Crop delineation using hybrid classification procedures: A case study in Scott, Saskatchewan

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Abstract

Currently, crop insurance companies rarely work in co-operation with remote sensing scientists as they believe that the data quality and resolution are too low to accurately delineate crop areas and predict yields. This is due to the cost of high spatial and temporal resolution data, which generally exceeds that of sending a field team to randomly inspect cropped areas. However, methods have been initiated recently, that increase the classification accuracy of medium resolution and coarse resolution data. In this study, SPOT-4 20 m resolution images for June, July and August were provided by Agriculture Financial Services Corporation (AFSC), Alberta for the area of Scott, Saskatchewan to ascertain the classification accuracy of current methodology and evaluate the possible applications of remote sensing data. Results show that hybrid classification and using normalized difference vegetation index (NDVI) are able to produce 85% classification accuracy for a three image multi-temporal stack. Using the normalized moisture difference index with the mid-infrared band for the August image resulted in 90% classification accuracy, although average per-crop-classifications were low. The best classification result was a July-August standard multi-image stack using hybrid classification (green, red, NIR-NDVI ISODATA for each image and the near-infrared band), offering higher per-crop classification accuracy than for any single image classification. The accuracy changes little with adding the June scene to the July/August multi-image stack.

1.0 Introduction

Determining crop class and area of agricultural land-use activities in the prairie provinces of Canada is a vital issue for crop insurance and marketing firms. These data are required in order to determine possible yield quantities based on area planted, crop health, growing season, and moisture level (AFSC, 2005). In Saskatchewan, data collection has traditionally been completed via random field surveys that could obtain accurate data for only a small area (Saskatchewan Agriculture, 2005). Provincial crop insurance companies (such as AFSC), or marketing firms (such as the Canadian Wheat Board) however, work with areas equal in area to half their province, suggesting that a larger area classification project should be attempted. Additionally, producers give oral and written reports based on crude plant density measurements, area planted, and local weather data. As weather stations are not necessarily directly near the fields or even within 100 km, the data obtained may cause substantial error in yield estimation. Remote sensing based data collected in addition to the random field data collection would be one way to accurately and feasibly achieve the twin goals of crop class delineation and area calculation for use in yield prediction estimates.

The use of remotely sensed data from different airborne and spatial platforms for crop classification has been well documented in the literature (e.g. Basnyat *et al.*, 2004; Lunetta *et al.*, 2003; Cohen and Shoshany, 2002). However, many crop insurance companies in Saskatchewan feel they cannot depend on remote sensing products for several reasons. Classification accuracy has not reached levels they can trust (≥85%) for such a project to be cost-effective. The general consensus has been that the growing season must be monitored extensively due to varying phenological or growth rates of different crop types. Satellite imagery with which temporal requirements may be met--MODIS or AVHRR--is very inexpensive but has very coarse spatial resolution (250m for MODIS and 1km for AVHRR). The AFSC has recently initiated a satellite monitoring program using the aforementioned MODIS and AVHRR to determine moisture levels and productivity in relation to resulting yield figures. Results from 2002 and 2003 showed that pasture yield was highly correlated ($r = 0.87$) to differences in the product of the NDVI of MODIS and AVHRR (Bedard and Crump, 2004). However, as many crop fields have a width smaller than this (quarter sections of land have an area of approximately 250m), these data sets are not an option to delineate or separate fields. Therefore, the need for a high spatial and high temporal resolution data set for this task is clear. Unfortunately, both high temporal and spatial resolution in other orbital platforms is not only difficult to attain but is also very expensive, leading the discussion back to cost-effectiveness. Therefore, the ability of medium spatial resolution data (e.g. SPOT-4 20m or Landsat TM 30m) to detect crop classes in Saskatchewan should thus be tested.

