ELSEVIER

Coordinating Methodologies for Scaling Landcover Classifications from Site-Specific to Global: Steps toward Validating Global Map Products

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The MODIS sensor to be launched on the EOS-AM platform will be the most important sensor for global vegetation mapping. Among the programmatic goals for the MODIS sensor are to assess and track changes in land use/landcover, leaf area index (LAI), and net primary productivity (NPP). For these products to be used in global models, they must be rigorously validated with site-specific data products. This article presents a review of some of the problems facing a regional- to global-scale validation effort and presents strategies for coordinating the land-cover classification process across multiple sites. We suggest the Enhanced Thematic Mapper (ETM+) as the source of remotely sensed data for validation, and that the IGBP 17-class land-cover classification system be used to provide a link between more complex site-specific systems and global-scale data products. We further recommend that the best site-specific land-cover classifications be obtained, using whatever ancillary data are found to be useful, as a basis for validation. In addition, we propose ways in which ambiguities in translation of classes, from specific to general systems, may be identified. Finally, we stress that even though standardization of methodology among sites may not be appropriate to the goal of obtaining the best possible land-cover products, there should be standardization of error analysis and metadata reporting.

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INTRODUCTION

Global models, whether to study climate, water, and energy fluxes, or ecosystem structure and function, require well-defined estimates of vegetation parameters such as radiation absorption and surface roughness to accurately characterize the surface of the Earth (Baldocchi et al., 1996; Sellers et al., 1996c; 1997). Satellite data are crucial for these activities (Ustin et al., 1991; Sellers et al., 1996a,b), as well as for direct correlations with Earth–surface phenomena (Nemani et al., 1993; Hunt et al., 1996; Li and Moreau, 1996). The MODIS sensor within the Earth Observing System (EOS) will be the most important sensor for global vegetation mapping, assuming the role currently held by AVHRR. Among the programmatic goals for the MODIS sensor are to assess and track changes in such biophysical variables as land use/landcover, leaf area index (LAI), and net primary productivity (NPP) (Privette et al., 1997; Running et al., 1994a). Satellite data have frequently been used to monitor landcover change (e.g., Chavez and MacKinnon, 1994; Green et al., 1994; Skole et al., 1994; Nemani et al., 1996) and carbon allocation (e.g., Foody et al., 1996; Veroustraete et al., 1996), but the EOS program initiates a new level of detail, both spatial and spectral, in the derivation of global metrics currently obtained from AVHRR imagery (Barron et al., 1995). Running et al. (1994a) indicate the need for rigorous validation of MODIS algorithms, and a group of 17 sites, from the Long-Term Ecological Research (LTER) network, the U.S. Department of Energy, and the BOREAS project, have joined to form the

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MODLERS (MODis land science team and Long-term Ecological Research network Synthesis) project to aid in validation efforts (Running et al., 1999, this issue).

Accurate land-cover maps developed for reference sites are key requirements for MODIS validation. In the MODLERS project, site-based cover maps will be used not only to compare against the MODLAND (MODIS Land Science Team) globally based cover maps, but also as a starting point for a number of subsequent analyses, including cover-type-specific functional correlations (with LAI and NPP), and to help interpret errors in MODLAND LAI and NPP products (Running et al., 1996; 1999, this issue). Different land-cover classification methodologies, and different philosophies underlying those methodologies, might impact the validity of the MODIS landcover products, and of LAI and NPP estimates that are based on a landcover stratification. This article presents some ideas concerning these uncertainties, and discusses several important issues in developing coordinated methods for land-cover mapping in multisite projects such as MODLERS.

The goals for MODLERS landcover classification are: 1) to develop an accurate landcover map at 25-m grain size containing cover classes that are functionally important in terms of LAI and NPP for each MODLERS site; and 2) to develop a methodology for deriving site-specific land-cover data products that are directly comparable with the globally generalized MODLAND landcover categorization scheme. For the site-specific landcover maps, a grain size of 25 m was selected because it nests neatly within the 1-km resolution of MODIS products, while being close to the resolution of Landsat Enhanced Thematic Mapper+(ETM+) data to be used for the validation effort at most of the MODLERS sites. While certain stages of the classification process will be standardized, such as atmospheric corrections (Ouaidrari and Vermote, 1999, this issue), georegistration, field sampling, and error assessment, the stated goals do not require that identical image classification methodologies be adopted at each site. This is because all classification methods depend to a great extent on uncontrolled factors, such as subjective human interpretation, either in the selection of training sets (for a supervised classification) or the *a posteriori* assignment of classes (for an unsupervised classification). Furthermore, methods that provide the highest classification accuracies may be different at each site, and every site has different ancillary data available and different environmental conditions. Also, frequent cloud cover (e.g., at the Luquillo Experimental Forest in Puerto Rico) will limit the amount of available imagery, such that ETM+ data may not be available and may need to be replaced by SPOT imagery or digital aircraft data. Given the goal of using local expertise and relevant ancillary data to develop for each site a highly accurate cover map that has functionally relevant classes, a separate set of site-specific landcover classes will be defined at each site. However, given the project's other goal of comparing the site-specific maps to MODLAND globally based maps for the purpose of MODIS validation, the site-specific maps must be generalized to MODLAND cover classes. To accomplish this, the site-specific classes must be unambiguously translatable into MODLAND classes. As this is not likely to be the case at many MODLERS sites, an alternative approach will involve classification directly into MODLAND cover classes using local data and expertise and ETM+ imagery. Translation of local cover classes into a global mapping framework is not uncommon (e.g., Turner et al., 1996; VEMAP, 1995), and the advantage afforded by having the three proposed cover maps at each site (site-specific, translated to MODLAND classes, and direct to MODLAND classes) permits evaluation of errors associated with such translations. Furthermore, the techniques will apply to other generalized schemes by changing the translation tables applied to the site-specific maps.

