CHAPTER 8

Approaches to IPCC Land-Use and Land-Use Change Reporting in Agriculture Areas with Remote Sensing

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ABSTRACT

Information on the spatial distribution of land use conversion to agriculture is required for UNFCCC and Kyoto reporting and for many other environmental studies. Such information is required over large geographical regions and multiple years. Remote sensing data and techniques combined with other data sources, such as census information can be used to provide spatially explicit information on crop type and extent. In this review, image classification techniques for extracting information from satellite data to support reporting for agriculture are discussed and evaluated. Three classification approaches are compared using LANDSAT images from south-eastern Ontario. Results do not strongly support a significant advantage of any one approach, but highlight the need for several dates of imagery over the growing season to effectively map crop type. Determining the area extent of agriculture is more straightforward and does not require multi-date imagery. However, it does need imagery from a specific temporal window where agricultural fields can be most effectively discriminated.

INTRODUCTION

Probabilistic forecasts of future climate outcomes based on historical observations and results of quantitative models suggest changes in climate processes due to human effects on the earth system’s energy balance. It is predicted that changes will affect all major components: atmosphere, hydrosphere, cryosphere, lithosphere, biosphere, and the interactions between them. Characterization of dynamic surface processes, resulting from a certain land surface composition is a source of information that improves our understanding of the causes of observed variability and change. Changes in land cover
affect exchanges of energy and water, and the exchange of greenhouse gases between the biosphere, lithosphere, and atmosphere. Land cover changes contribute to climate change and variability, and when combined, may have profound effects on the Earth’s habitability (U.S. Climate Change Science Program (CCSP), 2005).

Agriculture is one of the primary drivers of human-induced degradation of natural vegetation. Effects are twofold; 1) a reduction in potential carbon sinks through conversion of forested land into agriculture land, and 2) increases of greenhouse gas (GHGs - carbon dioxide, nitrous oxide, and methane) emissions due to cropping, improving pastures, and the application of fertilizers and animal wastes.

National reports to the United Nations Framework Convention on Climate Change (UNFCCC) are expected to contain data on carbon stocks, emissions, and removals of GHGs associated with land-use and land-use change. The UNFCCC and Kyoto protocol have initiated research on the carbon cycle, land-use, land-use change, and biological/ecological processes. The focus of this research is aimed at improving capacities for national carbon accounting for developing carbon sequestration strategies and alternative response options. Land cover information plays a major role in carbon balance modeling studies, which at a basic level includes the type and extent of vegetation (Houghton and Goodale, 2004). Knowledge of vegetation spatial distribution is also required for investigating and quantifying and scaling the local to regional ecosystem-atmosphere CO₂ fluxes. It has been recognized that remote sensing can contribute by providing systematic observations and temporal data archives that may reduce uncertainties in reporting on terrestrial carbon budgets. Thus, remote sensing combined with national and international in-situ measurement networks for monitoring aboveground biomass and land cover change can support the following five Kyoto requirements:

- Provision of systematic observations of land cover;
- Support the establishment of a 1990 carbon stock baseline;
- Detection and spatial quantification of land cover / land use change;
- Quantification of aboveground vegetation biomass stocks and associated changes;
- Mapping and monitoring sources of anthropogenic CH₄.
The Intergovernmental Panel on Climate Change (IPCC) has developed good practice guidelines for land-use, land-use change and forestry (LULUCF) estimates. The guidelines support the development of inventories that are transparent, documented, consistent, complete, comparable, assessed for uncertainties, and subject to quality control. The guidelines aim for efficient use of resources available to inventory agencies, and in which uncertainties can be reduced as better information becomes available (IPCC, 2003).

The IPCC guidelines contain little, if any, discussion on how to estimate land areas and changes in land area associated with LULUCF activities. In practice, countries use a variety of sources including agricultural census surveys, forest inventories, and remote sensing data, but methods and definitions used by different authorities in assembling the data are not always consistent (IPCC, 2003).

IPCC LULUCF provides suggestions for three approaches for representing areas of six broad land categories (forest land, cropland, grassland, wetland, settlement and other land) used for estimating and reporting greenhouse gas inventories. General characteristics of each approach are:

- **Basic land-use database** - This approach relies on existing national data including forest inventories, agriculture statistics, and census surveys. It does not require geographically explicit land area specification. The area of land use change is estimated at two points in time without determining inter-category relations. This approach does not necessitate explicit use of remote sensing data, but such data prepared for other purposes can be used.

