Implications of Land-Cover Misclassification for Parameter Estimates in Global Land-Surface Models: An Example from the Simple Biosphere Model (SiB2)

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Abstract

One of the primary applications of the global 1-km land-cover DISCover product is to derive biophysical and ecological parameters for a range of land-surface models, including biosphere-atmosphere, biogeochemical, and ecological models. The validation effort reported in this special issue enables a realistic assessment of the implications of misclassification errors for parameter estimates within the models. In most land-surface models, cover types are aggregated to coarser groupings than the 17 IGBP classes for estimating parameters, with aggregation schemes varying with individual models and individual parameters within each model. Misclassification errors are consequential only when they occur between cover types that are not aggregated by the model. We use examples of two biophysical parameters—leaf area index and surface roughness—as estimated for use in the Simple Biosphere Model (SiB2) and other modeling applications to quantify the effects of misclassification on parameter estimates. SiB2 relies on satellite data as well as land-cover information for estimating the biophysical parameters. Consequences of misclassification are likely to be greater for those models that do not use satellite data. Mean class accuracy based on those sites for which a majority of interpreters agreed (percentage of validation pixels classified correctly out of total number of validation pixels, averaged over all classes), adjusted by area of each cover type in the IGBP DISCover product, is 78.6 when all misclassification errors are included. By excluding misclassification errors when they are inconsequential for leaf area index and surface roughness length estimates, mean class accuracies are 90.2 and 87.8, respectively. The results illustrate that misclassification errors are most meaningfully viewed in the context of the application of the land-cover information.

Introduction

One of the fundamental requirements of global land-surface models is an accurate description of the vegetative cover on the Earth's land surface. Biosphere-atmosphere models describing exchanges of water, energy, and carbon between the land surface and the atmosphere, for example, have become increasingly sophisticated over the past 20 years (Sellers *et al.*, 1997). Such models now allow more realistic representations of land-atmosphere interactions within atmospheric general circulation models than the greatly oversimplified representations in previous generations of models. These advances are essential contributions towards fully coupled land/atmosphere/ocean models aimed ultimately toward a better understanding of the biological and physical responses of the Earth system to increasing atmospheric carbon dioxide concentrations, land-use change, and other types of global change.

Land-cover types are generally used indirectly in land-surface models to assign values to parameters that are then used for model calculations (Dickinson, 1995). For example, values for albedo will be assigned at least partially according to land-cover type based on local measurements or appropriate values from the literature. Numerous other parameters are assigned according to cover type, including surface resistance, leaf area index, and a large number of optical properties of the vegetation (Dickinson, 1995; Henderson-Sellers *et al.*, 1993). The degree to which parameter estimates rely on knowledge of land-cover type depends on the degree to which the particular model uses other sources of information about the land surface. Biosphere-atmosphere models, e.g., the second version of the Simple Biosphere Model (Sellers *et al.*, 1996), and biogeochemical models, e.g., CASA (Potter *et al.*, 1993; Field *et al.*, 1995), which use satellite data in addition to land cover, have reduced reliance on a land-cover classification because the satellite data inherently describe the spatial heterogeneity and other characteristics of the land surface. On the other hand, models which do not rely on satellite data (Dickinson *et al.*, 1993; Parton *et al.*, 1993) are more sensitive to errors in the land-cover classification.

Prior to the development of land-cover classifications derived from satellite data such as the IGBP DISCover product and others (DeFries and Townshend, 1994b; DeFries *et al.*, 1998; Hansen *et al.*, in press), these models relied on global land-cover data sets compiled from ground-based sources known to have a number of sources of errors, notably a lack of consistent definitions of cover types and source data collected at varying times with varying reliability Townshend *et al.*, 1991; DeFries and Townshend, 1994a). The creation of global land-cover data sets from satellite data alleviates some of these

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sources of error because they are based on internally consistent measurements, but, as described in this issue, errors do occur from noisy data, erroneous ancillary data, or mislabeling. Errors in land-cover classifications, whether ground-or satellite-based, propagate into the parameter estimates within the model and ultimately affect the accuracy of the water, energy, and carbon exchanges and, subsequently, the accuracy of other coupled models. While a systematic study of the sensitivity of model results to land-cover classification errors has not been carried out (Henderson-Sellers *et al.*, 1993), clearly the sensitivity depends largely on the particular details of the model. In many cases, the look-up tables which assign parameter values aggregate the land-cover types into coarser land-cover categories; for example, all forest types might be aggregated for assignment of a parameter which does not depend on knowledge of whether the forest is needleleaf or broadleaf. In this case, errors in land-cover classification between needleleaf and broadleaf forest types have no adverse consequence for the parameter estimate. Such information is essential in order to more fully interpret the results of the validation effort and to set priorities for future revisions of the IGBP DISCover product.

