MODIS Land Cover Product
Algorithm Theoretical Basis Document (ATBD)
Version 5.0

MODIS Land Cover and Land-Cover Change

Principal Investigator:

Alan Strahler
Center for Remote Sensing
Department of Geography
Boston University
Boston, MA

Document Prepared By

Alan Strahler,[1] Doug Muchoney,[1] Jordan Borak,[1] Mark Friedl,[1] Sucharita Gopal,[1] Eric Lambin,[2] and Aaron Moody[3]

[1]Boston University
[2]Université Catholique du Louvain
[3]University of North Carolina, formerly of Boston University

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Abstract

This document details the structural definition, development process, and functional flow of the MODIS Land-Cover Product. The Land Cover and Land-Cover Change Parameters were proposed by the MODIS Land Team, with Team Member Alan Strahler leading the effort. The Land Cover Parameter is a 1-km product provided on a quarterly basis beginning about one year following the acquisition of a global dataset by the MODIS instrument aboard the EOS-A platform (Terra) in July, 1999. The Land-Cover Change Parameter is a post-launch, near-term parameter also planned for quarterly delivery.

Both parameters rely on a 1-km gridded database composited from MODIS Level 2 and 3 products. Inputs include: (1) EOS land/water mask that restricts classification to land regions and shallow water regions; (2) Nadir BRDF-adjusted Reflectances (NBARs) derived from the MODIS BRDF/Albedo product (MOD43B4) in the MODIS Land Bands (1-7), adjusted to nadir view at the median sun angle of each 16-day period; (3) spatial texture derived from Band 1 (red, 250-meter) at 1000-m resolution MODAGTEX); (4) directional reflectance information at 1k for 16-day periods (MOD43B1); (5) MODIS Enhanced Vegetation Index (EVI) at 1km for 16-day periods (MOD13); (6) snow cover at 500m for 8-day periods (MOD10); (7) land surface temperature at 1 km for 8-day periods (MOD11); and (8) terrain elevation information (MOD03). These data are composited over a one-month time period to produce a globally-consistent, multitemporal database on a 1-km grid as input to classification and change characterization algorithms.

The Land Cover Parameter recognizes 17 categories of land cover following the International Geosphere-Biosphere Program (IGBP) scheme. This set of cover types includes eleven categories of natural vegetation covers broken down by life form, three classes of developed and mosaic lands, and three classes of non-vegetated lands.

Land cover classes are produced by processing the 32-day database using decision tree and artificial neural network classification algorithms to assign land cover classes based on training data. To reduce computational overhead and increase flexibility, classification proceeds by continents.

The Land-Cover Change 1-km Parameter is designed to quantify subtle and progressive land-surface transformations, *i.e.*, land cover modifications, as well as obvious and instantaneous changes, such as land cover conversions. As such, it is not a conventional change product that simply compares land cover databases at two different times and identifies changes in categorical land cover. The algorithm for the Land-Cover Change Parameter combines analyses of change in multispectral-multitemporal data vectors with models of vegetation change mechanisms to recognize both the type of change as well as its intensity.

The algorithm development and validation efforts for the Land Cover Product are based on a network of test sites developed to represent major global biomes and cover types. Prelaunch efforts have focused on sites for which temporal sequences of Thematic Mapper (TM) and Advanced Very High Resolution Radiometer (AVHRR) data, coupled with fine-resolution land cover and vegetation data, are available, especially in North and South America. In the postlaunch period, a global suite of sites will be used to train the classifier and validate its output. Landsat-7 and ASTER images will be particularly useful

for updating information about test sites and identifying local change processes. The validation procedure will characterize the accuracy of the product as well as provide information that can be used in spatial aggregation to provide land cover and land-cover change data at coarser resolutions.

Land Cover Parameter products will be released about three months after the acquisition of a year of 32-day composites for a given region. Full global production of land cover will be reached as global production of input products is achieved. In the interim, a number of prototype land cover products will be produced. The Land-Cover Change Parameter, which requires two years of data, will be similarly phased in, with interim prototypes made available in the early-postlaunch period.

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1. Introduction

1.1 Identification

MODIS Product No. 12 (MOD12)			
Parameter Number	*Parameter Name*	*Spatial Resolution*	*Temporal Resolution*
2669	Land Cover Type, 1-km	1 km	4/yr
TBD	Land Cover Type, CMG	1/4°	4/yr
2671	Land-Cover Change, 1-km	1 km	4/yr

1.2 Overview

This document details the structural definition, development process, and functional flow of the MODIS Land-Cover Product. It represents a revision of the Version 3.0 (Strahler *et al.*, 1995) and Version 4.1 (Strahler *et al.*, 1996) Land Cover ATBDs, and no longer contains ATBD reviews and responses. The Land Cover Parameter is a 1-km product provided on a quarterly basis beginning about one year following the acquisition of global data after the launch of the MODIS instrument aboard the EOS-AM1 (Terra) platform in July, 1999. It will also be prepared on a 1/4° grid for use by global modelers. The Land-Cover Change 1-km Parameter is a post-launch, near-term parameter. The Land Cover and Land-Cover Change 1-km Parameters rely on a 1-km gridded database assembled from MODIS Level 3 products produced on 8- or 16-day cycles. Inputs include:

(1) EOS Land/water mask that restricts classification to land regions and shallow water regions.

(2) Nadir BRDF-adjusted Reflectances (NBARs) derived from the MODIS BRDF/Albedo product (MOD43B4) in the MODIS Land Bands (1-7), adjusted to nadir view at the median sun angle of each 16-day period;

(3) Spatial texture derived from Band 1 (red, 250-meter) at 1000-m resolution MODAGTEX);

(4) Directional reflectance information at 1 km for 16-day periods (MOD43B1)

(5) MODIS Enhanced Vegetation Index (EVI) at 1 km for 16-day periods (MOD13);

(6) Snow cover at 500 m for 8-day periods (MOD10);

(7) Land surface temperature at 1 km for 8-day periods (MOD11);

(8) Terrain elevation information (MOD03);

The temporal resolution of this database is 32 days, corresponding to two complete MODIS orbit cycles.

The Land Cover Parameter recognizes 17 categories of land cover following the scheme adopted by the International Geosphere and Biosphere Programme (IGBP) (Belward and Loveland, 1995) for application to global 1-km AVHRR LAC NDVI (Advanced Very High Resolution Radiometer, Local Area Coverage, Normalized Difference Vegetation Index) composites. This set of cover types includes eleven categories of natural vegetation covers broken down by life form, three classes of developed and mosaic lands, and three classes of non-vegetated lands.

Land cover classes are assigned by processing the 32-day database using decision tree and artificial neural network classifiers trained by site data. To reduce computational overhead and increase flexibility, classification proceeds by continents.

The Land-Cover Change 1-km Parameter is designed to quantify subtle and progressive land-surface transformations, *i.e.*, land cover modifications, as well as obvious and instantaneous changes, such as land cover conversions. As such, it is not a conventional change product that simply compares land cover databases at two different times and identifies changes in categorical land cover. The algorithm for the Land-Cover Change Parameter combines analyses of change in multispectral-multitemporal data vectors with models of vegetation change mechanisms to recognize both the type of change as well as its intensity.

The algorithm development and validation efforts for the Land Cover Product are based on a network of test sites chosen to represent major global biomes and cover types. Prelaunch efforts have focused on sites for which temporal sequences of TM and AVHRR, and fine-resolution land cover and vegetation data are available, especially North and South America. Postlaunch, global sites will be used to train the classifier and validate its output. Landsat-7 and ASTER images will be particularly useful for updating information about test sites and identifying local change processes. The validation procedure will characterize the accuracy of the product as well as provide information that can be used in spatial aggregation to provide land cover and land-cover change data at coarser resolutions.

Land Cover Parameter products will be released about three months after the acquisition of a year of 32-day composites for a given region. Full global production of land cover will be reached as global production of input products is achieved. In the interim, a number of prototype land cover products will be produced. The Land-Cover Change Parameter, which requires two years of data, will be similarly phased in, with interim prototypes made available in the early-postlaunch period.

1.3 Document Scope

The remainder of this document is organized into four broad sections following the prescribed format. Section 2 will discuss the rationale for the development of the Land Cover Product, provide a historical context and background information, describe the system of land cover units, and discuss MODIS in terms of its ability to facilitate and improve capabilities for characterizing land cover and land-cover change on a global scale. The objective of section 3 is to define the overall structure of the algorithms; present the mathematics and practical descriptions of the primary algorithm components; present the use of training sites in calibration and validation; discuss sources of error and uncertainty; address practical issues that are likely to arise; discuss preprocessing considerations, computing needs, and reliance on other MODIS activities; detail the calibration and validation phase of the algorithms; and discuss postlaunch product validation. Section 4 addresses potential constraints and limitations.

1.4 Applicable Documents and Publications

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2. Overview and Background Information

2.1 Experimental Objective

Land cover, and human and natural alteration of land cover, play a major role in global-scale patterns of climate and biogeochemistry of the earth system. Although the oceans are the major driving force for the earth's physical climatology, the land surface has considerable control on the planet's biogeochemical cycles, which in turn significantly influence the climate system through the radiative properties of greenhouse gases and reactive species. Further, variations in topography, albedo, vegetation cover, and other physical characteristics of the land surface generate variations of weather and climate by forcing atmospheric circulation patterns that are driven by surface-atmosphere matter and energy fluxes and the momentum of the earth's rotation.

In this context, an important application of accurate global land-cover information is the inference of parameters that influence biophysical processes and energy exchanges between the atmosphere and the land surface as required by regional and global-scale climate and ecosystem process models (Townshend *et al.*, 1991). Examples of such parameters for climate modeling include leaf area index (LAI), roughness length, surface resistance to evapotranspiration, canopy greenness fraction, vegetation density, root distribution, and fraction of photosynthetically-active radiation absorbed (FPAR) (Sellers, 1991a, 1991 b). These serve as input variables that control surface energy and mass balances. Examples of ecosystem process model parameters for which land cover type may serve as a surrogate include leaf photosynthetic capacity, canopy conductance, type of photosynthetic system, and maximum photosynthetic rate (Running and Coughlan, 1988).

Most of these inferences are based on the structural character of the vegetation cover, which is sensible to remote sensing. The objective of the Land Cover Parameter is to identify a suite of land cover types amenable to such parameterization by exploiting the spectral, temporal, spatial, and directional information content of MODIS data. The objective of the Land-Cover Change Product is to detect and quantify the changes in land covers and the natural and anthropomorphic processes that bring them about so that global and regional models may be projected forward through changes in their driving surface parameters.

2.2 Historical Perspective

2.2.1 Global-Scale Land Cover Data

Land-cover datasets currently used for parameterization of global climate models are typically derived from a wide range of preexisting maps and atlases (Olson and Watts, 1982; Matthews, 1983; Wilson and Henderson-Sellers, 1985). This approach has several limitations. First, the reference sources may themselves present a range of different dates, spatial scales, and classification schemes. Confusion regarding the mapping of the reference class units to the classification system and scale used in the land-surface dataset may then lead to errors in the final product. For example, floristic and climatically-based classifications, while not inherently compatible, may need to be combined and reclassified to generate physiognomic cover types for a land-cover compilation (Townshend *et al.*, 1991). Second, the resulting datasets are fundamentally static, and can be assumed to perpetuate errors existing in the sources from which they were derived. Third, some datasets are maps of potential or climax vegetation, which is inferred from climatic variables such as temperature and precipitation rather than of the true vegetation type.

Townshend *et al.* (1991) compared the areal statistics and spatial distributions of a large number of land cover datasets. They documented considerable disagreement in the relative percentages of basic land-cover types among these products. Moreover, even when there was general agreement in the relative area covered by given vegetation types, the spatial distribution of these units differed. While such datasets have obvious limitations, they represent the state of the science for driving large scale process models, and have been designed specifically for this purpose.

Many researchers have attempted to produce regional-scale land cover datasets using coarse spatial-resolution, high temporal-frequency data from the AVHRR instrument aboard the NOAA series of meteorological satellites. Almost without exception, these efforts have involved the conversion of AVHRR bands 1 and 2 to normalized difference vegetation index (NDVI) values. A registered time series of NDVI images is then composited so that, for every pixel location, the maximum NDVI value encountered throughout the compositing period is output. The compositing procedure tends to select against measurements that are strongly influenced by atmospheric and aerosol scattering. These measurements have reduced NDVI values due to differential scattering effects in red and near-infrared bands. Cloud-contaminated measurements also produce lower NDVI values, as clouds reflect strongly in both the red and near-infrared wave bands. The compositing of NDVI values further reduces the variability associated with changing view and illumination geometry (Holben, 1986), although measurements near the forward-scattering direction tend to have slightly higher NDVI values and will thus be preferentially selected. Compositing periods are chosen based on a trade-off between the expected frequency of changes in vegetation and the minimum length of time necessary to produce cloud-free images.

The NDVI generally quantifies the biophysical activity of the land surface and, as such, does not provide land cover type directly. However, a time series of NDVI values can separate different land cover types based on their phenology, or seasonal signals (*e.g.* Lenney *et al.*, 1996). Reed *et al.* (1994) and DeFries *et al.* (1995) have developed and used multitemporal phenological metrics to derive land cover classifications from AVHRR data. Lambin and Ehrlich (1996a, 1996b) have found that using a time series of the ratio of surface temperature to NDVI provides a more stable classification than NDVI alone, primarily by isolating interannual climatological variability.

Townshend *et al.* (1987) performed supervised classifications on composited NDVI GAC (Global Area Coverage) data for South America. While they did not validate their results with test data, they found that accuracy for the training sites improved substantially with the increase in the number of images included in the time series. Koomanoff (1989) used annually-integrated NDVI values to generate a global vegetation map using NOAA's Global Vegetation Index product (GVI).This work represents nine vegetation types and does not rely on the seasonality of the NDVI. Lloyd (1990) employed a binary classifier based on summary indices derived from a time series of NDVI data. These phytophenological variables included the date of the maximum photosynthetic activity, the length of the growing season, and the mean daily NDVI value. The variables were fed through a binary decision tree classifier that stratified pixels based first on the date of the maximum NDVI, then the length of the growing season, and finally on the mean daily NDVI.

A coarse-resolution global land surface parameter database was released on five compact disks as an activity of the International Satellite Land Surface Climatology Project (ISCLSCP) (Sellers *et al*. 1994). The database includes land cover classes, absorbed fraction of photosynthetically-active radiation (FPAR), leaf area index (LAI), roughness length, and canopy greenness fraction, along with data on global meteorology, soils, and hydrology. The spatial scale of the database is 1 degree by 1 degree. Variables such as FPAR, LAI and canopy greenness fraction are derived from 8-km composited AVHRR NDVI data. The land cover classification is based on a spatial aggregation of the 8-km data to one degree followed by supervised classification of the temporal patterns in NDVI (DeFries and Townshend, 1994).

