A Multi-Sensor Approach to Inventorying Agricultural Land Use

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Abstract – Agriculture and Agri-Food Canada (AAFC) is developing an agricultural land information system to map and monitor both land cover and land use. These data products are needed to satisfy information requirements under a number of national programs. Methods are currently under development to exploit both optical (Landsat and SPOT) and SAR (RADARSAT-1 and Envisat ASAR) imagery to map annual crop inventories. This paper presents early results over one AAFC pilot site using both a Maximum Likelihood and a Decision Tree classification approach.

Keywords: crop inventory, maximum likelihood classification, decision tree classification, RADARSAT, ASAR, SPOT, Landsat

1. INTRODUCTION

To deliver a statement on the status and changing state of the national agricultural resource base, Agriculture and Agri-Food Canada (AAFC) is developing an agricultural land information system. Information on land cover and cropping systems is required under a number of AAFC national programs including the National Land and Water Information System, the National Agri-Environmental Health Analysis and Reporting Program and the National Carbon and Greenhouse Gas Accounting and Verification System. Once operational, reporting on agricultural land use and land use change will be completed annually. Land use coverage will not be spatially continuous, but will be based on a statistical area sampling framework. Land use information derived from this sampling framework will be scaled to a national level.

Successful crop identification using Earth Observation (EO) data relies on image acquisitions during key crop phenological stages. Thus a necessary component of the methodology under development at AAFC is the integration of data from multiple sensors, in particular the exploitation of data from SAR satellites. This paper presents crop classification results using both optical and radar imagery. Included are early results from a simple maximum likelihood classification approach and from a decision tree methodology currently under development at AAFC for land cover mapping.

2. METHODS

2.1 Data Acquisition and Image Pre-Processing

The methodologies to classify crop type from EO imagery are being developed on several pilot sites across Canada. Extensive EO data sets have been acquired over three pilot sites including one site in eastern Canada (Ottawa) and two sites in western Canada (Swift Current and Lethbridge). The EO data acquired over these pilot sites include multi-temporal images from Landsat, SPOT, Envisat ASAR and RADARSAT-1 sensors. Images have been acquired for both the 2003 and 2004 growing seasons. The results reported in this paper are limited to the 2004 data acquired over the Ottawa site. This site is dominated by corn, soybean, small grain and forage production.

Three SPOT-4 and one Landsat-5 multispectral images were acquired over the Ottawa site during the 2004 growing season. SPOT images were acquired on June 10, July 17 and August 22, with the Landsat-5 image acquired coincident to the July 17, 2004 SPOT image. Table 1 provides the details of the SAR data acquired over this site. All optical and radar images were orthorectified using orbital data and ground control points acquired from road vector layers. All images were resampled to a 30 m resolution, and subset over a study area for classification method testing. A larger subset area was initially selected based on the availability of ground data and the overlap areas of the SAR/Landsat acquisitions. A smaller subset area was used to test the performance of SPOT images in each of the classifiers due to the smaller coverage area for these images.

Table 1. RADARSAT-1 and Envisat ASAR Imagery Acquired in 2004 for the Ottawa Site

Date	Sensor	Beam	Polarization
June 17	RADARSAT	S7A	HH
July 1	RADARSAT	S5A	HH
July 2	ASAR	IS7A	VV
July 2	ASAR	IS7A	VH
July 18	ASAR	IS6A	VV
July 18	ASAR	IS6A	VH
July 25	RADARSAT	S5A	HH
Aug 22	ASAR	IS6D	VV
Aug 22	ASAR	IS6D	VH
Aug 26	RADARSAT	S6A	HH

All optical images were atmospherically corrected using the Atcor algorithm implemented in PCI software (Richter, 2004). Data were initially converted to at-sensor radiance using gain and offset calibration information provided with the data. The radiance was then converted to reflectance using a MODTRAN 4.2 radiative-transfer code to model atmospheric water vapour and aerosols. Aerosol visibility maps were calculated using this algorithm to compute aerosols on a spatially variable basis. Cloud masks were developed using a comparison of normalized radiance values in the blue/green wavelengths between clouded and cloud-free images. This method was less effective on SPOT imagery due to the absence of a blue band; therefore clouds were manually removed from the August 22nd SPOT image. Clouded areas were set to zero in each image after atmospheric correction to remove these areas from the classification.

Both Radarsat and Envisat data received were fully calibrated. Prior to image analysis, two passes of Gamma filter were applied to the radar data to remove speckle effects. Considering the small size of the fields under study, a 3 by 3 window size was adopted.