- **Survey of land use and land-use change** – This approach includes more information on change between land categories. It specifies land-use transitions for the reporting period by providing information on the nature of change. The report generated from this approach can be presented as a non-spatially explicit land-use change matrix.

- **Geographically explicit land use** – This is the most comprehensive approach requiring spatially explicit land-use and land-use change data. Spatial units such as grid or vector coverages are used to represent reporting areas. The location of spatial units should be unchanged during the reporting time. Remote sensing combined with ground survey sampling is a suitable way for providing data for this approach. IPCC-LULUCF suggests that countries with more difficult access to some regions, but
with access to good remote sensing data should adopt this approach and develop an accounting system with an emphasis on remote sensing observations and techniques.

The use of remote sensing for collecting land-use information is identified in the IPCC guidelines. However, details on actual information extraction procedures and fusion of remote sensing data with other available sources of information are not explicitly outlined. Therefore, the purpose of this paper is to evaluate some capabilities of remote sensing for obtaining information about land area required for estimating carbon stocks, removals, and greenhouse gas emissions associated with agricultural land use. A short overview of remote sensing data, classification approaches and methodological issues specific to mapping land-use in agricultural areas are presented and illustrated in two case studies.

**REMOTE SENSING DATA**

Commonly used sensors for land cover mapping include: at medium spatial resolution MERIS (300 m and 1200 m), MODIS (250 m, 500 m, and 1000 m), SPOT/VEGETATION (1000 m) and NOAA/AVHRR (1000 m); at fine spatial resolution LANDSAT (30 m and 15 m), ASTER (15m) and SPOT (5 m, 10 m, and 20 m); and at very fine spatial resolution OrbView, Quick Bird and IKONOS (1 m to 5 m).

Finer resolution multi-spectral systems that include mid-infrared bands, such as LANDSAT TM, ETM+ and SPOT HRVIR, are well suited for land cover mapping. Their spatial resolution (10-30 m) allows delineation of fragmented agriculture and forestland as well as separation of smaller natural and anthropogenic disturbances such as forest fire, logging, and urban and industrial developments. Examples where complete LANDSAT data coverage of the country has been used as a primary source for deriving land cover information include: US National Land Cover Database produced by USGS, the Australian National Carbon Accounting System NCAS (Furby, 2002) and the New Zealand Land Cover Database (NZLCDB, 2005). In Canada, the National Carbon and Greenhouse Gas (GHG) Emission Accounting and Verification System (NCGAVS) for agricultural land and the National Forest Carbon Accounting System (NFCAS) are in development and both rely on LANDSAT coverage generated by the National Canadian Consortium led by the Centre for Topographic Information-Sherbrooke
THE UNITED STATES 2001 NATIONAL LAND COVER DATABASE

Low and medium resolution sensors, allow cost effective monitoring of vegetation dynamics and land cover at a coarse scale (i.e. national coverage). Its role will likely be for monitoring and identifying areas of change where finer resolution data would have to be collected and processed for reporting (Fraser et al., 2005).

LAND COVER CLASSIFICATION

Digital classification of multispectral images is commonly used to obtain information on land cover. Despite long and extensive development the ultimate goal of a completely automated classification method has not yet been achieved due to the following constraints:

- Signal to noise ratio in satellite measurements can be high, as calibration, sensor response, geometric resampling, and geolocation are not perfect procedures;
- Difficulty in accurately characterizing atmospheric conditions during image acquisition hinders successful correction. Thus, apparent reflectance at the surface for the same target varies due to scattering from sub-pixel clouds, aerosol, haze and other atmospheric constituents;

Figure 1. Example 250 m resolution MODIS image (left) and LANDSAT image (right) displayed as red = near-infrared, green = short-wave infrared, and blue = red.
• Viewing geometry and shadowing effects introduce significant variability in the satellite measurements that are difficult to precisely correct;

• Surface reflectance is influenced by soil moisture and vegetation water content, leading to considerable variability in surface spectral properties;

• Measurements are acquired over different vegetation conditions and phenological stages. Thus, spectral properties are time and space dependent, limiting spectral generalization/extension of known surface types.

