An Analysis of the IGBP Global Land-Cover Characterization Process

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Abstract
The International Geosphere Biosphere Programme (IGBP) has called for the development of improved global land-cover data for use in increasingly sophisticated global environmental models. To meet this need, the staff of the U.S. Geological Survey and the University of Nebraska-Lincoln developed and applied a global land-cover characterization methodology using 1992–1993 1-km resolution Advanced Very High Resolution Radiometer (AVHRR) and other spatial data. The methodology, based on unsupervised classification with extensive postclassification refinement, yielded a multi-layer database consisting of eight land-cover data sets, descriptive attributes, and source data. An independent IGBP accuracy assessment reports a global accuracy of 73.5 percent, and continental results vary from 63 percent to 83 percent. Although data quality, methodology, interpreter performance, and logistics affected the results, significant problems were associated with the relationship between AVHRR data and fine-scale, spectrally similar land-cover patterns in complex natural or disturbed landscapes.

Introduction
The initial impetus to develop a 1-km global land-cover characteristics database grew from calls for improved land-cover data from numerous scientific organizations (i.e., National Academy of Sciences, 1990; National Aeronautics and Space Administration, 1994). There was a significant need to develop validated, contemporary, and spatially and thematically detailed global land-cover data for scientific inquiries associated with global change research, assessments of sustainable development, and operational functions such as weather forecasting. The available global land-cover data were determined to be inadequate for the coming generation of climate models (Sellers, 1993), carbon cycle assessments (S. Brown, *et al.*, 1993), ecological models (Schimel *et al.*, 1991), and conservation studies (Davis *et al.*, 1990). The catalyst for the development of an improved global land-cover product was the International Geosphere Biosphere Programme Data and Information System (IGBP-DIS). Through user requirements forums that canvassed the needs of IGBP core science projects (Rasool, 1992), the need and rationale for a new 1-km global land-cover characteristics database were defined (IGBP, 1992). The IGBP-DIS Land Cover Working Group subsequently devoted more than five years of technical planning and oversight to the definition, specification, and completion of a new global land-cover database, or DISCover, that was based on 1992–1993 Advanced Very High Resolution Radiometer (AVHRR) data acquired by the National Oceanic and Atmospheric Administration-11 polar orbiting satellite.

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Specifications for an Improved Global Land-Cover Characteristics Database
A set of specifications, based on the limitations of existing global land-cover products and on an understanding of the land-cover requirements for large-area environmental models, was formulated to guide the development of a new global land-cover characteristics database. The new database should be

- Of moderate spatial resolution and coherent temporal resolution (i.e., correspond to a specific baseline period, such as a 1- to 3-year window);
- Developed using an objective, repeatable, and systematic methodology;
- Sufficiently flexible to permit use of the data in a wide range of applications;
- Compatible with past, present, and future land-cover legends;
- Comprised of data and information on seasonal and interannual vegetation dynamics and on the biophysical characteristics of the landscape;
- Inclusive of the socioeconomic, cultural, and natural factors that affect the form and patterns of land cover found across the globe; and
- Validated at some level of generalization using a statistically sound accuracy assessment protocol.

The IGBP determined that 1-km AVHRR data were the appropriate choice for developing a new generation of global land cover. AVHRR data offer global daily coverage, appropriate resolution, low cost, and proven utility for deriving land-cover characteristics data (IGBP, 1992). The results produced earlier by Tucker *et al.* (1985), Townshend *et al.* (1987), Loveland *et al.* (1991), Stone *et al.* (1994), and Zhu and Evans (1994) yielded evidence that AVHRR data are appropriate for the development of a new global land-cover characteristics database.

An Approach to Global Land-Cover Characterization
The overall global land-cover characterization concept used to produce DISCover was first described by Loveland *et al.* (1991) and is summarized graphically in Figure 1. The strategy includes the use of a multitemporal, multisource classification strategy to produce a multidimensional database that can be modified as needed to meet the specific needs of individual applications. The use of multitemporal AVHRR data permits descriptions of the seasonal characteristics of land cover. However, the key element of the global land-cover characteristics database concept is a multiple attribute, multilayer database rather than a traditional single map of land cover based on a

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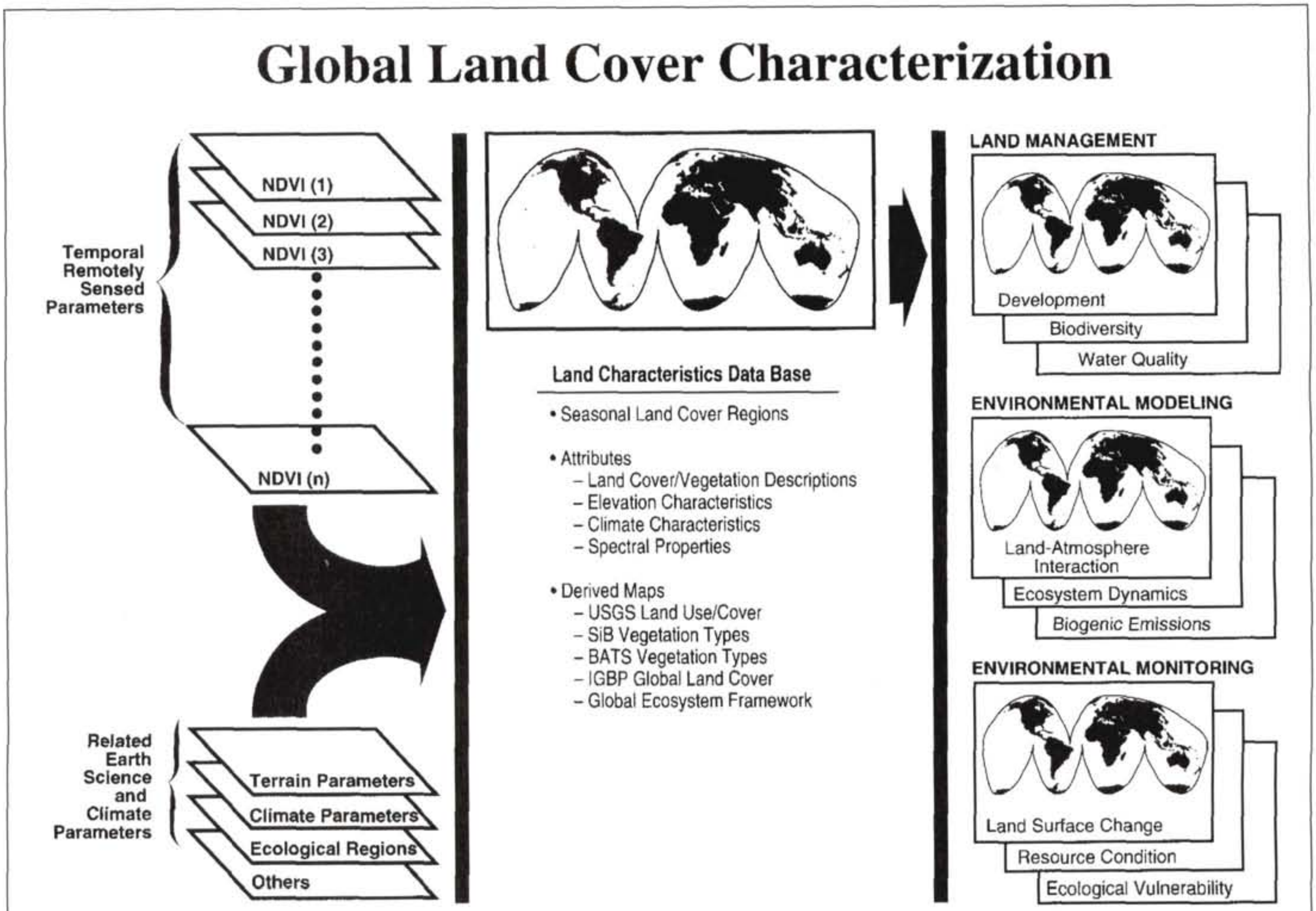

