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Alemu Gonsamo & Jing M. Chen

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Abstract. Land cover information is an important input parameter for retrieving key land surface biophysical parameters, such as leaf area index (LAI), often parameterized with geometrical-optical properties distinctive among land cover types. This paper presents a comparative assessment and evaluation of the 1 km Global Land Cover (GLC2000) and the 250 m North American Land Cover (NALC2005) over Canada. We used a 30 m Circa 2000 Land Cover from agricultural regions of Canada as a reference dataset. The comparative assessment and evaluation were made at six generalized class levels that were categorized based on relevance for parameterizations of key land surface biophysical parameter retrieval algorithms. The overall per-pixel agreement between the GLC2000 and the NALC2005 was 63.4%. The overall accuracies using the Circa 2000 reference data were 62.3% and 65.5% for the GLC2000 and NALC2005 datasets, respectively. Based on the improved version 2 University of Toronto LAI algorithm, up to a 42% difference in LAI estimation was noted over Canada due to differences in the two regional land cover datasets. This study assessed the performance of the newly produced NALC2005 product and presents, for the first time, the often overlooked land cover characterization impact on large scale LAI estimation.

Résumé. Les données sur l'occupation des sols sont un paramètre important pour estimer les paramètres terrestres clés tels que l'index de surface foliaire (LAI). Elles sont souvent paramétrisées avec des propriétés géométriques et optiques qui diffèrent selon le type d'occupation des sols. Cet article présente une étude comparative et une évaluation des données « Global Land Cover » (GLC2000) à 1 km de résolution et « North American Land Cover » (NALC2005) à 250 m de résolution sur le Canada. Nous avons utilisé les données d'utilisation des sols des régions agricoles du Canada Circa 2000 à 30 m de résolution comme données de référence. L'étude comparative et l'évaluation ont été conduites à six niveaux de classes généralisées qui ont été catégorisées en fonction de leur importance pour la paramétrisation des algorithmes d'estimation des paramètres terrestres clés. La correspondance générale par pixel entre GLC2000 et NALC2005 était de 63.4 %. La précision générale avec les données de références Circa 2000 étaient de 62.3 % et 65.5 % pour les données GLC2000 and NALC2005 respectivement. En utilisant la version 2 améliorée de l'algorithme d'estimation du LAI de l'Université de Toronto, jusqu'à 42 % de différence entre les estimation de LAI ont été constatées sur le Canada, dues aux différences entre les deux jeux de données régionales d'occupation des terres. Cette étude a évalué la performance du nouveau produit NALC2005 et a présenté pour la première fois l'impact souvent négligé de la caractérisation de l'occupation des sols sur l'estimation du LAI à grande échelle.

Introduction

A large number of international environmental agreements place global change at the top of scientific and political agendas; the Kyoto Protocol, the Convention on Biological Diversity, the Convention to Combat Desertification, the Ramsar Convention on Wetlands, International Geosphere-Biosphere Programme, Global Climate Observing System, World Climate Research Programme, and Intergovernmental Panel on Climate Change, to name a few. Among many surface parameters, land cover information is one of the crucial land surface parameters needed on a continual basis for global change studies. With the availability of improved spatial, spectral, geometric, and radiometric space-borne earth observation data (e.g., Moderate Resolution Imaging Spectroradiometer (MODIS) and Satellite Pour l'Observation de la Terre Vegetation (SPOT VGT)), ground-truth data, and improved classification algorithms, it is possible to produce comprehensive global land cover data sets (Friedl et al., 2002; Justice et al., 2002). Nevertheless, we are far from producing geospatially consistent high-quality data at an operational level because of challenges associated with landscape heterogeneity, mixed pixels, lack of consensus on land cover class definitions, and uncertainties with satellite data (e.g., Congalton, 1991; Foody, 2002; Giri et al., 2005; Herold et al., 2008).

Knowledge of land cover information, such as agriculture, forest, natural, and planted woody vegetation cover area, and information on their changing proportions is needed by legislators, planners, and government officials to determine better land use policies (e.g., Pannell and Roberts, 2009). Several government agencies also need land use data to

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A. Gonsamo[1] and J.M. Chen, University of Toronto, Department of Geography and Program in Planning, Sidney Smith Hall, 100 St. George Street, Room 5047, Toronto ON M5S 3G3, Canada.

[1]Corresponding author (e-mail: gonsamoa@geog.utoronto.ca).

assess the environmental impact resulting from the development of energy resources, to manage wildlife resources and minimize human–wildlife ecosystem conflicts, to make national summaries of land use patterns and changes for national policy formulation, and to prepare environmental impact statements and assess future impacts on environmental quality (Anderson et al., 1976; Pannell and Roberts, 2009). Globally, land cover information has often been a central piece of land use policies and environmental monitoring agreements.

Land cover information is also a crucial input parameter for retrieving other key land surface biophysical parameters from a regional scale to a global scale, such as leaf area index (LAI), fraction of absorbed photosynthetically active radiation (fAPAR), and clumping index (CI) (e.g., MODIS LAI and fAPAR products, Myneni et al., 1997; University of Toronto (U of T) LAI and CI products, Deng et al., 2006; Chen et al., 2005; CYCLOPES LAI product, Baret et al., 2007). Garrigues et al. (2008) reported that the interchange of biome types is one of the major factors of the unsatisfactory performance of global LAI products. Myneni et al. (2002) calculated the LAI difference to be up to 50% when distinct biomes are misclassified for a given pixel in a global MODIS LAI product. Given the moderate accuracy of regional or global land cover products (overall accuracy 60%–80%) (Herold et al., 2008) their impact on LAI and other critical land surface biophysical parameters may propagate large uncertainties, particularly for major biome interchanges with significant spectral differences. The impact of the uncertainties of the input parameters associated with land cover products is often overlooked in global LAI and other biophysical parameter product validations.

In an effort to improve the U of T regional LAI algorithm, we have implemented the MODIS 250 m reflectance data (Trishchenko et al., 2006) and the independently produced MODIS-based 250 m North American Land Cover (NALC2005) (NALC, 2005) to minimize pixel geo-location error while maximizing the pixel resolutions using the dataset from the same sensor (Gonsamo and Chen, 2011). The U of T LAI algorithm was used previously with the 1 km Global Land Cover for the year 2000 (GLC2000) dataset. This is too coarse for the current 250 m LAI algorithm and was noted by Garrigues et al. (2008) to have an interchange of biome types. MODIS also has standard 1 km and 500 m land cover products that are still coarse for our 250 m LAI algorithm and are not optimized for regional or local applications (Giri et al., 2005). Both the GLC2000 and the NALC2005 products followed a bottom-up approach by combining and harmonizing regional and country products and legends. As such, they are optimized for local use.