Global land cover at a 1-degree resolution for 11 land cover classes has been achieved by DeFries and Townshend (1994), Friedl and Brodley (1997), Friedl *et al.* (1999), and Gopal *et al.* (1996). Other global maps and databases of land cover that have been used to estimate and infer surface parameters include those of Matthews (1983), Olson (Olson and Watts 1982; Olson *et al.*, 1983) and Wilson and Hendersen-Sellers (1985). The 1-degree AVHRR analyses of DeFries and Townshend (1994), Friedl and Brodley (1998), Friedl *et al.* (1998) and Gopal *et al.* (1996) are based on the agreement of the maps of Matthews (1983), Olson (Olson and Watts 1982; Olson *et al.*, 1983) and Wilson and Hendersen-Sellers (1985) maps to define training and test data. While the global land cover of Loveland *et al.* (1995) is derived using an unsupervised approach and is currently being validated, only the 1-degree and 8-km maps of DeFries and Townshend (1994) have been based on site data for training and validation. In this instance, training and test site data were based on delineating polygons on Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) data and assigning them 11 categorical land cover labels.

Loveland *et al.* (1991, 1995) have produced land cover maps using the International Geosphere-Biosphere Programme (IGBP) classification and Seasonal Land Cover Region (SLCR) classification systems for North America. These maps were based on one year of monthly composited AVHRR-LAC data to generate an unsupervised classification of land cover types for the conterminous United States. The resulting clusters were further stratified based on ancillary environmental data such as elevation and ecoregion. Class labels were assigned based on the temporal curves of the clusters as well as a large number of ancillary sources. While obviously limited by the quality of the composited NDVI data and the accuracy of the ancillary sources, this dataset represents the most convincing large area classification of AVHRR data at 1-km spatial resolution to date.

Loveland’s efforts were expanded under the auspices of the IGBP-DIS (International Geosphere Biosphere Programme-Data and Information System), based on a global database of 1-km AVHRR observations received during the period April 1992 through

September 1993 (Belward and Loveland, 1995; Belward, 1996). These have been assembled and 10-day composited at the EROS Data Center (EDC) (Eidenshink and Faundeen, 1994). The 10-day composite AVHRR data were then monthly composited using maximum NDVI to remove cloud and topographic effects and extreme off-nadir pixels (Holben, 1986; Eidenshink and Faundeen, 1994), as well as scan angle dependence of radiance (Duggin *et al.,* 1982). The use of the monthly-composited AVHRR data may be problematic (Holben, 1986). An analysis by Zhu and Yang (1996) determined that compositing was biased towards selecting off-nadir pixels, especially in forward-scanning views in winter months in the northern hemisphere. As with any large-area projection, they also found that the effective mapping unit was geographically variable, in this case due to the Goode's homolosine projection system and resampling methods. Lack of sensor calibration confuses the temporal trajectory of the multitemporal NDVI signal (Cihlar, 1996). Temporal smoothing or generalization might enhance the meaning of the temporal signal (Van Dijk *et al.,* 1987).

The global NDVI data provided a multitemporal database for land cover classification using an unsupervised clustering and labeling approach. The global IGBP product has recently undergone validation based on a global network of some 400 stratified samples that were characterized using finer-resolution Landsat TM and SPOT-XS data following an expert interpretation approach (Estes *et al.,* in preparation).

2.2.2 Land Cover Classification Using Neural Networks

Neural networks have proven to be the most significant improvement in information extraction in remote sensing in the last 15 years. The classification of remotely sensed data using artificial neural networks began appearing in the remote sensing literature about ten years ago. Since then, examples and applications have become increasingly common. Remotely-sensed datasets processed by neural network-based classifiers have included images acquired by the Landsat Multispectral Scanner (MSS) (Benediktsson *et al.,*, 1990; Lee *et al.,* 1990) Landsat TM (Yoshida and Omatu,1994) synthetic aperture radar (Hara *et al.,* 1994) SPOT HRV (Tzeng *et al.,* 1994) AVHRR (Gopal *et al.,* 1994) and aircraft scanner data (Benediktsson *et al.,* 1993). A number of these studies have also included ancillary data *e.g*., topography (Carpenter *et al.,* 1997) and texture (Bischoff *et al.,* 1992). Many studies have been directed toward recognition of land cover classes, which have ranged from broad life-form categories (Hepner *et al.,* 1990) to floristic classes (Fitzgerald and Lees, 1994). Most use a supervised approach, but unsupervised classification using self-organizing neural networks has also been attempted (Hara *et al.,* 1994). In nearly all cases, the neural network classifiers have proven superior to conventional classifiers, often recording overall accuracy improvements in the range of 10-20 percent. As the number of successful applications of neural network classification increases, it is increasingly clear that neural network-based classification can produce more accurate results than conventional approaches for remote sensing. The reasons include: (a) neural network classifiers, which make no *a priori* assumptions about data distributions, are able to learn nonlinear and discontinuous patterns in the distribution of classes; (b) neural networks can readily accommodate collateral data such as textural information, slope, aspect and elevation; and (c) neural networks are quite flexible and can be adapted to improve performance for particular problems.

The bulk of neural network classification work in remote sensing has used multilayer feed-forward networks that are trained using the backpropagation algorithm based on a recursive learning procedure with a gradient descent search. However, this training procedure is sensitive to the choice of initial network parameters and to overfitting (Fischer *et al.*, 1997). The use of neural networks utilizing adaptive resonance theory (ART) can overcome these problems. Networks organized on the ART principle are stable as learning proceeds, while at the same time they are plastic enough to learn new patterns. Our MODIS land cover classification uses a class of ART neural networks called fuzzy ARTMAP (Carpenter *et al.*, 1991a; 1991b), for classification, change detection and mixture modeling. Fuzzy ARTMAP is a supervised learning system that synthesizes fuzzy logic and adaptive resonance theory models. It has been recently applied to forest vegetation mapping (Carpenter *et al.*, 1997).

Recent studies highlight the utility of the fuzzy ARTMAP architecture and its application to land cover classification. In one study, monthly composited AVHRR LAC NDVI data for one year from West Africa at 1.1-km spatial resolution were classified into six broad life-form classes using a fuzzy ARTMAP classifier (Gopal *et al.*, 1994). Per-class accuracies ranged between 66 and 98 percent, with an average accuracy of 83 percent, which compared favorably with a more typical feed-forward architecture trained by backpropagation that achieved an average accuracy of only 61 percent. Another study (Fischer *et al.*, 1997) evaluated the performance of Multi-Layer Perceptron (MLP), Radial Basis Function, and Fuzzy ARTMAP networks using a Landsat TM scene of the northern section of the city of Vienna, Austria. Higher overall results (in terms of accuracy and convergence time) were obtained using fuzzy ARTMAP followed by MLP (with weight elimination). The classification accuracy on unseen test data was 98 percent using Fuzzy ARTMAP compared with 90 percent using best MLP architecture.

2.2.3 Land Cover Classification Using Decision Trees

Decision tree classification techniques have been used successfully for a wide range of classification problems, but only recently been tested in detail by the remote sensing community (see for example Savafian and Landgrebe, 1991). These techniques have substantial advantages for remote sensing classification problems because of their flexibility, intuitive simplicity, and computational efficiency. As a consequence, decision tree classification algorithms are gaining increased acceptance for land cover classification problems, particularly at continental to global scales. For classification problems that utilize data sets that are both well understood and well behaved, classification trees may be defined solely on analyst expertise. This approach was proposed by Running *et al.* (1995) to define a global classification strategy for vegetation based on threshold values of the NDVI from AVHRR. In this framework, the actual values of the thresholds are defined a priori based on a combination of ecological and remote sensing knowledge. However, this procedure is difficult to implement in practice because the exact values of NDVI thresholds vary substantially in both time and space, and are therefore difficult to specify based on user knowledge alone.

More commonly, the classification structure defined by a decision tree is estimated from training data using a statistical procedure. Recently, a variety of work has demonstrated that decision trees estimated in this type of supervised fashion provide an accurate and efficient methodology for land cover classification problems in remote sensing (Friedl and Brodley, 1997; Hansen *et al.,* 1996; Swain and Hauska, 1977). For example, DeFries *et al.* (1998) used decision trees to map land cover using the 8 km AVHRR pathfinder data set with encouraging success. Similarly, Friedl *et al.* (1999) recently demonstrated that decision trees provide a robust classification methodology for land cover mapping problems at continental to global scales. Among the advantages of decision trees that are particularly useful for remote sensing problems are their ability to handle noisy and missing data (Quinlan, 1993; Savafian and Landgrebe, 1990). Further, they require no assumptions regarding the distribution of input data and also provide an intuitive classification structure.

2.2.4 Directional Information in Land Cover Classification

Although the application of spectral, temporal, and spatial information in classification of remotely-sensed data has long been established in the literature, it is only recently that the importance of directional information has been established (Hyman and Barnsley, 1997). In a study utilizing directional aircraft scanner imagery of an agricultural test site, Barnsley *et al.* (1990, 1997) noted that by using a principal components transformation and adding three view angles to two bands of spectral data, classification accuracies increased by approximately 20 percent. Abuelgasim and Gopal (1994; Abuelgasim *et al.*, 1996) used a hybrid unsupervised-supervised neural network classifier to distinguish five broad land cover classes in Minnesota subboreal forest from directional reflectances imaged by NASA's ASAS (Advanced Silicon Array Spectrometer) aircraft instrument (Irons *et al.,* 1991). Using seven directional images acquired in a single near-infrared band, the authors obtained 89 percent accuracy using the hybrid classifier, as compared to 85 percent for a conventional feed-forward back-propagated neural net and 61 percent for a maximum likelihood classifier.

2.2.5 Land-Cover Change

Global assessment of the changes in physical characteristics of the terrestrial surface cover is a fundamental input for models of global climate and terrestrial hydrology. While some changes in land cover, such as long-term changes in climate due to astronomical causes, or shorter-term vegetation successions produced by geomorphic processes are caused by natural processes, human activity increasingly modifies the land surface cover. These modifications arise through direct actions, such as deforestation, agricultural activities and urbanization, or indirectly, through human-induced climatic change. The importance of mapping, quantifying, and monitoring changes in the physical characteristics of land cover has been widely recognized in the scientific community as a key element in the study of global change (*e.g.* IGBP, 1994; Henderson-Sellers and Pitman, 1992; Nemani and Running, 1996, 1997).

Digital change detection is the process of determining and/or describing change based on co-registered, multitemporal remotely sensed data. The two principal approaches to change detection are 1) post-classification techniques, where independent classifications are compared and 2) pre-classification or merged data techniques where simultaneous analysis of multitemporal data occurs (Malila, 1980; Muchoney and Haack, 1994). Post-classification techniques have significant limitations. The comparison of land cover classifications for different dates does not allow the detection of subtle changes within a land cover class. Also, the change map product of two classifications exhibits accuracies similar to the product of multiplying the accuracies of each individual classification (Stowe *et al.*, 1980). Merged data techniques include image differencing/ratioing, change vector analysis, spectral-temporal (layered-temporal) change classification, regression techniques and principal components analysis.

The Land-Cover Change Parameter employs the pre-classification or merged data approach. Rather than analyzing isolated dates from two separate time periods, it is based on a comparison of the temporal development curve, or time-trajectory, for successive years of indicators. The indicators, derived from remotely sensed data, include such variables as vegetation indexes, surface temperature, or spatial structure (Lambin and Strahler, 1994a) and are provided by the 32-day composited database assembled for land cover classification.

2.2.5.1 Change Vector Analysis

The primary change detection technique for the 1 km Land-Cover Change Parameter is change vector analysis (Lambin and Strahler, 1994b). In this technique, each annual multitemporal set of indicator values is taken as a point in multitemporal space, and points from successive years are connected by a change vector, also in multitemporal space. The direction of the change vector quantifies the change process, while the magnitude of the change vector quantifies the amount of change (Lambin and Strahler, 1994b). Change vectors applied to different indicators reveal different change processes or different aspects of change processes (Lambin and Strahler, 1994a).

The application of change vectors in remote sensing was first described by Malila (1980) and by Colwell and Weber (1981), although the change vectors in these studies were multispectral rather than multitemporal. Michalek *et al.* (1993) applied multispectral change vectors to the monitoring of coastal environments. Change vector analysis in the temporal domain lends itself to AVHRR applications, since this instrument provides data with a high temporal frequency. Prior studies of change using AVHRR have used annual integrated NDVI, or isolated dates of NDVI or untransformed data. Examples are the studies of change in the Sahel of Tucker *et al.* (1986, 1991), Hellden and Eklundh (1988) and Hellden (1991); or studies of large-scale tropical deforestation by Tucker *et al.* (1984), Nelson and Holben (1986), Woodwell *et al*. (1987), and Malingreau *et al.* (1989). While the procedures used in these studies are appropriate to detect abrupt land-cover changes such as forest clearing, biomass burning, or the impact of a severe drought, the detection of more subtle forms of change, such as those associated with climate change or with slow rates of land degradation, requires a more sophisticated approach such as change vector analysis.

Change vector analysis has been explored in several studies that have been partially supported by, or coordinated with, the MODIS 1-km land cover effort. These have focused on multitemporal datasets of Africa at LAC and GAC resolutions made available by J.-P. Malingreau (Joint Research Center, Ispra, Italy). In a study of two years of LAC

NDVI data in the Sahel region, change vectors were calculated using monthly maximum-value composites, then subjected to principal components analysis (Lambin and Strahler, 1994b). The components were related to: 1) the timing of the start of the growing season; 2) vegetation scenescence rates in savannas during the onset of the dry season; 3) vegetation scenescence rates in herbaceous covers during the onset of the dry season; and 4) differences produced by haze and cloud contamination (Lambin and Strahler, 1994a). The analysis clearly demonstrated the ability of the technique to detect subtle variations in regional phenology, thus providing a basis for separating natural temporal variability from more permanent changes induced by human activity.

This analysis was extended to compare maximum-value composites of NDVI with maximum-value composites of surface temperature and spatial structure (Lambin and Strahler, 1994a). Spatial structure was quantified by calculating the standard deviation of NDVI values within an adaptive three-by-three pixel window. In the adaptive window procedure, the standard deviation is computed for each of nine three-by-three windows to which a pixel belongs, and the minimum value is selected (Woodcock and Ryherd, 1989). In this way, the texture measure is not inflated artificially by the contrast between land cover boundaries.

The analysis showed these indicators to have a low degree of redundancy. NDVI change vectors are driven by seasonal changes in rates of vegetation activity; surface temperature change vectors are driven on a shorter time scale by rainfall events, especially in the drier environments; and NDVI texture displays a seasonal variability that must be taken into account when assessing long-term change. Later studies of change in NDVI texture in the same region confirm the diagnostic nature of the temporal pattern of spatial heterogeneity (Lambin, 1996).

The change vector technique is the most mature of the available techniques suited to the 1-km Land-Cover Change Product, and thus will be the basis for initial 1-km Land-Cover Change Product provided early in the postlaunch period. Other approaches will be explored simultaneously, especially at our intensive study sites. These techniques are explored in the following section.

2.2.5.2 Neural Network and Transformation-Based Change Detection

In addition to change vector analysis, a number of techniques comprising artificial neural networks, principal components analysis and Gramm-Schmidt orthogonalization change detection techniques are being evaluated. These techniques are also used as benchmarks for evaluating the performance of the change vector technique.