Recent studies have shown that detecting crop class with higher spatial resolution imagery can still be very difficult. Inaccuracies in crop-parcel delineation have been the result of similar crop phenology (Lunetta, 2004; Vincent and Pierre, 2003) and heterogeneity within the fields themselves (Cohen *et al*., 2002; Basnyat *et al*., 2004). To combat the issue of crop phenology, several images--ranging from two to daily--are integrated together (called an image "stack") and used to "follow" the growth of the vegetation over the season. As daily images are only available for coarse resolution sensors such as AVHRR, many researchers opt for two to four images from SPOT, Landsat, or other medium spatial resolution sensors (e.g. Rydberg, 2000; Oro *et al*., 2003; Vincent and Pierre, 2003). This technique is called standard multi-temporal stack analysis (Van Niel and McVicar, 2004) and has been shown effective in detecting differences between rice and cereal fields (Barrett, *et al.,* 2003; Murakami, *et al*., 2001; Oro *et al*., 2003; Van Niel and McVicar, 2004).

One drawback to stacking images is that along with an increase in information, comes an increase in background and atmospheric noise. The most common method to reduce noise levels within images is to normalize the bands with respect to the targeted parameter by ratioing different spectral bands. The most common index used with crop areas is the NDVI (2.3.1., Jensen, 2004). NDVI is correlated to green, healthy vegetation and can indicate species cover (Rouse *et al*., 1974; Cohen and Shoshany, 2002; Basnyat *et al.,* 2004). To determine differences in moisture level, a second index called the normalized difference moisture index (NDMI) has been used in studies targeting canopy removal in forestry (Wilson and Sader, 2002). This index may be able to show moisture stress better than NDVI. It is unknown how well the index will perform to decipher minute differences between crops.

Multi-temporal stacks, even when used with vegetation indices, cannot classify crop boundaries or heterogeneity within field due to moisture differences or weed infestations. This creates problems with calculating area based on classified pixels. Arikan (2004) and Barrett (2001) digitized the crop parcels in an ArcGIS system and used the vector file to identify homogeneous land cover. Basically, the polygon would be classified as "potato" if the majority of pixels within that polygon were "potato" increasing post-classification accuracy. However, this introduces the problem of digitizing crop areas from a different media (the authors in both studies used air photos) which creates problems due to projection and edge distortion. Rydberg (2000) used a different method to automatically determine crop boundaries called a multispectral edge detector. Both of these methods are not general enough to be used in areas larger than their scenes. In the case of the latter, masking edges of fields may increase error in yield estimation due to inaccurate area measurements from resulting data. For that reason, unsupervised classification may be a more feasible way to cluster pixels into homogeneous groups as it is based on spectral signature and/or a vegetation index (such as NDVI) and location relative to one another (Lillesand *et al.,* 2004). The classified layer can then be used as an input with a band indicative of vegetation (such as near-infrared) with supervised classification to create an accurate classification, also called hybrid classification (Jensen, 2004). This method has been used extensively in other eco-regions, such as land cover and forested area (Keuchel *et al.*, 2003; Wulder *et al.*, 2004) but has limited coverage in agricultural areas (Cohen and Shoshany, 2002). Hybrid classification, when tested with multi-temporal data, should result in a higher accuracy map that is both time-wise and cost - effective.

This research focused on testing this hypothesis with a SPOT-4 20m spatial resolution for three separate dates (June, July, and August, 2004) to determine if the aforementioned methods could be feasible in Saskatchewan's shorter growing season. The specific objectives were to:

i) determine the best classification method using the NDVI and the NDMI for single date images comparing supervised, unsupervised, and hybrid techniques;
ii) establish the most accurate scene combination out of the three SPOT-4 scenes provided for a short growing season using the standard multi-temporal stack technique.

This resulting information could be used to determine crop yield (by area) for crop insurance purposes. Using higher resolution imagery would complement current coarse imagery acquisitions creating a larger information base from which both producers and marketers alike may draw. Lastly, due to higher levels of detail, resulting information and imagery may be important in future uses of precision agriculture.