Figure 1. The database concept used in this project consisted of the use a of multisource database to produce land-cover characteristics data sets that can be tailored for use in a range of applications.

predefined legend. The DISCover land-cover product is one of several such products resulting from the implementation of this strategy. Users thus have the opportunity to use the validated DISCover product or another land-cover data set if that data layer is better suited to a particular application. This approach is warranted because of the wide diversity of land-cover requirements within today's environmental assessment and modeling community. The approach provides the ability to meet project requirements for flexibility and compatibility with past, present, and future land-cover data sets.

Classification Methods

A complete description of the classification methods used to develop the global land-cover characteristics database and the DISCover land-cover product can be found in Loveland *et al.* (1999). The global land-cover characteristics database was developed on a continent-by-continent basis using 1992-1993 1-km normalized difference vegetation index (NDVI) composites derived from AVHRR imagery. The database uses the concept of seasonal land-cover regions as a framework for presenting the temporal and spatial patterns of vegetation (Loveland *et al.*, 1995). The regions are composed of relatively homogeneous land-cover associations (for example, similar floristic or physiognomic characteristics) that exhibit distinctive phenology (onset, peak, and seasonal duration of greenness) and have similar levels of relative primary production. Each seasonal land-cover region includes a unique set of land-cover, phenology, elevation, biogeographic, and temporal NDVI attributes. From these relatively detailed map units, a core of general maps was derived through the aggregation of seasonal land-cover regions. These thematic maps and primary applications include (1) Global Ecosystems, carbon cycle studies (Olson and Watts, 1982); (2) IGBP DISCover, IGBP global change investigations (Belward, 1996); (3) U.S. Geological Survey Land Use/Land Cover System, general applications (Anderson *et al.*, 1976); (4) Simple Biosphere Model-SiB, land-atmosphere interactions (Sellers *et al.*, 1986); (5) Simple Biosphere Model2-SiB2, land-atmosphere interactions (Sellers *et al.*, 1996); (6) Biosphere-Atmosphere Transfer Scheme-BATS, land-atmosphere interactions (Dickinson *et al.*, 1986); and (7) Running Global Land Cover, biogeochemical modeling (Running *et al.*, 1994).

The land-cover classification process was based on the unsupervised classification of monthly AVHRR NDVI composites for April 1992 through March 1993, followed by extensive postclassification refinement using other environmental data. The classification process involved four general stages: (1) data set preparation and assessment of AVHRR data quality, (2) preliminary greenness class clustering, (3) seasonal land-cover region development, and (4) derived land-cover product generation. The following sections summarize the overall classification methods.

AVHRR Data Preparation and Quality Assessment

The 1-km AVHRR data set was developed by the USGS using specifications prepared by the IGBP-DIS and supported by the NASA Earth Observing System Pathfinder Program. Daily AVHRR coverage acquired for the global land surface since April 1992 was processed into global 1-km 10-day composites based on a maximum value compositing strategy and presented in the interrupted Goode Homolosine Equal-Area map projection (Eidenshink and Faundeen, 1994). For the global land-cover classification, 36 10-day composites spanning the April 1992 through March 1993 were recomposited into 12 continental monthly NDVI data sets. The recompositing reduced atmospheric contamination, decreased the effects of off-nadir viewing effects, and reduced the NDVI data volume by two-thirds. A complete analysis of the quality of each monthly composite was made before classification to detect problems that could affect the land cover analysis (Zhu and Yang, 1996).

Preliminary Greenness Class Clustering

Preliminary greenness classes were produced through the unsupervised classification of the data set consisting of 12 monthly NDVI composites. The preliminary greenness classes represent unique patterns of seasonality, but they often correspond to several disparate land-cover types. Unsupervised clustering was done using an algorithm developed at the Los Alamos National Laboratory (Kelly and White, 1993). This algorithm was trained using Monte Carlo random sampling, where a new sample was selected for each clustering iteration, a K-Means clustering technique, and a minimum distance to the mean classifier. The number of greenness clusters created per continent is listed in Table 1.

A team of three interpreters developed draft land-cover descriptions for each preliminary greenness class. A wide range of references was used, including digital and hardcopy land-cover maps, atlases, and Landsat imagery. The descriptions provided a general indication of the land-cover types corresponding to each preliminary greenness class and indicated the potential need for postclassification refinement strategies.

Seasonal Land-Cover Region Development

Seasonal land-cover regions represent a unique mosaic of land-cover types and seasonal properties. Because the preliminary greenness classes represent unique patterns of seasonality, the development process for seasonal land-cover regions involved splitting the heterogeneous preliminary greenness classes, which often represented several disparate land-cover types, into homogeneous land-cover groups. The class splitting was done using several different methods, including (1) splits using ancillary data such as digital elevation or ecoregions, (2) user-defined polygons (onscreen digitizing), (3) multi-source combinations where ancillary data were augmented with user-defined polygons, or (4) spectral reclustering. A total of 956 seasonal land-cover regions were defined (see Table 1 for a summary of seasonal land-cover regions per continent).

Table 1. Average Sizes (km^2) of Preliminary Greenness Classes and Land Seasonal Land-Cover Regions (SLCR).

Continent	Land Area	Number of Clusters	Average Cluster Size	Number of SLCR's	Average SLCR Size
Africa	29,647,197	100	296,472	196	151,261
Australia-Pacific	10,816,644	100	108,166	136	79,534
Eurasia	50,568,007	150	337,120	254	199,087
North America	23,203,810	100	232,038	204	113,744
South America	17,552,163	80	219,402	166	105,736
Total	131,787,821	530	248,656	956	137,853

Once the preliminary greenness classes were split into homogeneous seasonal land-cover regions, final land-cover definitions were formulated. At least three interpreters labeled each class, and a consensus label was developed using a convergence-of-evidence approach, in which a wide range of sources was consulted.