To cope with this variability, supervised and unsupervised classification methods have evolved and remain as fundamental approaches. In general they fall into one of two groups: parametric and nonparametric classification algorithms. In the past, the most widely used supervised classifiers have been the parallelepiped, minimum distance and maximum likelihood. Recently, more sophisticated algorithms have emerged based on artificial neural networks (Benediktsson et al., 1990, Carpenter and Grossberg, 1988; Kohonen, 1989), decision trees, mixture modeling, and various combinations of neural-statistical approaches (Bruzzone et al., 1999; Benediktsson and Kanellopoulos, 1999; Wan and Fraser, 1999).

In unsupervised classification, no prior information about land cover types and their distribution is required in the clustering phase. A number of algorithms have been developed, as with supervised classification they can be either parametric or non-parametric, where the latter involve fuzzy and artificial neural network theory. The most widely used parametric methods include the Iterative Self Organized Data Analysis Technique referred to as ISODATA (Tou and Gonzales, 1977; Sabines, 1987; Jain, 1989) and K-means (Tou and Gonzales, 1977).

Conventional image classification techniques assume that all pixels within an image are pure, containing only one land cover type within the footprint of the pixel and assign the pixel to a single cluster known as “hard” classification. The alternative is “soft” classification, which assigns a membership or “agreement” value to each cluster. There are two paradigms in soft classification approaches: 1) fuzzy classification which defines membership based on spectral similarity; and 2) fractional, which is based on the mixed pixel effect and attempts to determine the fraction of each cover type within the pixel.
The following are a few examples of soft classification approaches:

- Fuzzy membership functions to estimate sub-pixel forest cover (Foody, 1994);
- Isolines in red and near infrared scatter plot to estimate sub-pixel fractional canopy density, using a geometric model of plant cover to infer the density associated with the isoline (Jensen, 1996);
- Empirical relationships between percent cover derived from high-resolution data and attributes of medium resolution data to extrapolate proportional forest cover over large areas (DeFries et al., 1997; Iverson et al., 1989, 1994; Zhu & Evans, 1994, Fernandes et al., 2001);
- Calibration of area estimates from spatial aggregation of land cover classifications derived from medium and fine resolution data (Mayaux and Lambian, 1997);
- Linear mixture modelling to deconvolve proportional land cover based on reflectance of end-members or pixels containing 100% of the vegetation types of interest (Adams et al., 1995);
- Relating the land cover composition of mixed pixels to artificial neural network classification output (Foody, 1996).

Object oriented classification is another recent approach that attempts to incorporate spectral, spatial, and contextual information into the classification decision. Objects are defined based on a segmentation procedure such as region growing or edge detection and edge following. The properties of these objects such as object spectral means, shape characteristics, within object spectral variance, object class membership at different scales, and object neighbour relations are used to improve classification (Baatz et al., 2003).

4. Case Studies

In two case studies remote sensing techniques for a) mapping land cover with predominantly agriculture land-use, b) mapping land-use change, and c) mapping crop type area distribution are presented. Examples of a) and b) are presented for the Chateauguay River region, while c), mapping crop type area distribution, is demonstrated for the Casselman Township area.

The study areas are located in the St. Lawrence Lowlands in an agriculture belt south of Ottawa.
and Montreal (Fig.2). In both areas, corn and soybeans are the two dominant crop types. Other crops include alfalfa and several varieties of cereal crops. Natural vegetation includes coniferous and mixed deciduous forest, wetland, and low ground cover vegetation such as grass.

**Data**

*Image Data*

Two LANDSAT scenes over Chateauguay River region were selected from the period after snow-melt and before crop emergence (May 1990 and June 2001). The images were selected from the beginning of the growing season where discrimination between agriculture land and natural vegetation was the highest.

The importance of selecting imagery from the appropriate time period is apparent from Figure (3). Two images acquired in July (3a) and November (3b) of the same area illustrate the difference in discriminating agriculture land from natural vegetation. The agriculture land mask given in (3c) has been generated from the November image shown in 3b. Confusion between natural vegetation and cropland in the July image (3a) was too high to permit generation of an accurate mask.

In case of the Casselman Township study, a multi year dataset was required to determine cropping pattern. Three LANDSAT and a SPOT image were selected from the July-August period. Two LANDSAT images for 2002 and 2003 were acquired in mid July. The only available clear sky image in 2000 was acquired in mid August with LANDSAT and in 2004 with SPOT 4 (Table 1). A November LANDSAT image was also acquired to aid in the separation of forest from non-forest.

