sellers et al., 1986; Henderson-Sellers and Pitman, 1992). The newest GCMs are planning to define seasonally dynamic landcover based on vegetation phenology (Henderson-Sellers, 1990), a capability offered by the daily repeat time of the AVHRR sensor (Loveland et al., 1991; Lloyd, 1990).

Additional parameterization requirements are needed by global carbon cycle models, for example, of leaf or canopy geometry (broadleaf, needleleaf, or grass) for gas exchange calculations. Plant carbon cycles are also strongly controlled by canopy longevity, deciduous versus evergreen habit, and physiological capacity, such as maximum photosynthetic rate (Korner, 1993). The continued development of global models is becoming hindered by the lack of an agreed upon classification logic from which to begin building these model parameterization datasets.

The objective of this article is to introduce a new logic for global vegetation classification that could solve a number of the problems stated. The logic 1) is based on simple, observable, unambiguous characteristics of vegetation structure that are important to ecosystem biogeochemistry and could be measured in the field for validation, 2) is remotely sensible so that repeatable global reclassifications of existing vegetation will be possible, and 3) directly translates into the biophysical parameters of interest by the global climate and biogeochemical models, including the ability for some advanced inferences of important vegetation properties that are not remotely sensible. Important to this logic is the *explicit separation of climate from the vegetation classification, to allow the classification to be based purely on observable remotely sensed vegetation properties.* Temperate, tropical, boreal, etc. designations can later be added with specific ranges of temperature and precipitation to produce refined subclasses for comparison with the potential biome classifications of Prentice et al. (1992) and Neilson (1993).

CLASSIFICATION LOGIC

We suggest that a complete global vegetation classification be derived from combinations of three primary attributes of plant canopy structure. These attributes are 1) permanence of aboveground live biomass, 2) leaf longevity, and 3) leaf type (Fig. 1). Possible combinations of these three vegetation attributes yield only six fundamental vegetation classes, although they occur across a range of climates, which we will deal with separately.

The first criteria of the classification defines whether the vegetation retains perennial or annual above-ground biomass, a critical question for seasonal climate and carbon balance modeling. This class separates vegetation with permanent respiring biomass (forests and woody stemmed shrubs) from annual crops and grasses that go through nongrowing season periods as seed or below-ground structures only. Consequently, this criteria represents a very fundamental life cycle distinction between these types of plants. This criteria also allows inference of some critical physiological attributes of plants. For example, in a global synthesis of plant gas exchange rates, Korner (1993) found on average that annual plants maintained 50% higher leaf photosynthetic capacity than perennial plants. Biomass permanence, as it relates to plant height also is the major vegetation determinant of the surface roughness length

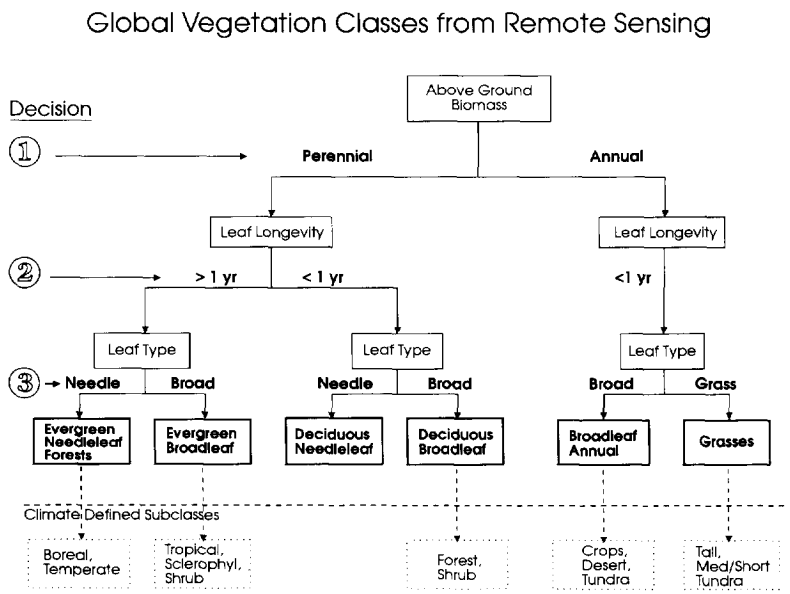

Figure 1. A flowchart of our global vegetation classification logic. Each simple box identifies the variable being defined, and each decision point is numbered. The final six classes of vegetation are shown in bold. Below the dotted line some potential climate-defined subclasses corresponding to more common classification schemes are suggested.

parameter that climate models require for energy and momentum transfer equations. The proposed distinction merely requires that remote sensing be able to detect presence / absence of aboveground biomass during the nongrowing season.