2.0 Methods

2.1 Study Area

Scott, Saskatchewan (Figure 1, 52°23'N, 108°54'W) is a typical farming community in West-Central Saskatchewan. Rural municipalities 349, 379, 380, 381, 409, and 410 from the 7B soil district (SD) were included incorporating a total area of ~3,000 km^2. This farming region is located in the moist mixed grassland eco-region of Saskatchewan, along the southern border of the aspen parkland. According to previous years data provided from by Saskatchewan Agriculture (2003, figure 2), producers in the soil region 7B grow approximately 50% wheat-spring/winter/durum, 20% Canola, barley, oat, ~20% Summer Fallow and 10% special crops (Lentil, pea, mustard, canary seed). Table 1 shows the crop classes further broken down by rural municipality with examples of yields per acre.

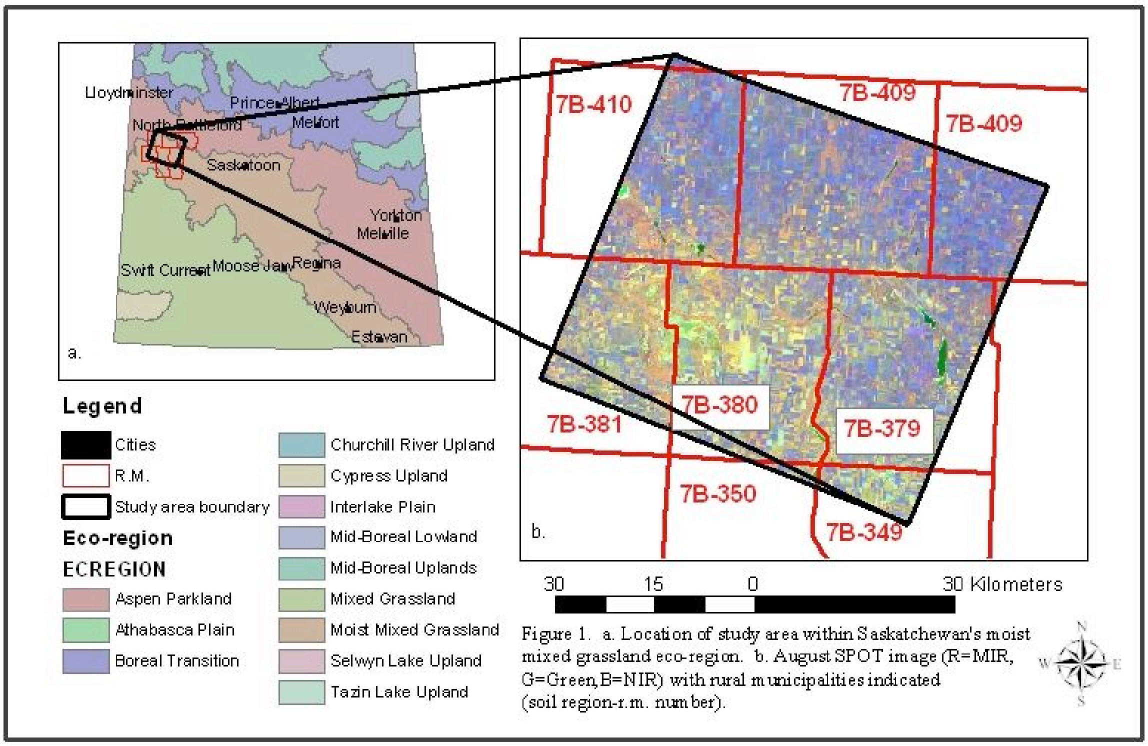

Figure 1. a. Location of study area within Saskatchewan's moist mixed grassland eco-region. b. August SPOT image (R=MIR, G=Green, B=NIR) with rural municipalities indicated (soil region-r.m. number).