![Figure 2. Geographic location of the study area.](image)
Field Data

Ground truth data were collected on August 18, 2004 for the Chateauguay River region. Samples were acquired for natural vegetation including forest, wetland, shrub land, grassland, and some agricultural areas. The objective of the fieldwork was to collect data to produce a regional land cover map required for other land cover related studies. In addition to fieldwork, air photos of the whole region were assembled and used for assessing accuracy of agriculture areas while ground truth data were used mainly for assessing accuracy in mapping natural vegetation. Fig. 4 shows the location of the field samples collected in the Chateauguay region.

Field data for the Casselman region was acquired on August 21, 2004 and overlaid on the 2004 SPOT image to determine crop type spectral properties. These properties were then used to select training and validation samples for each classification through visual interpretation in combination with air photos. Only agriculture classes were included in the sampling, as these were the classes of interest. Fig. 5 shows sample locations of field data collected for Casselman.

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<th>Date</th>
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</tr>
<tr>
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<td>TM</td>
<td>29/05/1990</td>
</tr>
<tr>
<td>Casselman</td>
<td>ETM+</td>
<td>05/11/2000</td>
</tr>
<tr>
<td>Casselman</td>
<td>ETM+</td>
<td>15/08/2000</td>
</tr>
<tr>
<td>Casselman</td>
<td>ETM+</td>
<td>20/07/2002</td>
</tr>
<tr>
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<td>TM 5</td>
<td>15/07/2003</td>
</tr>
<tr>
<td>Casselman</td>
<td>SPOT 4</td>
<td>18/08/2004</td>
</tr>
</tbody>
</table>

Table 1. Image data used in case studies
Figure 4. Chateauguay region sampling points depict location where ground truth was acquired. Sample mainly includes natural vegetation forest, wetland, shrub land, grassland and orchards.

Figure 5. Casselman region sampling. Letters correspond to crop type: C = corn, S = soybean, A = alfalfa, G = grass/low-lying vegetation, O = oats. The oat field in the lower left of the image has the same spectral characteristics as other barren fields in the image. Image is displayed as: red = near infrared, green = shortwave infrared, blue = red.
Image Pre-Processing

An integral part of generating land cover information from satellite imagery is image data pre-processing. The purpose of pre-processing is to geolocate imagery and reduce sensor and scene noise. In both studies image geometric rectification was performed using ground control points (GCPs) acquired from the National Ground Control Database, GeoGratis (http://geogratis.cgdi.gc.ca/clf/en). Additional GCPs were collected along digital baseline features from the National Topographic Database. Pixels corresponding to selected GCPs locations were identified on the LANDSAT images. Linear polynomial control point rectification with nearest neighbour resampling was conducted on the reference LANDSAT scene, resulting in an average RMS error of 0.65 of a pixel (30 m pixel spacing). An average RMS error below 1.0 pixel was targeted as acceptable. Other scenes were co-registered to existing orthorectified reference images of the area.

Variation in solar illumination condition, phenology, and detector performance results in differences in radiance values unrelated to changes in the land cover type. Radiometric normalization represents the first order data transformation approach used to reduce the variability between multi-temporal data sets acquired over the same geographic area. The process substantially reduces or normalizes the inter-scene variability resulting from different phenological conditions, atmospheric conditions, radiation incidence angles, and detector disparities. Relative radiometric normalization uses one image as a reference and adjusts the radiometry of the subject image to match the reference. The radiometric normalization of the LANDSAT images used in this study was performed only for Chateauguay region using the approach given by Du et al. (2001).

Results and Discussion

Chateauguay Region

The Chateauguay example demonstrates approach 1 for IPCC reporting, where the area of agriculture land is derived from remote sensing data, while other parameters such as crop type required for estimating greenhouse gas emissions can be obtained from other data. In this approach, the area converted from natural vegetation to cropland or vice-versa can be derived over different time steps
depending on needs. Annual change of the crop area between map dates can be interpolated following the procedure suggested in the IPCC good practice guidelines (IPCC, 2003). The need for area updates would be determined based on census data. If census data indicate a significant change in crop area, then spatial information can be updated more frequently using remote sensing. Integration of agriculture census and remote sensing data allow for 1) flexibility in selecting years of update when high quality remote sensing data are available and 2) increased report accuracy and consistency.

Classification by Progressive Generalization (CPG, Cihlar et al., 1998) was used to classify the 1990 and 2001 scenes into the following four categories: natural vegetation, cropland, urban land and water. The Fuzzy-K means clustering algorithm was used to generate 150 clusters and merged based on spectral and spatial similarity criteria (Latifovic et al., 1999). Final 52 spectral clusters were further agglomerated and labelled based on a subset of the field data.