Therefore, this paper presents the comparative performance assessment of two newly available Canadian regional land cover datasets. The first dataset is version2 (v2) Land Cover Map of North and Central America for the year 2000 (GLC2000) prepared by Canada Centre for Remote Sensing/Natural Resources Canada (CCRS/NRCan) and Earth Resources Observation and Science/United States Geological Survey (EROS/USGS) Data Centre (EDC) as a regional component of the Global Land Cover 2000 project (GLC2000: Latifovic et al., 2003) from which v1 had already been used in the U of T LAI algorithm. The second dataset, which has not yet been independently validated, is the newly available 250 m MODIS-based NALC2005 product produced by CCRS/NRCan, USGS, Insituto Nacional de Estadística y Geografía (INEGI), Comisión Nacional para el Conocimiento y Uso de la Biodiversidad (CONABIO) and Comisión Nacional Forestal (CONAFOR) (NALC, 2005).

All earth observation products are subjected to continuous validation exercises by independent experts. Therefore, although this study was performed for the U of T LAI algorithm refinement, it contributes to the validation activities of global and regional land cover products. The assessment is based on the six generalized classes (needleleaf forest, broadleaf forest, mixed forest, shrub, crops and grass, and water bodies) that are relevant for parameterization of global and regional LAI, fAPAR, and CI algorithms. However, this level of generalization is also relevant for other informed policy and land use and land cover decisions on larger scales. The goal of this study is to evaluate the accuracy of regional land cover products and their impacts on the U of T LAI algorithm with the following objectives: (*i*) compare the GLC2000 and NALC2005 land cover products over Canada based on six generalized classes; (*ii*) evaluate the two land cover products using the Circa2000 reference data; and (*iii*) assess the impact of land cover mixture and uncertainty on LAI estimation.

Methodology

Land cover data sources

GLC2000

The GLC2000 v2 North America 0.0089 degree (approx. 1 km) data were downloaded from http://bioval.jrc.ec.europa.eu/products/glc2000 (Latifovic et al., 2003) (accessed 30 June 2010). We acquired the data in the Geographic Coordinate projection system with the World Geodetic System 1984 (WGS1984) Datum and reprojected it to the Lambert Conic Conformal (LCC) projection system. The GLC2000 land cover classification was derived using the four 1 km bands of SPOT VGT data from the growing season of 2000 (Latifovic et al., 2003). The GLC2000 land cover mapping was accomplished in two phases: initial clustering and cluster agglomeration using a classification procedure that combines unsupervised and supervised classification approaches. The enhanced classification method (ECM) and classification by progressive generalization (CPG) were used as a combined classification method to obtain the final land cover classes (Latifovic et al., 2003). Although there was a slight modification in the v2

GLC2000, the class names are different from those reported in v1 (Latifovic et al., 2003, 2004).

NALC2005

The NALC2005 250 m data were downloaded from www.cec.org (accessed 30 June 2010). The data were acquired in the Lambert Azimuthal Equal Area projection system and reprojected to the LCC projection system into a 1 km pixel based on the majority land cover prevalence of a 4×4 group of 250 m pixels. The NALC2005 classification was derived from a time composite from summer 2005 of seven land bands of level 1B MODIS data (collection 5) and ancillary geographic information system (GIS) layers following similar ECM and CPG classification approaches as the GLC2000 (NALC, 2005). Both land cover datasets were created using different input datasets and number of classes (**Table 1**) but had the same purpose of providing accurate land cover information for environmental modelers and policy makers.

Circa 2000

For validation, we used the 30 m Circa 2000 reference land cover data for agricultural regions of Canada that were compiled by Agriculture and Agri-Food Canada (AAFC) in universal transverse mercator projections. They were then reprojected by the LCC projection system into a 1 km pixel, based on the majority land cover prevalence. The Circa 2000 land cover is derived from Landsat-5 Thematic Mapper (TM) and (or) Landsat 7 Enhanced Thematic Mapper (ETM+) multispectral imagery and ground reference training data using various supervised classification approaches, including a hierarchical decision-tree process. Image object segmentation, pixel filtering, and post editing were applied as part of the image classification. The classification product is based on a set of images that were collected between the 1998 and 2003 growing seasons. The reference data used to train the classifier were collected from a variety of sources, such as crop insurance databases, high-resolution air or satellite imagery, visual interpretation of Landsat images, topographic maps, field data, digital elevation data and its derivatives, and soil databases. Although there are two other Circa 2000 datasets of the remaining forest region and northern territories of Canada, we have not included these as references because of lack of availability, inconsistent accuracies among individual scenes, and classifier variations among the dataset.

This Circa 2000 dataset covering approximately 3.7 million square kilometres is compiled by AAFC, but it also integrates products mapped by other provincial and federal agencies with the appropriate legend translations. Thus, the classification consists of various supervised classification approaches depending on the agencies responsible for the specific geographic region. The Circa 2000 land cover for agricultural regions has considerable accuracy for use with the validation dataset. Positional accuracy was within 1 pixel (30 m). A cross-validation measure based on input training data of each of the 97 scenes resulted in an average overall accuracy of 86.6% (minimum 72.8% and maximum 96.3%). A thematic (pixel) consistency measurement of 151 overlapping cases resulted in an average percentage consistency of 92.1% (minimum 72.9% and maximum 98.9%). An overall accuracy measure using 3164 independent ground reference sample

Table 1. Generalized land cover class legend with corresponding cover types and ID number from the individual dataset.