The next step of the classification, leaf longevity, or often termed evergreen versus deciduous canopy, is an extremely critical variable in carbon cycle dynamics of vegetation, and is important for seasonal albedo and energy transfer characteristics of the land surface. This leaf longevity class defines whether a plant must completely regrow its canopy each year, or merely a portion of it, with direct consequences to ecosystem carbon partitioning, leaf litterfall dynamics, and soil carbon pools. Reich et al. (1992) suggest that canopy conductance and maximum photosynthetic rate are inversely proportional to leaf longevity. Hence, certain global attributes of canopy gas exchange capacity may be inferred based on this leaf longevity criteria.

To make the class discrimination simple enough to be remotely sensed and for compatibility with existing vegetation schemes, we define only leaf longevities of less than or greater than one growing season, effectively evergreen versus deciduous. Most needle-leaved biome types are evergreen, the exception being the deciduous conifer Larix, or larch forests of temperate and boreal regions. Most grasses are deciduous, but this criteria separates evergreen broadleaved forests and shrublands from deciduous forests, annual crops, and climate-dependent annual vegetation such as desert and tundra.

The third classification criteria defined is a simple leaf type or shape. Based on both the spectral / optical properties of leaves and their gas exchange characteristics, we feel only three leaf types need to be defined, needleleaved, broadleaved, and grasses. The needleleaved and grass classes are fairly straightforward representations of those vegetation types; however, the broadleaf class includes trees, shrubs, herbs, and crops that fit this leaf type criteria. Hence, the third criteria requires the sequential solution of the first two criteria (perennial / annual and evergreen / deciduous) to provide meaningful discrimination of vegetation. This criteria also allows significant specificity in defining some key ecological parameters for biogeochemical modeling. Running and Hunt (1993) defined a maximum stomatal conductance for three lifeforms of 1.6 mm s^{-1}, 2.5 mm s^{-1}, and 5.0 mm s^{-1} for evergreen needleleaved forest, deciduous broadleaved forest, and annual grass, respectively.

After this three step classification, climate descriptors can be included from a variety of sources. Mean global climate data can be used to derive subclasses like tropical / temperate / boreal from either classic Holdridge or Koppen type schemes (K. C. Prentice, 1990) or newer rule based bioclimate models (Prentice et al., 1992; Neilson, 1993). The difference between previous classifications and ours is that we have *defined specific vegetation attributes that are remotely sensible, and climate is independently added so as to simplify the classification logic.*

A FIRST AVHRR BASED IMPLEMENTATION

We tested whether this logic would provide meaningful vegetation discrimination using current satellite systems with the procedures described below. Virtually all current remote sensing based global vegetation analysis is done with the daily polar-orbiting Advanced Very High Resolution Radiometer (AVHRR). The well-known normalized difference vegetation index (NDVI) is the most

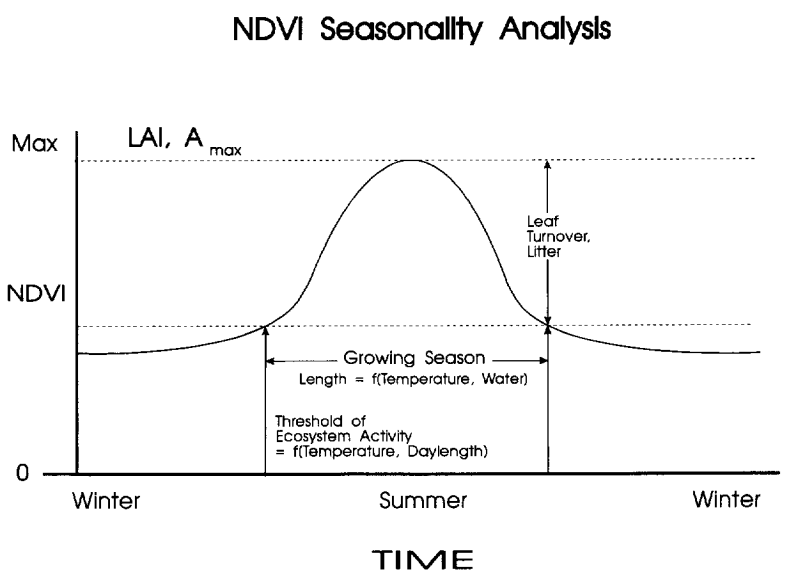

Figure 2. A conceptual diagram of how the seasonal trace of NDVI data may be used to distinguish perennial from annual above-ground biomass types using minimum thresholds, and leaf longevity, or evergreen from deciduous classes using NDVI amplitude.

commonly used measure of vegetation, and a long literature of studies exists on NDVI (Justice et al., 1985; Goward et al., 1987; Loveland et al., 1991). The specific challenge in this article is to propose an NDVI-based analysis for making the three decisions required in our classification hierarchy. The strength of global NDVI data is the high temporal information content. The common compositing time of 10–14 days provides at least 25–30 global NDVI datasets per year. Thus, beyond the absolute NDVI value, we propose that the seasonal dynamic of the NDVI can define important attributes of vegetation phenology (Fig. 2). It should be recognized that quantitative use of the NDVI requires a high quality NDVI product, for which sun angle and view angle normalization and atmospheric corrections have been done, so that the final reflectances are maximally sensitive to the vegetation (Goward et al., 1991). Early global NDVI products have done none of these corrections beyond temporal compositing.