Artificial neural networks have only recently been applied to change detection. Gopal *et al.* (1996) evaluated the use of the fuzzy ARTMAP neural network for land cover classification and change detection at global scales using multitemporal AVHRR NDVI. These techniques were also applied locally in a supervised approach to detect changes in forest cover attributes over time (Gopal and Woodcock, 1996). A change detection study that assessed the environmental impact of the Gulf War forms the basis for the proposed approach. An ARTMAP network was modified to construct a system to derive a set of category representations that could be successfully employed to detect changes between known land cover classes, establish new category representations for unknown land cover classes, and provide quantitative measures of the significance of changes in terms of category likelihood or intensity. In this study, fuzzy ARTMAP recognized six land cover classes for a period before the Gulf War. The trained network was then used to detect changes that occurred as a direct result of the Gulf War. The network successfully detected (1) areas of no change: land cover remained the same after the war; (1) between-class change: categorical change into one of the existing land cover classes (that the network already "learned"); and (3) new categories: The network recognized nine new categories that have directly resulted due to the impact of the Gulf War. The adaptive fuzzy network proved more successful than the conventional *k*-means multidate classification in accurately predicting land cover change. It also offered a more comprehensive and unified treatment of the varieties of change encountered by simultaneously providing categorical and quantitative measures of change in the form of adaptive fuzzy membership values.

The artificial neural network used in a supervised approach to develop the Land Cover Parameter, by its nature, also includes a change detection component. As new data are presented to the Fuzzy ARTMAP neural network, the input either matches an existing category, or a new category must be created. If a new data presentation does not match an existing category then it will be necessary to determine whether the new data represent a fundamentally new condition (change) or whether the vigilance parameter needs to be relaxed so that an existing category (presumably a pixels previous category) can now accommodate the new input. This feature is especially useful for flagging change in the training process, when training data may be from an earlier period.

Another feature of neural network classifiers is that probability of membership by class can be evaluated on a pixel-by-pixel basis to track the probability that a specific pixel belongs to a certain class. When a specified threshold has been crossed, that pixel has moved into a new class and a categorical change has occurred. For the 1-km Land-Cover Change Parameter, a direct supervised approach to change detection using neural networks (Gopal and Woodcock, 1996) will also be investigated for targeting specific types of change in specific areas.

Principal components analysis, or the related Karhunen-Loeve (K-L) transformation (Duvernoy and Leger, 1980), is a multivariate statistical technique in which data axes are rotated into principal axes, or components, that maximize data variance. The original data are then transformed to the new principal axes, or components. In this manner, correlated data sets can be represented by a smaller number of axes, while maintaining most of the variation of the original data. PCA has been widely applied to detect, isolate and determine the nature of changes in the remote sensing signal over time (Byrne *et al.*, 1980; Muchoney and Haack, 1994). For the 1-km Land-Cover Change Parameter, PCA will serve two functions. First, it will be used as part of the QA procedure, as a means of evaluating the nature of variance in the time series for anomalies and artifacts due to sensor characteristics and data processing. Second, PCA will be used at the intensive studies sites for land cover change to evaluate the performance of the change vector and neural network techniques.

The Gramm-Schmidt orthogonalization change detection technique (Collins and Woodcock, 1994) will be employed in the QA process to evaluate the global change detection algorithm (change vector). It may also be used to discriminate specific types of change or region-specific change, and to describe the nature of change as determined by change vector analysis. Gramm-Schmidt is a more physically-based, less-empirical approach to rotational transformation than PCA. Gramm-Schmidt change detection is a modification of the technique that was initially used to derive coefficients of the tasseled-cap transformation for single-date imagery (Kauth and Thomas, 1976) to accommodate multitemporal data. In this case, the coordinate scores of rotated multitemporal pixel vectors directly represent inter-date change.

2.3 Land Cover Units

The primary objective of the land cover parameter is to facilitate the inference of biophysical information from land cover for use in regional and global modeling studies. Thus, the specific classification units of land cover need not only to be discernible with high accuracy from remotely-sensed and ancillary data, but also need to be directly related to physical characteristics of the surface and primarily to surface vegetation. A set of 17 such global land cover classes has been developed by the IGBP-DIS in conjunction with the IGBP Core Projects specifically for this purpose (Belward, 1996). They were applied to a classification of the global 1-km composited AVHRR LAC NDVI database assembled at EROS Data Center (Belward and Loveland 1995, Belward, 1996). Since the IGBP system of units was developed for a global land cover product at a similar 1 km resolution for a similar purpose (biophysical parameterization for modeling), the IGBP classification will also be used for the MODIS Land Cover Product.

Table 1 provides a list of the IGBP land cover units with accompanying descriptions. The list includes eleven classes of natural vegetation, three classes of developed and mosaic lands, and three classes of nonvegetated lands. The natural vegetation units distinguish evergreen and deciduous, broadleaf and needleleaf forests, where one of each pair of attributes dominates; mixed forests, where mixtures occur; closed shrublands and open shrublands; savannas and woody savannas; grasslands; and permanent wetlands of large areal extent. The three classes of developed and mosaic lands distinguish among croplands, urban and built-up lands, and cropland/natural vegetation mosaics. Classes of nonvegetated land cover units include snow and ice; barren land; and water bodies.

Note that the IGBP classes can be re-labeled ("cross-walked") to provide compatibility with current and future systems used by the modeling community. Table 2 provides an example in which the IGBP classes are translated to three other schemes. SiB2 (Sellers, *et. al*, 1996) is a surface-atmosphere interaction model for use in GCMs; the classification of Running and Nemani (Nemani and Running, 1996; Running *et. al*., 1994a; Running *et al*., 1995) is intended primarily for parameterization of global carbon and nutrient cycle models; and Myneni's classification is used in radiative transfer modeling for the MODIS and MISR LAI/FPAR products. For nearly all classes in these schemes, there is a direct mapping of one or more IGBP classes to their equivalents. A problem arises where some classes have no equivalents. For example, wetlands and urbanized areas do not appear in these three schemes, presumably because they are not recognized in the models receiving the land cover type input. However, these classes may be quite important for trace gas emission models, for example. The IGBP strategy was to recognize those classes that would be most useful across all the modeling disciplines of the IGBP, in effect requesting modelers to consider all relevant classes with significant areal extent on the earth's land surface.

Table 1. IGBP Land Cover Units	
Natural Vegetation	
Evergreen Needleleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.
Evergreen Broadleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Almost all trees and shrubs remain green year round. Canopy is never without green foliage.
Deciduous Needleleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
Deciduous Broadleaf Forests	Lands dominated by woody vegetation with a percent cover >60% and height exceeding 2 meters. Consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
Mixed Forests	Lands dominated by trees with a percent cover >60% and height exceeding 2 meters. Consists of tree communities with interspersed mixtures or mosaics of the other four forest types. None of the forest types exceeds 60% of landscape.
Closed Shrublands	Lands with woody vegetation less than 2 meters tall and with shrub canopy cover >60%. The shrub foliage can be either evergreen or deciduous.
Open Shrublands	Lands with woody vegetation less than 2 meters tall and with shrub canopy cover between 10-60%. The shrub foliage can be either evergreen or deciduous.
Woody Savannas	Lands with herbaceous and other understory systems, and with forest canopy cover between 30-60%. The forest cover height exceeds 2 meters.
Savannas	Lands with herbaceous and other understory systems, and with forest canopy cover between 10-30%. The forest cover height exceeds 2 meters.
Grasslands	Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.
Permanent Wetlands	Lands with a permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present in either salt, brackish, or fresh water.
Developed and Mosaic Lands	
Croplands	Lands covered with temporary crops followed by harvest and a bare soil period (*e.g.*, single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.
Urban and Built-Up Lands	Land covered by buildings and other man-made structures.
Cropland/Natural Vegetation Mosaics	Lands with a mosaic of croplands, forests, shrubland, and grasslands in which no one component comprises more than 60% of the landscape.
Non-Vegetated Lands	
Snow and Ice	Lands under snow/ice cover throughout the year.
Barren	Lands with exposed soil, sand, rocks, or snow and never has more than 10% vegetated cover during any time of the year.
Water Bodies	Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt-water bodies.

Table 2. Classification Comparisons			
Classification			
IGBP	SiB2 Biome	Running & Nemani	Myneni
Objective			
General Model Parameterization	Surface Interactions in GCMs	Carbon and Nutrient Cycling Models	Radiative Transfer for LAI, FPAR
Class Breakdown			
Evergreen Needleleaf Forests	Needleleaf-Evergreen Trees (4)	Evergreen Needleleaf	Needle Forests
Deciduous Needleleaf Forests	Needleleaf-Deciduous Trees (5)	Deciduous Needleleaf	Needle Forests
Evergreen Broadleaf Forests	Broadleaf-Evergreen Trees (1)	Evergreen Broadleaf	Leaf Forests
Deciduous Broadleaf Forests	Broadleaf-Deciduous Trees (2)	Deciduous Broadleaf	Leaf Forests
Mixed Forests	Broadleaf and Needleleaf Trees (3)		
Woody Savannas	C-4 Grassland (6)	Savannas	Savanna
Savannas	C-4 Grassland (6)	Savannas	Savanna
Grasslands	C-4 Grassland (6)	Grasses	Grasses/Cereal Crops
Closed Shrublands	Dwarf Trees and Shrubs (8)		Shrublands
Open Shrublands	Shrubs with Bare Soil (7)		Shrublands
Croplands	Agriculture or C-3 Grassland (9)		Broadleaf Crops
Cropland/Natural Vegetation Mosaics			
Permanent Wetlands			
Urban and Built-Up Lands			

2.3.1 Biophysical Parameterization

Taken together, the sets of natural vegetation and developed lands units can be used to differentiate several fundamental distinctions among cover types that are essential for ecological process modeling. One of these is annual vs. perennial habit, distinguished by whether or not the vegetation retains perennial or annual aboveground biomass. This attribute separates vegetation with permanent respiring biomass (forests and woody-stemmed shrubs) from annual crops and grasses that go through non-growing season periods as seeds or below-ground structures only. The annual-perennial distinction allows inference of several critical physiological attributes of plants. For example, in a global synthesis of plant gas exchange rates, Korner (1993) found on average that annual plants maintained a 50 percent higher leaf photosynthetic capacity than perennial plants. Biomass permanence, as it relates to plant height, also is the major vegetation determinant of the surface roughness length parameter that climate models require for energy and momentum transfer equations.

Another fundamental attribute that is distinguishable using this set of units is leaf longevity, which distinguishes between evergreen and deciduous plant covers. This attribute is a critical variable in carbon cycle dynamics of vegetation, and is important for seasonal albedo and energy transfer characteristics of the land surface. The leaf longevity class defines whether a plant must completely re-grow its entire canopy each year, or merely a portion of it, with direct consequences to ecosystem carbon partitioning, leaf litterfall dynamics and soil carbon pools. Reich *et al.* (1992) suggest that canopy conductance and maximum photosynthetic rate are inversely proportional to leaf longevity. Hence, certain global attributes of canopy gas exchange capacity may be inferred based on a leaf longevity criterion.

A third vegetation attribute recognizable within the IGBP units is the leaf type or shape of the dominant vegetation cover. Three leaf shapes are distinguished among the various categories: needleleaf, broadleaf, and graminoid (grasses). This attribute also correlates well with key ecological parameters for biogeochemical modeling. Running and Hunt (1993) defined maximum leaf area index values of 10, 6 and 3, and maximum canopy conductance values of 1.6, 2.5, and 5.0 mm/sec, for needle-leaved trees, broad-leaved trees, and grass covers, respectively.

Still other intrinsic biophysical parameters may be inferred from these units. For example, Dorman and Sellers (1989) assigned a series of optical properties, physiological properties and physical parameters to a set of vegetation classes, based on those of Matthews (1983) and Kuchler (1983), specifically for global application to the Simple Biosphere Model of land surface-atmosphere interaction (Sellers *et al.*, 1986). In a somewhat different application, Sellers *et al.* (1994) devised an algorithm for determining global FPAR, LAI, and canopy greenness fraction from monthly composited NDVI at 1-degree resolution. Although the method is based on NDVI, their algorithm stratifies NDVI-FPAR-LAI relationships by vegetation cover types, using broad structural classes similar to those of the IGBP classification. Note that FPAR and LAI will be produced from MODIS using separate biogeophysical algorithms in MODIS Product MOD15.

2.3.2 At-Launch Provisional Land Cover Parameter

In order to provide land cover information for other MODIS algorithms that require land cover as an input, an at-launch provisional land cover parameter has been provided by MODIS Team Member John Townshend of the University of Maryland. This provisional parameter will be used by the Land Team in preparation of several at-launch land products, including LAI/FPAR (MOD15), annual net primary productivity and photosynthesis parameter (MOD16, MOD17), snow cover (MOD10), and BRDF/Albedo (MOD43), to infer various types of biophysical information as required for their investigations. The University of Maryland has selected two at-launch land cover products: that of the IGBP global land cover database described above (Belward and Loveland, 1995; Belward, 1996), and a modified IGBP classification that was developed by the University of Maryland using supervised decision tree classification of the 1 km 1992-93 USGS dataset. The IGBP dataset is currently undergoing intensive global validation (Estes *et al.*, in preparation).

2.4 Spatial Resolution

The Land Cover Product will be produced at 1-km spatial resolution. This scale is the finest that is practically achievable with the MODIS instrument. Although the MODIS land bands are imaged at 250- and 500-m spatial resolution, these are nominal values for nadir pixels. At the edge of the MODIS swath, pixels grow by a factor of 2 in the along-track direction and by a factor of 5 in the across-track direction. Moreover, there will be geolocation error in computing the center of each pixel that is produced by uncertainties in the knowledge of the location of the spacecraft and its orientation. The best current estimates of pointing error are +85 m along-track and +153 m across-track (MODIS geolocation workshop, 8/8/96, GSFC). These are three standard-deviation (3 sigma) values projected to nadir, and will increase with look angle in a fashion similar to that of pixel size.

Geolocation errors, together with pixel size growth, give an effective instantaneous field of view (EIFOV) of 1087 m in the along-track direction and 1591 m in the across-track direction for the composited sequence of measurements input to the 32-day land cover database. This EIFOV does not include optical blurring or scatter within the instrument, and thus is a conservative estimate of effective spatial resolution. Given pixel size effects and geolocation uncertainties, it seems reasonable to use a grid cell size of 1-km. Finer resolution information would be redundant and incur significant costs to produce and store.

The 1-km spatial resolution is well-suited to the needs of the global and regional modeling community. In a recent report, the IGBP-DIS Land Cover Working Group noted (IGBP, 1992):

> "There is an emerging view regarding the appropriate scale for analyzing land cover and land cover conversion. The suitability of 4-8 km GAC data for delineating broad land cover types and phenology has been demonstrated (Malingreau, 1986; Malingreau and Tucker, 1988). The utility of 8-15 km data for land cover classification and phenology has also been shown by a number of authors (*e.g.*, Justice *et al.*, 1985, and Tucker *et al.*, 1985), but it is too coarse for monitoring land cover conversion and reliable detection of land transformation requires resolutions of 1 km or finer (Townshend and Justice, 1988). This observation is supported by detailed analyses of tropical deforestation, which suggests that even 1 km data might be too coarse for quantifying the area and rate of deforestation in some regions (C. J. Tucker, personal comm.), although a 1 km data set would assist stratified sampling."