Post classification change detection (Fig. 6) was employed to quantify the change in area under crops. The method assumes that reference and compared images are classified into a common legend and that the classification method utilized for mapping provides high accuracy (>95%) for both images. Such high accuracy with LANDSAT data is possible only for classifying a few classes e.g. natural vegetation, cropland or forest non-forest. Landscape changes are simply detected as differences between pixel labels. For a comprehensive review of change detection methods see (Choppin et al. 2004).

Visual evaluation of the maps was performed through comparison to a large number of air photos. The assessment showed very good delineation accuracy of agriculture fields. Results of post classification change detection revealed that 8% of the area changed between 1990 and 2001 (Fig. 7). Some of this change is misclassification in the 2001 image, which was acquired when of few crops were starting to emerged. Thus, the actual change is smaller than the remote sensing estimate. In cases where more precise estimates are needed, a procedure that calibrates remote sensing estimates based on field data such as that outlined by Ambrosio and Martinez (2000) can be used.
Figure 6. Post-classification change detection procedure. Years given do not correspond to those used in this analysis.

Figure 7. Example agriculture areas of the Chateauguay region for 1990 and 2001. Left side - shows the LANDSAT imagery red = near infrared, green = shortwave infrared, and blue = red band. Right - shows agriculture area mask. Figure at the bottom shows change mask.
Casselman Region

Three methods for crop type classification (maximum likelihood, CPG, and object oriented classification (OOC)) were compared based on accuracy and temporal consistency. The intention of the comparison was to determine if one of the methods strongly outperformed the others for basic crop type mapping.

Initial classification attempts showed that the broadleaf forest class was frequently mixed with agriculture classes, mainly corn. The class location in feature space is presented in Fig. 8 consisting of red, near infrared and shortwave infrared spectral measurements. It is evident that corn and broadleaf forest values populate the same part of feature space.

To improve map accuracy of agriculture crop types, a mask of natural vegetation was created using a late November LANDSAT image (Fig. 9a). At this time, the forest class is very distinct from other classes making the extraction straightforward. An urban mask was also created using an existing road coverage of the area, available from National Road Network, Canada, Level 1, (www.geobase.ca/geobase/en/list.jsp). The road coverage was converted to a raster mask through a series of dilatation and erosion operations to fill in areas with high-density roads (Fig. 9b). The remaining area that was not under natural vegetation and urban masks was classified using one of the three methods.

Maximum Likelihood

For maximum likelihood classification, training data were selected from the imagery and checked for normality. Class spectral distributions were almost all normal except for the soil and grass classes, which had bimodal histograms. These classes were split and re-merged post-classification. A sieve filter was applied post-classification to merge clusters smaller than 9 pixels to their largest neighbor.

Classification by Progressive Generalization

CPG classification was implemented with the K-means classifier to generate an initial 150 spectral clusters. Cluster agglomeration was performed based on cluster spectral similarity and spatial proxim-
Figure 8. Feature space representing mid July class spectral properties.

Figure 9. A) November LANDSAT image (left), natural vegetation mask (right). B) Road vector coverage (left), urban area mask (right).
ity following a procedure described in (Latifovic et al., 1999). The agglomeration yielded fifty-five different spectral clusters. In the labeling procedure, those fifty-five were grouped into 14 thematic classes according to the legend provided in Table 2. Post-classification refinement included a sieve filter applied to merge clusters smaller than 9 pixels to their largest neighbor. The same procedure was repeated for each year to produce a complete crop type time series.

<table>
<thead>
<tr>
<th>Value</th>
<th>Label</th>
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<tbody>
<tr>
<td>1</td>
<td>Water</td>
</tr>
<tr>
<td>2</td>
<td>Cloud shadow</td>
</tr>
<tr>
<td>3</td>
<td>Cloud</td>
</tr>
<tr>
<td>4</td>
<td>Urban</td>
</tr>
<tr>
<td>5</td>
<td>Bare soil</td>
</tr>
<tr>
<td>6</td>
<td>Low Vegetation (open field, grass)</td>
</tr>
<tr>
<td>7</td>
<td>Shrubland</td>
</tr>
<tr>
<td>8</td>
<td>Wetland</td>
</tr>
<tr>
<td>9</td>
<td>Mixed coniferous-deciduous forest</td>
</tr>
<tr>
<td>10</td>
<td>Coniferous forest</td>
</tr>
<tr>
<td>11</td>
<td>Soybean</td>
</tr>
<tr>
<td>12</td>
<td>Alfalfa</td>
</tr>
<tr>
<td>13</td>
<td>Corn</td>
</tr>
<tr>
<td>14</td>
<td>Cereals</td>
</tr>
</tbody>
</table>

Table 2. Classification legend.