2.2 Classification Methodologies

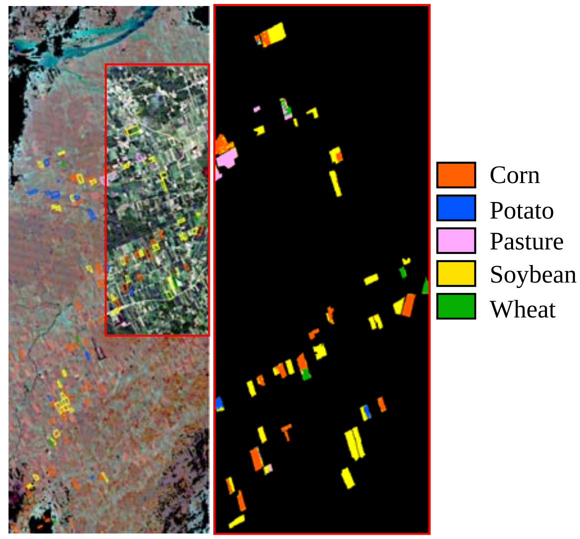
Per-pixel classification was performed using both a supervised Maximum Likelihood Classifier (MLC) and a Decision Tree (DT) approach. Decision boundaries for multivariate DTs are defined by combinations of features and a set of linear discriminate functions are applied at each test node (Pal and Mather, 2003). Decision boundaries and coefficients for the linear discriminate function are estimated empirically from the training data. DT methodologies permit the integration of disparate geospatial data and unlike maximum likelihood classifiers, the DT approach does not make any assumptions regarding the statistical distribution of these data. Radar data are almost without exception, non-Gaussian. The results for this paper were generated using inputs of optical and SAR imagery within the See5 DT software. The same set of training samples and testing sites were used for both the MLC and DT classifications. For each crop type, training sites were selected from half of the individual study fields. Testing sites were selected from the remainder of the study fields (i.e. training and testing areas were not located in the same fields). There was no overlap between the training and testing pixels. The training areas selected cover a large portion of the individual field and were away from the field boundaries to reduce contamination from headland areas and mixed pixels.

3. CLASSIFICATION RESULTS

Landsat, SPOT and SAR images over the Ottawa study site are provided in Fig. 1 and Fig. 2. Also included in these figures is the classification of the test fields located in the site.

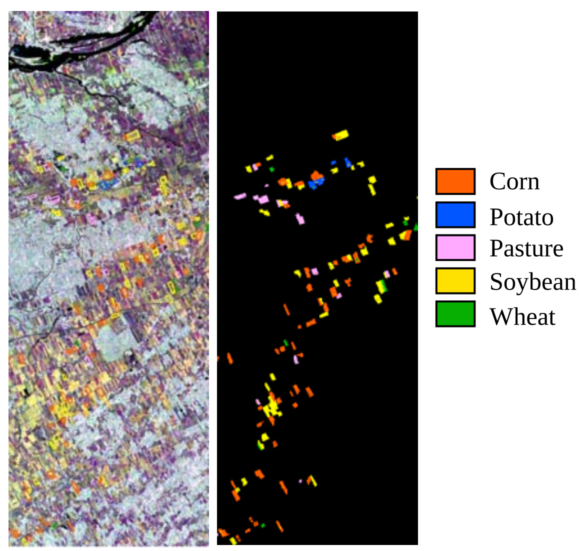
3.1 Classification Results from SPOT Data

The Kappa coefficients from the MLC and DT classification of the SPOT data are presented in Table 2. The Kappa coefficient accounts for errors of omission and commission and the effects of chance agreement (Lillesand and Kiefer, 2000). The Kappa coefficient is thus considered a more robust indicator of classification accuracy.



Left: Landsat imagery with field boundary overlay. The inset is the extent of the SPOT imagery used in the analysis.
R: Landsat Band 4 G: Landsat Band 2 B: Landsat Band 3
Right: MLC result using SPOT-4 July and August images.

Figure 1. MLC Classification of SPOT Imagery



Left: Colour composite of radar imagery with field boundary overlay.
R:July 1 RADARSAT G:July 2 ASAR VV B:June 17 RADARSAT
Right: DT classification using all RADARSAT and Envisat ASAR data plus all 6 TM bands.

Figure 2. DT Classification of Landsat, RADARSAT-1 and Envisat ASAR Imagery

Table 2. Kappa Coefficients for Maximum Likelihood (MLC) and Decision Tree (DT) Classifications of SPOT Imagery

	MLC	DT
All 3 SPOT	0.72	0.61
SPOT June 10	0.42	0.33
SPOT July 17	0.72	0.62
SPOT August 22	0.83	0.66
SPOT June-July	0.62	0.64
SPOT July-August	0.82	0.66
SPOT June-August	0.64	0.67

In most cases, the MLC classifier outperformed the DT classifier. For all DT classifications, the Kappa fell below 0.7. The best result was obtained using a single SPOT image (August 22) and the maximum likelihood classifier (Table 3). Using this SPOT image, all crops except potatoes were classified to an accuracy of greater that 85% (Table 3). Integrating multiple SPOT images into the MLC or DT classifier did not improve the overall accuracy when compared to the classification results obtained from a single (August 22) image. Using the maximum likelihood classifier, each SPOT image could consistently classify soybeans to an accuracy of greater than 85%. For most dates, the accuracy with which corn crops were identified was above 75%. Classification of pasture fields was the most problematic. The classification confusion may be related to the diversity in cover and condition of pasture land across the site. The success at which wheat crops were correctly identified was highly variable. The developmental stage of this small grain crop varies considerably from field to field due to differences in planting dates. There were limited training and testing areas in the smaller image subset used for SPOT classification, particularly for wheat, potato and pasture areas. This may have influenced the performance of the classifier for both testing and training.