LAND COVER CATEGORIZATION SCHEMES

MODLAND Categorization

There are a number of schemes that have been proposed for regional- to global-scale landcover categorization, including the International Geosphere–Biosphere Programme Data and Information Systems Land Cover Working Group (IGBP-DIS LCWG) landcover categorization system (Belward and Loveland, 1995), a six-class biome categorization (Running et al., 1994b; 1995), the Simple Biosphere Model (SiB; Dorman and Sellers, 1989; SiB2; Sellers et al., 1996c), and the Federal Geographic Data Committee vegetation characterization and information standards (FGDC, 1996). Of these alternatives, the IGBP system was selected to match 1-km products from the MODLAND Science Team.

The IGBP Fast-track Land Cover Product identifies 17 cover classes (Belward and Loveland, 1995; Table 1). The land-surface categorization complexity of the IGBP scheme lies between site-specific and highly generalized. For example, Running et al. (1994b; 1995) proposed a scheme of just six classes, with decision rules at three levels: Is above-ground live biomass perennial or annual, is leaf longevity less than or more than 1 year, and is the leaf type broad, needle, or grass? This six-class scheme is a structural categorization which enables researchers to identify characteristics important to ecosystem biogeochemistry in an unambiguous manner using relatively coarse-resolution satellite data. The classes were designed to be readily validated in the field (assuming access on the ground or through higher-resolution remotely sensed data such as aerial photographs); to be refined based on local ancillary knowledge such as climate or LAI (Nemani and Running, 1996); and by defin-

Table 1. Land Cover Structural Characteristics of the IGBP Cover Classes (from Belward and Loveland, 1995)

Land-Cover Type	*Above-Ground Biomass*	*Leaf Longevity*	*Leaf Type*	*Percent Woody*	*Woody Height*
Evergreen needleleaf forests	Woody	>1 year	Needleleaf	>50%	>2 m
Evergreen broadleaf forests	Woody	>1 year	Broadleaf	>50%	>2 m
Deciduous needleleaf forests	Woody	<1 year	Needleleaf	>50%	>2 m
Deciduous broadleaf forests	Woody	<1 year	Broadleaf	>50%	>2 m
Mixed forests	Woody	Either <1 or >1 year	Broadleaf and needleleaf	>50%	>2 m
Closed shrublands	Woody	Either <1 or >1 year	Broadleaf or needleleaf	>20%	<2 m
Open shrublands	Woody	Either <1 or >1 year	Broadleaf or needleleaf	<20%	<2 m
Woody savannas	Woody/ nonwoody	Either <1 or >1 year	Grass, needle-, or broadleaf	30–50%	>2 m
Savannas	Woody/ nonwoody	Either <1 or >1 year	Grass, needle-, or broadleaf	10–30%	>2 m
Grasslands	Nonwoody	Either <1 or >1 year	Grass	<10%	<2 m
Permanent wetlands	Woody/ nonwoody	Either <1 or >1 year	Grass, needle-, or broadleaf	0–100%	Either <2 or >2 m
Croplands	Nonwoody	<1 year	Grass or broadleaf	<10%	<2 m
Urban and built-up	N/A	N/A	N/A	N/A	N/A
Cropland/natural vegetation mosaics	Woody/ nonwoody	Either <1 or >1 year	Grass, needle, or broadleaf	<60%	Either <2 or >2 m
Snow and ice	N/A	N/A	N/A	N/A	N/A
Barren	N/A	N/A	N/A	N/A	N/A
Water bodies	N/A	N/A	N/A	N/A	N/A

ing mixtures of the six basic classes. The IGBP scheme embraces the same philosophy but with modifications to be compatible with existing schemes used by environmental modelers, to incorporate land use in addition to landcover, and to represent mosaics (Belward and Loveland, 1995). The IGBP categorization is hierarchical, first defining land as vegetated or nonvegetated. For vegetated land, above-ground biomass is classed as woody or nonwoody, then further subdivided based on leaf longevity (less than or more than 1 year). Below that level, leaf type is broad, needle, or grass. Further refinements are then made based on the percent cover and height of woody vegetation. The scheme includes classes that are mixtures of these characteristics as well as mosaics of cropland and natural vegetation.

Site-Specific Categorizations and Translations

A major objective of the MODLERS project is to derive accurate maps of LAI and NPP at each site based on landcover stratification (Turner et al., 1999, this issue; Reich et al., 1999, this issue). LAI mapping and NPP modeling will be based on the site-specific landcover classes to allow more precise comparison against field measurements than would be possible with a generalized classification. Therefore, relevant site-specific landcover classifications are needed. Table 2 lists proposed site-specific classes for several MODLERS sites and illustrates how they might be translated into IGBP classes.