Object Oriented

OOC was carried out using the commercial software package eCognition. Numerous parameter combinations were evaluated to segment objects and the best set, determined visually, was used in the classification. For classifier training, objects were selected from the imagery and only the spectral data was used in the initial classification. Additional classifications included the standard deviation of each object for each band (Stdv) and the length to width ratio (Shp) of each object.

The results from each classification are shown in Fig. 10. Visual comparison of the classification results to the original imagery shows that the classified images preserved the spatial pattern of agricul-
ture fields in the original 3 band images. Overall, the maps appear to contain similar information, but some differences are evident. OOC produced the most spatially generalized results due to the classification of image objects instead of pixels, whereas the MLC and CPG methods were much more spatially variable. The disadvantage of object-based classification is that it makes a much larger error for a given misclassification since the entire area of the object is incorrect. Using a per-pixel approach reduces this, as not all pixels within the object will be incorrectly classified, but individual pixels are typically more difficult to classify than objects. For example, the narrow cornfield in the upper right of Figure 10 was classified as shrub by OOC, but was predominantly classified as corn by CPG and partly corn by MLC.

Accuracy Assessment

Accuracy was assessed for each cover type separately using an accuracy index that incorporated both omission and commission error into a single summary value.

![Figure 10. Example classification results. In the example yellow - soybean, brown - corn, orange - alfalfa, red - cereals, grey - low-lying vegetation, green - forest, light blue - soil, blue – built-up, pink - wetlands.](image)
AI = ((n-o-c)/n)×100

Where n is the number of validation samples for the class, o is the number of omission errors (i.e. where validation samples for the given class and map did not agree), and c is the number of commission errors (i.e. where the given map class and validation samples overlapped).

Table 3 shows the classification results for 2000-2003. Data for 2004 were not available when these results were complied. All methods performed well and were close enough that subjectivity in each could account for the observed differences. However, some general trends are evident and confidence in the results is enhanced by the consistency of the results over multiple dates. The object oriented classification using only spectral information produced the lowest overall result, but including either

<table>
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<tr>
<th>Year</th>
<th>Method</th>
<th>Soil</th>
<th>Low Veg.</th>
<th>Soybean</th>
<th>Alfalfa</th>
<th>Corn</th>
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Table 3: AI values (%) for comparison with test data.
shape or within object variance improved results. CPG produced the best overall result and was the most consistent, suggesting that this was the optimal approach considering only crop type accuracy.

**Crop Type Temporal Distributions**

The temporal distribution of crop types derived using the CPG classification approach is presented in Fig 11. It shows the effect of image acquisition date on the crop area estimates. For July dates (2002 and 2003), the area of bare soil is higher than the August dates (2000 and 2004). Soybean is also the lowest for the July dates, indicating that it is the last crop to emerge and develop being misclassified as bare soil at this time. Considering only the August dates, it appears the crop distributions have not changed substantially, except for soybean in 2004. The July dates show more variability in area, likely due to the underdeveloped crop canopies. The area of cereal crops was similar in both 2002 and 2003. Cereal crops could not be mapped for the August dates as their spectral properties were not distinct from other cover types in August.

![Figure 11. Crop type area estimates from the CPG classification results.](image)
CONCLUSIONS

These case studies highlight the potential contribution of remote sensing for greenhouse gas reporting based on the IPCC land-use, land-use change framework. In both cases, selecting imagery from the appropriate time period is critical to success. This is especially true in the case of crop type mapping. Deriving the agriculture area from remote sensing is relatively straight forward and combined with census data should provide a reasonably precise means of reporting. Crop type mapping has the potential for improved accuracy, but also increased error and reduced precision, as crop spectral signatures can be confused amongst themselves and with other land cover classes. Successful mapping will likely require several images throughout the growing season in order to map all crop types and separate natural vegetation from crops.

REFERENCES


Fraser, R.H., A. Abuelgasim, and R. Latifovic. (2005). A method for detecting large-scale forest cover