We have executed a first test of this logic, for the United States where 1-km AVHRR data and a comprehensive landcover database were already available. In this exercise, the 159 seasonal land cover regions originally defined in Loveland et al. (1991) were translated into the three attribute criteria and then combined into the six classes defined in Figure 1. Images illustrating the component binary decision logic of Figure 1 were produced to evaluate the problems and potential inherent in this classification scheme.

Decision 1—Perennial or Annual Above-Ground Biomass

The most direct distinction of perennial versus annual vegetation is the presence or absence of live above-ground biomass in the nongrowing season (Fig. 3). Note that this simple discrimination separates all forests (broadleaf and evergreen) and shrublands from grasslands, crops, and desert/tundra ephemeral vegetation. The Great Plains grasslands form the largest continuous class of defined annual vegetation, with the midwest and Mississippi River agricultural areas clearly delineated. We acknowledge that many grasses survive the nongrowing season with perennial root systems, so are technically not annuals. However, grasses are functionally most similar to annual plants, so we include them in that vegetation class. The desert Southwest is defined as perennial despite sparse cover due to the perennial pinyon-juniper shrubs that dominate that landscape. Clearly the causal factors involved here are a combination of climate constraints and/or human perturbation.

Two thresholds were used to distinguish vegetated from nonvegetated land in the nongrowing season. One is a minimum NDVI threshold; 0.1 was used in Loveland et al. (1991), below which the pixel is considered nonvegetated. The second logic evaluates the time period of NDVI above a threshold, a greenness duration, given in days. Longer greenness duration implies perennial vegetation.

We are concerned that those NDVI thresholds alone will not provide a globally applicable logic, so alternative analyses to NDVI are also being considered. Although the NDVI is usually higher over vegetated than nonvegetated areas regardless of the presence of green leaf area, the best discrimination may be done with single AVHRR Channel 1 data alone, of shortwave reflectance. For example, in seasonally snow-covered areas, permanent vegetation stands above the ground snow cover, while areas of annual vegetation show a purely snow covered surface. Alternatively, addition of surface temperature from the AVHRR thermal Channels 4 and 5 has improved biome type discrimination. Nonvegetated surfaces have much lower thermal inertia

than vegetated surfaces, so surface temperature extremes may identify nonvegetated areas (Nemani et al., 1993). We recognize that choosing a single general logic for processing Decision 1 globally may be difficult, so plan an active testing of alternative analyses in the near future.

Decision 2—Evergreen or Deciduous Canopy

The second decision in the hierarchy of Figure 1 is to discriminate deciduous from evergreen vegetation. This decision is already partly answered in Decision 1, annual vegetation is always deciduous; but, among perennial vegetation, the distinction between evergreen and deciduous separates major forest types and shrub types. The image representing the simple dichotomy of Decision 2 lumps all of the annual grasses and crops from Decision 1 with the eastern deciduous forests (Fig. 4). The evergreen perennial class, primarily conifer forests of the West and Southeast remain rather constant because of limited areas of evergreen–deciduous forest mixing.

The seasonal amplitude of NDVI, the difference between the lowest NDVI before spring leaf growth, the peak midsummer NDVI usually provides a clear distinction between evergreen and deciduous vegetation (Fig. 2) (Loveland et al., 1991). Evergreen vegetation retains a much higher year around NDVI due to continuous foliage, so that the NDVI amplitude is much smaller (Spanner et al., 1990). However, much of the apparent seasonal trend of simple NDVI products actually relates to changing illumination angle (Goward et al., 1991). These optical effects must be removed in future NDVI datasets to make the quantitative evaluations of NDVI dynamics proposed here.

Decision 3—Needleleaf, Broadleaf, or Grass

The final Decision 3 distinguishes needleleaf versus broadleaf versus grass, three fundamental leaf types with highly contrasting energy transfer and ecological characteristics (Fig. 5). This discrimination is the most difficult from current remote sensing. Nadir viewing AVHRR data produces variable reflectances at the two extreme classes; evergreen needleleaf forest and grasses are often readily distinguished because of large albedo differences. Loveland et al. (1991) found that the evergreen forests that predominate in the Pacific Northwest and Southeast were clearly discriminated by both "duration of greenness" and "onset of greenness" seasonal NDVI criteria. The Great Plains grasslands are also consistently separated by these criteria.

The large variety of broadleaf vegetation, ranging from the deciduous forests, to western sagebrush would be very difficult to discriminate from NDVI alone. However, if the initial Decisions 1 and 2 discriminations are done correctly, this final decision is much more tractable. If necessary, because evergreen needleleaf forests and evergreen broadleaf forests rarely intermix geographically, they could be separated by simple climate zones. The deciduous needleleaf tree Larix intermixes with deciduous broadleaf forests in temperate regions of North America and Asia.