At the Luquillo Experimental Forest (LUQ; Table 2e), there are 13 important site-specific classes. While there is little ambiguity in the translation, these 13 classes collapse into only seven IGBP classes, with seven of the original 13 translating into a single IGBP class that coincidentally covers the vast majority of the study area. At most sites, several classes translate neatly into a single IGBP class, with a corresponding collapse in the number of classes. For example, at North Temperate Lakes (NTL; Table 2f) 16 site-specific classes condense into 10 IGBP classes. Figure 1 is an example of this from the H. J. Andrews site (AND; Table 2a), showing a marked reduction in landscape complexity associated solely with translation and the potential implications on estimating NPP. Clearly, the use of a generalized classification scheme can have a serious impact on estimated NPP for a site such as the Andrews, where different site-specific classes that are represented by a single IGBP class have greatly varying mean NPP values (Fig. 2). It is important to note here that this problem of NPP errors associated with generalization is not due to translation from site-specific classes to IGBP classes, but rather from the use

Table 2. Translation of Site-Specific Land-Cover Classes to IGBP Classes

(a) H. J. Andrews Experimental Forest

Site-Specific Class[a]	*IGBP Class*
Open (0–30% cover)	Open shrublands
Semiclosed (30–70% cover)	Open shrublands
Closed hardwood	Deciduous broadleaf forests
Closed mixed cr diam 0–2 m	Mixed forests
Closed mixed cr diam 2–5 m	Mixed forests
Closed mixed cr diam 5–8 m	Mixed forests
Closed mixed cr diam 8–12 m	Mixed forests
Closed mixed cr diam >12 m	Mixed forests
Closed conifer cr diam 0–2 m	Evergreen needleleaf forests
Closed conifer cr diam 2–5 m	Evergreen needleleaf forests
Closed conifer cr diam 5–8 m	Evergreen needleleaf forests
Closed conifer cr diam 8–12 m	Evergreen needleleaf forests
Closed conifer cr diam >12 m	Evergreen needleleaf forests

(b) Bonanza Creek

Site-Specific Class	*IGBP Class*
Balsam poplar	Deciduous broadleaf forests
Balsam poplar/white spruce	Mixed forests
Aspen	Deciduous broadleaf forests
Paper birch	Deciduous broadleaf forests
Paper birch/aspen	Deciduous broadleaf forests
White spruce	Evergreen needleleaf forests
White spruce/aspen/birch	Mixed forests
Black spruce	Evergreen needleleaf forests/deciduous needleleaf forests/woody savannas/savannas
Black spruce dominated mix	Evergreen needleleaf forests/deciduous needleleaf forests/woody savannas/savannas
Alder/alder-spruce	Deciduous broadleaf forests/mixed forests
Nonforest	Grassland/permanent wetlands
Rivers/lakes	Water bodies
Sand/gravel	Barren
Highway right of way	Urban and built-up

(c) Cedar Creek

Site-Specific Class	*IGBP Class*
Mature deciduous forest	Deciduous broadleaf forests
Young deciduous forest	Deciduous broadleaf forests
Mixed deciduous/conifer forest	Mixed forests
Conifer forest	Evergreen needleleaf forests
Mixed forest/grass/shrub	[b]
Row crop agriculture	Croplands
Pasture agriculture	Grasslands
Mown grass	Grasslands
Suburban—open vegetated	[b]
Surburban—forest	[b]
Urban	Urban and built-up
Bare soil	Barren
Water	Water bodies

(d) Konza Prairie

Site-Specific Class	*IGBP Class*
Residential	Urban and built-up
Commercial/industrial	Urban and built-up
Urban-grassland	[b]
Urban-woodland	[b]
Urban-water	[b]
Cropland	Croplands
Grassland	Grasslands
Woodland	Deciduous broadleaf forests
Water	Water bodies
Other	Unclassified

Table 2. (continued)

(e) Luquillo Experimental Forest

Site-Specific Class	*IGBP Class*
Tabonuco forest	Evergreen broadleaf forests
Colorado forest	Evergreen broadleaf forests
Palm forest	Evergreen broadleaf forests
Dwarf (cloud) forest	Evergreen broadleaf forests
Native plantations	Evergreen broadleaf forests
Exotic plantations—roble	Evergreen broadleaf forests
Exotic plantations—pine	Evergreen needleleaf forests
Secondary forest	Evergreen broadleaf forests
Managed pasture	Grasslands
Recently abandoned pasture	Savannas
Scrubland	Woody savannas
Houses, barren	Urban and built-up
Water	Water bodies

(f) North Temperate Lakes

Site-Specific Class	*IGBP Class*
Unclassified	Unclassified
Water	Water bodies
High-quality hardwoods	Deciduous broadleaf forests
Jack pine	Evergreen needleleaf forests
Medium-low quality hardwoods	Deciduous broadleaf forests
Disturbance regeneration (older)	Closed shrublands
Red pine/hardwood	Evergreen needleleaf forests
Red pine/white pine	Evergreen needleleaf forests
Clearcut (older)	Open shrublands
Nonforested wetland	Permanent wetlands
Cranberry bog	Croplands/closed shrublands
Forested wetland	Mixed forest
Clearcut (younger)	Open shrublands
Disturb. regeneration (younger)	Open shrublands
Agriculture	Croplands
Urban/built-up	Urban and built-up

(g) Virginia Coast Reserve

Site-Specific Class	*IGBP Class*
Sand	Barren
Pine/hardwood forest	Mixed forests
Pine/evergreen shrub	Closed shrublands/ evergreen needleleaf forests/ evergreen broadleaf forests
High salt marsh	Permanent wetlands
Low salt marsh	Permanent wetlands
Water	Water bodies

(h) Walker Branch Watershed

Site-Specific Class	*IGBP Class*
Water	Water bodies
Urban land	Urban and built-up
Evergreen forest	Evergreen needleleaf forests
Evergreen plantation	Evergreen needleleaf forests
Mixed forest	Mixed forests
Deciduous forest	Deciduous broadleaf forests
Transition	[b]
Barren	Barren
Clouds	Unclassified

[a] cr diam=crown diameter.
[b] Designation uncertain.