Crop reports for June 28, July 19, and August 15, 2004 were obtained from Saskatchewan Agriculture, Food, and Rural Revitalization (2004) and are summarized below. These dates correspond to image acquisition dates (June 28, July 18, and August 13) and indicate precipitation received the previous week, crop conditions, and harvest progress.

At the end of June, crop conditions in the 7B SD were in good to excellent condition. Canola and peas had incurred a bit of damage due to frost and a late start to the growing season. Producers in the region reported that crop development was 76% behind normal as a direct result. Top soil moisture conditions were exacerbated due to low precipitation

(< 1mm). Pasture conditions had also worsened since May. Hay was 3% cut at this point at a fair to good quality.

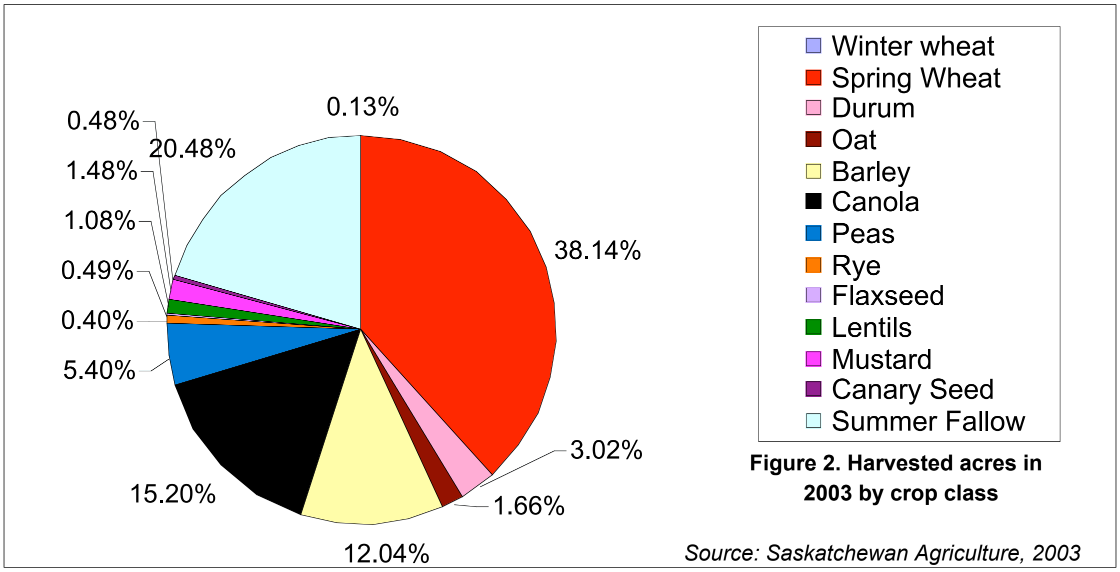

Figure 2. Harvested acres in 2003 by crop class

Source: Saskatchewan Agriculture, 2003

In mid-July summer had finally arrived resulting in a hot and humid week and the 7B SD region received 5mm of precipitation. Due to storm activity, there was scattered hail and flooding damage across the district, resulting in some cases with 100% damage. However, crops were still in good to excellent condition and topsoil moisture was listed as adequate. Crop development ranged from 19% to 81% behind and some leaf diseases and mildew on peas were reported resulting in application of fungicide. Hay was 25% harvested and 33% cut at this point.

During the week of August 8-15, drought stress and burning was reported throughout the 7B district, although precipitation averaged between 2mm to 45mm over the area. Other sources of crop damage were caused by insects, blight, leaf disease and large antelope herds (especially in pea fields). Four percent of fall rye and winter wheat were combined and two percent of the other crops were lying in swath. Topsoil moisture was rated adequate (34%) and crop conditions in hay and pasture lands had also improved.