Derived Land-Cover Product Generation

The final step was the assembly of the final continental databases and the generation of derived land-cover products. A set of attributes describing land cover, average monthly NDVI, seasonality, biogeographic zones, and elevation was generated for the continental seasonal land-cover regions. The process involved (1) assigning individual seasonal land-cover regions to the appropriate category in Olson's Global Ecosystems (Olson, 1994), and (2) aggregating the Olson classes into classes from the six other land-cover legends previously mentioned. The Olson legend was used because it is somewhat detailed (94 classes), is designed to encompass regionally significant types of land cover and land use, and includes descriptions of associated climate, floristic elements, and physiognomy. While there are cases where the relationship between Olson classes and seasonal land-cover regions is imperfect, this process was followed because it was expected to increase the efficiency and improve the consistency for assembling the global derived land-cover layers. Plate 1 presents the DISCover map.

The continental data layers were joined to form global land-cover data sets. The global data sets are presented in the interrupted Goode Homolosine Equal Area projection, and the continental data sets are cast in both the Goode and Lambert Azimuthal Equal Area projections. The continental seasonal land-cover regions and the seven derived land-cover data sets were released following this process. All data used or generated during the course of the project, unless protected by copyrights or trade secret agreements, are part of the final database that is available at **http://edcwww.cr.usgs.gov/landdaac/glcc/glcc.html**.

Peer review of completed data sets was used to improve the reliability of the derived results. The amount of feedback received depended on the time available for the review. Because the North and South America databases were produced first, there was ample time for user feedback, but little feedback was received for the Eurasia and Australia-Pacific databases because they were completed shortly before the database was frozen for validation. Comments received before June 1997 were incorporated into the database; after this date, the database was frozen for the DISCover validation.

Assessment of DISCover Classification Methods

The methodology used to produce the global land-cover characteristics database involved an integrated analysis of both multitemporal spectral transforms and ancillary data. Because a single methodology was applied, it may be expected that a consistent global classification was produced. Generally, the classification methods were consistently applied to each continent. Even when a single approach is used, there are still several factors that may affect the continental classifications, including (1) satellite data quality, (2) suitability of reference data, (3) classification methods, (4) interpreter skills and performance, and (5) resources. The discussion in the following sections illustrates the ways each of these factors affected the consistency of the global land-cover classification.

Satellite Data Quality

The quality of the 12 monthly AVHRR NDVI composites was crucial to the land-cover classification. Poor AVHRR data quality,

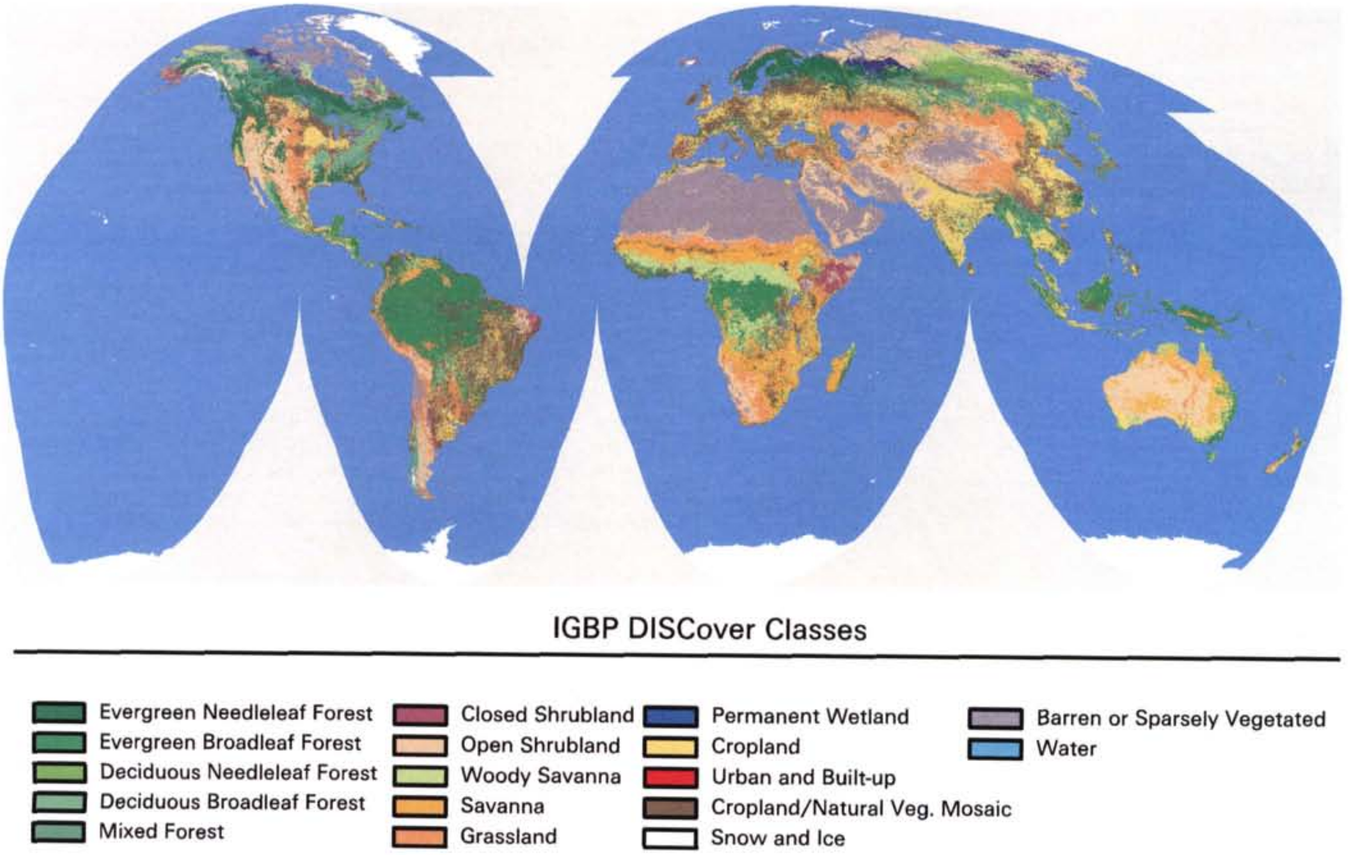

Plate 1. Global land cover based on the IGBP DISCover legend.

whether the result of ambient environmental conditions (e.g., clouds, humidity, dust, smoke) or of inadequate preprocessing strategies, can affect the ability to detect and identify land-cover patterns. Poor image quality would reduce the already ambiguous relationship between spectral data and land cover. Sensor radiometric calibration, atmospheric effects, and sensor spectral and spatial response are key variables that affect image classification (Duggin and Robinove, 1990). The impacts of sensor response are increasingly well understood (e.g., Cihlar and Huang, 1994; Cihlar *et al.*, 1994; Moody and Strahler, 1994), and the AVHRR preprocessing strategy used by the USGS was designed to reduce the impact of well known problems (Eidenshink and Faundeen, 1994). The AVHRR composites used here were consistently calibrated using postlaunch calibration coefficients (Tiellet and Holben, 1994). Although imperfect, data processing was consistent for all AVHRR data.

Atmospheric effects vary in time and space, and, therefore, may have a significant impact on the consistency of the classification. The AVHRR composite development process outlined by Eidenshink and Faundeen (1994) included several atmospheric corrections that theoretically reduce or eliminate many atmospheric artifacts, especially those caused by Mie scattering and variable ozone concentrations. The maximum value compositing methods also have the potential to reduce atmospheric contaminants by selecting the greennest, or least contaminated, pixel. However, it was quite apparent that the composites contained artifacts from clouds, and other forms of atmospheric contamination were frequently observed. The major impacts of atmosphere on AVHRR data come from atmospheric aerosols and water vapor, which were not corrected in the AVHRR processing.