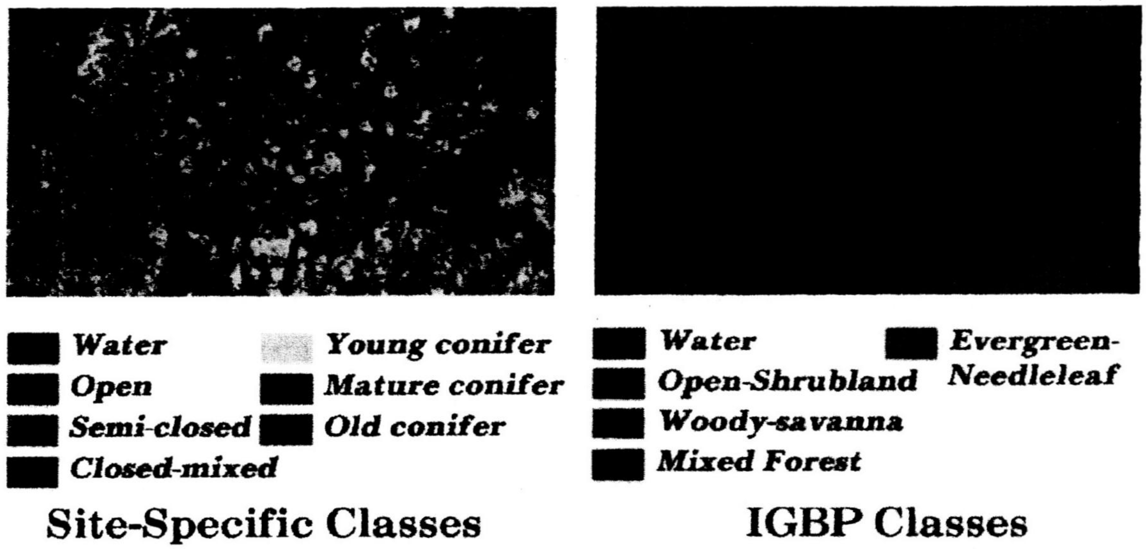


Figure 1. A site-specific cover-class map for the H. J. Andrews Experimental Forest MODLERS site in western Oregon, and the translation of that map into IGBP classes. The primary difference is the collapse of the three site-specific conifer classes into a single IGBP class.

of a generalized classification scheme versus a site-specific scheme. Mapping a generalized scheme even at 25-m resolution will bias against mosaic classes, since patches are more homogeneous at finer resolutions. To aid in validation, the 1-km MODIS grid will be superimposed on each of the three 25-m resolution map products, and a listing of the proportion of each landcover type in each of the 1-km cells will be generated. This will allow an analysis of which heterogeneous classes are the most problematic when the results are scaled up. Milne and Cohen (1999, this issue) address the issues associated with scaling of the classifications.

A perhaps more serious problem is evident in the ambiguity of translations (Table 2). For example, at Bonanza Creek (Table 2b), black spruce could be classified as one of three different IGBP classes, depending on specific site conditions. Similarly, at the Virginia Coast Reserve (VCR; Table 2g) and NTL (Table 2f), a single class at each site could be any of three (VCR) or either of two (NTL) different IGBP classes. At Cedar Creek (CDR; Table 2c) and Konza Prairie (KNZ; Table 2d), there are three site-specific classes that cannot easily be translated directly to IGBP classes because of a lack of correspondence between the two classing schemes. At Walker Branch (WBW; Table 2h) there is one such class. These ambiguities will have consequences when images are classified directly to IGBP classes, because they are not solely a function of the translation process, but rather they stem from variability on the ground that cannot be neatly categorized into an IGBP, or any other generalized, landcover class.

The IGBP classification is based on the following three components: vegetative structure, leaf longevity, and leaf type. One purpose of using vegetative structure is to obtain a surface roughness length parameter for global models, and for that reason structure is defined by a number of different factors: whether the land is vegetated; if vegetated, whether perennial or annual cover; the relative proportion of woody and nonwoody components; canopy height; and canopy percent closure. Additional problems in translation from site-specific to IGBP classes may occur because, while most of the sites use the same three major components for site-specific classification schemes, the factors contributing to vegetative structure differ widely. Table 3 summarizes these factors at a number of the sites. The IGBP scheme includes five categories under Vegetative Structure; only one of the sites (NTL) uses all five, while two sites, AND and WBW, use only one. Most, but not all, of the sites use Leaf Longevity and Leaf Type in their site-specific schemes.