Classes	GLC2000 v2 cover type and (ID)	NALC2005 cover type and (ID)	Circa2000 cover type and (ID)
Needleleaf forest	Needleleaf evergreen forest with closed and open canopies and needleleaf mixed forest with closed canopy (4, 5, 6, 20)	Needleleaf forest (1, 2)	Coniferous (210)
Broadleaf forest	Broadleaf deciduous or evergreen forest with closed or open canopies (1, 2, 3, 29)	Broadleaf evergreen and deciduous forest (3, 4, 5)	Deciduous (220)
Mixed forest	Mixed broadleaved or needleleaf forest with closed canopy (7, 8)	Mixed forest (6)	Mixed (230)
Shrub	Broadleaf or needleleaf deciduous or evergreen shrubland with closed or open canopies and mixed broadleaf or needleleaf dwarf-shrubland with open canopy (9, 10, 11, 12)	Shrubland and shrubland with lichen and moss 7, 8, 11)	Shrubland (50)
Crops and grass	Grassland, grasslands with tree or shrub or dwarf-sparse shrub layer, cropland and crop with shrub or woodland, wetlands, and herbaceous wetlands (13, 14, 15, 16, 17, 18, 19, 27, 28)	Grassland, wetland, cropland, grassland with lichen and moss, and barren land with lichen and moss (9, 10, 12, 13, 14, 15)	Wetland, grassland, and agriculture (80, 110, 120, 121, 122)
Water bodies	Water bodies (24)	Water (18)	Water (20)
Other*	Burns, disturbances, snow, ice, urban and built-up areas (21, 22, 23, 25, 26)	Urban, snow and ice (16, 17, 19)	Exposed land and developed land (30, 34)

*Areas corresponding to the "other" category in any of the three datasets have been excluded from comparison. For the Canadian land mass, not necessarily all of the cover types listed in the table are present. All noninland water bodies are masked out from comparison in all the three datasets.

points, collected based on a stratified systematic sampling grid across the 3.7 million square kilometres, resulted in an accuracy of 82%.

Land cover intercomparison and accuracy assessment

Although all three land cover products were reprojected into the LCC projection system to fit the U of T LAI algorithm input data scheme, all the area calculations were made using the actual pixel size based on Albers Equal-Area Conic projection system. For the purposes of this study, the "other" and "noninland water" categories were not included in the comparison (**Table 1**); however, significant differences may occur between the products for inland water. Although the main aim of this work was to compare the two regional land cover datasets, we attempted to evaluate their differences based on the Circa 2000 dataset. The results are first presented for the GLC2000 and NALC2005 comparisons followed by evaluation using the Circa 2000 data. It is assumed that there will be only minor thematic changes in the six generalized classes between 2000 and 2005 because urban, built-up areas, and disturbances are masked out from the comparisons. All the comparisons are made at the coarsest pixel size (1 km) level among the three datasets.

Although most quantitative methods for classification accuracy assessment use an error matrix derived from independent classification and reference datasets, recent studies have focused on sampling scheme, sampling size, classification scheme, land cover heterogeneity, accuracy of the ground truth or reference data, spatial distribution of error, and spatial autocorrelation (Congalton, 1991; Friedl et al., 2000; Stehman and Czaplewski, 1998; Foody, 2002; Latifovic and Olthof, 2004). The error matrix is expected to satisfy the statistical distribution of map information, the representativeness of the sampling unit, the number of samples collected, and the choice of sampling units (Congalton and Green, 1999). Considering these factors, we have first tried to consider the representativeness of the Circa 2000 reference data. **Figure 1** shows the proportional distribution of the six aggregated classes across the three datasets. Although the geospatial representativeness of the sampling unit is not fully achieved over Canada entirely (Circa 2000 only covers part of Canada), **Figures 1** and **2** show that the six classes are proportionally represented in the reference dataset. **Figure 2** shows that the northern territories are characterized by homogeneous land cover classes mostly composed of the "crops and grass" and "water bodies" classes. Therefore, the accuracy results based on the southern portion of reference data may underestimate the actual performance of the GLC2000 and NALC2005 products. To avoid autocorrelation, we have selected the reference data based on the classic stratified random sampling techniques with proportional sample sizes based on the prevalence of the six generalized classes. The final selected reference sample size equals approximately one-third of the original Circa 2000 pixels. Given that the regional or global land cover product validations have often been hampered by the lack of availability of reference data, we assume that our evaluation based on Circa 2000 is reasonable.

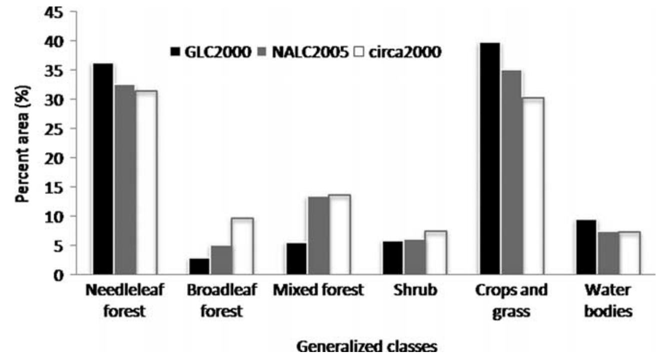

Figure 1. Percent area totals of the three land cover classification datasets. GLC2000 and NALC2005 percent area totals are calculated for all of Canada whereas Circa 2000 is only available for the section of southern Canada as presented in Figure 2 for all the three datasets.

The intercomparison between GLC2000 and NALC2005 was made by visual, area, per-pixel, and per-class comparisons. Furthermore, GLC2000 and NALC2005 were compared based on class interchanges, (i.e., the proportion of a particular class from one land cover data allocated to other classes in the other land cover data and vice versa). The spatial distribution of per-pixel agreements and disagreements were further discussed and evaluated using the Circa 2000 reference data. Standard techniques were used for quantitative accuracy assessments such as producer and user accuracies and kappa coefficient (Foody, 2002), which were often followed by qualitative interpretations of the error matrices and disagreements.

Qualitative validations following Mayaux (2002) were performed wherever possible using visual interpretations of Google Earth maps (http://www.earth.google.com), the Canadian National Topographic Database (NTDB), and Terrestrial ecozones of Canada (**Figure 3** and Wiken, 1986). Google superimposes high-resolution images over coarser images according to image availability, quality, and date. In Canada, most of the high-resolution Google Earth images are from Digital Globe's Quick Bird satellite, spanning from 2002 to 2010 at a spatial resolution of 0.6 m and above, and from the SPOT satellite, at a spatial resolution of 2.5 m and above. The NTDB is a digital cartographic reference product generated by NRCan and it includes features such as watercourses, boundaries, urban areas, railways, roads, vegetation, and relief (Edition 3.1 data, NTDB, NRCan). Canada's physiographic and ecological regions contain 15 ecozones, areas of the Earth's surface representative of large and very generalized ecological units characterized by interactive and adjusting abiotic and biotic factors (Wiken, 1986). These ecozones are often used for environmental reporting purposes. We use the ecozones in this paper to refer to areas that need further attention for land cover