An examination of the NDVI profiles for individual seasonal land-cover regions illustrates the challenges and their extent encountered by the interpreters (see Figure 2 for a global map of atmospheric contamination). Contaminated regions have NDVI curves with significant growing season dips in monthly NDVI values (an NDVI drop greater than 0.05). The regions tend to be spatially fragmented and often did not present readily identifiable spatial patterns or had less interpretable NDVI signals. A total of 335 of the 956 (35 percent) non-water seasonal land-cover regions had contamination in at least one of the 12 months. Continents with large tropical areas were most affected. Australia-Pacific had 53 percent of its 137 seasonal land-cover regions contaminated, and almost 47 percent of the South America regions had contaminated composites. Africa, while almost entirely tropical or subtropical, had only 30 percent of its 196 land regions affected. The vast extent of deserts, the lower percentage of humid tropical forests, and the increased number of AVHRR receiving stations covering Africa may account for this difference. The temperate/arctic continents had the lowest percentage of contaminated seasonal land-cover regions: North America had 25 percent of its regions affected, and Eurasia had problems in 27 percent. Generally, one month of contaminated NDVI did not pose significant interpretation challenges. However, when two or more months were affected, interpretation difficulty increased (e.g., confusion between cloud contamination and phenology). South America and Australia-Pacific had the largest number of seasonal land-cover regions with multiple-month contamination. These figures suggest a greater degree of difficulty interpreting and labeling the seasonal land-cover regions for Australia-Pacific and South America.

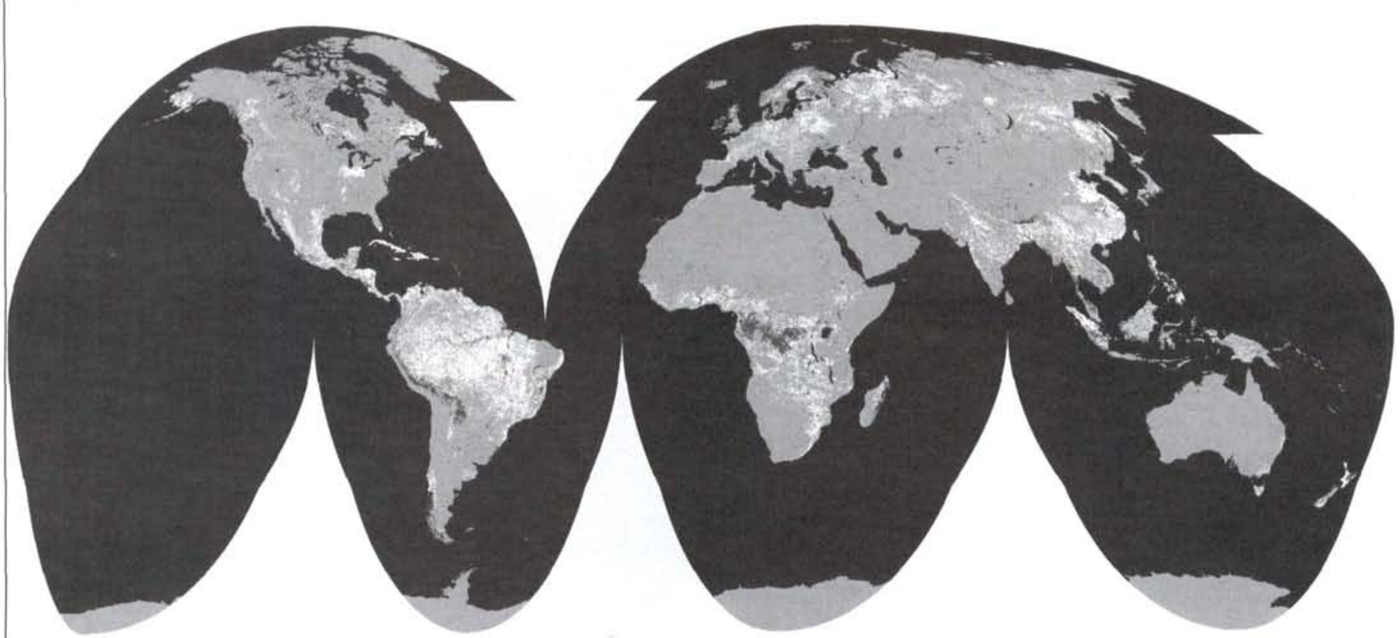

Figure 2. Global patterns of contaminated NDVI data. Gray areas have no detected atmospheric contamination, white areas have one month of contamination, and darker tones have two or more months of contamination.

An inspection of NDVI contamination by general land-cover type (Table 2) shows that evergreen broadleaf forest lands clearly have the highest amount of land area affected, with 66 percent having contaminated AVHRR data. In general, forested lands had the highest percentage of land area contaminated (evergreen broadleaf forests—66 percent, mixed forests—42 percent, evergreen needleleaf forest-32 percent, deciduous needleleaf forests-16 percent, and deciduous broadleaf forests-12 percent). At the other extreme, barren or sparsely vegetated areas have negligible cloud cover (0.02 percent). Grasslands (5 percent) and shrublands (6 percent) were also low. Croplands were generally high. Dryland croplands have 27 percent contamination, but irrigated crops have 42 percent contamination. The higher level of contaminated NDVI associated with irrigated crops probably is associated with humid rice production areas in tropical and subtropical regions.

Although contaminated NDVI composites were difficult to work with, they were still interpretable. In areas that are essentially homogeneous, interpreters working with adequate supporting information were able to determine the correct land cover. However, in areas with complex land-cover patterns, such as shifting agriculture in evergreen broadleaf forests, discriminating the different cover types is more difficult. In most cases, seasonal land-cover regions developed from contaminated NDVI tended to be only half the size of uncontaminated regions. Because the clustering process results in homogeneous groups of temporal NDVI values, the unique patches of

TABLE 2. CONTINENTAL SUMMARY OF THE PERCENTAGE OF GENERAL LAND-COVER TYPES AFFECTED BY CONTAMINATED NDVI COMPOSITES. NR (NOT REPRESENTED) DESIGNATIONS SIGNIFY CLASSES THAT WERE NOT FOUND IN A PARTICULAR CONTINENT.