These considerations led directly to the development of the IGBP 1-km Land Cover Database described above. In addition, 1-km scale input is required for other 1-km MODIS land products as noted in section 2.3.2.

2.4.1 Aggregation and Scaling

The effect of scaling on land cover proportions has been explored in the research literature in recent years. Several studies have established that changing the spatial resolution of land cover maps has important effects on the proportion of a landscape occupied by a particular land cover type (Henderson-Sellers *et al.,* 1985; Turner *et al.,* 1989; Moody and Woodcock, 1994; 1995 a and b). In general, the proportions of smaller, more fragmented cover types decrease with aggregation, while those of the larger classes increase. Similar effects were noted by Townshend and Justice (1988), who observed large changes in the proportions of test site images falling within specific NDVI ranges as scenes were progressively degraded to coarser resolutions. These observations conform with more theoretical results obtained by Jupp *et al.* (1988, 1989) and Woodcock and Strahler (1987) on scaling, resolution, and spatial pattern.

The results obtained by these researchers suggest that where different covers differently influence biophysical relationships (*e.g.*, NDVI-FPAR relationships, Sellers *et al.*, 1994), the aggregated behavior of an areal unit will be different from that of a single cover type that dominates it. This effect has been documented in surface energy balance modeling by Henderson-Sellers and Pitman (1992).

There are two further implications of the scaling behavior of land covers for the MODIS product. First, if 1-km land cover classes are to be aggregated to a coarser grid, the product should provide a vector of proportions by classes within coarse grid cells, rather than a label derived from a single dominant class. In this way, users will have sufficient information to treat the area as heterogeneous if desired. This approach will be used in the Land Cover 1/4-degree Climate Modeler's Grid (CMG) Product.

A second implication lies at subpixel scales. Many studies of fine resolution satellite imagery have established the fact that the spatial pattern structure of real landscapes is often finer than 1 km in linear dimension (*e.g.*, Townshend and Justice, 1988; Townshend *et al.*, 1992). These findings suggest that even at 1-km resolution most pixels are mixed. If pixels are mixed and the proportions matter, then it is important to document the way that proportions change with pixel size within ecoregions so that subpixel effects may be accommodated in coarser-scale aggregations (Moody and Woodcock, 1995a). Such documentation will require validation studies at test sites (discussed in a later section).

Several approaches to correction of cover-type proportions have been explored in the literature. These have ranged from simple regression methods in which fine-resolution proportions are associated with coarse-resolution spectral variables (Zhu, 1996) to regression-tree models predicting coarse-scale proportions from a suite of fine-scale spatial pattern quantifiers using regression trees (Moody and Woodcock, 1995a, 1995b). In a recent study examining the determination of tropical forest area from AVHRR LAC data, Mayaux and Lambin (1995) provide a two-step procedure in which the Matheron index, which measures the length of boundary per unit area for a class, estimates the slope and intercept for a regression linking fine- and coarse-resolution proportions. They recently extended their work to inverse calibration of cover proportions using several measures of spatial textures, including a simulation of the MODIS scenario of 1-km classification with a standard deviation texture measure derived from a 250-m band (Mayoux and Lambin, 1995). They showed that the 250-m texture was the most effective of the measures available, reducing residuals in observed versus modeled proportions to less than 9 percent.

These studies suggest that areal proportion estimation must be done carefully with appropriate use of fine-scale information, such as 250-m spatial texture. Moreover, proportion estimation is dependent on the spectral characteristics of the classes as well as their spatial structures. For the Land Cover Product, we will provide subpixel proportion estimation information as an ancillary dataset for those regions in which we have sufficient information to compute it. In the post-launch era, we may be able to provide a specific global product with this information.

2.5 Instrument Characteristics

Several problems have been consistently encountered in attempting to process AVHRR data for large-area land-cover discrimination. Although the red and near-infrared channels capture the primary variance in the vegetation signal, other spectral bands that can provide important information in reflective wavelengths are missing. Furthermore, the AVHRR bands are broad and include some atmospheric absorption features that unduly influence the ground signal. Despite the use of the maximum value compositing procedure to screen for clouds, many cloud-covered pixels are still included in composited images. This leads to a misrepresentation of the time trajectory and can cause faulty classification results.

Composited images can also include large numbers of poorly-registered off-nadir pixels, a circumstance that results in a blurred image appearance, reduced image variance, and variable within-scene spatial resolution. Part of the reason for this lies in the instrument's conical scan mirror, which provides rotated and overlapping instantaneous fields of view at the edge of the scan. Other limitations to the processing of AVHRR data include poor spectral and radiometric calibration, poor pointing knowledge, and difficulties in providing accompanying atmospheric correction.

The design of the MODIS instrument alleviates many of these problems. Seven of the MODIS bands in the reflective region have been selected expressly for land applications based on experience with Landsat Thematic Mapper and AVHRR. These bands are positioned to sample the solar spectral curve in wavelength regions that provide specific information about the land surface, while their bandwidths are chosen so as to maximize radiometric precision and avoid atmospheric absorption. This will lead to the production of vegetation indices that are more meaningful and more resistant to atmospheric effects than those produced from AVHRR data, and will also provide for greater utility and interpretability of the individual bands. All of the reflective bands and several combinations of these bands will be potentially useful for discriminating land cover units and monitoring change (Townshend *et al.,* 1991). In addition, thermal channels were found to be also prove to be useful in characterizing and discriminating land cover types.

In contrast to AVHRR, MODIS possesses an extensive on-board capability for radiometric and spectral calibration. Calibration subsystems include for shorter wavelengths the spectroradiometric calibration assembly (SRCA), the solar diffuser and solar diffuser stability monitor, and, at longer wavelengths, a blackbody for thermal band calibration. The instrument will also view dark, deep space as part of its normal scan, and at certain times will image both deep space and the moon as part of the calibration procedure. The inclusion of specific bands for atmospheric sensing on the MODIS instrument provides for dynamic atmospheric correction and allows the estimation of surface directional reflectances in the MODIS land bands (King *et al.*, 1991) (MOD09; 2015).

The use of surface reflectances instead of top-of-the-atmosphere radiances allows a strategy for assembling multidate imagery without relying on specific transforms, such as NDVI, that suppress atmospheric noise. MODIS bands also allow the application of multiple algorithms for the detection of different types of clouds so that cloud-covered pixels may be identified reliably (MOD06). Moreover, in the case of high, thin cirrus clouds, data can be corrected for cloud effects. With atmospherically-corrected and cloud-screened data, measurements can be composited through the fitting of semiempirical BRDF functions (MOD43), allowing calculation of the best-fit nadir reflectance in each of the seven land bands within a 16-day period. In this way, data are obtained that are free of clouds, atmospheric contamination, and angular view and illumination effects.

Rectification has posed particular difficulties for AVHRR processing in producing composited images, analyzing time trajectories of land surface data, and comparing data from multiple time periods to assess change. These problems should be significantly reduced with the in-flight navigation capabilities of MODIS. Geolocation error estimates, discussed in more detail in section 2.5, combined with the growth of pixel size with scan angle, will provide an effective pixel size close to 1-km using the 500-m and 250-m land bands as inputs. Although AVHRR LAC data are commonly composited to 1-km spatial resolution, the data are quite redundant at that scale. For example, normal geolocation error for EDC processing of LAC data is on the order of 2-3 pixels (T. Loveland, personal communication). This error smooths the data greatly and is especially noticeable at abrupt contrast boundaries, such as coastlines. MODIS will thus provide a very significant improvement to 1-km data quality.

3. Algorithm Description

3.1 Overall Algorithm Structure

3.1.1 Practical Description of Algorithm

3.1.1.1 Land Cover Parameter

Figure 1 provides an overview of the Land Cover algorithm logic. In brief, reflected and emitted radiation, as measured remotely through time and over space, are combined with ancillary data to provide a database for distinguishing land covers that includes spectral, directional, spatial, temporal, and collateral information. This database is processed using decision tree and neural net classification algorithms.

3.1.1.1.1 Database Assembly and Compositing

In the temporal dimension, remotely sensed data are not retained in full temporal resolution. Rather, the volume of measurements is reduced to a set of summary measurements for each cell in a 1-km grid for a 32-day period (MOD12M—an interim product). Studies using AVHRR data acquired over large regions have concluded that a period of at least 30 days is required to assemble a dataset that is largely uninfluenced by cloud cover (e.g., Lambin and Strahler, 1994a, 1994b; Moody and Strahler, 1994). The 32-day cycle used here is keyed to the platform orbit, which repeats in a 16-day cycle and 8-day half cycle.

Remotely sensed inputs to the 32-day database include:

- *Land/Water Flag*
  Locations permanently covered by moderate or deep water are not investigated by the MODIS Land Cover Classification algorithm. Each 1-km cell in the 32-day database includes a land/water flag retrieved from the EOS land/water mask.

- *Nadir BRDF-Adjusted Reflectances (NBARs).*
  The MODIS BRDF/Albedo product (MOD43B4) provides nadir BRDF-adjusted reflectances (NBARs) to the MODIS Land Cover algorithm in all seven land bands at 1-km resolution. Each observation in this global dataset is the modeled reflectance that would be observed for a given ground location at nadir with the median solar illumination angle for the overpasses over a 16-day period. Thus, two NBARs are available over a 32-day period.

- *Texture Channel*
  The MODLAND Aggregation Product (MODAGTEX) includes a spatial texture layer. Spatial texture is measured as the ratio of standard deviation to mean of the 250-m surface reflectances falling within each 1-km grid cell during a 16-day period. Studies have demonstrated the utility of this spatial measure in classification of land covers (*e.g.*, Borak and Strahler, 1996). Since texture measures across spectral bands are typically strongly correlated, only the texture for MODIS Band 1 (red, 250-m nominal resolution) is used. This is a daily product, thus as many as 32 texture measures can be available over a 32-day period.

- *Vegetation Index*
  An Enhanced Vegetation Index (EVI) is provided by the MODIS Level 3 Vegetation Index Product (MOD13). The spatial resolution of this input is 1km and its temporal resolution is 16 days. Thus, two EVIs are available over a 32-day period.

- *Directional Information*
  The MODIS BRDF/Albedo Product (MOD43B1) includes parameter sets describing the fits of semiempirical BRDF models to surface reflectances obtained from MODIS and MISR in the seven land bands. For input to the Land Cover Product, parameters describing the BRDF shape are extracted from this product along with the relevant quality control information. Relationships between BRDF and land cover are currently under investigation using AVHRR data (see MODIS BRDF/Albedo Product ATBD for details). Generally, the value of using BRDF information in land cover classification derives from the fact that relatively coarse multidirectional class signature boundaries fall across the boundaries of spectral classes. This allows identification of subtleties that may not be apparent in spectral data alone.

- *Snow/Ice Cover*
  The MODIS Level 3 Snow Cover Product (MOD10A) provides 8-day maps of snow cover at a 500m resolution. Thus 4 snow products are available over a 32 day period. because of the spatial inconsistency with the other 1-km products, the snow flag accompanying the reflectance data QA will be used as a surrogate at-launch.
- *Land Surface Temperature*
  The MODIS Land Surface Temperature Product (MOD11) provides an 8-day product of daylight land surface temperature (LST). Thus 4 LSTs are available over a 32-day period. Temperature data are nominally at 1-km resolution.

The accumulation procedure carried out in the production of 32-day MOD12M involves examining the overall quality associated with each set of measurements in order to select the best measurements available for the 32-day period. The best data are generally those produced with the highest degree of scientific validity according to the MODIS Science Team members responsible for generating the input datasets, *i.e.*, values with optimal quality flags. Often, the degree of validity is related to cloud cover, but it also takes other elements of the production stream into account. Inputs that contain no valid information over a 32-day period are treated as missing data. Scientifically useful observations from input products that are produced at shorter time steps than 32 days are aggregated to a 32-day time step in the following ways. The two maximum Land surface temperatures are retained. Snow cover is accumulated from the four 8-day products produced over the 32-day period. The best quality 16-day spectral NBARs and directional reflectance information from MOD43B are retained for each cell. Both 16-day EVIs are retained.

3.1.1.1.2 Data Reduction

The classification algorithm operates on a sequence of twelve 32-day MOD12M databases along with an EOS-wide 1-km topographic database to generate seasonal land cover labels. Data reduction has been used extensively in remote sensing and classification problems. Probably the most common approach is to employ some sort of linear transformation on the original dataset to produce a smaller set of factors or components (Kauth and Thomas, 1976; Jackson, 1983; Ingebritsen and Lyon, 1985). Most of the original variance is retained with a significant reduction in data volume.

The decision tree classifier (DTC) used as the MODIS at-launch classification algorithm provides an approach to data reduction that is well known in the pattern recognition literature, but has appeared relatively recently in the remote sensing literature (Michaelsen *et al.,* 1994, Hansen *et al.,* 1996, Borak and Strahler, 1999. The DTC operates in a supervised mode, and thus requires data from training sites. The algorithm employs tree-structured rules that recursively partition the input dataset into increasingly homogeneous subsets based on a splitting rule (Breiman *et al.,* 1984). These subsets are represented as nodes in the tree structure. The top node root) consists of the entire input dataset. Nodes at the bottom of the tree (leaves) are the output cover classes. The hierarchical nature of the classifier thus separates important discriminatory information near the top of the tree from redundant information near the bottom of the tree. Another method of feature reduction is the use of simple summary variables, such as maximum and minimum values, max-min differences, annually integrated values, etc. These methods have been explored by Lloyd (1990), and more recently, by DeFries *et al.*, 1995. The at-launch data reduction algorithm requires hands-on preparation at the Scientific Computing Facility, and results will be sent to the DAAC for incorporation into the production environment on a quarterly basis.

3.1.1.1.3 Classification

In the classifier stage, a sequence of 32-day databases is input to the classifier along with the EOSDIS 1-km topographic database (MOD03). In the post-launch period, the 32-day sequence will involve two years of acquisitions. During the first two years of acquisitions, the sequence will necessarily be shorter. The 32-day databases and ancillary data are then processed by a neural network classifier. Recent applications of neural networks in classification of remotely sensed data were discussed in section 2.2.2. The candidate neural network and decision tree architectures are described in detail in the following section.

For greater processing efficiency and classification accuracy, processing will proceed by continents. Note that the full spectral and temporal resolution of the land cover database may not be needed within each continental region. For example, trials may show that classification accuracy remains unaffected if the annual cycle is represented by a subsample of three or four months. Or, perhaps only a subset of variables within each 32-day composite will be required. In any event, we may predict that the choice of months or variables will vary from continent to continent.