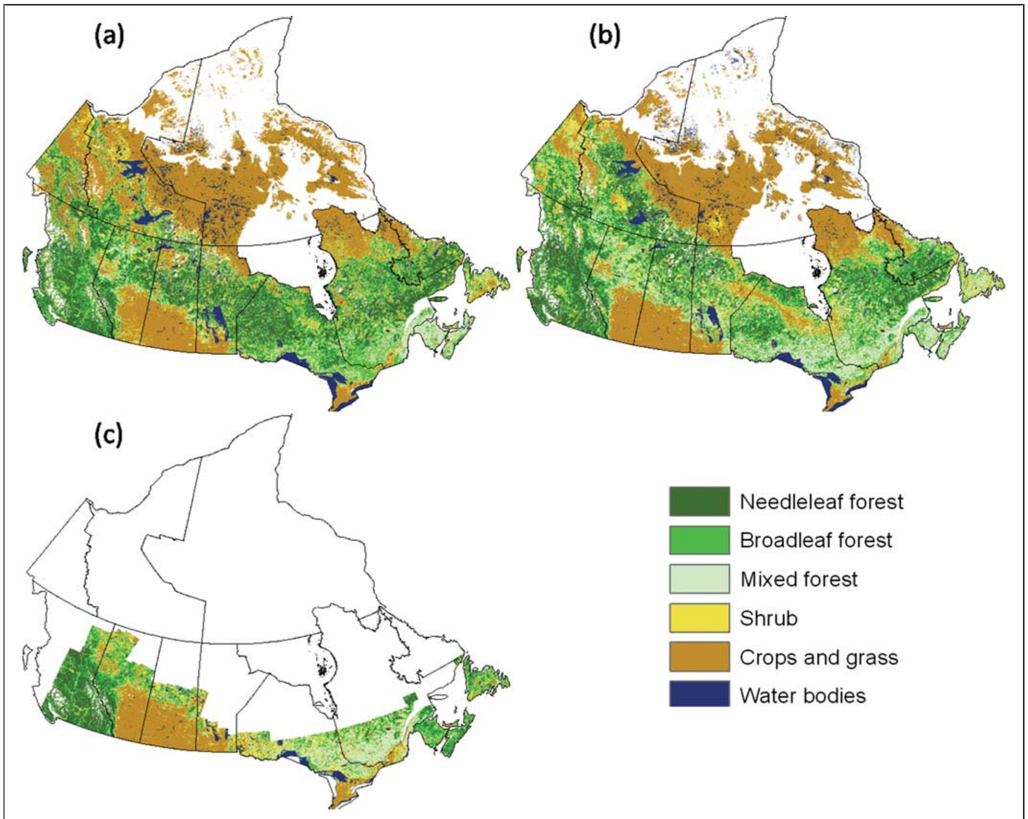

Figure 2. Land cover classification of Canada with six generalized classes using (a) GLC2000, (b) NALC2005, and (c) reference data from Circa 2000.

classification because of spatial disagreements among the land cover datasets.

Impact of land cover mixture and uncertainty on LAI estimation

We have used the U of T LAI algorithm (Deng et al., 2006) that was developed based on a 4-scale geometrical optical model with a multiple scattering scheme. The algorithm makes use of the 4-scale simulations characterized by the LAI relationship with the bi-directional reflectance distribution function (BRDF) of the red (ρ_R), near infrared (NIR, ρ_{NIR}), and shortwave infrared (SWIR, ρ_{SWIR}) reflectances for each distinctive land cover type. The land cover types with similar structural characteristics are combined to form six biomes based on canopy architecture: needleleaf

Figure 3. Terrestrial physiographic and ecological ecozones of Canada, adapted from Wiken (1986).

forest, tropical forest, broadleaf forest, mixed forest, shrub, and cropland and grassland. Nonvegetated land and water surfaces are assigned an LAI value of zero. The LAI is retrieved from a lookup table (LUT), which is in turn generated from the BRDF of the three spectral bands producing simple ratio (SR), SR $= \frac{\rho_{NIR}}{\rho_R}$, and reduced simple ratio (RSR),

$$\mathrm{RSR} = \frac{\rho_{\mathrm{NIR}}}{\rho_{\mathrm{R}}}\left(1 - \frac{\rho_{\mathrm{SWIR}} - \rho_{\mathrm{SWIR_{min}}}}{\rho_{\mathrm{SWIR}} - \rho_{\mathrm{SWIR_{min}}}}\right)$$

vegetation indices based on the interactions of incidence solar radiation and the vegetated surface represented by a priori range of ancillary parameters (e.g., land cover types, soil and leaf optical properties, canopy shape and height, and vegetation clumping at the plant and canopy scales). $\rho_{\mathrm{SWIR_{max}}}$ and $\rho_{\mathrm{SWIR_{min}}}$ are the maximum and minimum SWIR reflectances selected for specific land cover types, respectively. The RSR is used for forest land cover because it reduces the impact of the forest background and heterogeneity variations on LAI estimations, whereas SR is used for other vegetated land cover LAI estimations.

In v1 of the U of T LAI algorithm, the LUT is parameterized for each aggregated land cover type. These parameterizations include the land cover specific use of vegetation indices (RSR or SR), clumping index, $\rho_{\mathrm{SWIR_{max}}}$ and $\rho_{\mathrm{SWIR_{min}}}$, BRDF–LAI relationships, and other ancillary parameters. As such, the land cover data is indispensable for obtaining accurate LAI estimates. This is the common approach for large-scale LAI estimation algorithms. Gonsamo and Chen (2011) have further improved the U of T LAI algorithm and produced v2 U of T that uses the same LUT and only differs from v1 by mathematically incorporating the measured background reflectance, spatially explicit clumping index, and local pixel topography consideration in the LAI estimation. However, the impact of land cover remains the same in v2 U of T although a spatially-explicit pixel-based clumping index is used in contrast to the land cover specific values used in v1. The clumping index modeling itself is land cover specific (Pisek et al., 2011). The use of RSR in the U of T LAI algorithm further minimized the impact of land cover on LAI estimation unlike other global LAI products (e.g., MODIS LAI (Myneni et al., 1997) and CYCLOPES LAI (Baret et al., 2007)).