Land-Cover Category	Africa	Australia	Eurasia	North America	South America	Global
Dryland Cropland	39.1%	33.8%	19.7%	30.4%	55.6%	26.7%
Irrigated Cropland	0.0%	NR	43.3%	11.7%	NR	41.6%
Cropland/Woodland	34.8%	94.0%	39.3%	11.2%	56.1%	41.5%
Cropland/Grassland	41.4%	39.5%	15.5%	12.4%	25.6%	20.7%
Grassland	5.2%	27.5%	0.9%	8.3%	11.0%	4.7%
Mixed	0.0%	4.6%	0.0%	21.9%	0.0%	2.3%
Shrubland	0.0%	0.1%	19.9%	7.4%	0.0%	5.7%
Savanna	9.1%	6.4%	24.1%	10.3%	39.9%	15.9%
Deciduous Broadleaf	0.0%	NR	12.1%	11.3%	56.2%	11.9%
Deciduous Needleleaf	NR	NR	15.7%	NR	NR	15.7%
Evergreen Broadleaf	69.8%	63.4%	46.4%	47.9%	67.1%	65.8%
Evergreen Needleleaf	NR	NR	48.12%	22.9%	100.0%	31.9%
Mixed Forest	NR	NR	33.2%	69.6%	100.0%	41.8%
Deciduous	23.7%	NR	6.8%	0.0%	40.3%	20.8%
Evergreen Woodlands	NR	7.5%	100.0%	17.3%	NR	32.3%
Wetlands	20.4%	0.0%	34.0%	8.2%	0.0%	25.7%
Tundra	NR	0.0%	13.5%	0.0%	0.0%	7.8%
Snow and Ice	NR	0.0%	0.0%	0.0%	0.0%	0.0%
Barren or Sparsely	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%
Average % Clouds	14.9%	22.2%	18.7 %	14.3%	45.3%	20.8%

contaminated data tended to result in large numbers of small like-contaminated clusters. This isolated contaminated data into localized patches that were then interpreted in their local context.

Reference Data Quality

Reference data are essential to the classification of global land cover. High quality reference data should improve the specificity and accuracy of land-cover labels developed by interpreters. Because field-based data collection is impractical at the global level, and because higher resolution satellite data are costly, it was necessary to make extensive use of existing published references for interpretation and labeling decisions. Country-level maps at a scale of 1:2,000,000 or larger were preferred for this purpose, though smaller scale maps were often used.

Over 270 country maps, representing land cover, land use, vegetation, forest cover, and agriculture, were used. Most of these maps were traditional vegetation or land-cover maps. Almost all represented periods earlier than the 1992–1993 AVHRR composites. These covered 109 countries, with most maps covering Northern Hemisphere countries. The availability of maps was most limited for African nations. This problem was partly offset because the Africa mapping was done at the European Commission's Joint Research Centre, where there was ready access to African land-cover experts. However, few references covered South America and the Middle East. Additionally, analysis of Central and South America was challenged by the pervasive emphasis on potential vegetation in the available references. Another problem was the scarcity of agricultural references. This was particularly troublesome in emerging agricultural areas of South America, Africa, and the tropical Pacific. Because map quality varied, it was necessary to use all references cautiously.

Greater use of high resolution satellite imagery during the interpretation process would have helped. The high cost and sparse availability of contemporary Landsat Thematic Mapper data made this option unviable. Changes in the Landsat 7 acquisition and pricing policies will undoubtedly make Landsat 7 more suitable for future global land-cover mapping initiatives.

Classification Methods

Classification methods have long been identified as an issue in determining classification accuracy (Fleming *et al.*, 1975; Hutchinson, 1982; McGwire *et al.*, 1996). Any methodology should provide the flexibility to detect significant land-cover patterns consistently and under a wide range of environmental conditions. The methodological debate has largely dealt with the performance of individual classifiers, training methods, or other elements of the classification methodology. Results of such studies give rise to interesting debates but avoid the nagging issue: does computer-assisted image classification provide consistent land-cover classifications for large study areas?

The methodology used in this study specified that the classifications would be developed on a continent-by-continent basis to accommodate image processing and interpretation efficiency considerations, and to reduce the variability of environmental factors affecting land-cover patterns. Clustering parameters and postclassification methods were tailored to each continental data set. The initial cluster parameters, including number of classes and intracluster and intercluster differences, affected the spatial patterns of the preliminary greenness classes. The diversity and nature of land-cover characteristics within each preliminary greenness class determined the postclassification strategy used for each continent. Thus, the clustering strategy used for each continent could affect the internal consistency of the global classification.

Preliminary Greenness Class and Seasonal Land-Cover Region Numbers and Sizes

There is evidence that clustering parameters (e.g., number of classes, intracluster and intercluster distance tolerances, and convergence criteria) modify the patterns of spectral classes (Vanderzee and Ehrlich, 1995). However, the impact of different parameters on classification accuracy is uncertain. In this research, it was assumed that different numbers of clusters were needed for each continent because of the inherent differences in land area, latitude and longitude ranges, and environmental diversity. The original strategy called for the number of clusters per continent to decrease from the largest (Eurasia) to the smallest land mass (Australia-Pacific). In reality, a larger number of clusters were developed for Australia-Pacific than for the next smallest continent, South America, because of problems with NDVI quality in the Pacific islands.

Table 1 contains a summary of the number of land clusters (preliminary greenness classes), seasonal land-cover regions, their average area, and area differences. The five continents were clustered into 530 land classes. The largest number of clusters was created for Eurasia due to the expected diversity associated with the large landmass; land-use history; and latitudinal, longitudinal, and altitudinal range. In spite of having the largest number of clusters, the Eurasia data still had the largest average cluster size (337,120 km^2). Africa clusters were also quite large at 296,472 km^2. Australia-Pacific had the smallest average cluster size (113,859 km^2). Average cluster sizes for the other two continents were similar to each other (North America, 232,038 km^2, and South America, 219,402 km^2).

Even after the clusters were extensively split using postclassification stratification methods to create the seasonal land-cover regions, the size inconsistency remained. While the 530 global land clusters were transformed into 956 seasonal land-cover regions which reduced the average class size by 44.6 percent, the Eurasian regions remained the largest (average area of 199,087 km^2), and Australia-Pacific remained the smallest with an average size of 79,534 km^2. The large size of the Eurasia regions was because of a deliberate decision to keep the number of classes under 256 in order to display the full Eurasia classification on 8-bit computer monitors.

The spread in average continental cluster sizes suggests that there may be inconsistent spatial detail among the continents. However, without careful consideration of the relationship between class size and the complex continental patterns of topography, parent materials, climate, and human impacts, conclusions regarding spatial inconsistency are speculative.

Postclassification Refinement

As noted, extensive splitting of the preliminary greenness classes was necessary in order to produce the more homogeneous seasonal land-cover regions (Table 3). The amount of initial land-cover confusion appears to be related to the relative levels of continental landscape diversity. The increase in classes was similar for South America, North America, and Africa clusters (107 percent, 104 percent, and 96 percent,

TABLE 3. INCREASES IN THE NUMBER OF LAND CLASSES RESULTING FROM POSTCLASSIFICATION REFINEMENT.

Continent	Number of Clusters	Number of SLCR's	Number of New Splits	% Increase
Africa	100	196	96	96.00%
Australia-Pacific	100	136	41	41.00%
Eurasia	150	254	104	69.33%
North America	100	204	104	104.00%
South America	80	166	86	107.50%
Total	530	956	411	77.55%

TABLE 4. SOURCES OF LAND-COVER CONFUSION WITHIN PRELIMINARY GREENNESS CLASSES.