COORDINATED METHODOLOGY

To the extent possible, there is a great need to coordinate the procedures used in landcover mapping for a multi-site project such as MODLERS. Although the exact classification strategy is not specified, to take advantage of local expertise and data availability, certain constraints and procedures can be universally prescribed.

Study Areas

The footprint for each study site (Fig. 3) is nominally 10 km by 10 km, to allow a minimum of 100 pixels even at the MODIS sensor's lowest spatial resolution of 1 km. Because of current uncertainties about the path characteristics of the EOS-AM satellite, each site has added a 500-m buffer around the target area, so that a full 100 1-km MODIS pixels will be included regardless of the exact final alignment. The sites were selected based on

Table 3. Factors Influencing the Components of Selected Site-Specific and IGBP Classification Schemes

	Site[a]									
Factor	*IGBP*	*AND*	*BNZ*	*CDR*	*CWT*	*KNZ*	*LUQ*	*NTL*	*VCR*	*WBW*
Vegetative structure										
Vegetated/nonvegetated	✓		✓	✓	✓	✓	✓	✓	✓	✓
Woody/nonwoody	✓		✓	✓	✓	✓	✓	✓	✓	
Annual/perennial	✓			✓	✓	✓		✓		
% Canopy closure	✓	✓						✓		
Canopy height	✓			✓	✓			✓		
% Woody canopy							✓			✓
Floristics/community type			✓				✓		✓	
Tree crown diameter		✓								
Leaf Area Index								✓		
Leaf longevity	✓	✓	✓	✓	✓			✓	✓	✓
Leaf type	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

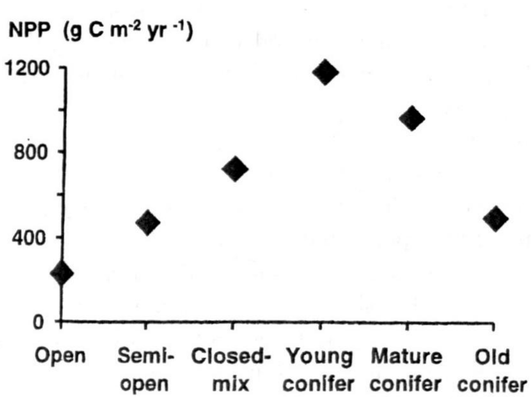
[a] See Figure 3 for site acronyms.

their representation of different biomes and vegetative conditions and the availability of field-measured data on leaf area index and net primary productivity. Typically, the sites are subsets of existing long-term and well-characterized ecological research areas, although in some cases they may extend outside previous study-area boundaries to increase the range of vegetative cover types. While the original plan was for sites of an exact 11 km×11 km (10 km×10 km plus the 500 m buffer), most are slightly off square (e.g., 10 km×12 km), again to include the widest range of characteristic vegetation types possible.

All of the 13 vegetated IGBP global landcover classes (EOSDIS, 1997) are represented at one or more of the MODLERS sites (Table 4). Some of the classes are very well represented. For example, evergreen needleleaf forests, deciduous broadleaf forests, and mixed forests are each found at eight different sites. These three classes combined account for 44% of the vegetated land surface of North America. Closed shrublands, grasslands, and croplands account for an additional 22%, and they are each represented at four sites. Evergreen broadleaf forest, open shrublands, and permanent wetlands occupy 17% of the vegetated surface of North America, and they are each found at three MODLERS sites. The remaining four classes are rather more restricted within the MODLERS sites, but occupy only 17% of the vegetated surface of North America. Woody savannas (9%) are represented at two sites, while cropland/natural vegetation mosaics (8%) and savannas (0.4%) are each found at only one site. One IGBP vegetated landcover class not included in the EOSDIS (1997) map of North America, deciduous needleleaf forest, is found at one site.

At the global level, the picture is somewhat different. The three classes most commonly encountered at MODLERS sites occupy only 14% of the vegetated surface of the globe, while the classes represented at only one or two sites occupy 33%. Thus, while the MODLERS sites are highly representative of the IGBP classes found in North America, they are not as complete in their coverage of global vegetation types. This is not surprising given the differences in percent area occupied by the cover types in North America compared to the world as a whole (Table 4). For the long term, the procedures developed under MODLERS will need to be applied at sites outside North America and the Caribbean. However, the MODLERS techniques are inherently biome-independent, so that these methodologies will be transportable to other sites.

Figure 2. Mean values of total NPP for each site-specific class at the H. J. Andrews. As each of the conifer classes has vastly different amounts of NPP, the actual proportional mix of these classes is important for accurately estimating NPP at the site.