The implementation of the U of T LAI algorithm can be done using any regional or global land cover products aggregated to the general classes as shown in **Table 1**. For the purpose of this study, we have used v2 of the U of T LAI algorithm. The 10-day composite of 1 km SPOT VGT data (atmospherically corrected and free from cloud, cloud shadow, and snow) was acquired between 1 and 10 June 2003 with the associated view-target-sun geometry files being used as input to simulate LAI.

Assuming that the 30 m Circa 2000 reference land cover data contain the highest resolution cover type relevant for the radiative transfer characterization of the U of T LAI algorithm, the individual LAI value of a 1 km pixel can be decomposed to a higher resolution product. This high-resolution LAI, derived from LAI unmixing, is used as a reference LAI for comparison of land cover mixture and uncertainty in LAI estimation. Probabilistic models for unmixing spectral reflectance of a pixel to individual constituents of end members are becoming common decomposition methods for optical remote sensing (e.g., Bateson, et al., 2000). The model could also be adapted to remote sensing products assuming that the pixel is a linear composition of deterministic land cover types, a usual assumption for optical data unmixing:

$$\mathrm{LAI_{Pixel}} = \int \mathrm{LAI_i}\omega_\mathrm{i} + \varepsilon \qquad (1)$$

where $\mathrm{LAI_{Pixel}}$ is the LAI value of the coarse resolution pixel constituting the sub-pixel $\mathrm{LAI_i}$ contributions from each land cover type represented by the area fraction weight, (ω_i) of that land cover compared with the total vegetated surface of the pixel, and ε is an error term. Assuming that there are no interaction effects of land cover types at 30 m resolution (a fairly valid assumption), the 1 km $\mathrm{LAI_{Pixel}}$ values derived using the GLC2000, NALC2005, or the 1 km aggregated Circa 2000 land cover input data can be decomposed using the the weighted (ω_i) (where subscripts n, b, m, s, and g stand for needleleaf, broadleaf, mixed forests, shrub, and grass covers, respectively) contribution of $\mathrm{LAI_i}$ from each of the constituting generalized land cover classes

$$\mathrm{LAI_{Pixel}} = \mathrm{LAI_n}\omega_\mathrm{n} + \mathrm{LAI_b}\omega_\mathrm{b} + \mathrm{LAI_m}\omega_\mathrm{m} + \mathrm{LAI_s}\omega_\mathrm{s} + \mathrm{LAI_g}\omega_\mathrm{g} + \varepsilon \qquad (2)$$

The ω_i of each land cover constituting the 50 km grid "zone" is extracted from the vegetated surface of the Circa 2000 dataset. The 50 km grid is an arbitrarily sized zone selected as a compromise between: (1) computing efficiency and (2) large scale land cover uncertainty, heterogeneity, pixel misregistration, and spatial autocorrelation. The LAI was simulated assuming that the entire scene had the same land cover which produced five sets of LAI products for each specific generalized land cover type (**Table 1**). Then the $\mathrm{LAI_{Pixel}}$ was derived using Equation (2) based on the product of ω_i and $\mathrm{LAI_i}$ values of that zone for that land cover type. This LAI was used as reference data to evaluate the LAI derived from each of the three land cover products. However, the LAI over all of Canada was first calculated using the two major land cover datasets (GLC2000 and NALC2005).

Results

Comparison of the GLC2000 and NALC2005 land cover products

Initially, a comparison of percentage of area totals for the two regional land cover datasets assigned to each of the six generalized classes was performed (**Figure 1**). In **Figure 1**, there is a reasonable agreement of area totals between the GLC2000 and NALC2005 datasets for the shrub classes. However, disagreement occurs between the datasets for the remaining five classes, with broadleaf and mixed forest showing the highest proportional differences. Even if we merge all forest classes and compare the area totals between the two datasets, the differences are still considerable (44.9% and 51.2% area totals of forest cover for the GLC2000 and NALC2005 datasets, respectively).

The total forested area cover over Canada is 3 601 856 km^2 and 4 109 135 km^2 from GLC2000 and NALC2005, respectively. The difference of forested area from the two land cover datasets is approximately 0.5 million sqaure kilometres, which is very significant particularly for reporting forest carbon budget from regional ecosystem models. According to the 2001 Canada's Forest Inventory (CanFI2001: Powel and Gillis, 2006), the forested area over Canada is 4 021 000 km^2 which is in close agreement with the NALC2005 estimate. The slight underestimation of forested area from the NALC2005 data compared with the CanFI2001 data is mainly because the Hudson Plains area in Northern Ontario is classified as a forest of low proportional area in CanFI2001, whereas in the NALC2005 data it is classified as a wetland which belongs to the crops and grass cover type in the aggregated six classes. Whereas, the large underestimation of forest area from the GLC2000 compared with both the NALC2005 and CanFI2001 is explained by the fact that forest areas are underestimated in the northwestern provinces and territories (e.g., northern British Columbia and Alberta, and the Yukon and Northwest Territories) in the GLC2000 dataset (**Figure 2**, Power and Gillis, 2006).

Figure 4 presents a spatial comparison of the distribution of agreement and disagreement between the two datasets. The 3 km × 3 km resampling of majority land cover to reduce the possible pixel misregistration error has significantly reduced the overall agreement between the GLC2000 and NALC2005 datasets (**Figure 4**). According to **Figures 2** and **4**, the major generalized category classified similarly between the two datasets is the crops and grass class. Although the disagreements are fairly uniformly distributed for the forest classes, the major disagreements are visibility concentrated around the boreal and taiga plains and shields of Canada (**Figures 3** and **4**). These areas are predominantly covered by a mixture of boreal forests that are barren or are wetlands or grasslands. For example, the Hudson Plains area, which is south of Hudson Bay (**Figure 3**) and where strong disagreement was observed, is actually dominated by peat and grasslands; this is correctly classified in the NALC2005 but not in the GLC2000. In addition, the northern limit of the GLC2000 for fo rest is lower in latitude than that for the NALC2005. The visual interpretation with Canada's forest regions in Google Earth indicates that the NALC2005 has captured the forest region in the northern territories better than the GLC2000 for areas dominated by boreal forest and taiga (**Figures 2** and **3**).