Continent	Number of Clusters	Natural Land-Cover/ Agriculture Confusion	Natural Land-Cover/Natural Land-Cover Confusion	Agriculture/ Agriculture Confusion	Total Number of Splits
Africa	100	43	32	1	76
Australia-Pacific	100	45	12	1	58
Eurasia	150	77	33	14	124
North America	100	43	37	3	83
South America	80	29	20	7	56
Average	530	47.4	26.8	5.2	79.4

respectively). Eurasia only required 69 percent of the classes to be split, and Australia-Pacific required the least post-classification refinement, with only 41 percent of the classes needing to be split. The number of Eurasia seasonal land-cover regions would have been greater if the 8-bit limitation were not a factor.

As has been observed in other research (Brown *et al.*, 1993), most of the spectral confusion dealt with during the postclassification analysis was between natural or seminatural land cover and agricultural land cover (Table 4). Globally, nearly 60 percent of the confusion was with clusters having agriculture and natural or seminatural land cover represented in a single class. The problem was highest for Australia-Pacific, where 45 of 58 classes (78 percent) were found to be confused between agriculture and natural or seminatural land cover. The least confusion between agriculture and natural land cover was in North and South America, where only 52 percent of the preliminary greenness classes needed to be split. The low level for North America may be due to the relatively large and homogeneous patterns of cropland in the United States and Canada. In South America, it may simply relate to the relatively small cropland area.

Although confusion between different natural or seminatural land-cover types was encountered in about 34 percent of the global preliminary greenness classes, much of this confusion was between somewhat similar cover types (e.g., grasslands and alpine meadows, tall shrubs and deciduous broadleaf forests). The "cost" of these errors in applications may not be as significant as confusion between natural and anthropogenic land cover.

Interpreter Skills and Performance

The interpreter's experience, knowledge, and familiarity with the area being mapped and the purpose for which the land-cover data are used are crucial to successful land-cover mapping. The classification methodology called for at least three interpreters to classify each class, with the final class labels being based on a consensus between the interpreters. This approach was used to mitigate the variability between analysts that had been found in tests by McGwire (1992). Although the interpretation team members all had several years of land-cover mapping experience using AVHRR data, it was expected that differences in background (e.g., geographic foci, discipline training, and overall experience levels) could lead to individual interpretation biases.

Interpreter performance was not measured, but it was clear that each interpreter had unique perspectives about different geographic domains and landscape types. While this may have improved overall interpretation consistency, there were still problems when mapping transitional landscapes. For example, there was, typically, considerable variability when mapping land cover on the basis of tree density. While interpretations of closed canopy forests were generally similar, differences between open forests and woodlands were problematic. Differences between (1) mixed forest versus other forest cover types, (2) cropland mosaics, (3) savannas and woodlands, and (4) wetlands were common. On the other hand, interpreters generally agreed on cropland patterns and any cover type occupying large, homogeneous land areas.

Resources

Of the factors considered, staff and budget resources may have the greatest overall impact on the quality of results. Adequate time and budget enable the development and use of robust analysis strategies, the acquisition of better data, and access to top quality interpreters. All other elements can be improved with adequate budget, staff, and time. For example, data quality can often be improved with additional processing, use of more images, or ancillary data (e.g., water vapor data for atmospheric corrections). However, because this research was designed to contribute to operational science initiatives of the IGBP, it was conducted within tight constraints.

The time required by the core project team to develop the global database was approximately 10.5 staff-years, spanning 27 months. In addition, nearly 2.0 staff-years were devoted to gathering reference materials, ensuring the quality of the monthly AVHRR composites, and doing other premapping tasks. The cost of data preparation and mapping was nearly $2.25 million. This expense, while significant, represents a fraction of the total investment needed to complete the project. The cost of acquiring the global daily 1-km AVHRR data and generating 10-day composites exceeded the mapping costs. In addition, the cost of interpretation assistance must also be recognized.

The project had a firm completion deadline. The IGBP required delivery of the IGBP DISCover data layer to the IGBP validation team by 01 July, 1997. The first 12-month set of AVHRR composites for North America was completed in March 1995, and the mapping process began at that time and ended when the Australia-Pacific database was finished 27 months later (see Table 5 for the continental mapping schedule). The time available for mapping North and South America and Africa was greater than the time available for Eurasia and Australia-Pacific. The mapping team considered the time spent on Eurasia and Australia-Pacific to be too short. The short mapping period for these two continents was complicated by the lack of time for external review before preparing the final global land-cover database. As a result, the Eurasia and Australia-Pacific databases did not receive the same external scrutiny as the others.

TABLE 5. COMPLETION SCHEDULE FOR THE DRAFT CONTINENTAL DATABASES.

Continent	Start Date	Completion Date	Duration of Analysis
North America	March 1995	January 1996	10 months
South America	December 1996	August 1996	9 months
Africa	April 1996	December 1996	9 months
Eurasia	September 1996	April 1997	8 months
Australia-Pacific	March 1997	June 1997	4 months

The budget remained constant throughout the project. As a result, it probably did not have any significant impact on overall consistency. However, the research and mapping were constrained by the budget. While additional time was not possible due to the IGBP deadline, a larger operating budget would have permitted adding more interpreters. This would have allowed a more indepth analysis and perhaps more time for external review.

Synthesis of Data Quality Issues

While there are no accuracy standards for large-area land-cover mapping with AVHRR data, a small number of research studies have reported accuracy, which provides a measuring stick for understanding the results of this investigation. Accuracy figures ranging from 50 to 80 percent have been reported for studies over small study sites (Fleischmann and Walsh, 1991; Frederiksen and Lawesson, 1992; Nelson and Horning, 1993). The majority rule global DISCover accuracy figure (only samples in which there is a consensus of the "true" cover type) of 73.5 percent reported by Scepan (1999, in this issue) suggests that the overall classification strategy was successful when compared to these figures. The DISCover accuracy assessment is based on the validation of 25 random samples stratified by 15 of the 17 DISCover classes (water and snow and ice classes were not validated). High resolution satellite data covering each sample were each analyzed by three independent interpreters to determine the true cover types. The majority rule accuracy figures are based on 306 of 375 possible samples where there was a consensus between the three interpreters regarding the "true" land cover. Scepan (1999, in this issue) provides a thorough analysis of the validation protocol, and the strengths and limitations of the validation results.

A synthesis of Scepan's majority rule accuracy results for the DISCover data set is presented in Table 6. These figures provide a basis for assessing the consistency of each continental classification and the impact the five factors described previously had on the accuracy of the DISCover data set. It is important to note that all subglobal accuracy figures are not statistically significant because of the small sample size. It also must be recognized that these figures are specific to the DISCover land-cover map and to no other derived land-cover product. Nevertheless, dissecting the DISCover accuracy results into different geographic domains provides insights about geographic consistency and the factors that can affect classification accuracy.