In this paper, we explore the consequences of misclassification errors in the IGBP DISCover product, as quantified by the validation effort reported in this special edition, on parameter estimation in biosphere-atmosphere models. Because of the large number of models and the numerous parameters that are at least partially dependent on cover type within each model, we choose to illustrate the sensitivity of parameter estimates to classification errors for two biophysical parameters, leaf area index and surface roughness, as estimated for use in the Simple Biosphere Model (SiB2) and other modeling applications.

Derivation of Biophysical Parameters for the Simple Biosphere Model

The Simple Biosphere Model (SiB2) (Dorman and Sellers, 1989; Los, 1998; Sellers *et al.*, 1996) was designed for use in atmospheric general circulation models to describe the climatogically important interactions between the terrestrial biosphere and the atmosphere, including fluxes of radiation, momentum, sensible heat, and latent (evapotranspiration) heat. Early versions of the model (simple SiB) did not use satellite data to estimate biophysical parameters. Later versions (SiB2) include a more realistic model of leaf photosynthesis and conductance and use satellite data along with maps of land cover and soil type to drive the model (Sellers *et al.*, 1996).

In addition to a large number of time-invariant land-surface properties stratified by land-cover type, SiB2 requires time-varying fields of three parameters—fraction photosynthetically active radiation (FPAR), leaf area index (LAI), and surface roughness length—to calculate the carbon assimilation or gross photosynthesis in addition to fluxes of heat, water, and momentum (Sellers *et al.*, 1996). Algorithms for calculating the three parameters are given in Sellers *et al.* (1996) and Sellers *et al.* (1994). These algorithms have subsequently been revised based on field measurements as described in Los (1998) and Los and Pollack (submitted).

In summary, monthly values of the Normalized Difference Vegetation Index (NDVI) are used to estimate FPAR, which in turn are used to estimate leaf area index (Figure 1). Surface roughness length is then derived from the leaf area index. The FPAR derivation is according to the following:

$$\mathrm{FPAR} = 0.5\mathrm{FPAR}_{\mathrm{NDVI}} + 0.5\mathrm{FPAR}_{\mathrm{SR}}$$

where

$$\mathrm{FPAR}_{\mathrm{NDVI}} = (((\mathrm{NDVI}-\mathrm{NDVI}_{\min})*0.94)/\mathrm{NDVI}_{\max}-\mathrm{NDVI}_{\min}) + 0.01,$$

$$\mathrm{FPAR}_{\mathrm{SR}} = ((\mathrm{SR}-\mathrm{SR}_{\min})*0.94/\mathrm{SR}_{\max}-\mathrm{SR}_{\min}) + 0.01,$$

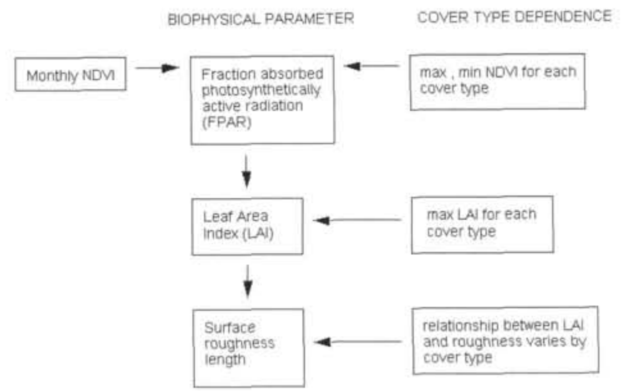

Figure 1. Derivation of biophysical parameters as used in the Simple Biosphere Model (SiB2).