To illustrate the variations between the two datasets, we have presented the percent allocation of the total per-class pixels from the GLC2000 to the NALC2005 classes (**Table 2**) and vice versa (**Table 3**). With six aggregated land cover classes, the overall per-pixel agreement is 63.4% and the Kappa coefficient is 0.494 between the GLC2000 and the NALC2005. In **Tables 2** and **3**, the crops and grass classes show the maximum agreement between the two datasets. For example, in **Table 2**, 72.5% of the crops and grass class from the GLC2000 is allocated to the same class of the NALC2005 while it is 81.9% when reversed (**Table 3**). The least per-pixel agreement is obtained for the shrub class, which is in contrast to the shrub class being the best matching class between the two datasets based on the area totals comparison (**Figure 1**). The class-specific per-pixel

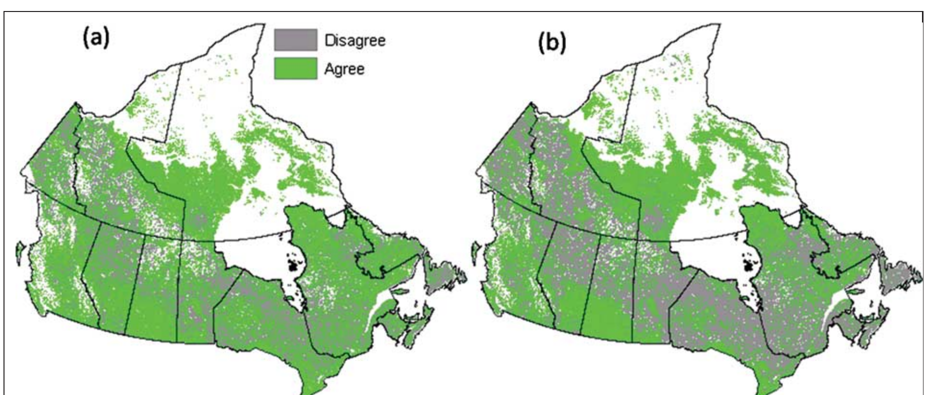

Figure 4. Spatial agreement and disagreements between the GLC2000 and NALC2005 data (a) 1 km × 1 km (spatial per-pixel agreement 63.4%), and (b) 3 km × 3 km majority land cover resampling (spatial per-pixel agreement 46.3%).

Table 2. Percent confusion matrix among the 6 generalized classes of GLC2000 compared with NALC2005.

	NALC2005					
GLC2000	Needleleaf forest	Broadleaf forest	Mixed forest	Shrub	Crops and grass	Water bodies
Needleleaf forest	**65.5**	1.0	16.7	4.3	9.6	2.8
Broadleaf forest	3.9	**45.6**	38.4	0.3	10.5	1.3
Mixed forest	8.5	28.5	**52.3**	0.2	10.0	0.6
Shrub	30.9	13.5	23.0	**12.2**	19.7	0.8
Crops and grass	10.7	2.3	4.1	9.1	**72.5**	1.2
Water bodies	21.9	1.2	4.2	2.5	9.1	**61.1**

Note: Producer accuracy (spatial agreement) is in boldface.

spatial agreements were 52.9%, 19.6%, 18.2%, 6.3%, 62.5%, and 52.4% for needleleaf forest, broadleaf forest, mixed forest, shrub, crops and grass, and water bodies, respectively, between the GLC2000 and NALC2005 datasets.

There are several reasons for the disagreements obtained between the GLC2000 and NALC2005 datasets. Latifovic et al. (2004) noted that in North America, the central and core forested areas were in good agreement, while disagreement occurred mostly along edges and transition zones when comparing four global land cover datasets that included the GLC2000. However, our results show that the major disagreement between the two datasets occurs across the forest and shrub region classes being confused within the dataset (Giri et al., 2005). Often, one obvious discrepancy comes from the application of different thresholds of average tree height and canopy cover for separating various classes (Latifovic and Olthof, 2004). For example, more pixels of shrub class from the GLC2000 data are classified to needleleaf forest, broadleaf forest, mixed forest, or crops and grass in NALC2005 dataset than are classified as a shrub class (**Table 2**), whereas most of the shrub pixels of the NALC2005 dataset are classified either to the needleleaf forest or crops and grass classes in the GLC2000 (**Table 3**). The confusion of class definitions among the forest and shrub, shrub and grasslands, mixed forest and pure forest classes may explain the major discrepancies (**Tables 2** and **3**) as there is little confusion between the broadleaf and needleleaf forest classes. Additionally, the water bodies class is confused with the crops and grass class and needleleaf forest cover types (**Tables 2** and **3**). The confusion between the crops and grass class with the water class can be explained by the misrepresentation of wetland (which is categorized here as crops and grass) with water features. The confusion between needleleaf and water can be explained because of the high patchy water level during the early spring (time of image aquisition) which is typical of the northern needleleaf forest of Canada. This discrepancy could be captured by the 250 m NALC2005 but not by the approximately 1 km GLC2000 dataset (see **Figure 2**). These conclusions are derived using the NTDB to distinguish between water and wetland and Google Earth maps to determine the northern needleleaf forest areas.

Evaluation of the GLC2000 and NALC2005 land cover products

Table 4 shows the class-specific accuracies for the GLC2000 regional dataset in comparison with the Circa 2000. The crops and grass class appears with high producer and user accuracies in both the GLC2000 and NALC2005 datasets (**Tables 4** and **5**) and thus are quite accurately mapped. Classes with high producer and low user accuracies indicate overmapping. Examples of this are classes such as broadleaf and mixed forest cover types in both the GLC2000 and NALC2005 (**Tables 4** and **5**). The high user accuracies of the crops and grass and waterbody classes in both the GLC2000 and NALC2005 indicate that most of the pixels in the reference dataset for these two classes are accurately mapped in both regional datasets. These two classes also have higher producer accuracies indicating higher spatial agreements. Both user and producer accuracies in both datasets have similar trends except that more shrub class is misclassified as needleleaf or crops and grass classes in the

Table 3. Percent confusion matrix among the 6 generalized classes of NALC2005 compared with GLC2000.

	GLC2000					
NALC2005	Needleleaf forest	Broadleaf forest	Mixed forest	Shrub	Crops and grass	Water bodies
Needleleaf forest	**73.2**	0.3	1.5	5.5	13.1	6.4
Broadleaf forest	7.3	**25.6**	31.3	15.3	18.2	2.2
Mixed forest	45.0	8.2	**21.8**	9.9	12.2	2.9
Shrub	25.5	0.1	0.2	**11.5**	58.7	3.9
Crops and grass	9.9	0.9	1.6	3.3	**81.9**	2.5
Water bodies	13.5	0.5	0.5	0.6	6.7	**78.3**

Note: Producer accuracy (spatial agreement) is in boldface.