Imagery

There are numerous sources of remotely sensed data for landcover classification. The most commonly used is Landsat Thematic Mapper (TM) because of its combination of relatively high spatial and spectral resolution and low cost. This sensor will be replaced by the ETM+ instrument on Landsat 7 (Lauer et al., 1997), and all the sites will use newly acquired ETM+ imagery if available. To the extent possible, the imagery used for classification

Table 4. Vegetated IGBP Classes Represented at Selected MODLERS Study Sites and Their Relative Areas

	Site[a]											Area[b]	
Vegetated IGBP Cover Class	*AND*	*BNZ*	*CDR*	*CWT*	*HBR*	*KBS*	*KNZ*	*LUQ*	*NTL*	*VCR*	*WBW*	*N. Am.*	*Global*
Evergreen needleleaf forest	✓	✓	✓	✓	✓				✓	✓	✓	20	6
Evergreen broadleaf forest				✓				✓		✓		2	11
Deciduous needleleaf forest		✓										0	2
Deciduous broadleaf forest	✓	✓	✓	✓	✓		✓		✓		✓	8	3
Mixed forests	✓	✓	✓		✓	✓			✓	✓	✓	16	6
Closed shrublands	✓	✓							✓	✓		3	4
Open shrublands	✓	✓							✓			13	17
Woody savannas	✓							✓				9	9
Savannas								✓				0	9
Grasslands			✓	✓			✓	✓				9	10
Permanent wetlands		✓							✓	✓		2	1
Croplands			✓			✓	✓		✓			10	12
Cropland/natural veg mosaics						✓						8	13

[a] See Figure 3 for site acronyms.
[b] Percent of vegetated area of North America (N. Am.) and the world (Global) occupied by each class (from EOSDIS, 1997).

must be contemporaneous with MODIS imagery used to develop the products we are validating to allow a valid comparison between the two sources. However, as described earlier, some sites (e.g., Luquillo, with its frequent cloud cover), may require some flexibility in imagery and date selection. For sites with pronounced seasonality, several images within the target year (1999) will be acquired, and some sites may use additional sensor data (such as AVIRIS) to help refine important functional classes.

Image Rectification and Georeferencing

Image rectification and georeferencing are crucial in that they allow remotely sensed data to be combined and enhanced with ancillary spatial data, and to be compared to precisely located ground observations. Georeferencing/rectification is easiest in study areas with flat terrain and when using ETM+ or other data from high resolution, mapping satellites. Terrain and tilt distortions are typically small and control points most easily identified on high-resolution, low-relief imagery, and in these cases an affine transformation typically provides subpixel accuracy when there are sufficient ground control points (GCPs). A minimum of 12 points is recommended, with a target of 20 well-distributed points for the 100 km^2 study area. The density of GCPs required is thus 1 per 5 km^2 to 8 km^2. Positional errors with an affine transformation increase as terrain variation increases, and may be quite significant; for example, in steep mountains the horizontal displacement may surpass 100 m (Welch and Usery, 1984). Analytical rectification will removė much of this distortion, and it is recommended when relief displacement reaches hundreds of meters within the scene. As with classification, positional accuracy should be estimated through analyses on the rectified imagery. The target accuracies should be a mean positional bias of less than 0.1 pixel, a root mean-square (RMS) error of less than 1 pixel, and a maximum positional error of 1.5 pixels. This maximum error allows for any GCP/image pixel boundary alignment. Positional accuracy should be assessed by field visits to points for which coordinates may be accurately determined. Where possible, these points should be randomly selected from a large population of candidate points. However, because in many cases only a few points may be precisely identified in an image, the population of candidate points is typically so small that a random selection is not practical. Furthermore, location is often biased, for example, many times points are concentrated in a populated portion of the image, or along rivers or roadways. We recommend, if possible, an additional 20 positional accuracy assessment points known to 0.5 pixel accuracy, independent of those used for image rectification, and distributed as uniformly as possible across the image. It is noted that at some sites it may prove difficult to find the full target numbers of rectifica-