3.1.1.2 Land-Cover Change Parameter

The Land-Cover Change parameter will rely primarily on the change vector technique, which will compare pixel-by-pixel the temporal development curve of a set of biophysical and spatial indicators derived from MODIS data. These features are described more fully in section 3.1.1.1.1 above. The change vector technique represents the seasonal dynamic of these indicators by a point in a multidimensional space, with each dimension of this space corresponding to a time-composited observation. Changes in the accumulated value and seasonal dynamic of the indicator between successive years are quantified by a change vector between successive points in the temporal multidimensional space. The magnitude of change is reflected by the length of the vector, while its direction in multitemporal measurement space indicates the timing and nature of the change.

Where a long history of change observations exists, a useful reference standard for change may be a ‘best-conditions’ year, a monthly time trajectory that is constructed for every pixel from an analysis of its historical performance over the period of record. In this process (Lambin and Ehrlich, 1996a), the best ecological conditions that occurred throughout the observation period are identified for each pixel by selecting the maximum (or minimum) value of an indicator (*e.g.*, maximum NDVI) for each month in the annual cycle. A best-conditions year is thus constructed that takes into account the ecological and edaphic constraints of every pixel. Any land-cover change can then be expressed with reference to this time trajectory. Note that the reference year will need to be updated at regular intervals to integrate new observations, thus allowing for a better categorization of change processes over multiannual periods. This approach has proven very useful in characterizing land-cover change in Africa using AVHRR GAC data for the 1982-1991 period (Lambin and Ehrlich, 1996b).

Although the change vector technique is the best documented approach thus far to land-cover change at coarse resolution, we also plan to examine other approaches to change characterization. These alternative approaches are identified in section 2.2.5.

3.1.2 Mathematical Description of Algorithm

3.1.2.1 Land Cover Parameter

3.1.2.1.1 Feed-Forward Networks Trained by Backpropagation

While there are a variety of different neural network models, most remote sensing applications have used a supervised, feedforward structure employing a backpropagation algorithm that adjusts the network weights to produce convergence between the network outputs and the training data. In overview, the neural network classifier is composed of layers of “neurons” that are interconnected through weighted synapses. The first layer consists of the classification input variables and the last layer consists of a binary vector representing the output classes. Intermediate, “hidden” layers provide an internal representation of neural pathways through which input data are processed to arrive at output values or conclusions.

In a supervised approach, the neural network is trained on a dataset for which the output classes are known. In this process, the input variables are fed forward through the network to produce an output vector. During a following backpropagation phase, the synapse weights are adjusted so that the network output vector more closely matches the desired output vector, which is a binary-coded representation of the training class. The network weights, or processing element responses, are adjusted by feeding the summed squared errors from the output layer back through the hidden layers to the input layer. In this fashion, the network cycles through the training set until the synapse weights have been adjusted so that the network output has converged, to an acceptable level, with the desired output. The trained neural network is then given new data, and the internal synapses guide the processing flow through excitement and inhibition of neurons. This results in the assignment of the input data to the output classes. The basic equations relevant to the backpropagation model are presented in Fischer and Gopal (1992).

3.1.2.1.2 Adaptive Resonance Theory Neural Networks

Although the feed-forward back-propagation neural network has been shown to better or at least equal the performance of conventional statistical classifiers in remote sensing applications (see section 2.2.2), this architecture can require lengthy training and can sometimes fail to converge. A newer neural network architecture, relying on adaptive resonance theory (ART), lacks these disadvantages and shows significantly higher accuracies (Gopal *et al.*, 1994). Neural networks employing adaptive resonance theory are designed to be stable enough to preserve significant past learning while still allowing new information to be incorporated in the neural network structure as such information appears in the data input stream. The description of ART networks below follows Carpenter and Grossberg (1987a, 1987b), Carpenter (1989), Carpenter *et al.* (1991a, 1991b, 1992), and Gopal *et al.* (1994).

The ART-1 module of Carpenter and Grossberg demonstrates the essential features of adaptive resonance theory. This module is actually a learning structure that organizes the patterns it receives into a consistent set of responses. In this way, its function is similar to that of an unsupervised classifier. The ART-1 module consists of a two-level network. An input signal in the form of a binary vector (F_0) is received by the first level (F_1) and propagated forward to the second level (F_2) by a set of weights that constitute the long-term memory. A further feature of the F_2 level is that the nodes at the F_2 level interact through lateral inhibition. The result is to produce an F_2 pattern vector in which only the node associated with a single class is significantly activated. This vector is then propagated backward to the F_1 level where it is compared with the original input vector. If the two patterns are close, "resonance" occurs and long-term memory is altered to include the new observation.

If the two patterns differ significantly, the ART module enters a search mode. In this mode, the prior active node at the F_2 level is first disabled. The signal is then propagated forward once again, but since the prior active F_2 node is disabled, a second pattern associated with a different class node is selected. This pattern is then propagated back to the F_1 level and compared with the input vector as before. If the fit is acceptable, then resonance proceeds and the system has "learned" a new input pattern. If not, the second F_2 node is disabled and another attempt to find a good match is made. If cycling in this fashion does not eventually produce a good match, the system adds a new F_2 node and associates the input pattern with it in long-term memory.

Further developments of adaptive resonance theory to neural networks by Carpenter and co-workers include ART-2 and fuzzy ARTMAP. ART-2 modifies ART-1 so that it no longer requires a binary input vector, but instead may accept analog inputs. (A form of scaling is applied to the inputs first, however.) Note that neither ART-1 nor ART-2 are associative memory systems, in which associations between pattern pairs are learned with the ability to be recalled. Fuzzy ARTMAP, however, is such a system.

In fuzzy ARTMAP, two ART-2 modules (ART_{A} and ART_{B}) are connected together through an associative learning network called a map field (ART_{AB}). In the training phase, input vectors and desired output vectors are presented as pairs to F_2 and ART_{B} respectively, and the outputs of the ART modules are associated by the map field ART_{AB}. If a mismatch occurs, F_2 is placed in search mode to find, and possibly learn, a better choice. Or, a new node may be added to the F_2 layer in F_2 that is a better predictor of the desired output. As noted previously in section 2.2.2, the fuzzy ARTMAP classifier has performed very well in applications to monthly-composited AVHRR LAC data as well as to Thematic Mapper data.

3.1.2.1.3 Decision Tree Classifiers

Decision tree classifiers recursively partition data into related or homogeneous subregions based on a set of decision rules. The structure of the tree consists of a root node, intermediates nodes or splits, and terminal nodes (leaves). Input data at the root node is subdivided at decision nodes based on univariate and/or multivariate decision rules (Brodley and Utgoff, 1995). Although decision trees have only recently been applied to remote sensing data, they offer tremendous potential for classification and feature selection. Decision trees can either be applied independently or coupled with other analytical procedures in hybrid classification models.

Research into the applicability of decision trees to MODIS Land Cover continues to be conducted at both site and global scales. Lloyd (1990) used a binary decision tree classifier using multitemporal phenological indexes or metrics derived from a time series of NDVI data to stratify vegetation phenology classes. A time series dataset was used to examine feature selection and land cover classification for a MODIS-like scenario in the semiarid environment of the Walnut Gulch/Cochise County site (Borak and Strahler, 1999. The dataset consisted of numerous input fields derived from an intra-annual sequence of seven Landsat TM acquisitions, along with ancillary elevation information. A decision tree classifier was used to select the features that provided the best descrimination among land cover types. Three classification algorithms were then applied to the reduced feature space: the decision tree itself, a maximum-likelihood classifier and an artificial neural network (Fuzzy ARTMAP). Results indicated that decision tree classifiers are useful tools for extracting essential features in data sets of high dimensionality, and that the neural network performed best on the reduced set of features.

Friedl and Brodley (1997) applied univariate, multivariate and hybrid decision trees to the global 1-degree AVHRR NDVI dataset, the Conterminous US 1-km AVHRR NDVI dataset, and a TM data set for Lake Tahoe, California, and compared them to both linear discriminant functions (LDF) and a maximum likelihood (ML) classification algorithm. All three decision tree algorithms outperformed the LDF and ML algorithms on all datasets. Hybrid trees, where different classification algorithms are used in different subtrees of a larger tree, were superior due to their ability to better resolve complex relationships among feature attributes and class category labels.

3.1.2.2 Land-Cover Change Parameter

The change vector analysis method of identifying land-cover change has been presented by Lambin and Strahler (1994b). This method assesses change by calculating the distance between the location of an indicator variable in multitemporal space at two different time periods on a per-pixel basis. For example, if the indicator were monthly composited NDVI values, and it was desired to assess change between two subsequent years, the difference between the location of the NDVI vector in 12-dimensional (monthly) space for the two years would be calculated. The magnitude of this difference, or change vector, is representative of the magnitude of the change, and the direction of the change vector relates to the type of change. The type of change is then characterized by the segment of the multidimensional temporal space into which the vector has moved. This approach (1) allows quantification of the intensity of change; (2) allows classification of the type of change; (3) is based on a historical database for each pixel; and(4) is mathematically simple.

More explicitly, the temporal state of the land cover can be represented by the location of a variable such as NDVI in a multidimensional space, where each dimension represents one of the time periods for which the variable was measured. For example, the location of the variable can be represented by the vector:

$$p'(i,y) = [I(t_1) \;\; I(t_2) \;\; . . . \; I(t_n)]$$

where $\mathbf{p}'(i,y)$ is the multitemporal vector for pixel i in processing period y, I are the values of the variable of interest for pixel i at time periods t_1 to t_n where n is the number of time periods at which the variable was measured. The vector magnitude represents the integral of the variable over time periods 1, 2, . . . , n and the direction of the vector represents the seasonal pattern. Any change in the state of a pixel's land cover between processing periods y and z is defined by a change vector:

$$c(i) = p(i,z) - p(i,y)$$

The magnitude of the change vector is simply taken as the Euclidean distance d between the two vectors:

$$d^2 = \mathbf{c}'(i)\, \mathbf{c}(i)$$

In work by Lambin as cited above, it has been shown that the magnitude and direction of the change vector are related to the intensity and type of change process, respectively.

A further extension is to explore the Mahalanobis distance, d_{M}:

$$d^2_M = \mathbf{c}'(i)\, \mathbf{V}^{-1}(i)\, \mathbf{c}(i)$$

where $\mathbf{V}(i)$ is a variance-covariance matrix of change vectors that quantifies the distribution of change vectors as observed over time within a region. This distance scales the magnitude of a vector by the variance normally observed in its direction of change. As for the Land Cover product, Land-Cover Change will require assembling a multitemporal data set (Figure 2).

3.1.3 Training, Testing and Validation Sites and Database

The MODIS Land Cover and Land-Cover Change Parameters require ground information for training and validation. This information will be obtained for a network of global test sites described in the following sections. The Land Cover and Land-Cover Change validation and test site approach follows that developed for the MODIS Land Team. Land Cover and Land-Cover Change also have specific needs for global sites that can be used to train and test algorithms, and to validate map products. We are currently completing the development and population of a set of global Validation and Test Sites (VATS) using the System for Terrestrial Ecosystem Parameterization (STEP), a site database developed for this purpose.

3.1.3.1 STEP Site Database

As stated, global training and testing of algorithms, as well as land cover product validation, require that a network of sites be developed. To meet the requirements for a multivariable site model and database for training, testing and validation, the System for Terrestrial Ecosystem Parameterization (STEP) was developed. STEP is a multivariable site database framework for describing site vegetation, environment, and other biophysical parameters. STEP is a formal model that relates multisource remote sensing, field, and thematic data to landscape biogeophysical attributes to permit training, testing, parameterization and validation. It provides for continuous acquisition and update of plot-level data that can be applied to classification algorithm training, testing, and validation, as well as to more comprehensive ecological/environmental description. It is a classification-free approach that is appropriate at multiple scales and for multiple landscape classifications that utilize physiognomic, functional, structural and phenologic criteria. STEP allows for training and testing of classification algorithms, and validating map product accuracy (Muchoney *et al.,* 1999).

STEP is being used to create a global database of land cover test sites and associated parameters which can also be applied to direct generation of multiple classification systems and specific biophysical parameters. Feature extraction and parameterizing the STEP database involves assigning labels to appropriate categories of a suite of parameters. STEP provides for explicit description of the structural, functional and compositional components of the vegetation and landscape tied to specific sites and plots. Its primary purpose is to provide a comprehensive model of the land surface that can be used to train and test algorithms and to validate land surface products. Formal sites are established and described based on high-resolution remote sensing, ancillary and field plot data. STEP can be used to translate multiple classification systems as an alternative to commonly used look-up table approaches. This accommodates the wide array of classifications used by various models to parameterize biophysical processes such as those of Biosphere-Atmosphere Transfer Scheme (BATS) (Dickinson *et al.*, 1993), Biome-BGC (Myneni *et al.,* 1997; Nemani and Running 1996; 1997; Running *et al.*, 1994, 1995), the Land Surface Model (LSM) (Bonan, 1996), and the Simple Biosphere models SiB (Sellers *et al.,* 1986) and SiB2 (Sellers *et al.,* 1996).

The development of the global STEP test site database for Land Cover is intended to represent the earth's diversity of land covers and types of land cover change. Land-Cover Change Parameter training and validation requires that the site network represent global, regional and local change processes due to both natural and anthropogenic factors. Change criteria include phenological class (seasonal grassland, deciduous forest), anthropogenic (urbanization, agriculture, conversion, biomass burning), interface (land/snow, land/water), biotic (insect and pathogen), and hydrologic (seasonal inundation) representation. Early warning and indicator sites are necessary for monitoring processes that may indicate climatological or other changes. These sites include, for example, high-elevation spruce-fir forests and ecological ecotones. A number of critical sites and "hotspots" sites are included in the network because of their particular conservation, political, economic and/or social significance. While site selection criteria have been defined, because of the time and expense of developing an independent test site database, the site selection process has also been driven by data made available to Boston University by a number of cooperators and data sources.

The VATS database presently includes over 1000 sites for North America and an additional 500 sites for South America. The strategy is to develop the 400 global Core and Confidence sites of IGBP into STEP format for the rest of the globe, to augment these sites in Africa, Eurasia and Australia based on gaps in their distribution to be ready for global training, testing and validation within 5 months following EOS AM-1 launch.

3.1.3.2 Site Data Sources and Institutional Cooperation

A global site network is an ambitious endeavor that requires cost sharing and inter-institutional cooperation. Test sites are promoted to take advantage of cost savings by using data that have already been generated and where research is continuing. This site network is being coordinated within MODLAND, EOS and the larger remote sensing community, especially IGBP. Boston University is working with other MODLand teams in developing site data.

One important source of test site data is the Landsat Pathfinder Global Land Cover Test Sites (GLCTS) program, for which data are now being assembled at the EROS Data Center. GLCTS was proposed by an informal network of researchers largely connected to MODIS, EOS and/or the IGBP. Each site is known to have some associated ground information on local land cover or related data. For each GLCTS site, a database of remotely-sensed imagery that includes Landsat MSS, TM, and AVHRR data is being assembled by the GLCTS program. Landsat images include both recent and historical acquisitions (for change detection). AVHRR images include LAC data in a 500-km by 500-km window centered on each test site; they are being acquired as part of the data acquisition phase for the AVHRR global 1-km dataset, and acquistions are expected to continue into the future along with this program. Databases have been completed at eight sites. The present list of GLCTS test sites includes 130 locations globally, although there is a commitment now for only database development at some 30 sites. Although the completed sites are data-rich, there is no consistency in the level of land cover information that has been derived at each site. It will therefore be necessary to extract land cover data for the GLCTS sites to make them usable for MODIS Land Cover training and validation.