Table 4. Class-specific confusion matrix and overall accuracy among the 6 generalized classes of GLC2000 compared with Circa2000.

	GLC2000							
circa2000	Needleleaf forest	Broadleaf forest	Mixed forest	Shrub	Crops and grass	Water bodies	User accuracy	Overall
Needleleaf forest	**75.1**	2.9	11.3	5.1	3.3	2.2	65.4	
Broadleaf forest	16.7	**26.4**	41.2	4.7	9.0	2.0	16.4	
Mixed forest	37.2	19.4	**35.8**	3.4	1.3	2.9	30.2	
Shrub	32.0	8.9	14.3	**19.0**	22.4	3.4	19.2	
Crops and grass	10.6	4.3	6.9	6.5	**70.6**	1.1	88.9	
Water bodies	24.7	3.8	4.4	2.2	3.8	**61.0**	75.2	
Accuracy								62.4
Kappa								0.492

Note: Confusion matrix and accuracy figures are given in percentages. Producer accuracy (spatial agreement) is in boldface.

GLC2000 compared with the broadleaf and mixed forest classes in the NALC2005 (**Tables 4** and **5**).

Mayaux et al. (2006) reported an overall accuracy of 68.6% for the nonaggregated GLC2000 land cover classes compiling reference data from across the world excluding North and South America. Latifovic and Olthof (2004) reported an overall accuracy of approximately 62% between the GLC2000 and the 1 km aggregated reference data over all of Canada that was derived from Landsat TM/ETM+ scenes collected across Canada. Our result of an overall accuracy of 62.4% is in good agreement with the study by Latifovic and Olthof (2004). This agreement suggests that we can draw a sound conclusion for Canada using the Circa 2000 data that covered only the southern portion of Canada (**Table 4**). The reason for the confusion in the GLC2000 and the Circa 2000 for needleleaf and mixed forest classes is that GLC2000 defines needleleaf forest as having a broad range of 25%–75% canopy cover for which the open canopies may be mixed with broadleaf or shrub, whereas the Circa 2000 defines needleleaf forest as a predominantly needleleaf treed area that includes mixed forest and shrub. This may create fuzzy boundaries between the two classes and the disagreement for these two classes may not be necessarily as high as reported in **Table 4**. The same may be true for the shrub class in **Table 4**.

The reason for the confusion of the mixed forest with the needleleaf forest classes and the shrub class with the other forest classes between the NALC2005 and Circa 2000 is most likely due to the confusion of class definitions, as is shown in the compared results obtained between the GLC2000 and Circa 2000. We hypothesize the reason as there was no class definition for the NALC2005. Although there was no independent validation for the NALC2005 dataset, the preliminary validation from the NALC2005 indicates that, for the 13 class aggregate, the overall accuracy was between 59% and 69% with an average accuracy of 65% (NALC, 2005). This is in close agreement with our result for the aggregated six classes with an overall accuracy of 65.5% (**Table 5**).

Implications of land cover mixture and uncertainty of LAI estimation

The U of T LAI algorithm uses the RSR vegetation index among the forest classes. Therefore, no major differences were expected in the LAI values among forest cover type confusion (higher LAI values in **Figure 5**) between the GLC200 and NALC2005. Most of the discrepancies are in low LAI values (<2) which are explained by the confusion of forest and nonforest cover types between the GLC2000 and NALC2005 in prairie areas, the Hudson plains, and the northernmost forest boundaries (**Figure 3**). This agrees with Deng et al. (2006) who reported that the major discrepancy usually comes from the confusion of forest with nonforest cover types. **Table 3** shows that there is large confusion among shrub and other forest classes between the GLC2000

Table 5. Class-specific confusion matrix and overall accuracy among the 6 generalized classes of NALC2005 compared with circa2000.

	NALC2005							
circa2000	Needleleaf forest	Broadleaf forest	Mixed forest	Shrub	Crops and grass	Water bodies	User accuracy	Overall
Needleleaf forest	**63.5**	6.0	22.1	4.1	3.8	0.6	77.4	
Broadleaf forest	6.8	**41.9**	41.5	0.3	8.8	0.7	16.4	
Mixed forest	15.5	16.7	**65.6**	0.2	1.1	0.8	33.6	
Shrub	14.0	32.9	36.9	**7.3**	8.3	0.7	18.2	
Crops and grass	4.9	7.4	7.1	1.6	**78.6**	0.4	92.1	
Water bodies	15.2	3.6	8.1	0.5	3.5	**69.0**	91.9	
Accuracy								65.5
Kappa								0.545

Note: Confusion matrix and accuracy figures are given in percentages. Producer accuracy (spatial agreement) is in boldface.

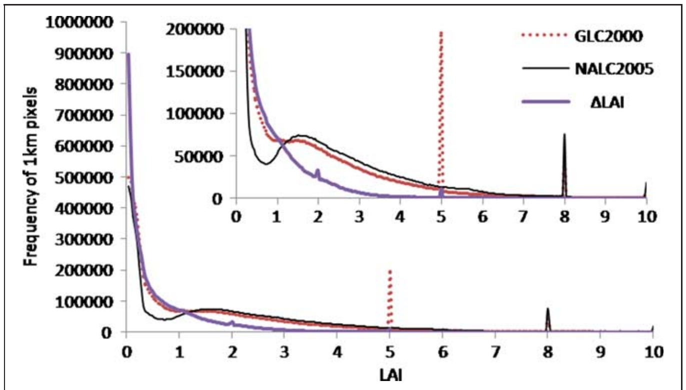

Figure 5. Canada-wide LAI value distribution based on v2 U of T LAI algorithm using GLC2000 and NALC2005 land cover products. The frequency is given in 1 km pixel numbers of valid land pixels of the Canadian land mass. The absolute LAI difference obtained by using the two land cover types is plotted along with the actual LAI frequencies.

and NALC2005, which explains some of the differences observed in low LAI distribution in **Figure 5**. The overall pixel-by-pixel mean absolute difference is 0.665 LAI, which is 42% and 35% of the mean LAI values obtained over Canada from 1–10 June 2003 using v2 U of T LAI algorithm with the GLC2000 and NALC2005 land cover products, respectively.