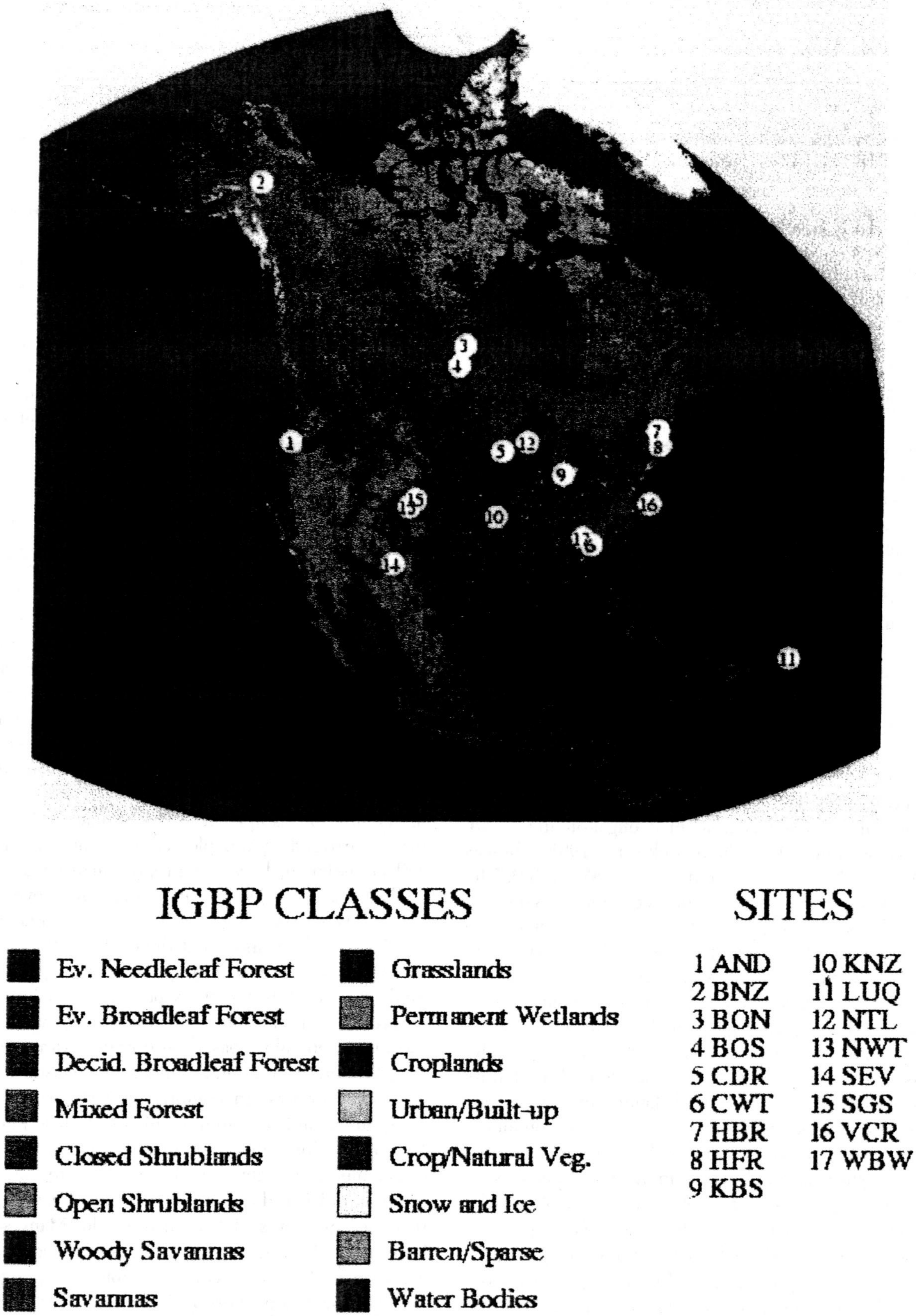


Figure 3. Location of MODLERS sites on IGBP class map of North America and the Caribbean (EOSDIS, 1997). The site acronyms are: AND: H. J. Andrews Experimental Forest, Oregon; BNZ: Bonanza Creek Experimental Forest, Alaska; BON: BOREAS North Site, Canada; BOS: BOREAS South Site, Canada; CDR: Cedar Creek Natural History Area, Minnesota; CWT: Coweeta Hydrologic Laboratory, North Carolina; HBR: Hubbard Brook Experimental Forest, New Hampshire; HFR: Harvard Forest, Massachusetts; IGBP: IGBP classification scheme; KBS: Kellogg Biological Station, Michigan; KNZ: Konza Prairie, Kansas; LUQ: Luquillo Experimental Forest, Puerto Rico; NTL: North Temperate Lakes, Wisconsin; NWT: Niwot Ridge/Green Lakes

tion and accuracy GCPs, and at these sites an intensive effort to find and record suitable GCPs is encouraged.

Classification Methodology

There are several image spectral classification methods, including unsupervised and supervised (Jensen, 1986), hybrid (Hardin, 1994), and neural net (Foody et al., 1995) techniques. Furthermore, the incorporation of ancillary data (Satterwhite et al., 1984; Atkinson and Thomlinson, 1991; Brondizio et al., 1996) and spatial or textural information (Gong et al., 1992; Barnsley and Barr, 1996) can improve classification accuracies. No constraints were placed on the individual MODLERS sites for obtaining their best site-specific classification, since total consistency of methodology was not considered to be of paramount importance.

Each site will perform classification in at least three different ways: i) best site-specific, using ancillary information if necessary; ii) translated from site-specific [classification i)] to IGBP; and iii) direct to IGBP classes using satellite imagery alone. Classifications ii) and iii) will be compared to assess possible errors that will be introduced when the MODIS sensor data are used for direct classification.

Field Sampling and Accuracy Assessment

Valid cross-site landcover comparisons require a uniform and rigorous accuracy assessment (Congalton and Mead, 1983; Congalton, 1988; Fitzpatrick-Lins, 1981; Thomas and Allcock, 1984; Janssen and van der Wel, 1994). The proposed approach uses a stratified random sampling procedure, with landcover categories in the final map used as the basis for stratification. LAI and NPP vary among and within cover classes, so that strata that subdivide the cover classes may be defined at some sites, to decrease within-strata variation in LAI and NPP. Identified relationships between LAI, NPP, and mapped site factors (e.g., soils, slope position) will be used to identify meaningful substrata within each landcover class. A target of 30 points per landcover class should be obtained, with as large a number as practical truthed via field visits. We suggest an absolute minimum of 10 points site-visited for each class that covers more than 5% of the study area. The remaining points in each class (up to 20) may be truthed based on high resolution imagery, typically from aerial photographs, but also perhaps from high-resolution scanner or satellite imagery. Interpretation errors on these image-truthed points should be no larger than 2%, and must be verified by previous or current studies involving at least 50 points which have been ground-visited and photointerpreted. Overall and per-class accuracy will be reported via contingency tables and K statistics (Congalton and Mead, 1983; Hudson and Ramm, 1987) developed from field- and image-interpreted data, with and without pooling. We note the difference between spatial accuracy and thematic accuracy and will represent assessments of both types of error. Horizontal positional errors for all ground points must be within 12.5 m (2σ), and will in most cases be ensured by appropriate use of GPS technology (Deckert and Bolstad, 1996). The criteria for the landcover categorization are 85% minimum overall, and 70% per-class accuracy. Data not reaching this level will require mandatory reclassification or class aggregation.