Another source of test sites is the IGBP-DIS Global 1-km Land Cover Database project. IGBP is completing validation of the IGBP AVHRR global land cover classification using statistical sampling based on over 400 remote sensing Core observation sites. These data will be available and may be easily applied to validation of the MODIS product, even though they are not designed specifically for that purpose. Boston University, as a contribution to IGBP Global Land Cover, has been able to expand the initial Core sites into a set of global confidence sites to provide local-scale land-cover information for both methodological development and accuracy assessment of the 1-km land cover database (IGBP-DIS, 1995). The IGBP Confidence Site characterization approach is an adaptation of the STEP model, therefore supporting continuity with Boston University’s global STEP site database.

Other sources of test sites are international field experiments, such as the Boreal Ecosystem-Atmosphere Study (BOREAS) in boreal Canada; the SALT transect (Savanna on the Long-Term) in West Africa; the French test sites for the POLDER (Polarization and Directional Earth Reflectance) instrument, MODLERS/Bigfoot sites and SAFARI 2000.

As part of the larger MODLand, MODIS, and EOS activities, a network of fully-instrumented tower sites is being developed. We will use these sites for pre-launch evaluation as they become available and for continuous observation in the post-launch era. They will be visited during field campaigns in order to map and parameterize local land cover types and observe change. Additional intensive study sites we have identified include BOREAS, Olancho, Honduras; the Yucatan; Glacier National Park; Plumas National Forest; Harvard Forest LTER; Hubbard Brook LTER; Virginia Coast LTER; and Hapex-Sahel. Five of these were selected as high-priority, regional STARs for ASTER data validation: Olancho, Honduras; Shenandoah National Park/George Washington National Forest, Virginia USA; Burkina Faso, Africa; Cockpit Country, Jamaica, Caribbean; northern Canada; and Mosquitia, Nicaragua/Honduras.

3.1.4 Prelaunch Algorithm Development and Validation

3.1.4.1 Prelaunch Land Cover Algorithm Development and Validation

The MODIS land cover team has undertaken a number of studies to validate the classification procedure and algorithms for the land cover and land-cover change products. The following are abstracts of these studies with references to publications relating to these studies. The MODIS Land Cover/Land-Cover Change Product Accuracy and Sensitivity Summary is also provided as Appendix A.

- *Central America Terrestrial Ecology Study*
  While mapping vegetation and land cover using remotely sensed data has a rich history of application at local scales, it is only recently that the capability has evolved to allow the application of classification models at regional, continental and global scales. The development of a comprehensive training, testing and validation site network for the globe to support supervised and unsupervised classification models is fraught with problems imposed by scale, bioclimatic representativeness of the sites, availability of ancillary map and high spatial resolution remote sensing data, landscape heterogeneity, and vegetation variability. The System for Terrestrial Ecosystem Parameterization (STEP), a model for characterizing site biophysical, vegetation and landscape parameters to be used for algorithm training and testing and validation, has been developed to support supervised land cover mapping. This system was applied in Central America using two classification systems based on 428 sites. The results indicate that 1) it is possible to efficiently generate site data at the regional scale, 2) implementation of a supervised model using artificial neural network and decision tree classification algorithms is feasible at the regional level with classification accuracies of 75-88 percent, and 3) the STEP site parameter model

is effective for generating multiple classification systems and thus supporting the development of global surface biophysical parameters (Muchoney *et al.,* 1999).

- *Walnut Gulch MODIS-Data Simulation Study Using Decision Tree and Neural Networks*
  In this study, a time series data set was used to examine feature selection and land cover classification for a MODIS-like scenario in a semiarid environment (Borak and Strahler, 1999). The data set consisted of numerous input fields derived from an intra-annual sequence of seven Landsat TM acquisitions, along with ancillary elevation information. A decision tree classifier selected the features that were most discriminatory, with respect to land cover, from the full measurement space. Three classification algorithms were applied to the reduced feature space: the decision tree itself, a maximum-likelihood classifier and an artificial neural network (Fuzzy ARTMAP). Results indicated that decision tree classifiers are useful tools for extracting essential features in data sets of high dimensionality, and that the neural network classified the reduced set of features with highest accuracies.

- *Global 1-Degree Classification Studies*
  Using an annual sequence of composited Normalized Difference Vegetation Index (NDVI) values from AVHRR data set composited to 1 degree, DeFries and Townshend (1994) classified eleven global land-cover types with a maximum likelihood classifier. Gopal *et al.* (1999) classified the same data using fuzzy ARTMAP. Their findings are (1) when fuzzy ARTMAP is trained using 80 percent of the data and tested on the remaining (unseen) 20 percent of the data, classification accuracy is more than 85 percent compared with 78 percent using the maximum likelihood classifier; (2) classification accuracies for various splits of training testing data show that an increase in the size of training data does not result in improved accuracies; (3) classification results vary depending on the use of latitude as an input variable similar to the results of DeFries and Townshend; and (4) fuzzy ARTMAP dynamics including a voting procedure and the number of internal nodes can be used to describe uncertainty in classification. This study shows that artificial neural networks are a viable alternative for global scale land cover classification due to increased accuracy and the ability to provide additional information on uncertainty.

- *Vegetation Mapping Using Neural Networks At TM Scales*
  We recently developed and tested a new system for mapping lifeforms and species associations based on fuzzy ARTMAP that directly integrates Landsat spectral data, terrain variables and geographic location. This approach requires many training sites, but once the data are collected, the processing stream is greatly simplified compared to the current operational methods. Our tests of this approach compare fuzzy ARTMAP results with those obtained by the current operational methods (*i.e.,* an "expert map") for the Sierra National Forest of eastern California. The results demonstrate that fuzzy ARTMAP (without editing) performs better than an expert unedited map and almost as well as an edited

expert map for Sierra Forest data. Fuzzy ARTMAP is also far superior to expert unedited map in predicting life form. The unedited expert map uses spectral data in predicting lifeform with an accuracy of 64 percent compared with the fuzzy ARTMAP's 78 percent for this same input, and 85 percent when terrain data are added. The neural network accuracies are almost as good as the expert edited map, while the expert edited map requires months of labor to make, requiring field work to identify natural regions and development of a set of terrain-based rules to derive species associations.

The voting strategy used in ARTMAP simulations can provide a measure of confidence and uncertainty for each prediction. Fuzzy ARTMAP uses an internal voting strategy which can be used to provide a measure of the confidence of its predictions. Our tests show that the accuracy of predictions is closely related to this confidence measure. This output from Fuzzy ARTMAP can be used in two ways. First, it can be used as a guide to highlight the areas where manual editing will be most effective. Second, it can provide an "uncertainty map" which can be used in conjunction with the vegetation map.

An application of the mixture algorithm in the Plumas National Forest of eastern California shows that fuzzy ARTMAP produces the best overall results. It is able to make accurate estimations of proportions of hardwood and conifer cover in sites where brush is not present in the understory. ARTMAP classification does better than maximum likelihood. It is able to predict 89 percent of total predictions within 20 percent range of accuracy while maximum likelihood predicts 74 percent within the same range. The RMS error for all classes (conifer, hardwood and barren) is less for fuzzy ARTMAP. We also tested the use of linear mixture models in this context using both an "exterior" and an "interior" set of spectral endmembers. ARTMAP outperforms these models by a substantial amount. ARTMAP predicts 96 percent of total sites within the 20 percent range compared with 76 percent for the exterior and 83 percent for the interior mixture models. Uncertainty information is provided by the fuzzy ARTMAP voting rule. Different ordering of the input set causes fuzzy ARTMAP to make different predictions. The voting process allows combination of the results from varying predictions. This process can be thought of as a committee of independent experts where the members of the committee vote during testing so that the predicted class is the one that receives the largest number of votes from the committee. This approach has two advantages. First, it can improve the classification accuracy, as indicated by some of our recent studies on land cover mapping at regional scales (Carpenter *et al.*, 1997). Second, it provides a way of evaluating uncertainty in the results on a pixel-by-pixel basis.

- *Decision Tree Studies*
  Decision tree classifiers present an alternative to neural networks in preparing the land cover product. Friedl and Brodley (1997) recently tested the performance of decision tree algorithms for land cover classification. Three different decision tree algorithms were tested on several different training data sets. The decision tree algorithms included univariate decision trees (UDT) (Breiman *et al.*, 1984), multivariate decision trees (MDT) (Brodley and Utgoff, 1995) and hybrid decision

trees (HDT) (Brodley, 1995). Univariate decision trees test a single feature at each internal node, whereas multivariate decision trees use linear combination tests to define the splitting criteria at each internal node. Hybrid decision trees employ multiple classification algorithms within the framework of a single decision tree structure. The performance of these algorithms was evaluated using three different datasets with different spatial, spectral and temporal properties. The first was the 1-degree AVHRR composited NDVI dataset of Los *et al.* (1994) that was used by Townshend and DeFries (1994) and Gopal, Woodcock and Strahler (1996) as described above. Training labels for these data were derived by DeFries and Townshend (1994). The second dataset tested was derived from the 1990 Conterminous US AVHRR Dataset compiled at EROS Data Center (Eidenshink *et al*., 1992) and consists of a time series of maximum NDVI values during each month of the growing season in 1990. Class labels were assigned to these data by reclassifying the labels provided by Loveland *et al.* (1991) to the IGBP classification (see section 2.3). The data used here were extracted at 10,000 random locations and exclude water bodies. The final dataset was composed of a random sample of roughly 2000 values of raw Landsat Thematic Mapper (TM) data acquired over a forested area surrounding Lake Tahoe, California. These data were extracted from a single image and include all TM bands except band 6 (thermal). Class labels were assigned using a combination of automated classification procedures that incorporated the use of ancillary data, manual labeling using field data, and aerial photography (Woodcock *et al*., 1994).

To evaluate the classification performance of each of the decision tree algorithms identified above, a set of ten cross-validation runs were performed using each classification algorithm to classify each of the datasets. To do this, each dataset was split into three parts: 70 percent training, 20 percent pruning, and 10 percent testing. In this way, the trees were estimated, pruned, and evaluated using independent data for each step. This procedure was repeated to generate ten versions of the data with different random combinations of training, pruning, and testing data. To provide a baseline of the performance of the decision tree algorithms a parallel cross-validation procedure was performed using both a maximum likelihood and linear discriminant function classifier. Results show that the decision tree algorithms consistently and significantly outperformed more conventional classification algorithms. Although for some classes maximum likelihood gave more accurate results, superior performance on the larger classes gave decision trees an overall accuracy advantage of 7-9 percent. It is notable that classification accuracies are in general lower for the NDVI 1-km and TM datasets than for the NDVI 1-degree dataset. At 1-km resolution, the data are significantly noisier than at one degree. The NDVI 1-km dataset suffers from multidate registration inaccuracies and is also not fully corrected for atmospheric effects. In contrast, the 1-degree dataset is filtered and smoothed (Los *et al*., 1994) as well as averaged over a much larger grid cell size. Note that both multidate registration and atmospheric correction will be much better for MODIS than for the AVHRR NDVI 1-km dataset. Noise and mixed pixels are also characteristic of the TM dataset (Woodcock *et al*., 1994).

In addition to this assessment of decision tree performance, Brodley and Friedl (1996) developed a consensus filter technique based on machine learning theory to filter training data for mislabeled observations. Given the importance of training data quality to the performance of both neural net and decision tree classification algorithms, this method is of potentially high utility for the implementation of operational land cover and land-cover change algorithms. Specifically, the technique provides an automated and objective method for tagging mislabeled observations in training data that are input to supervised classification algorithms (Brodley, 1995). To test this procedure, we simulated labeling errors in training data by randomly introducing error between classes that are likely to be confused in real data (*e.g.*, grassland versus wooded grassland). To do this we used the training dataset generated by DeFries and Townshend (1994) for 1^{o} the AVHRR composited NDVI dataset (Los *et al*., 1994). Results from this analysis show that the procedure is capable of detecting and removing fairly substantial levels of noise in training data. Note also that the procedure is amenable to use in training the classifier for the MODIS land cover product, since it operates on training data rather than the entire global dataset.

3.1.4.2 Land-Cover Change Parameter

Prelaunch and early postlaunch algorithm development of the Land-Cover Change Parameter has three primary objectives: (1) to validate the multitemporal change vector technique at broad spatial scales (continental) and over a decade or more of observations; (2) to refine the logic for land-cover change characterization; and (3) to define the linkage between the land-cover change technique and ancillary data (thematic information and high resolution information) for a more detailed monitoring of “hot spots” or areas of rapid change. This work extends the research of Lambin and Strahler (1994a, 1994b) on the application of change vector analysis to AVHRR LAC data from west Africa.

The objectives above require a long time series of high temporal-frequency satellite observations. Only AVHRR GAC data meet these requirements. There are two important sources of GAC data for this purpose. First is the AVHRR Pathfinder dataset, comprised of 12 years of daily cloud-screened GAC data that are calibrated, corrected for ozone absorption and Rayleigh scattering, and registered to a map projection. Another important time sequence of AVHRR data is the GAC dataset of the African continent produced by the Monitoring Tropical Vegetation Unit of the European Union’s Joint Research Center in Ispra, Italy. This dataset has already been used extensively in developing the change-vector technique by former Associate Team Member Eric Lambin (Lambin, 1996; Lambin and Ehrlich, 1996a, 1996b, 1997).

It is important to note that because the spectral bands of the AVHRR are limited, these data do not provide the full information content of the MODIS database. However, AVHRR data do provide the temporal signal that is expected to be most important in the detection and characterization of land-cover change. In the prelaunch period, algorithm development activities are focusing on understanding and exploiting the information content of the AVHRR temporal signal.

Specific near-term activities in algorithm development of the Land-Cover Change Parameter include: (1) continuing analysis of change vectors over ten years of African NDVI and surface temperature data; (2) validating the change magnitude and change processes that are detected using a variety of sources, such as FAO reports, FEWS Bulletins, NCAR Climate Impact Maps, published reports on land-cover change, and high resolution data analysis; and (3) defining typical temporal patterns of land-cover change to establish the basis of a future classification system for land-cover change processes.

The first and second of these near-term activities are already underway. For example, the utility of change vectors and other temporal metrics of land-cover change has been examined in sub-Saharan Africa (Borak, 1999). The metrics are derived from AVHRR Pathfinder data over sixteen test sites for which fine spatial resolution remote sensing data are available. Change is modeled in the fine-resolution data as a function of the coarse spatial resolution metrics without regard to the type of change. Results indicate that coarse spatial resolution temporal metrics (1) relate in a statistically significant way to aggregate changes in land cover, (2) relate more strongly to fine spatial resolution change metrics when including a measure of surface temperature instead of a vegetation index alone, and (3) are most effective as land-cover change indicators when various metrics are combined in multivariate models.