LAI estimates from remotely sensed optical data usually saturate at relatively low LAI values depending on the leaf spectral albedo (single-scattering albedo), forest background reflectances, and the view or illumination geometry. For example, MODIS's main LAI algorithm saturates at dense vegetation areas and often the backup algorithm is used in such cases. In the backup algorithm, which is based on the Normalized Difference Vegetation Index–LAI relationship, the upper end of LAI is usually below 6.5 for all biome types (Shabanov, et al., 2005). Contrary to the MODIS product, the U of T LAI algorithm has a higher flexible threshold for the upper LAI bound for forested (approx, 6–8) and nonforested (approx. 4–6) vegetation cover types. In the case of nonforest vegetation typical LAI is low, and the estimated typical LAI should not reach saturation domain. However, as explained in previous sections, a large amount of forest pixels are classified as nonforest vegetation cover type in the GLC2000. The spike at the LAI value of 5 for the GLC2000 land cover indicates that a large number of pixels that were classified as grass and crop cover types actually resulted in a saturated upper end of the U of T LAI value. This indicates that a large number of GLC2000 shrub and forest cover types are misclassified as grass and crop cover types. The reason for the spike at an LAI value of around 8 is explained by the fact that some forest pixels are in saturation domain in both land cover datasets as the LAI was derived in the height of the growing season.

Figure 6 shows the effects of land cover mixture and uncertainty in the U of T LAI algorithm estimations. The results from the Circa 2000 1 km majority-based aggregated land cover and the Circa 2000 30 m LAI show that the land cover mixture has a negligible effect on LAI estimations (**Figure 6a**). The mean LAI values for Circa 2000 (0.8038), GLC2000 (0.8228), and NALC2005 (0.8741) are statistically different from the mean LAI values obtained from the Circa 2000 30 m (0.7811) (two-tailed t-test: p value <0.0001). The reason for obtaining lower LAI estimates from the three 1 km land cover products compared with the high-resolution 30 m land cover of Circa 2000 is that the larger (1 km) pixels, which have a significant mix of the shrub and grass and crops classes with the forest class are labelled as forest land cover classes because of proportionally larger forest cover types. However, all the mismatches of the water class were filtered out of the comparison, which might have had a larger overall effect on LAI estimation using different land cover products. In the U of T LAI algorithm, water classes are assigned a LAI value of zero. The new improved v2 U of T LAI algorithm (Gonsamo and Chen, 2011), which incorporates a spatially explicit clumping index and background reflectance values, may have reduced the spurious land cover impact on LAI estimation compared with empirically determined land cover specific clumping index

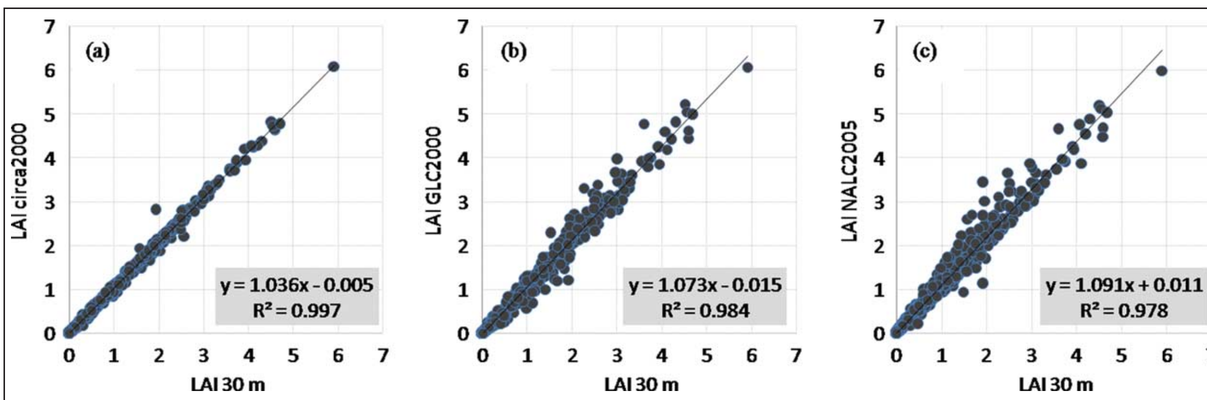

Figure 6. Scatter plots of LAI derived from the v2 U of T LAI algorithm using (a) Circa 2000, (b) GLC2000, and (c) NALC2005 land cover datasets, averaged over 50 km grid zones and plotted along with the LAI derived using the 30 m Circa 2000 land cover fraction per grid zone.

values used in U of T v1, MODIS, and ECOCLIMAP LAI algorithms (Myneni et al., 1997; Masson et al., 2003; Champeaux et al., 2005; Deng et al., 2006).

Conclusion

This study has attempted to comparatively assess and evaluate agreement and map uncertainties with using the GLC2000 and NALC2005 land cover products over Canada. The main objective was to assess the six aggregated classes that were chosen based on the relevance for global LAI, fAPAR, and CI algorithms parameterization. From our work, it can be shown that even in such broad-scale aggregation classes there can be large disagreements among the same classes of various regional land cover datasets. The two main reasons, among many that have been discussed in previous studies, are the class definitions and the temporal-spectral dynamics of land cover that is usually viewed at a global and regional scale as static phenomena. Based on our comparison and validation, we would like to echo the long-recognized concern to internationally establish homogeneous land cover definitions and reporting schemes.

Our study indicates that the NALC2005 has better quantitative accuracy over Canada than the GLC2000 based on the Circa 2000 reference data and visual and qualitative assessments. The NALC2005 exhibits better spatial distribution, such as capturing the northern limit of forest zones. The main disagreement areas, such as the boreal forest and taiga region of Canada, may receive special attention in future land cover classification and accuracy assessments. The total forested area over Canada is 3 601 856 million km^2 and 4 109 135 million km^2 based on the GLC2000 and the NALC2005, respectively, with a large difference of estimated forested area (approx. 0.5 million km^2) between the two land cover types. The pixel-by-pixel mean absolute difference of 0.665 LAI, obtained using the improved v2 U of T LAI algorithm over Canada based on the GLC2000 and NALC2005 land cover datasets, shows that land cover misclassification is a great uncertainty source in LAI estimation. For the first time, we have systematically investigated the impact of land cover maps on biophysical parameter retrieval from remote sensing data. Additionally in this study, the newly developed NALC2005 data has been evaluated independently for the first time. It is also important to note that the implication of particularly mixed needleleaf and broadleaf forest classes and their confusion with other pure leaf type forest classes may hold large uncertainties in studying land surface biophysical parameters that require land cover as crucial input. The implications of misclassification of global or regional fAPAR and CI algorithms following various methods have yet to be studied.

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