$\mathrm{SR} = (1 + \mathrm{NDVI})/(1-\mathrm{NDVI})$, and
$\mathrm{NDVI}_{\max}$ and $\mathrm{NDVI}_{\min}$ are the maximum and minimum NDVI values for each cover type.

The only dependency on land-cover type in the FPAR derivation is the scaling of the NDVI value based on the maximum and minimum NDVI for each cover type. Hence, the FPAR estimate is primarily driven by the NDVI value and not the cover type.

Green leaf area index is subsequently estimated from the FPAR estimate according to

$$L_{g,fv} = \log(1-\mathrm{FPAR}_{fv})L_{\max,i}/\log(0.05)$$

where $L_{g,fv}$ is the green leaf area index for vegetation cover fraction fv, FPARfv = FPAR/fv, $L_{\max,i}$ = maximum leaf area index for

TABLE 1. MAXIMUM LEAF AREA INDEX AND SURFACE ROUGHNESS LENGTH VALUES FOR DERIVATION OF BIOPHYSICAL PARAMETERS. SiB CLASSES AND THE CORRESPONDING IGBP CLASSES ARE LISTED.

Maximum LAI (m^2/m^2)	Surface Roughness Length (m) for LAI = 2	SiB Class	IGBP Class
7	3	1 Evergreen broadleaf	2 Evergreen broadleaf forest
7	0.8	2 Broadleaf deciduous	4 Deciduous broadleaf forest
7.5	1	3 Broadleaf and needleleaf	5 Mixed forest
8	1.1	4 Evergreen needleleaf	1 Evergreen needleleaf forest
8	1.1	5 Deciduous needleleaf	3 Deciduous needleleaf forest
5	0.15	6 Subtropical drought deciduous woodland	9 Savanna
5	0.15	7 Grassland and shrub cover	10 Grasslands
5	0.15	8 Evergreen broadleaf woodland	8 Woody savanna
5	0.1	9 Shrubland with bare soil	7 Open shrubland
5	0.1	10 Tundra	6 Closed shrubland
5	0.15	11 Bare soils	16 Barren
5	0.15	12 Agriculture	12 Croplands
			14 Croplands/natural vegetation mosaic

Table 2. Confusion Matrix for IGBP DISCover Global 1-Km Land-Cover Classification Based on the Validation Samples. Samples for which a Majority of Interpreters Agreed on the Cover Type Were Used to Construct the Matrix. Values Are Percentages of Samples for the Cover Type. Columns Are the Cover Type in the IGBP DISCover Product, Rows Are Cover Types Identified in the Validation Effort.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	75.00	0	0	0	5.00	0	0	0	0	0	5.00	5.00	0	5.00	0	5.00	0
2	0	87.50	0	0	0	0	0	0	0	0	4.17	0	0	4.17	0	4.17	0
3	0	0	55.56	0	0	0	0	0	0	0	22.22	22.22	0	0	0	0	0
4	0	0	0	62.50	6.25	0	0	0	0	0	0	18.75	0	6.25	0	0	0
5	4.55	0	0	4.55	68.10	0	13.64	0	0	0	0	4.55	0	4.55	0	0	0
6	0	0	0	0	0	75.00	0	0	0	5.00	5.00	0	0	0	0	5.00	10.00
7	0	0	0	0	0	0	87.50	0	0	4.35	0	0	0	0	0	8.33	0
8	0	0	0	0	0	0	0	69.23	15.38	3.58	0	11.54	0	0	0	0	0
9	0	0	0	0	0	0	0	17.65	64.71	0	0	5.88	0	11.76	0	0	0
10	0	0	0	0	0	0	5.00	0	0	75.00	0	10.00	0	5.00	0	5.00	0
11	7.69	0	0	0	0	0	38.46	0	0	7.69	38.46	0	0	0	0	7.69	0
12	0	0	0	0	0	0	0	0	0	4.76	0	85.71	4.76	4.76	0	0	0
13	0	0	0	0	8.33	0	0	0	0	0	0	8.33	66.67	8.33	0	4.17	4.17
14	8.70	13.04	0	0	4.35	0	0	0	0	0	0	13.04	4.35	56.52	0	0	0
15	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.0	0
17	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

cover type i, and fv is estimated by scaling the maximum FPAR value over the year in each grid cell by the maximum possible FPAR (0.95). The value for maximum leaf area index varies according to cover type (Table 1); hence, LAI is moderately dependent on cover type.