Since the change vector approach is appropriate for detecting subtle forms of change, the relationship of change vectors to interannual climate variability is also of interest. Over the continent of Africa, change vectors have been calculated from AVHRR Pathfinder data on a seasonal time step. The indicators that are employed in the change vector analysis are NDVI, Ts and the Ts/NDVI ratio. Comparison of these change vectors to measures of interannual climate variability shows that they relate both qualitatively and quantitatively, that stronger metric/climate couplings exist for some vegetation types than for others and that lag effects are also important (Borak, 1999). The qualitative comparisons are drawn by examining meteorological records from the period of data acquisition (1981–1991). Quantitative information consists of monthly Southern Oscillation Index data averaged over three month intervals during the same period of record as the satellite data.

3.1.5 Sources of Error and Uncertainty

Sources of error include preprocessing operations associated with development of the land cover product as well as problems with pre-processing of data provided to the land cover process. Two phases of processing are necessary for generation of the MODIS Land Cover Product: data compositing and data analysis. In the compositing phase, the 32-day composited databases are assembled from MODIS Level 3 inputs. In the analysis phase, a year of 32-day composites are processed by the land cover and land-cover change algorithms to produce the quarterly output products.

3.1.5.1 Inputs

Both the Land Cover and Land Cover Type Change Parameters rely on the 32-day 1-km gridded database MOD12M which accumulates appropriate MODIS Level 3 products. Inputs include (1) EOS land/water mask; (2) Nadir BRDF-Adjusted surface Reflectances

(NBARs) at a 1-km spatial resolution in the MODIS Land Bands (1-7) (MODIS Product MOD43B4); (3) daily spatial texture derived from Band 1 (red) at 250-m resolution; (4) directional reflectance information derived from the MODIS BRDF/Albedo Product (MOD43B1); (5) 16-day Enhanced Vegetation Index (EVI) (MOD13); (6) 8-day snow cover at 500m (MOD10A); (7) 8-day Land Surface Temperature (LST) at 1 km MOD11); and (8) ancillary terrain elevation information. The data are accumulated over a 32-day time period to produce a globally-consistent, multitemporal database on a 1-km grid as input to classification and change characterization algorithms. The ability to meet validation objectives may be influenced by changes in the input data. The input data can affect the land cover product because of the nature of the data or by affecting algorithm or process. This influence can be minimized if the algorithms are robust and promote multivariable, convergence-of-evidence approaches rather than relying on a single input parameter. At any rate, the nature and validity of input data must be monitored for its impact on land cover product validity.

3.1.5.2 Clouds

Persistent cloud cover will impede acquisition of high quality time trajectories of reflective or thermal data for use in characterizing land cover types. Even for a compositing period of 32 days, lack of cloud-free data will be a significant problem at some times of year in some regions, especially the humid tropics. Cloud screening occurs in the production of the products that are input to the composited database. Therefore, the problem for the Land Cover Product should be one of missing rather than cloud-contaminated data. The classifier will then have to work on the reduced time trajectory of available features.

3.1.5.3 Registration

Misregistration may be another significant source of error. Since each MODIS measurement is geolocated, this problem amounts to uncertainty in true geolocation (geolocation error is discussed in section 2.4).

3.1.5.4 Gridding and Binning

Multidate registration of Level-2 products to the Level-3 grid will be influenced by errors in geolocation. Excluding blunders, these are likely to be larger at larger scan angles. BRDF-fitted reflectance will be an improvement over selection by maximum value or by simply selecting against large view zenith angles. Output at 1-km resolution instead of the nominal 250-and 500-m resolutions for surface reflectance will reduce errors in spatial overlay.

3.1.5.5 Topographic Data Error

Elevation is a key factor in geolocation of pixels. Elevation also must be accommodated in atmospheric correction, since it influences path length as a function of view angle. We may expect that both of these sources of error will be substantially corrected prior to compositing in the production of input products.

3.1.5.6 Data Dependencies

Since the Land Cover Product uses other MODIS products such as vegetation index, snow cover and BRDF/Albedo products as well as a Land/Water Mask as inputs, its accuracy will depend partly on the accuracies of those products. However, it is not likely to be very sensitive to small errors in these input parameters. Based on the long history of successful land cover classification using remotely sensed data, we expect the spectral, spatial, temporal and directional signals to be quite robust in their information content for land cover, given that the instrument at least approaches its signal-to-noise ratio specifications. Because the classifier operates empirically, biases are not likely to be a problem as they might be for algorithms that produce quantitative geophysical parameters. Further, the accumulation process that assembles the products into the MOD12M 32-day database will read quality flags and discard low-quality observations wherever possible. For all data dependencies, it is necessary to track changes in inputs and their effect on algorithms, processing, flow, and product validity. Land cover and land-cover change are linked by the relationship of multitemporal characterization of land cover and multitemporal discrimination and description of land-cover change. This is manifest in the use of change detection to isolate multitemporal signal noise and change for validation of process and algorithm, as well as characterization of land cover types and optimization of field sampling.

3.1.5.7 Temporality

Error may be introduced when training and validation data are not temporally coincident with MODIS observation. This can especially be a problem with detecting and describing change. Although data aggregation and accumulation is prescribed, it will be necessary to define meaningful temporal generalizations of land cover based on successive observations. A further issue of temporality is assuring the temporal continuity of algorithms and processes.

3.1.5.8 Algorithm

Within the Land Cover Parameter, errors are generated when the classification algorithm selects the wrong class. With respect to a particular class, errors of omission occur when pixels of that class are assigned wrong labels; errors of commission occur when other pixels are wrongly assigned the label of the class considered. These errors occur when the signal of a pixel is ambiguous, perhaps as a result of spectral mixing, or when the signal is produced by a cover type that is not accounted for in the training process. These errors are a normal part of the classification process. They can be minimized, but not voided entirely. Although they cannot be identified on a pixel-by-pixel basis due to processing constraints, they can be characterized in a statistical sense.

3.1.5.9 Reference Data

Reference data include both test site data and ancillary land cover and other environmental data. The quality and availability of adequate training/validation data derived from field sites and existing maps and tabular data is the most limiting factor to land cover and land-cover change validation (Muchoney *et al.*, 1996). The quality of reference map data is a function of their inherent locational and thematic accuracy, while their utility may be restricted by incompatible classification systems or time of creation and validation.

Accuracy assessment of land cover products depends on the type and accuracy of reference ("truth") data comprising field observation, remote sensing and collateral data sources. For individual test sites, the utility and quality and of the ground truth will be variable. Data utility is influenced by the classification system that is applied or parameters that are derived for a site. Site data utility is also a function of the source data since this impacts discrimination of features; what is observable using TM does not necessarily translate (at least directly) into comparable MODIS-discernible features. Source data also influence the minimum mapping unit and dimension.

The factor which primarily affects the quality of reference data is the underlying accuracy of the ground truth classification which may not be known. The time difference for the source data used in developing a reference dataset, the reference (presumably field-based) date and the MODIS acquisition dates impact both utility and accuracy of test site data.

Because factors relevant to validation vary considerably from test site to test site, validation will require assessment of the utility and accuracy of data available at each test site and most probably reworking site data to extract information specifically useful to land cover and land cover change. This argues strongly for the development of a high-resolution reference dataset that might be derived from other remote sensing sources, standardization of classification subunits or parameters, standardization of procedures for deriving classification subunits and parameters and development of a global sampling scheme and associated database.

High spatial resolution imagery will be available from a number of sources including ASTER, which will be on the EOS-AM platform with MODIS, and the Landsat-7 ETM instrument, launched on 15 April 1999. With high spatial resolution data available, spatial heterogeneity of the test sites and the classes they contain can be further characterized and monitored. As a continuing data source, these instruments will also allow updating of land cover ground truth at test sites through the EOS era. Use of collateral remote sensing datasets such as TM and ASTER provide for a number of additional benefits of redundancy and complementarity that can be derived using data integration and data fusion techniques.

3.2 Practical Considerations

3.2.1 Numerical Computation Considerations

We do not anticipate problems with numerical stability and/or round-off errors.

3.2.2 Programming/Procedural Considerations

Two phases of processing are necessary for the MODIS Land Cover Product: data accumulation and data analysis. In the accumulation phase, the 32-day MOD12M databases are assembled from MODIS Level 3 inputs. In the analysis phase, twelve 32-day databases are processed by the land cover algorithm and by the land-cover change algorithm to produce the quarterly output products.

Allowing for quality flags, average daily volume will be approximately 4.1 GB. The processing power required is about 40 MFLOPS in order to assemble the 32-day database in one week. This power is about that of a mid-range engineering workstation. Similarly, in order to generate the quarterly products, about 250 MFLOPS of CPU will be required to produce the 6 GB output databases.

3.2.3 Postlaunch Validation

3.2.3.1 Land Cover Parameter

Proper validation of a global dataset is not a simple task. Whereas validation of a biophysical parameter might entail developing a quantitative estimate or sense for the physical meaning of the parameter under consideration (Kahn *et al.*, 1991), land cover validation provides an indication or estimate of confidence that a pixel or segment has been correctly labeled as to a thematic class. Therefore, validity is dependent on how we define land cover classes. If the objective is to place a bounded estimate on the global per-pixel accuracy of the classification, then a formal sample design, based on a random, random-stratified, or systematic spatial sample, is required (Cochran, 1977). Such a sample requires obtaining reference data at many locations on the globe. The cost of acquiring such knowledge is therefore prohibitive, given the postlaunch resources for validation available to the MODIS Land Team. Instead, we must turn to the test sites for which we have high-resolution land cover information available. Because the test sites are a biased sample, accuracy statistics derived at test sites cannot be regarded as proper statements of global accuracy. However, if the test sites are reasonably representative of their region as is planned, test site statistics can at least point to weaknesses and strengths in the dataset and allow users to anticipate how errors might impact their own research.

There are several approaches to the selection of pixels for comparison. First, accuracies may be reported by comparing the results obtained by the classifier in back-classifying training sites. Typically, this method is used to benchmark relative accuracy of classifiers rather than to establish a practical standard of accuracy. Given the nature of the algorithms, they back-classify (reclassify) training data to accuracies approaching 100 percent. Therefore, it is not useful to use this jackknife approach to assess thematic accuracy. Second, a set of test samples that is separate from training samples may be classified. We have adopted evaluating accuracy by both splitting the site data into sets of training and independent testing subsets based on an 80/20 train-to-test ratio by both pixels and by polygons (sites) and reporting both accuracies (Friedl *et al.*, 1999). Note that for convenience in processing, training pixels are sometimes included in this set when they comprise only a small proportion of the total test pixels. If these samples are selected according to a proper sample design, accuracies obtained by this method can be used to establish overall and per-class classification accuracy for the domain sampled (Green *et al.*, 1993). They may also be used to place bounds on areal estimates of coverage by class within the domain (Cochran, 1977).

Accuracy assessment has progressed through four development epochs over the last 25 years. The present stage may be described as the age of the error (confusion) matrix (Congalton, 1994). Classification accuracy is described using tables that document errors of commission and omission by cross-tabulating per-pixel labels output by the classifier with labels obtained from ground truth mapping or by classification of higher-resolution imagery (Story and Congalton, 1986). The kappa coefficient (Cohen, 1960) has become a standard statistic to evaluate overall classification accuracy, providing a more realistic estimation than a simple percentage agreement value. The kappa coefficient considers all cells in the confusion matrix, providing a correction for the proportion of chance agreement between the reference and test data sets (Rosenfield and Fitzpatrick-Lins, 1986). A *Z*-statistic can also be used as a pair-wise test of significance between two techniques based on the error matrices at specified probability levels (Congalton *et al.*, 1983). However, it has been found that kappa overestimates the proportion of chance agreement and consequently underestimates overall accuracy (Foody, 1992). Ma and Redmond (1995) present an alternative statistic for assessment of overall classification accuracy, the tau coefficient. This statistic is based on a *priori* probabilities of class membership rather than the *a posteriori* probabilities that are the basis for kappa. Tau is reported to better adjust percentage agreement to compensate for chance agreement, and to be easier to calculate and interpret. As with kappa, pair-wise tests of significance may be performed.

The confusion-table approach to accuracy assessment operates on the paradigm that each sample can be properly labeled into a single class, both by the classifier and by the process that establishes the ground reference (truth) data. It should be recognized that classification accuracy assessment may contain either conservative or optimistic bias. Simple interpretation of confusion matrices and related statistics without consideration of these error sources in the reference data may generate misleading conclusions (Verbyla and Hammond, 1995; Hammond and Verbyla, 1996). Sources of conservative bias in accuracy assessment (*i.e.* factors that reduce observed accuracies) include registration errors between reference and test data sets, use of a minimum mapping unit that is larger than the size of pixels in the classified image (Verbyla and Hammond, 1995), and the assumption that the reference data are perfectly correct (Congalton and Biging, 1992; Congalton and Green, 1993). Sources of optimistic bias (*i.e.* factors that increase observed accuracies) include sampling from training sites, non-independence of reference and training data and sampling from homogenous blocks of pixels (Hammond and Verbyla, 1996).

Accuracy statements about the product clearly depend on the accuracy of the ground truth. For individual test sites, the quality of the ground truth will be variable. Factors affecting the quality of the ground truth include (1) the underlying accuracy of the ground truth classification; (2) the units of land cover classification at the test site and their correspondence with those of the Land Cover Parameter; and (3) the difference in time between the acquisition of ground truth data and the remotely sensed data that are classified. Because these factors will vary from test site to test site, validation will require an individualized assessment of the characteristics of the product within ecoregions.

As an assessment of the accuracy of each land cover product, we will embed in each tile the confusion table for the continental region to which it belongs. The confusion table will be generated from unseen training sites and thus be the most conservative estimate of accuracy. In addition, we will provide as ancillary data a set of within-class error variances derived from the cross-tabulations that can be used to set standard errors on areal aggregations, as well as a discussion and interpretation of accuracy issues and areal aggregation statistics that is geared to applications of the land cover parameter.

This validation strategy is similar to that adopted by the IGBP-DIS Land Cover Validation Working Group for the IGBP-DIS Global Land Cover Database (IGBP-DIS, 1995; see section 2.3.2). IGBP has undertaken analyses of classification accuracy and other characterization activities at a network of core and confidence sites (see section 3.1.3). The IGBP confidence sites use a subset of Boston University's STEP site parameters to characterize land cover at their 400 global sites. We are compiling the confidence site data into our global STEP site database for use in training, testing and validation.

The IGBP-DIS global land cover sites were selected by a formal sample design. At the confidence sites, high resolution imagery (TM or SPOT) were photointerpreted to validate the label of each pixel selected for sampling. The core and confidence site analyses were conducted in October 1998. Boston University is leading the development of the land cover confidence sites, providing this global dataset as a web resource.

Another important factor in test site analysis for product validation is that high spatial resolution imagery will be obtainable from two sources: ASTER, which will be on the Terra platform with MODIS, and the Landsat-7 ETM instrument, which was launched in April 1999 in a near-simultaneous orbit with Terra. With high spatial resolution data available, spatial heterogeneity of the test sites and the classes they contain can be readily characterized and monitored. Further, as a continuing data source, these instruments will allow updating of land cover ground truth at test sites through the EOS era.