Several overall observations can be drawn from Scepan's (1999, in this issue) majority rule accuracy statistics relating to the earlier assessment of the five factors affecting land-cover accuracy:

- *Atmospheric Contamination.* Composite contamination probably caused the most significant problems in the complex heterogeneous landscapes of the subtropical, temperate, and boreal biomes. The complex forest patterns of the boreal zone (patchwork of shrubs, different forest types, and wetlands) were particularly difficult to map accurately. The combination of complex land-cover patterns and contaminated NDVI composites posed significant interpretation problems. While the AVHRR composites of the tropical regions are clearly contaminated, the significant tracts of homogeneous lands covered with evergreen broadleaf forests were interpreted accurately (87.5 percent). In spite of the many fragmented tropical seasonal land-cover regions, the interpreters still labeled the forest patterns correctly.
- *Reference Data.* The continental DISCover data set accuracy figures do not provide any evidence that continents with limited reference data availability had reduced accuracy. In addition, the global cropland category was one of the most accurate (85.7 percent), so the lack of agricultural references did not have an adverse impact.
- *Classification Methods.* The impact of methods is likely to be the least understood issue. There is evidence to suggest that the aggressive postclassification refinement strategy was both necessary and effective, and it led to the consistent and accurate classification of cropland (85.7 percent). This classification approach appears to have contributed to resolving the confusion between natural vegetation and cropland. However, the impact of clustering parameters is unknown and requires greater consideration and analysis.
- *Interpreter Performance.* The validation results do not support the premise that interpretations would be most accurate for familiar areas. In this investigation, the continents where the interpreters were least familiar with land-cover conditions had the highest accuracy (e.g., Africa-83 percent, Australia-Pacific-73 percent). Perhaps the team approach provided balance and strengthened interpretations in less known areas.
- *Resources.* Because of the relatively high accuracy of Eurasia (69 percent) and Australia-Pacific (73 percent), there is no evidence to support the claim that accuracy was lower because of less review time. It can be argued that a peer review process would permit the identification and resolution of land-cover misclassification. However, it is not possible to estimate the extent of improvement, nor is it possible to attribute higher performance to the peer review of the other data sets.

The evidence suggests that landscape complexity, as represented by spatial configuration and spectral/temporal separability of land cover, were the overriding factors affecting the quality of results. This is especially the case in the highly modified or disturbed parts of the boreal, temperate, and subtropical biomes. It is quite likely that the five factors discussed

TABLE 6. SUMMARY OF CONTINENTAL AND GLOBAL ACCURACY BASED ON THE MAJORITY RULE SAMPLES REPORTED BY SCEPAN (1999, IN THIS ISSUE).

Cover Name	North America	South America	Africa	Eurasia	Australia -Pacific	Global
Evergreen Needleleaf Forest	83.3%			75.0%		75.0%
Evergreen Broadleaf Forest	85.7%	100.0%	100.0%			87.5%
Deciduous Needleleaf Forest				55.6%		55.6%
Deciduous Broadleaf Forest	40.0%	50.0%		57.14%		47.6%
Mixed Forest	50.0%			88.8%		68.1%
Closed Shrubs	50.0%	100.0%	87.5%	50.0%		75.0%
Open Shrubs	85.7%		66.7%	100.0%	100.0%	87.5%
Woody Savanna		33.3%	84.2%	50.0%		61.5%
Savanna			66.7%	100.0%	50.0%	64.7%
Grassland		33.3%	100.0%	76.9%	100.0%	75.0%
Wetland	14.3%		100.0%	60.0%		38.5%
Cropland	90.0%	100.0%	100.0%	77.8%		85.7%
Urban and Built-up	72.7%			61.5%		66.7%
Cropland Mosaics	66.7%	40.0%	75.0%	54.5%		56.5%
Barren			100.0%	100.0%		100.0%
TOTAL	62.6%	70.0%	82.9%	68.6%	72.7%	73.5%

earlier contributed to interpretation difficulty in these and other areas. The following sections provide a continent-specific analysis of the DISCover results.

North America

The overall North America accuracy of 63 percent was based on 91 valid samples. However, there were significant differences in regional quality. The boreal and arctic parts of North America were mapped with lower accuracies (42 percent) than the temperate (71 percent) and tropical/subtropical regions (83 percent). There were clear problems mapping the boreal land-cover mosaic of forest cover, shrubs, and wetlands. It is possible that AVHRR composite contamination in the high latitudes may have affected the ability to accurately distinguish between these classes. The fundamental problem, however, is more likely attributed to the difficulty of using coarse resolution satellite data to map relatively fine-scale land-cover patterns that comprise cover types with overlapping spectral signatures. Cropland/natural vegetation mosaics were also mapped inconsistently (67 percent), providing further evidence of the challenge in mapping complex landscapes with 1-km AVHRR data. Conversely, large homogeneous patterns of land cover on this continent, including evergreen needleleaf (83 percent) and evergreen broadleaf forests (86 percent), open shrubs (86 percent), and cropland (90 percent) were mapped with acceptable results.

Eurasia

Overall, the Eurasia DISCover classification had an accuracy of nearly 69 percent (based on 105 valid samples). The Middle East has the highest regional accuracy (89 percent) due to the correct labeling of large extents of spectrally unique homogeneous barren land cover. The highly contaminated Southeast Asia and Pacific Islands region land cover had the lowest accuracy (29 percent). Composite quality was poor because of extensive atmospheric contamination, and this most likely had a negative impact. The complex land-cover patterns of the boreal zone were also mapped inconsistently. Problems were also encountered in Southeast Asia and Western Europe, dominated by complex land-cover patterns comprising spectrally similar land cover, such as crop mosaics, forest cover, and urban areas. Overall, the Eurasia mosaic accuracy was less than 55 percent.

It is likely that two key factors affected the Eurasia classification: (1) AVHRR composite contamination, and (2) the 8-bit limitation on the number of seasonal land-cover regions. Together, these factors may have reduced the ability to map the complex boreal land-cover patterns and the fragmented, human-modified land cover of Europe, the India subcontinent, and Southeast Asia.

South America

The relatively high (70 percent) South America accuracy (30 valid samples) is most likely the result of the accurate identification of evergreen broadleaf forests in the Amazon. While AVHRR contamination was significant in tropical South America, evergreen broadleaf forest cover was spectrally unique and distributed in large homogeneous tracts. Most problems involved complex settled regions of South America, such as southeast Brazil, Chile and Argentina, and Venezuela. Distinguishing cropland mosaics from interspersed savannas, woody savannas, and shrubs was problematic and inconsistent. Cropland mosaics had an accuracy of 40 percent. The cropland and cropland mosaic interpretations were also affected by reference data biased toward natural vegetation.

Australia

The 73 percent accuracy of Australia is based on a sample too small (11 valid samples) to provide significant insights regarding classification issues. While classification results may have been affected by interpreter unfamiliarity, a short classification timeline, and no time for peer review, there is no concrete evidence supporting such claims.

Africa

The Africa land-cover accuracy was the highest of all continents (83 percent based on 82 valid samples). The accuracy was the result of overall good AVHRR data quality, interpreter familiarity, and adequate time for peer review. Perhaps more important is the dominance of two expansive, homogeneous, and spectrally unique regions. The extensive deserts, with barren land cover, and the evergreen broadleaf forests of the humid tropical belt of Africa were both accurately mapped (100 percent in each case). However, the more complex settled areas, such as the Horn, Sahel, and southern Africa, had less positive results, with the mapping of savannas (67 percent) and open shrubs (67 percent) being particularly difficult. The cropland and cropland mosaic characterizations are areas that were undersampled, making any assessment of their accuracy suspect.