A variety of vegetation types fall into the broadleaf annual class, including most crops, and many desert and tundra types in climates too harsh to sustain perennial plant life. For purposes of biophysical parameterization, these plant types can all be defined together, and so form the final class of this remote sensing based logic. However, when finer discrimination is required, the climatic subclassification easily separates agricultural crops from drought-limited deserts and temperature-limited tundra. Even without explicit climate definition, the time integration of NDVI, or the simple growing season duration in days defined by NDVI seasonality, discriminates these classes (Loveland et al., 1991).

We suggest a more general solution may involve differentiating the bidirectional reflectance distribution function (BRDF) of these canopy types (Fig. 6). Vegetation canopies are not anisotropic; their reflectance and shadowing changes directionally with illumination and view angles. The use of directional reflectances to improve these vegetation discriminations could be a specific application of the theoretical work in canopy radiative transfer modeling currently under way (Asrar et al., 1992; Myeneni et al., 1990; Li and Strahler, 1992). Since AVHRR viewing geometry extends to 55° off-nadir, specific processing of this off-nadir data may allow testing of the utility of directional data. However, the normal NDVI compositing procedures cannot be used, because the maximum value logic usually selects against off-nadir pixels (Goward et al., 1991). Currently available directional airborne sensors such as the Airborne Solid-State Array Spectroradiometer (ASAS) (Irons et al., 1991) provide a better testbed for these BRDF theoretical studies, and could be flown over complex landcovers for tests. High spectral resolution data from the Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) may also improve the difficult detection of needleleaf, broadleaf, and grasses because of spectral sensitivity of BRDFs.

The final vegetation classification, the intersection of the three decision classes, describes six different basic classes or lifeforms of global vegetation from Figure 1. A first test of this complete logic, for the United States where 1-km AVHRR data were already available, is shown in Figure 7. There were clear advantages to mapping vegetation based on the logic in Figure 1, compared to the original classification of Loveland et al. (1991). In the original classification, almost 85% (60 of 71) of the preliminary regions defined by initial spectral-temporal clustering algorithms of the NDVI data contained multiple land cover types that required

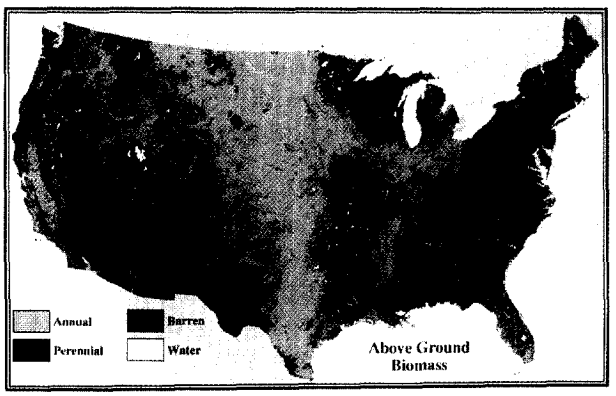

Figure 3. An image of the continental United States illustrating the distinction defined in Decision 1 between vegetation with perennial or annual above-ground biomass, derived from the 1-km landcover database of Loveland et al. (1991).

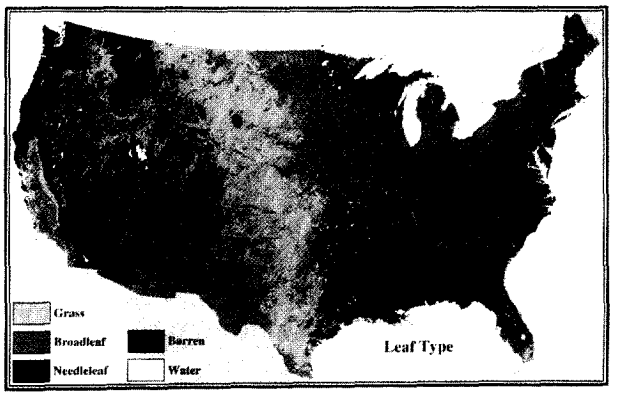

Figure 5. The three class discrimination produced by Decision 3, among needleleaf, broadleaf, and grass leaf type vegetation, derived from the database of Loveland et al. (1991).

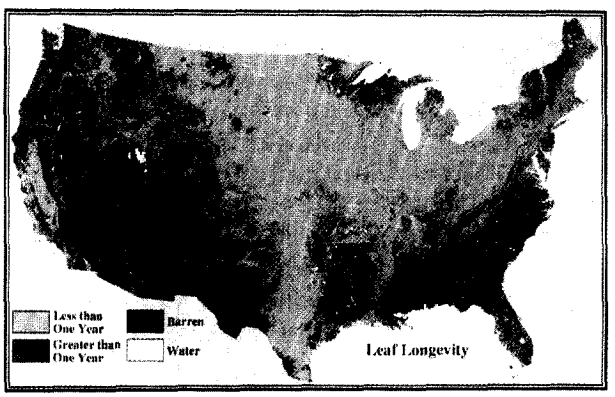

Figure 4. Implementation of Decision 2, distinguishing between evergreen and deciduous vegetation types, from the database of Loveland et al. (1991).