Surface roughness length is calculated from leaf area index using a cover type-dependent look-up table that was calculated with a first-order closure model (Sellers *et al.*, 1989). The look-up table provides values for surface roughness length for each cover type for different values of LAI. Roughness length is

Table 3. Sensitivity of the Derivation of Leaf Area Index (Table 3a) and Surface Roughness Length (table 3b) for Use in SiB2 to Land-Cover Classification Errors. 0 Indicates that Estimate Is not Sensitive to Confusion between the Cover Types in the Row and Column and 1 Indicates that the Estimate Is Sensitive. Cover-Type Codes Are for IGBP Classes.

(a)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	—	1	0	1	1	1	1	1	1	1	—	1	—	1	—	1	—
2	1	—	1	0	1	1	1	1	1	1	—	1	—	1	—	1	—
3	0	1	—	1	1	1	1	1	1	1	—	1	—	1	—	1	—
4	1	0	1	—	1	1	1	1	1	1	—	1	—	1	—	1	—
5	1	1	1	1	—	1	1	1	1	1	—	1	—	1	—	1	—
6	1	1	1	1	1	—	0	0	0	0	—	0	—	0	—	0	—
7	1	1	1	1	1	0	—	0	0	0	—	0	—	0	—	0	—
8	1	1	1	1	1	0	0	—	0	0	—	0	—	0	—	0	—
9	1	1	1	1	1	1	0	0	—	0	—	0	—	0	—	0	—
10	1	1	1	1	1	0	0	0	0	—	—	0	—	0	—	0	—
11	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
12	1	1	1	1	1	0	0	0	0	0	—	—	—	0	—	0	—
13	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
14	1	1	1	1	1	0	0	0	0	0	—	0	—	—	—	0	—
15	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
16	1	1	1	1	1	0	0	0	0	0	—	0	—	0	—	—	—
17	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

(b)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	—	1	0	1	1	1	1	1	1	1	—	1	—	1	—	1	—
2	1	—	1	1	1	1	1	1	1	1	—	1	—	1	—	1	—
3	0	1	—	1	1	1	1	1	1	1	—	1	—	1	—	1	—
4	1	1	1	—	1	1	1	1	1	1	—	1	—	1	—	1	—
5	1	1	1	1	—	1	1	1	1	1	—	1	—	1	—	1	—
6	1	1	1	1	1	—	0	1	1	1	—	1	—	1	—	1	—
7	1	1	1	1	1	0	—	1	1	1	—	1	—	1	—	1	—
8	1	1	1	1	1	1	1	—	0	0	—	0	—	0	—	0	—
9	1	1	1	1	1	1	1	0	—	0	—	0	—	0	—	0	—
10	1	1	1	1	1	1	1	0	0	—	—	0	—	0	—	0	—
11	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
12	1	1	1	1	1	1	1	0	0	0	—	—	—	0	—	0	—
13	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
14	1	1	1	1	1	1	1	0	0	0	—	0	—	—	—	0	—
15	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
16	1	1	1	1	1	1	1	0	0	0	—	0	—	0	—	—	—
17	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

highly dependent on vegetation type. Typical values for LAI greater than 2 are approximately 3 m for tropical forests, 1 m for other tall vegetation types, and 0.1 m for short vegetation types (Table 1).

The biophysical parameters calculated with this method have been applied in biosphere-atmosphere models such as SiB2, biogeochemical models such as CASA, and models estimating net primary production (Cramer*et al.*, in press) and have been made available through the International Satellite Land Surface Climatology Project (ISLSCP) (Meeson *et al.*, 1995).

Methods and Results

The misclassification errors reported by the validation effort for the IGBP DISCover product (Table 2) represent the confusions occurring between the validation and classification results. To ensure confidence in the validation result, we use only those samples from the validation effort for which a majority of interpreters agreed (Scepan, 1999, in this issue). The values given in Table 2 are percentages of validation pixels identified correctly in the classification out of the total number of validation pixels for which the majority of interpreters agreed for each cover type.