Land-Cover Legend Impacts

The validation results reported in this paper are related to the DISCover global land-cover data set. The global land-cover characteristics database, however, comprises seven land-cover maps, all derived from seasonal land-cover regions. Understanding how land cover, when derived from a common database, varies among commonly used land-cover legends used in environmental assessments is therefore quite consequential. This issue is important because applications requiring land cover sometimes use land-cover databases with legends that are ill-suited to a particular application.

To illustrate the differences between land-cover products, Table 7 shows how various land-cover types are represented in different map legends. This comparison was developed by mapping the categories of six legends into a common set of general land-cover classes. While the table illustrates differences in land-cover legends, the process of generalization to the six classes is imperfect and so the results should be used cautiously.

The consistency of the area estimates for the general land-cover categories varies significantly. Overall, the forest-cover estimates (including both woodland and forest-cover components) are most consistent among land-cover legends, while urban, tundra, and wetlands vary the most. The high variability of these last three classes results from the absence of those classes in several of the land-cover legends. The Olson, DISCover, and USGS maps had identical urban area estimates, while the SiB, SiB2, and BATSlegends did not have an urban class. The urban land-cover data used for Olson, IGBP DISCover, and USGS Anderson came from the Digital Chart of the World database instead of being interpreted from the AVHRR composites. Wetlands offered a similar situation. The area estimates are very close for all legends except SiB2, which has no wetlands class. The tundra area estimates were also similar, except for the DISCover legend, which does not have a tundra class. Instead, in DISCover, tundra regions are classified according to the form of vegetation that covers the permafrost regions.

Nonvegetated lands (barren or sparsely vegetated, and snow and ice) would have had quite consistent overall area estimates if it were not for the SiB2 estimates of non-vegetated lands. The SiB2 land-cover scheme does not have a barren category, so barren lands are included in the SiB2 "shrubs with bare soil" category.

There is substantial variability in the global area of most land-cover types, largely because of idiosyncrasies associated with different land-cover legends. The selection of specific land-cover data must be made on the basis of a strong understanding of the intended application. The assumptions inher-

TABLE 7. COMPARISON OF GLOBAL LAND-COVER AREAS (KM^2) BASED ON DIFFERENT GLOBAL LAND-COVER LEGENDS.

General Land Cover	Land-Cover Classification System					
	Olson	IGBP	SiB	SiB2	BATS	USGS
Agriculture						
Cropland	14,193,844	14,021,263	25,034,586	29,624,408	17,702,209	14,175,812
Cropland/Other Cover	12,836,972	13,940,392	0	0	17,746,431	13,825,275
Total Agriculture	27,030,816	27,961,655	25,034,586	29,624,408	35,448,640	28,001,087
Urban And Built-Up	260,092	260,092	0	0	0	260,086
Tree Covered						
Forests	30,136,628	29,907,128	32,915,906	34,983,497	31,427,733	33,101,541
Woodland	9,873,624	10,174,311	0	0	0	0
Total Tree Covered	40,010,252	40,081,439	32,915,906	34,983,497	31,427,733	33,101,541
Shrub Covered	15,365,094	20,658,276	14,594,765	29,956,444	17,223,984	17,203,551
Grass Covered						
Savannas	8,811,905	9,333,888	22,980,527	0	0	14,545,328
Grasslands	11,564,948	11,039,833	7,372,495	23,221,969	20,037,114	10,999,520
Total Grass Covered	20,376,853	20,373,721	30,353,022	23,221,969	20,037,114	25,544,848
Wetlands	1,299,208	1,299,208	1,336,457	0	1,385,551	1,299,208
Tundra	7,541,912	0	8,831,125	10,834,685	7,542,839	7,652,585
Nonvegetated Lands						
Barren	17,161,416	18,410,598	15,979,128	0	15,979,128	15,982,083
Snow and Ice	16,572,460	16,573,114	16,573,114	0	16,573,114	16,573,114
Total Nonvegetated	33,733,876	34,983,712	32,552,242	16,997,100	32,552,242	32,555,197
Unclassified Lands	78,742	78,742	78,742	78,742	78,742	78,742
Total Land Area	145,696,845	145,696,845	145,696,845	145,696,845	145,696,845	145,696,845

ent in any application must be accommodated in the data used in the analysis, or the results may be misleading or incorrect.

Conclusions

The effort to develop an improved global land-cover characteristics database, which includes a data set based on IGBP DISCover specifications, achieved most stated objectives. A flexible 1-km resolution database was developed using contemporary AVHRR data. The flexible database strategy provides data sets suited to climate studies, carbon cycle investigations, biogeochemical modeling, and other environmental applications. The database also provides a means to derive other land-cover data sets that are required to meet emerging applications. Because the fundamental spatial layer-seasonal land-cover regions-is based on land-cover composition, phenology, and relative levels of annual primary productivity, information on seasonal and interannual vegetation dynamics and on the biophysical characteristics of the landscape are inherent. The results of the IGBP accuracy assessment provide evidence that the methodology was objective, systematic, and suited to the socioeconomic, cultural, and natural forms and patterns of land cover found across the globe. Whether or not the methodology is repeatable has yet to be established. Perhaps most unique about this initiative is that one layer of the database, the DISCover map, has documented accuracy based on a statistically sound accuracy assessment protocol. The results of this assessment, as well as feedback from users of the preliminary data sets, will now be used for revising and improving the global land-cover characteristics database.

There are many lessons remaining to be learned regarding global land-cover characterization. Specific to this research are the following issues:

- What are the implications of DISCover accuracy to the other land-cover legends in the global land-cover characteristics database?
- How repeatable is the classification methodology used in this investigation?
- Does a 1-km global land-cover database contribute to improvements in global and continental environmental assessments?
- Are the results of this project an improvement over previous global land-cover data sets?
- Is the DISCover legend appropriate for a 1-km global land-cover product?

It is important to recognize that land-cover mapping at any scale yields imperfect results. Considering this, the results of this investigation are generally positive. The accuracy assessment provides evidence of the geographic consistency of the DISCover data set. On the basis of Scepan's (1999, in this issue) majority rule statistics, the continental classifications have overall accuracies of around 70 percent. It is important to recognize that the most significant variability in accuracy corresponds to biomes rather than continents. Because most variability is associated with biomes, it may be suggested that problems associated with large-area land-cover classification are not necessarily methodological, but are associated with the relationship between multitemporal spectral data, landscape characteristics, and land-cover legend category definitions. The accuracy figures indicate that there are fundamental problems associated with using 1-km AVHRR data to map fine-scale land-cover patterns. Highly disturbed landscapes and regions with complex patterns of human settlement are particularly challenging. This is especially true when the spectral signatures of intermingled land-cover types are similar. Perhaps the primary limitation to improving the quality of land-cover maps is the data used in the analysis, rather than the algorithms or methods.

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