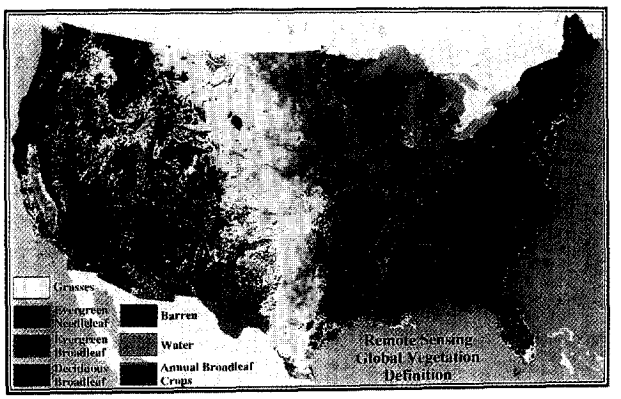

Figure 7. A final map of the six proposed vegetation classes for the continental United States derived from the 1-km land classification database of Loveland et al. (1991).

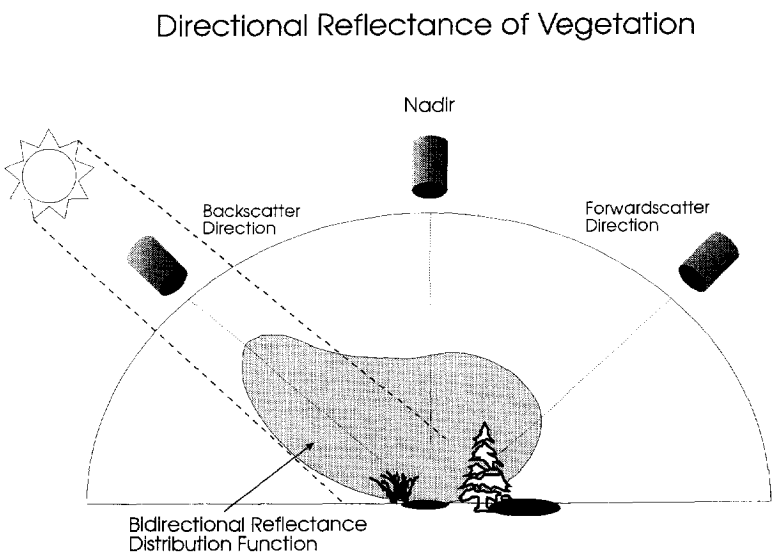

Figure 6. A conceptual diagram illustrating how directional remote sensing could be used to evaluate the bidirectional reflectance distribution function (BRDF) of these vegetation classes to improve accuracy of identification. The needleleaf/broadleaf/grass discrimination, Decision 3, may specifically require BRDF analysis.

use of elevation, climate, and ecoregion variables to eliminate confusion. However, when translating the original 71 classes to the logic in Figure 1, only 28% contained unacceptable attribute conflicts. The emphasis on structural aspects of vegetation rather than floristic or taxonomic elements clarifies the spectral and temporal classification process considerably.

In all cases, confusion points involved the separation of land into perennial versus annual above-ground biomass when annual irrigated broadleaf crops shared a similar NDVI temporal profile with high elevation evergreen needleleaf forests in the western United States. The NDVI signal in these forests was reduced during the fall, winter, and spring due to snowcover, while the harvested crops were also reduced in NDVI. In the spring, the melting of snow produced a perceived "onset of greenness" nearly identical to the germination of these row crops.

CLASSIFICATION ENHANCEMENTS

Our goal here is a classification procedure that is accurate, computationally efficient, and minimizes the need for multiple satellite sensors and ancillary data. Our initial priority is to test how well seasonal NDVI data alone can implement the three decisions required in Figure 1. As we identify specific problems that cannot be solved by NDVI data alone, we will proceed to more complicated solutions. The use of AVHRR thermal infrared data in conjunction with NDVI is an efficient way in some situations to enhance biome discrimination while working from the same AVHRR database (Nemani et al., 1993).

Standardized global databases can also be used efficiently to make discriminations beyond the capability of the NDVI. The most available and important global datasets to enhance vegetation discrimination will be topography and average climate. Digital topographic data is already available, although at varying resolutions for each continent (Brown et al., 1993). The discrimination problem found between snow-covered evergreen needleleaf forest and annual crops may be most easily resolved by identifying mountainous areas with the topographic database. The biome distribution logic of Prentice et al. (1992) and Neilson et al. (1992) provide specific climatic thresholds that allow definite exclusion of certain biome types from certain climatic regimes. Evergreen needleleaf forests do not occur in tropical areas where monthly temperatures remain above 5°C (Prentice et al., 1992). Available moisture limits the distribution of perennial forests such that an annual precipitation map could be used to verify discriminations between forests and grasslands.