If errors occur between cover types for which the model does not make a distinction in estimating a particular parameter, the error is essentially zero. With this in mind, we assess the errors with respect to two parameters, leaf area index and surface roughness. These parameters were chosen as examples that are moderately and highly dependent on land-cover type, respectively.

Leaf Area Index

The relationship used to derive LAI from FPAR for use in SiB2 and other models depends on the maximum LAI value assigned for the cover type (Table 1). As such, the sensitivity of this parameter to misclassification occurs only when vegetation types with different values for leaf area index are confused (Table 3a). Taking this into account, the class accuracies can be adjusted so that errors within cover types that have the same values for maximum LAI are excluded. Mean class accuracy in this case is 84.5 percent (90.2 percent when accuracies are weighted by land area of each cover type in the IGBP DISCover classification), compared with a mean class accuracy of 74.0 percent (78.6 percent when adjusted by area) if errors between all land-cover types are considered equally (Table 4).

Surface Roughness

In the case of surface roughness length estimates within SiB2, estimates are more highly dependent on land-cover type (Table 1) and sensitivity to misclassification errors is greater than in the case of LAI (Table 3b). Excluding the errors between cover types that are aggregated for the purpose of estimating surface roughness, mean class accuracy is 82.4 percent (87.8 percent when adjusted by area) (Table 4).

Simulations of leaf area index and surface roughness length for an NDVI value of 0.5 illustrate the errors from land-cover misclassification that propagate from the FPAR to the LAI and finally to the surface roughness length estimates (Figure 2). Figure 2 shows the differences between the estimated value of LAI (Figure 2a) and surface roughness (Figure 2b) for the correct cover type and the estimated value if the land-cover type were misclassified as broadleaf evergreen forest (tall vegetation), mixed forest (medium vegetation), and open shrubland (short vegetation). LAI estimates are less sensitive to misclassification error than surface roughness because the former is more strongly dependent on the FPAR estimate than is the latter. The maximum error in LAI estimates occur when grassland is confused with broadleaf evergreen forest (Figure 2a), and the maximum error in surface roughness length estimates occurs when open shrubland is confused with broadleaf evergreen forest (Figure 2b). The examples show, as expected, that errors are largest when tall vegetation is confused with short vegetation.

TABLE 4. CLASS ACCURACIES WHEN ALL MISCLASSIFICATION ERRORS ARE WEIGHTED EQUALLY AND WHEN ERRORS TO WHICH PARAMETER ESTIMATES ARE INSENSITIVE ARE EXCLUDED.

Cover Type	Area in IGBP DISCover Product (km^2 × 10^6)	Class Accuracy for all Errors Equally Weighted (%)	Accuracy Adjusted for Derivation of LAI in SiB2 (%)	Accuracy Adjusted for Derivation of Surface Roughness in SiB2 (%)
1 Evergreen needleleaf forest	6.37	75.00	75.00	75.00
2 Evergreen broadleaf forest	12.08	87.50	87.50	87.50
3 Deciduous needleleaf forest	1.96	55.56	55.60	55.56
4 Deciduous broadleaf forest	3.23	62.50	62.50	62.50
5 Mixed forest	6.25	68.10	68.10	68.00
6 Closed shrubland	2.58	75.00	85.00	75.00
7 Open shrubland	18.08	87.50	100.00	87.50
8 Woody savanna	10.17	69.23	100.00	100.00
9 Savanna	9.34	64.71	100.00	100.00
10 Grasslands	11.04	75.00	100.00	95.00
11 Permanent wetlands	1.30	38.46	—	—
12 Croplands	14.02	85.71	95.23	95.23
13 Urban and Built-up land	0.26	66.67	—	—
14 Cropland/natural vegetation mosaic	13.94	56.52	69.56	69.56
15 Snow and ice	16.57	—	—	—
16 Barren	18.41	100.00	100.00	100.00
17 Water bodies	—	—	—	
Mean*		74.03	84.49	82.37
Area adjusted mean**		78.56	90.21	87.80

*excluding classes 11 and 13 which do not have corresponding classes in SiB2and classes 15 and 17 for which validation statistics are not reported
**area adjusted mean is calculated by weighting the class accuracy by land area in the DISCover classification; excludes classes 11, 13, 15, and 17