Travel costs to randomly selected points may be prohibitive, but they may be reduced by cluster sampling. In cases where navigation and travel are difficult, expensive, dangerous, or time-consuming, satellite points may be systematically sampled within short known distances from a randomly selected cluster center. Field samples will be collected at these spatial clusters, which will consist of a randomly located central plot, plus four additional plots, one in each cardinal direction, at 75 m from the cluster center. Land cover will be field-determined and LAI, NPP, and associated variables will be indirectly measured for all five plots in each cluster. Measurement and/or estimation of LAI and NPP is discussed in Gower et al. (1999, this issue). Land cover will be visually determined for the sample area (18-m diameter circle, subpixel) surrounding the plot center. The dominant class will be assigned; however, proportional mixtures will be ocularly estimated when more than one cover class or stratum is present. LAI, NPP, and associated variables will be directly measured at the center plot in each cluster. Subsample numbers (e.g., number of quadrats, sampled trees, or litterfall traps per plot) will be sufficient to provide estimates that are on average within 5% of the measured value, based on observed variance at each site. We propose a minimum of four clusters for each cover-type or stratum comprising more than 5% of the study area, and a minimum of 40 clusters per MODLERS site. This will assure a minimum of 40 plots where direct measurements of LAI and NPP are made, and a minimum of 200 direct measurements of cover and indirect measurements of LAI in the field. Many sites may have more clusters, depending on the landcover mix and variation in LAI and NPP. Additional sampling will be directed towards proportionally increasing representation of major cover-class strata and to include important minor strata.

Cluster sampling is efficient and adequate, provided that clusters are not too large (Congalton, 1988), and, al-

Valley, Colorado; SEV: Sevilleta National Wildlife Refuge, New Mexico; SGS: Shortgrass Steppe, Colorado; VCR: Virginia Coast Reserve, Virginia; WBW: Walker Branch Watershed, Tennessee.

though we do not expect bias due to the systematic cluster sampling from random centers, we will be able to test for it through the strength of the autocorrelation functions. Little time is spent traveling among ground-truth points within a cluster, substantially increasing sample number. However, increased sample numbers may come at the cost of sample independence. Classification errors may show spatial autocorrelation, with errors clustered. Many processes may lead to positive spatial autocorrelation in classification errors, for example, when a portion of the spectral domain is poorly represented by the training statistics developed in specifying a spectral-based classifier.

The above sampling will form the basis for error assessment documentation on the 25 m cell-size maps of landcover, LAI, and NPP. These fine-grain maps will then be considered as the "truth" for comparison with other products, typically modeled or aggregated for more coarse-grained spatial data (Running et al., 1999, this issue). Cluster sampling, with highly accurate point locations, will allow identification of misregistration bias and spatial autocorrelation for each attribute (i.e., landcover, LAI, and NPP).

Spatial autocorrelation functions may be estimated if the location of each ground-truth point is determined, data that are easily collected using commonly available GPS technology. Field crews will precisely determine ground-truth plot locations via differentially corrected GPS technology, using receivers and methods that provide 95% horizontal ground positional error of 5 m or less (Deckert and Bolstad, 1996). Typical position measurement will include the collection of a minimum of 200 position fixes per test plot, although more fixes will be required for some sites, prescribed by established relationships between accuracy and canopy/terrain conditions. Our sampling design takes 8–12 points at specified distances away from the cluster center, for example, at 50 m and 100 m from the cluster center in each cardinal direction or parallel and perpendicular to local aspect. The landcover category and other required measurements (e.g., LAI, biomass) will be determined at each point, along with location, and the accuracy, spatial periodogram, and other measures of autocorrelation may then be determined.

Metadata

Consistent metadata sets among sites are essential; while the methodology may not be completely consistent from site to site, the documentation must be if the results are to be compared cross-site. Examples of methodological metadata that must be included with each classification are the parameters used for atmospheric corrections, algorithms for derivation of vegetation indices, and the details associated with classification. Source metadata must include complete imagery information, such as platform and sensor, date, time of day, sun azimuth and elevation, etc., and a thorough description of ancillary data used. Accuracy metadata should include the number of points sampled in the field and from photos for each cover type, overall accuracy of the classification, and producers' and users' accuracies for each class. A detailed description of proposed information for documentation and metadata is described by Olson et al. (1999, this issue).

SUMMARY

Within the MODLERS team it was recognized that there are problems inherent in relating site-specific land-cover classifications to global data products. For this reason we elected to determine a suitable level of methodological coordination, if not standardization, among sites. In general, the individual sites should use the same imagery (ETM+) for the classifications, but no constraints were placed on ancillary data products to be used. In addition, the classification scheme to be used was standardized on the 17-class IGBP system, and accuracy goals and metadata reporting requirements were also specified. However, there was no standardization of classification algorithms to be used, since for the purposes of validation, the "best" landcover product at each site is desirable, and the means of obtaining this may differ from site to site. There will always be problematic translation ambiguities from one landcover class system to another; for this reason, parallel classifications will be made at each site. One classification will be to site-specific classes which will then be translated to IGBP classes, while the other will be direct to IGBP classes. These two thematic maps will be compared to identify potential sources of confusion in validation of the MODIS products.

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