The vegetation variable of greatest utility that was *not* included in this original classification logic is vegetation height. Plant canopy height is a necessary component of roughness length parameters used by climate models, and is highly related to the permanance of the vegetation: Trees are taller than grasses and crops. However, at 1-km pixel resolution, we see no way that tree height can be remotely sensed by AVHRR type sensors. If even a modest definition of canopy height classes were possible with, for example, synthetic aperture radar, canopy height would be added to our classification logic as an additional discriminator.

FUTURE REMOTE SENSING CAPABILITIES

With the launch of the NASA Earth Observing System in 1998, implementation of this global vegetation classification should be easier and even more accurate. The Moderate Resolution Imaging Spectrometer (MODIS) is the daily global coverage sensor for EOS. MODIS has nested spatial coverage of 250 m, 500 m, and 1 km at nadir and 36 spectral channels. The radiometric accuracy, sensor calibration, image navigation, and atmospheric corrections planned for MODIS will dramatically improve the quality of satellite vegetation index products, and of derived products like this global vegetation classification (Running et al., 1994). Additionally, the directional analyses of BRDF suggested in Figure 6 will be possible from another EOS sensor, the Multiangle Imaging Spectroradiometer (MISR) (Diner et al., 1992).

The classification test in this article was done using 2-week maximum composite NDVI datasets (Eidenshank, 1992), but at the original 1.1-km pixel resolution, rather than the spatially subsampled AVHRR data used in GAC and GVI datasets. A number of improved spectral vegetation indices are already being developed and tested with current AVHRR data. These new indices aim to reduce atmospheric and soil background influences on NDVI, and include the global environmental monitoring index (GEMI) (Pinty and Verstaete, 1992), soil-adjusted vegetation index (SAVI) (Huete et al., 1992), and the atmospheric resistant vegetation index (ARVI) (Kaufman and Tanré, 1992). These new remote sensing products, when implemented globally, should improve discrimination ability for the vegetation types in this classification scheme.

INFERRED ECOSYSTEM VARIABLES

An important requirement of this classification was that the final classes be easily translatable to biophysical parameters for global modeling. Basic principles relating simple plant structure to physiological activities of plants have emerged from recent ecological research (Field and Mooney, 1986; Reich et al., 1991; Gower and Richards, 1990). The common inference logic relates climate to leaf area index and specific leaf area, then to photosynthetic capacity, leaf nitrogen, and lignin concentrations.

Important new syntheses of a wide variety of ecolog-

ical field data from different biome types are finding a number of causal relationships between leaf longevity and important ecosystem variables (Gower and Richards, 1990; Reich et al., 1992; Pierce et al., 1994; Korner, 1994):

Leaf longevity → specific leaf area (m^2 / kg)
leaf nitrogen % (g/g)
maximum leaf conductance (mmol / m^2 / s)
maximum photosynthetic rate (mmol / g / s)
relative growth rate (m / month)
production efficiency (kg / kg / yr).

Although the specific functions relating all of these variables are complicated and beyond the scope of this article, they represent very stable and useful principles of plant structure to function that are appropriate generalities for representing vegetation globally. These relationships are important to global ecology because leaf longevity may be the most directly measured by remotely sensed greenness duration or similar seasonal NDVI analyses (Fig. 2) (Loveland et al., 1991). Consequently, these important ecosystem variables that could never be remotely sensed directly, now may be inferred with some confidence for global biogeochemical modeling. Korner (1994) has synthesized existing field data of leaf conductances and photosynthesis rates into basic principles for global modeling. Pierce et al. (1994) have tested the strength of these general principles with field data from a climatic transect of evergreen forests. Running and Hunt (1993) have explored the basic comparison of physiological factors required to parameterize evergreen forests, broadleaf forests, and grasslands with these simple inferences.

Future versions of this classification may even treat leaf longevity as a continuous variable, rather than the binary choice evergreen / deciduous in order to better exploit the inferences of ecosystem properties produced by this logic. These new principles for defining biophysical parameters for global vegetation could, when implemented, dramatically improve the realism of future global biogeochemical models. More biome specific parameterization of vegetation functional characteristics will allow substantially more defensible analyses of potential responses by the terrestrial biosphere to future global changes in climate, atmospheric chemistry, and hydrology.

The vegetation parameters of greatest interest to climate modeling are leaf area index, albedo, maximum surface conductance, and roughness length (Dickinson et al., 1986; Dorman and Sellers, 1989). Albedo is directly retrieved from AVHRR Channels 1 and 2 after the removal of atmospheric effects; however, the transformation of AVHRR / NDVI to estimated leaf area index requires knowledge of the vegetation class (Spanner et al., 1990). Hence, after determining the vegetation class from the logic in this article, the calculation of LAI should be more straightforward. Estimates of roughness length may be improved given knowledge of the six classes in this article, trees will always have longer roughness lengths than grasses or crops, for example. However, further definition of roughness length will require some estimation of canopy height, which we do not see as possible with current AVHRR data. The maximum leaf conductance that is inferred above from leaf longevity is directly analogous to the minimum surface resistance used for vegetation parameterization in the GCMs.