3.2 Classification Results from Landsat, RADARSAT and Envisat ASAR Imagery

When comparing the MLC and DT classifications of the SAR and Landsat imagery, See5 provided slightly higher classification accuracies relative to those achieved with the MLC (Table 4). However, of importance is the consistency with which the DT classifier performed at the individual crop class level. As an example, using all SAR and Landsat bands, the MLC class accuracy ranged from 49.6% for wheat to 96.1% for soybeans. In contrast using See5, the range in individual crop classification accuracies ranged from 75.8% (potatoes) to 96.2% (soybean).

Among all the band combinations compared, integrating all SAR data and all six Landsat bands in the DT classifier produced the highest overall classification (90.6%) and the best Kappa (0.86) (Table 4). Classification accuracies on a crop basis were reported as 89.3% (corn), 75.8% (potato), 83.8% (pasture) 96.2% (soybean) and 84.5% (wheat). Overall accuracies of 80% were achieved using either SAR or TM imagery alone. However, the accuracy with which individual crop classes were identified was not acceptable using this approach. Acceptable levels of accuracies for individual crop classes are only achieved with the fusion of radar and optical data.

Table 3. Maximum Likelihood Classification Results from SPOT Data

	All 3 SPOT	SPOT June 10	SPOT July 17	SPOT August 22	SPOT June-July	SPOT July-August	SPOT June-August
Corn	79.3	53.4	93.4	89.5	71.6	89.0	72.2
Potato	61.8	100.0	96.1	6.6	92.1	11.8	72.4
Pasture	32.2	19.7	17.8	97.4	16.4	65.8	26.3
Soybean	99.6	84.1	93.2	95.6	99.3	99.2	97.0
Wheat	75.8	0.0	0.0	87.1	4.8	96.8	46.8
Overall Accuracy	**83.0**	**64.0**	**83.0**	**89.0**	**77.2**	**88.1**	**78.0**
Kappa Coefficient	**0.72**	**0.42**	**0.72**	**0.83**	**0.62**	**0.82**	**0.64**

Table 4. Maximum Likelihood (MLC) and Decision Tree (DT) Results for Landsat, RADARSAT-1 and Envisat ASAR

Method	Sensor	Corn	Potato	Pasture	Soybean	Wheat	Overall Accuracy	Kappa Coefficient
MLC	All 10 SAR images	81.5	73.2	63.3	88.3	63.0	81.0	0.72
DT	All 10 SAR images	77.3	62.6	74.8	90.1	44.3	79.3	0.69
MLC	ASAR (July 2 & Aug 22)	77.3	62.1	48.8	69.8	38.5	68.7	0.56
DT	ASAR (July 2 & Aug 22)	75.6	17.4	55.3	87.3	20.9	72.3	0.58
MLC	All 6 TM bands	84.9	76.8	46.6	86.5	59.1	80.2	0.71
DT	All 6 TM bands	86.4	72.1	32.3	88.4	65.9	80.5	0.70
MLC	10 SAR + 6 TM	93.3	81.6	74.8	96.1	49.6	89.4	0.84
DT	10 SAR + 6 TM	89.3	75.8	83.8	96.2	84.5	90.6	0.86
MLC	10 SAR + TM345	90.4	67.4	65.5	94.8	54.9	86.7	0.80
DT	10 SAR + TM345	88.7	72.1	84.7	96.9	81.7	90.4	0.85

4. CONCLUSIONS

This paper reports on early results from the classification of SPOT, Landsat, RADARSAT-1 and Envisat ASAR to support a national crop inventory. Imagery acquired over a pilot site in eastern Canada was classified using both a Maximum Likelihood (MLC) and a Decision Tree (DT) approach. Overall classification accuracies were comparable between these two classification approaches. However, the DT classifier tended to provide more consistent classification accuracies at the individual crop level. The DT classifier also permits the integration of disparate data sources. Fusion of additional geospatial data with the EO imagery within a DT classifier will be explored in the next phase of the method development.

Classification accuracies above 80% were achieved with a number of the EO data sets. However these methods must be rigorously tested on other data sets, including those from other pilot sites, to establish the robustness of these approaches. This is important considering the varied cropping systems found across Canada. Building on the results from the RADARSAT-1 and Envisat ASAR classifications, the project will test these methods using RADARSAT-2 data. As well, several Hyperion hyperspectral data sets have been acquired over these pilot sites, and the advantages of these data for crop classification will also be investigated.

5. REFERENCES

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