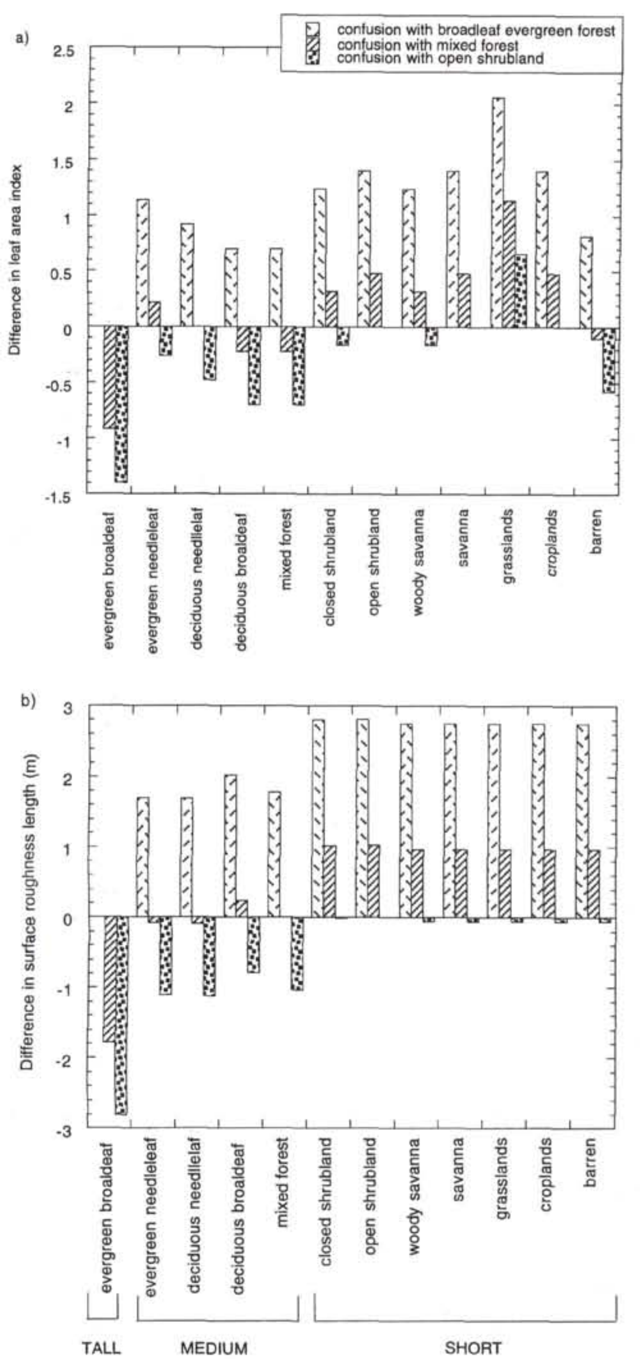

Figure 2. (a) Differences in estimates of leaf area index and (b) surface roughness length, if land-cover types are confused, for NDVI = 0.5.

If the confusion occurs between short vegetation types, for example, between open shrubland and savanna, errors in surface roughness length are small. For the purpose of adjusting the class accuracies, we assume that the parameter estimate is equally sensitive to these two types of confusion, suggesting that the values in Table 4 underestimate the class accuracies in cases where the parameter estimate is only slightly sensitive to misclassification error.

Conclusions

Here we show two examples of biophysical parameter estimates for use in SiB2 and other models to illustrate the sensitivity of parameter estimation to land-cover classification errors in IGBP DISCover. Because land-cover types are aggregated within the model for the purpose of estimating parameters, area-adjusted mean class accuracies are 90.2 percent and 87.8 percent for leaf area index and surface roughness length, respectively, compared with 78.6 percent when all land-cover misclassifications are weighted equally. There are many other parameters estimated within SiB2, and many other biosphere-atmosphere and global biogeochemistry models, each with its own aggregation scheme. These results serve only as examples to illustrate that errors in land-cover classifications should be viewed only in the context of the application of the land-cover information. For some applications, such as biodiversity assessments and resource management, or for more sophisticated biosphere-atmosphere models in the future, it is likely that detailed land-cover information will be required and misclassification errors will have significant consequences for a particular application. For other applications where a coarse description of the land surface is required, misclassification errors may be of lesser consequence.

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