Although some GCMs define many vegetation classes (BATS currently defines 15; R. Dickinson, personal communication) the unique parameter specification sets for the above vegetation variables warrants a much smaller number of classes. Most of the 15 cover classes used in BATS are defined with the same maximum LAI, 6, the same minimum surface resistance, 250 s m^{-1} (4 mm s^{-1} surface conductance). Each of our six vegetation classes will have a unique set of biophysical attributes which will be finalized in a later paper. For example, Running and Hunt (1993) defined the following parameters for evergreen needleleaf forest, deciduous broadleaf forest, and grass, respectively: maximum LAI 10, 6, and 3; specific leaf area 25 m^2 kg °C, 75 m^2 kg °C, and 25 m^2 kg °C; maximum leaf conductance 1.6 mm s^{-1}, 2.5 mm s^{-1}, and 5.0 mm s^{-1}.

GCMs also typically require a fractional vegetation cover definition for each cell; however, this classification is implemented at 1-km resolution, such that a fractional cover could be computed for any GCM cell size.

CONCLUSIONS

We think that this classification logic successfully meets the requirements set forth in the introduction: unambiguous, remotely sensible, and translatable into biophysical parameters. However, we recognize that this classification logic is not sufficient for all users of global landcover classifications. We acknowledge that for some purposes, particularly social and economic analyses, more exacting classifications are required. We recommend that, rather than starting from different logic, these other classifications build hierarchically from ours. Our evergreen needleleaf forest class could easily be subdivided locally at a next level into common forest species mixtures. The broadleaf annual class could be subdivided into various crop designations. Then, a multistep processing could be developed with the first step being these initial remote sensing based classes, followed by a second more detailed processing, possibly including supervised classification techniques, time series analysis, etc. in an expert systems context. The final product

would retain the benefits of our remote sensing based classification, while providing the enhanced classification needed for these other purposes.

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REFERENCES

Asrar, G., Myneni, R. B., and Choudhury, B. J. (1992), Spatial heterogeneity in vegetation canopies and remote sensing of Absorbed Photosynthetically Active Radiation: a modeling study, *Remote Sens. Environ.* 41:85–101.

Brown, J. F., Loveland, T. R., Merchant, J. W., and Reed, B. C. (1993), Using multisource data in global land cover characterization: concepts, requirements and methods, *Photogramm. Eng. Remote Sens.* 59:977–987.

Dickinson, R. E., Henderson-Sellers, A., Kennedy, P. J., and Wilson, M. F. (1986), Biosphere-atmosphere transfer scheme (BATS) for the NCAR Community Climate Model, NCAR Tech Note NCAR / TN-275 + STR, 69 pp.

Diner, D., Bruegge, C. J., Martonchik, J. V., et al. (1991), A multi-angle imaging spectroradiometer for terrestrial remote sensing with the Earth Observing System, *Int. J. Imaging Syst. Tech.* 3:92–107.

Dorman, J. L., and Sellers, P. J. (1989), A global climatology of albedo, roughness length and stomatal resistance for atmospheric general circulation models as represented by the Simple Biosphere Model, *J. Appl. Meteorol.* 28:833–855.

Eidenshink, J. C. (1992), The 1990 conterminous U.S. AVHRR data set, *Photogramm. Eng. Remote Sens.* 58:809–813.

Field, C., and Mooney, H. A. (1986), The photosynthesis-nitrogen relationship in wild plants, in *On the Economy of Plant Form and Function* (T. J. Givnish, Ed.), Cambridge University Press, Cambridge, pp. 22–55.

Goward, S., Dye, D., Kerber, A., and Kalb, V. (1987), Comparison of North and South American biomes from AVHRR observations, *Geocarto Int.* 1:27–39.

Goward, S. N., Markham, B., Dye, D. G., Dulaney, W., and Yang, J. (1991), Normalized difference vegetation index measurements from the Advanced Very High Resolution Radiometer, *Remote Sens. Environ.* 35:257–277.

Gower, S. T., and Richards, J. H. (1990), Larches: deciduous conifers in an evergreen world, *Bioscience* 40:818–826.

Henderson-Sellers, A. (1990), Predicting generalized ecosystem groups with the NCAR CCM: first steps towards an interactive biosphere, *J. Clim.* 3:917–939.

Henderson-Sellers, A., and Pitman, A. J. (1992), Land-surface schemes for future climate models: specification, aggregation, and heterogeneity, *J. Geophys. Res.* 97:2687–2696.