3.2.3.2 Land-Cover Change Parameter

Validating land-cover change maps is a complex task since it requires the observation of land-cover characteristics before and after an area is affected by a process of change. Our global test site development initiative (see Section 3.1.3) is producing an a priori list of test sites for land-cover change validation based on a sampling, deforestation fronts, ecotones and ecological gradients, record of current change processes and hot spots where human pressure is high and where it is likely that land-cover conversion will take place. In most areas, a time interval of several years is necessary to detect significant land-cover changes and to be able to characterize accurately change processes and impacts. The case of the African Sahel is exemplary: several authors have shown that the interannual climatic variability in this region is such that only time series longer than a decade would allow for detection of any secular trend in land-cover change (Tucker *et al.*, 1991; Hellden, 1991). In addition to developing a sampling scheme for validating land-cover change, we are increasing our efforts in site-level analysis of change processes using AVHRR, Landsat and MODIS-simulated data.

3.2.4 Quality Control and Diagnostics

Quality control follows the MODLand Quality Assurance (QA) Plan. The plan outlines run-time and post run-time QA procedures for MODLand standard products. The QA data fields consist of those mandated by ECS, those common to all MODLand products, and product-specific metadata. Run-time QA information is generated in the production environment, and is either spatially explicit (per-pixel) or global (per-tile) in scope. Mandatory MODLAND QA is generated on a per-pixel basis. The 8-bit flag associated with MOD12Q1 consists of 3 cloud-state bits, 1 bit describing product usefulness and up to 4 additional bits for product summary as specified by the science team member responsible for each product. In the case of MOD12Q1, the land/water mask is retained in this portion of the QA.

Run time quality assurance data specific to the Land Cover Parameter is given separately as an 8-bit Land Cover Assessment data field and primarily conveys confidence in the label of each grid cell. Per tile accuracy tables and statistics are maintained in the Core Metadata as additional parameters. Run time QA issues related to the Land-Cover Change Parameter are still in early research stages owing to the post-launch status of the data product. Post run time QA is generated at the SCF and at the Land Data Operational Product Evaluation (LDOPE) facility, a centralized QA installation. The main role of the LDOPE is to carry out routine QA evaluation, while the SCF staff handles situations that require greater scientific expertise. When data fail any quality test at the DAAC or LDOPE (as defined by either ECS or the SCF), the SCF will be notified by the DAAC or LDOPE. At that point, SCF staff may elect to examine the data at the SCF, or in cooperation with LDOPE personnel. Results of post run time QA are then sent to the DAAC, where they are included as part of the mandatory ECS metadata.

3.2.5 Exception Handling

Exception handling, which covers data generated during infrequent events such as platform maneuvers, eclipses, and the like, will primarily be the responsibility of the input products. Thus, these events will produce missing data fields.

3.2.6 Data Dependencies

Since the Land Cover Product uses Level-3 products as inputs, its accuracy will depend partly on the accuracies of those products. However, it is not likely to be very sensitive to small errors in these input parameters. Based on the long history of successful land cover classification with remotely sensed data, we expect the spectral, spatial, temporal and directional signals to be quite robust in their information content for land cover, given that the instrument at least approaches its signal-to-noise ratio specifications. And, because the classifier operates empirically, biases are not likely to be a problem, as they might be for algorithms producing quantitative geophysical parameters. Further, the accumulating process that assembles the products into MOD12M will read quality flags and discard low-quality observations wherever possible.

3.2.7 Output Products

Output from the Land Cover Product and the Land-Cover Change Product are encoded as categorical variables that are stored as byte data. We anticipate releasing the first Land Cover Parameter at 15 months after launch, revising the product quarterly thereafter. Prototype products will, however, be generated beginning with the availability of MODIS data. The first Land-Cover Change Parameter will be released 27 months after launch, based on two years of monthly composites. As in the case of Land Cover, prototype change products will be produced as data become available. The Land Cover GCM Product is especially tailored for global climate modeling at coarse resolutions. It will be provided on a quarterly basis and will contain the proportions and areal estimates associated with each land cover class within a 1/4-degree grid cell. Accompanying each byte will be approximately 15 bytes of attribute information which consist of entries such as quality flags and data-field characteristics. The global data volume per parameter is about 8.8 GB.

4. Constraints, Limitations, Assumptions

Constraints, limitations and assumptions are discussed in appropriate sections *ad seriatim* in the preceding text of this document. For example, both the Land Cover and Land-Cover Change Parameters require properly registered and resampled data that are cloud-screened and atmospherically corrected (sections 3.1.1.1.1, 3.1.5).

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Figure 1. Land Cover Parameter process flow

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Figure 2. Land-Cover Change Parameter process flow.

Appendix A. Product Accuracy and Sensitivity Document

(Prepared 09/17/98)

Product accuracy and sensitivity summary: MODIS Land Cover/Land-Cover Change

PRODUCT NAME: Land Cover/ Land-Cover Change

PRODUCT NUMBER: MOD12

Coverage: global land

Spatial/temporal characteristics: 1000m and 1/4 degree resolution, 96-day (quarter-annual)

Science team member and point of contact:

Alan H. Strahler, Team Member, Boston University: alan@bu.edu

Douglas M. Muchoney, Associate Team Member, Boston University: muchoney@bu.edu

SHORT DESCRIPTION of the product

The Land Cover/ Land-Cover Change products comprise:

MOD12, parameter number 2669, land cover type, 1-km, 96-day

MOD12, parameter number TBD, land cover type - Climate Modeler's Grid (CMG); 1/4 degree, 96-day

MOD12, parameter number 2671, land-cover change, 1-km, 96-day

The Land Cover and Land-Cover Change 1-km Parameters rely on a 1-km 32-day gridded database assembled from MODIS Level 3 products produced on 8- or 16-day cycles:

Input	Source	Description	Timestep
BRDF	MODIS BRDF	shape information	32-day
location	MODIS Geolocation	latitude/longitude	fixed
land/water	USGS Land/Sea Mask initially (eventually based on on previous quarterly MODIS Land Cover)	terrestrial/ marine boundary	fixed fixed
reflectance	MODIS Reflectance	BRDF-adjusted, 7-channel nadir reflectance	32-day
snow/ice	MODIS Snow/Ice	snow and ice	32-day
surface temp.	MODIS Surface Temp.	maximum	16-day
texture	MODAGG	max texture based on 250m channel 1	32-day
topography	USGS DEM	slope aspect, slope gradient, elevation	fixed
vegetation index	MODIS VI	EVI	16-day

The 1-km inputs are aggregated into monthly datasets, and a rolling 12-month set of over 250 features is used to generate the quarterly Land Cover Product. Classification is based on applying supervised artificial neural network and decision tree classifiers to the inputs using site-based training labels. The land cover types are based on the 17-class IGBP classification system. Global ecosystem and vegetation types will also be provided. The 1-km Land Cover data will also be generalized to the CMG 1/4 degree grid.

The 1-km Land-Cover Change parameter is designed to quantify subtle and progressive land surface transformations, as well as instantaneous changes such as land cover conversions. The algorithm for the Land-Cover Change Parameter combines analyses of changes in multispectral/ multitemporal data vectors with models of vegetation change mechanisms to recognize both the type and intensity of change.

Optimal conditions for derivation from EOS data:

Most (or all) input features available for 12 monthly periods

Non-optimal conditions:

Reduced features due to cloud cover, instrument failure, or problems with the algorithms and production of other MODIS products used as input.

Other caveats:

A global dataset of sites is required that can be used to train the classification algorithms and to validate the global land cover product

Physical quantity 1: Land Cover type @ 1-km

THEORETICAL ACCURACY: TM and NOAA AVHHR data indicate that classification accuracies of 70-90 % for IGBP land cover types may be expected under optimal conditions.

PRELAUNCH VERIFICATION:

Pre launch verification is based on testing our classification procedure using operational algorithms and code on 1-km AVHRR data and on simulated MODIS data. Validation data are a network of sites which are described by their primary structural, physiognomic, physical and morphological attributes. Development of this Validation and Test Sites (VATS) database allows for quantified, statistical measure of classification accuracy based on contingency table analysis and measures of agreement. Boston University has developed site data for supervised classification and accuracy of Central America, and will complete a comprehensive testing and validation site database for North America by mid-October 1998.

ALGORITHM VALIDATION:

We have performed a number of studies to test algorithm performance using remote sensing data.

Global 1-degree AVHRR Dataset

We applied neural network, decision tree and maximum-likelihood classifiers to the 1-degree AVHRR FASIR dataset using a train and test site database developed by DeFries and Townshend (1994). These train/test data are based on agreement of the global land cover and vegetation maps of Matthews (1983), Olson (Olson and Watts 1982; Olson *et al.*, 1983) and Wilson and Hendersen-Sellers (1985). Table 1 provides the results of these tests with the neural network and maximum-likelihood classifiers using 80% of the global pixels to train and 20% to independently test results, while the decision tree classifiers used 70% to train, 20% to prune the tree and 10% to test. In addition to the monthly composited AVHRR NDVI data, the neural network classification was performed with and without latitude as an ancillary variable.

Multiscale Testing

The performance of the decision tree and maximum-likelihood classification algorithms was tested using three different datasets with different spatial, spectral and temporal properties. The first was a 1-degree composited AVHRR dataset (Los *et al.*,1994), using training labels developed by DeFries and Townshend (1994). The second dataset was derived from the 1990 Conterminous US AVHRR Dataset compiled at EROS Data Center (Eidenshink,1992) and consists of a time series of maximum monthly NDVI values during each month of the growing season in 1990. Class labels were assigned to these data by reclassifying the labels provided by Loveland *et al.* (1991) to the IGBP classification system. The data were extracted at 10,000 random locations exclusive of water bodies. The third dataset was composed of a random sample of approximately 2000 values of raw Landsat Thematic Mapper data acquired for a forested area near Lake Tahoe California. Class labels were assigned using techniques reported in Woodcock *et al.* (1994). Overall results are summarized in Table 2, with the ARTMAP neural network classifier only applied to the 1-degree dataset.

Central America Study

Multitemporal NOAA-AVHRR satellite data were used to apply supervised classifications based on artificial neural network, decision tree, and maximum-likelihood classifiers. The AVHRR data of USGS were monthly composited using maximum NDVI to remove cloud and topographic effects and extreme off-nadir pixels (Holben 1986; Eidenshink and Faundeen 1994), as well as scan angle dependence of radiance (Duggin *et al.*, 1982). Plot/site data were obtained through feature extraction at some 450 sites based on Landsat TM, Satellite pour l'Observation de la Terre (SPOT), AVHRR, and existing vegetation and land cover data. Table 3 provides a summary of classification results based on five random samples of the site data into training (80%) and testing (20%) subsets.

The results indicate that regional, continental and global classification and validation are feasible using our site database. Accuracies of greater than 80% were achieved for most classes and should improve significantly using 7-band MODIS data.

POSTLAUNCH VERIFICATION:

Postlaunch verification will be based on independent training and testing, and contingency table analysis to quantify classification accuracies using our global test site database. In addition, we have intensive study sites that will provide detailed information on classifier performance.

Physical quantity 2: Land-Cover Change

THEORETICAL ACCURACY:

The thematic accuracy target for land-cover change is to equal or exceed 80% overall.

PRELAUNCH VERIFICATION:

Pre launch verification is based on site-based testing, especially in the southwest US and Africa. Because this product depends on at least two years of global-scale, 7-band, well-registered data, it cannot be easily prototyped in the prelaunch period.

POSTLAUNCH VERIFICATION:

Post launch verification will be based on independent training and testing, and contingency table analysis to quantify classification accuracies using our global test site database. In addition, we have intensive study sites that will provide detailed information on classifier performance for change detection.

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Table 1. Classification Results for AVHRR Composited NDVI 1° Dataset (percent)

Land Cover Category	total train/test pixels	ARTMAP with Latitude	ARTMAP without Latitude	Maximum-Likelihood	Univariate Decision Tree	Multi-variate Decision Tree	Hybrid Decision Tree
Broadleaf evergreen forest	628	97.6	91.3	84.0	95.7	96.1	96.3
Coniferous evergreen forest/woodland	320	68.8	53.1	69.0	81.0	80.0	78.1
High latitude deciduous forest/woodland	112	86.4	90.9	100.0	85.4	92.7	99.1
Tundra	735	95.9	94.6	86.0	94.5	94.7	95.1
Mixed deciduous and evergreen forest/woodland	57	63.6	72.7	40.0	34.0	56.0	58.0
Wooded grassland	212	88.1	45.2	95.0	82.9	86.7	86.7
Grassland	348	80.0	68.6	35.0	70.6	66.2	70.3
Bare ground	291	100.0	89.7	100.0	95.2	95.6	97.3
Cultivated	527	74.3	79.5	81.0	76.6	78.5	80.2
Broadleaf deciduous forest/woodland	15	0.0	0.0	100.0	0.0	0.0	0.0
Shrubs and bare ground	153	80.6	77.4	100.0	84.7	86.0	92.7
Pixel total	3398						
Overall accuracy		86.6	76.7	78.8	85.6	86.4	87.7

Table 2: Multiscale Classification Results

Classification Method	**NDVI 1°**	**NDVI 1-km**	**TM**
Univariate decision tree	85.6	71.0	75.2
Multivariate decision tree	86.4	71.7	75.9
Hybrid decision tree	87.7	80.1	76.0
Linear discriminant functions	78.7	51.7	70.6
Maximum-likelihood classifier	78.8	62.2	69.0
Fuzzy ARTMAP neural network	85.7	na	na

Table 3. Central America Classification Results (% classification accuracy)

IGBP Class	class name	train/test pixels	DTC: non-boosted	DTC: boosted	Gaussian ARTMAP	Fuzzy ARTMAP
1	Evergreen needleleaf forest	1515	74.87	88.18	84.49	79.00
2	Evergreen broadleaf forest	3575	84.55	96.15	91.55	79.00
3	Deciduous needleleaf forest					
4	Deciduous broadleaf forest	370	63.82	81.97	75.41	83.90
5	Mixed forest	845	65.55	82.18	72.31	76.90
6	Closed shrublands	125	54.15	58.40	46.40	83.00
7	Open shrublands	335	65.66	83.61	82.69	93.00
8	Woody savannas	470	65.12	82.46	77.66	85.80
9	Savannas	60	34.25	37.58	15.00	78.10
10	Grasslands	845	70.48	85.38	78.22	81.20
11	Permanent wetlands	800	65.92	78.17	72.00	80.60
12	Croplands	1950	70.37	86.96	83.69	68.00
13	Urban and built-up	265	57.25	77.69	71.32	82.90
14	Cropland mosaics	365	68.62	83.42	76.99	91.70
15	Snow/Ice					
16	Barren or sparsely vegetated	35	29.83	81.83	28.57	72.20
17	Water bodies	440	98.48	98.89	97.05	95.40
accuracy			74.79	88.16	82.77	79.30