Huete, A. R., Hua, G., Qi, J., Chehbouni, A., and van Leeuwem, W. J. D. G. (1992), Normalization of multidirectional red and NIR reflectances with the SAVI, *Remote Sens. Environ.* 40:1–20.

Irons, J., Ranson, D., Williams, D., Irish, R., and Huegel, F. (1991), An off-nadir-pointing imaging spectroradiometer for terrestrial ecosystem studies, *IEEE Trans. Geosci. Remote Sens.* 29:66–74.

Justice, C., Townshend, J., Holben, B., and Tucker, C. (1985), Analysis of the phenology of global vegetation using meteorological satellite data, *Int. J. Remote Sens.* 6:1271–1318.

Kaufman, Y. J., and Tanré, D., (1992), Atmospheric resistant vegetation index, *IEEE J. Geosci. Remote Sens.* 30:261–270.

Korner, C. (1994), Leaf diffusive conductances in the major vegetation types of the world, in *Ecophysiology of Photosynthesis* (E. D. Schulze and M. M. Caldwell, Eds.), Ecological Studies 100, Springer-Verlag, New York, pp. 463–490.

Li, X., and Strahler, A. H. (1992), Geometric-optical bidirectional reflectance modeling of the discrete-crown vegetation canopy: Effect of crown shape and mutual shadowing, *IEEE Trans. Geosci. Remote Sens.* 30:276–292.

Lloyd, D. (1990), A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery, *Int. J. Remote Sens.* 11:2269–2279.

Loveland, T., Merchant, J., Ohlen, D., and Brown, J., (1991), Development of a Land-Cover characteristics database for the conterminous U.S., *Photogramm. Eng. Remote Sens.* 57: 1453–1463.

Matthews, E. (1983), Global vegetation and land use: new high-resolution data bases for climate studies, *J. Clim. Appl. Meteorol.* 22:474–487.

Myeneni, R., Asrar, G., and Gerstl, S. A. W. (1990), Radiative transfer in three dimensional leaf canopies, *Trans. Theory Stat. Phys.* 19:1–54.

Neilson, R. (1993), Vegetation redistribution: a possible biosphere source of CO2 during climate change, *J. Water Air Soil Pollut.*, forthcoming.

Neilson, R., King, G., and Koerper, G. (1992), Toward a rule-based biome model, *Landscape Ecol.* 7:27–49.

Nemani, R., Pierce, L. L., Running, S. W., and Goward, S. N. (1993), Developing satellite derived estimates of surface moisture status, *J. Appl. Meteorol.* 32:548–557.

Pierce, L. L., Running, S. W., and Walker, J. (1994), Regional scale relationships of leaf area index to specific leaf area and leaf nitrogen content, *Ecol. Appl.* 4:313–321.

Pinty, B., and Verstaete, M. M. (1993), GEMI: A non-linear index to monitor global vegetation from satellites, *Vegetatio.* 101:15–20.

Prentice, C., Cramer, W., Harrison, S., Leemans, R., Monserud, R., and Solomon, R. (1992), A global biome model based on plant physiology and dominance, soil properties and climate, *J. Biogeogr.* 19:117–134.

Prentice, K. C. (1990), Bioclimatic distribution of vegetation for general circulation model studies, *J. Geophys. Res.* 95: 11,811–11,830.

Reich, P., Uhl, C., Walters, M., and Ellsworth, D. (1991), Leaf lifespan as a determinant of leaf structure and function among 23 amazonian tree species, *Oecologia* 86:16–24.

Reich, P. B., Walters, M. B., and Ellsworth, D. S. (1992), Leaf lifespan in relation to leaf, plant and stand characteristics among diverse ecosystems, *Ecol. Monogr.* 62:365–392.

Running, S. W., and Hunt, E. R. (1993), Generalization of a forest ecosystem process model for other biomes, BIOME-BGC, and an application for global-scale models, in *Scaling Physiological Processes: Leaf to Globe* (J. Ehleringer and C. Field, Eds.), Academic, New York.

Running, S. W., Justice, C. O., Salomonson, V., et al. (1994),

Terrestrial remote sensing science and algorithms planned for EOS / MODIS, *Int. J. Remote Sens.*, forthcoming.

Sellers, P. J., Mintz, Y., Sud, Y. C., and Dalcher, A. (1986), A simple biosphere (SiB) model for use within general circulation models, *J. Atmos. Sci.* 43:505–531.

Spanner, M., Pierce, L., Running, S., and Peterson, D. (1990), The seasonality of AVHRR data of temperate coniferous forests: relationship with leaf area index, *Remote Sens. Environ.* 33:97–112.

Townshend, J., Justice, C., Li, W., Gurney, C., and McManus, J. (1991), Global land cover classification remote sensing: present capabilities and future possibilities, *Remote Sens. Environ.* 35:243–255.

Woodward, F. I. (1987), *Climate and Plant Distribution*, Cambridge University Press, Cambridge, 174 pp.