Table 1. Crop Yield in 2003 for Scott Saskatchewan Area

RM	Winter wheat	Spring wheat	Durum	Oats	Barley	Fall Rye	Flax	Canola	Mustard	Lentils	Peas	Canary Seed
	bu/ac	bu/ac	bu/ac	bu/ac	bu/ac	bu/ac	bu/ac	bu/ac	lbs/ac	lbs/ac	lbs/ac	lbs/ac
349		20.4	18.9	17.6	27.3	15		10.8	452	630	825	
379		21	18.6	32.1	30.6			9.3	340	548	1130	
380		20.1		38.5	33.5			11.4	675		1394	
381	36.1	20.5	20.2	29.9	29.5	25	10	12.2	320		929	400
409	6.5	19.5		28	23		13.5	11.9		665	999	
410		22.5	21.3	39.6	32	30		13.7		1200	1064	

2.2 Field Data collection

Field data were collected on August 4, 2004 for the Scott, Saskatchewan area. 544 Random GPS points of different field crop type (Summer fallow, wheat, barley, canola, lentil, mustard, oat or pea) or land-cover type (grass) were recorded per location for training data and post-classification analysis. Ground control points (GCPs) were also collected for geo-rectification (at road intersections in both rural areas and within the town site) of the three SPOT-4 images.

2.3 Imagery and pre-processing

Three SPOT-4 images (20 m resolution) were acquired for the same area on the dates of June 28, July 18, and August 13 of 2004. All three images were orthorectified using 44 GCPs (RMSE less than 0.5 pixels) and the Saskatchewan Digital Elevation Model (SkDEM). All three scenes were reprojected to UTM, zone 13, datum NAD-83; D-04. Both the normalized difference vegetation index (NDVI) and the normalized difference moisture index (NDMI) were calculated for each image and the data range was stretched. The formulas are as follows:

$$NDVI = \left(\frac{NIR - red}{NIR + red}\right) * 256 \qquad \text{(Rouse } et\ al.\text{, 1974)} \qquad 2.3.1$$

$$NDMI = \left(\frac{NIR - MIR}{NIR + MIR}\right) * 256 \qquad \text{(Wilson and Sader, 2002)} \qquad 2.3.2$$

where red is band 2; NIR is near infra-red band 3, and MIR is the mid-infrared band 4 for SPOT-4 imagery.

All imagery was mosaiked in PCI GCP-works to ensure that all images overlaid each other perfectly and further analysis could be done using the new standard multi-date image stack. To ensure that all layers were of covered the same area a polygon was traced around the “stacked” bands in order to apply classification schemes to only that area covered by all three bands (Figure 1, study area boundary).

2.4 Classification Procedures

The classification processes used in this study were completed on each single image, two-date stacks (June/July, June/August, July/August), and the three-date stack. All combinations were tested on single images and stacks and compared for both classification and post-classification accuracy. Training data for all classifications was consistent and composed of approximately 250 GCP points. These points were randomly located in the targeted fields. To optimize the training data, histograms were viewed to make sure that the classes were uni-modal that all spectral classes within one major crop class were separated. Two to four pixels were chosen from each identified field that visually represented the most “pure” reflectance value. Wheat, barley, and canola were sub-classified into two or three clusters based on visual detection of spectral differences (Lillesand and Kiefer, 2004).

2.4.1. Supervised Classification

Many different input combinations were tested using the maximum likelihood classifier due to its low CPU time (Emrahoglu *et al.*, 2003), accuracy (Arikan, 2004; Jensen, 2004; Lillesand and Kiefer, 2004), and ease of use with PCI. SPOT-4 bands two, three, and four (red, NIR, and MIR) were tested in combination with either vegetation index (NDVI or NDMI) in order to ascertain the importance of full spectra data complemented by a vegetation index. We also compared using the NDMI with the NIR band and the NDVI index with the MIR band. Lastly, the NDVI alone was used as the lone input to test its ability to separate differences in every image set.

2.4.2. Unsupervised Classification

Unsupervised classification was used focusing on the ISODATA algorithm, proven useful in agricultural areas (Cohen and Shoshany, 2002; Lunetta *et al.*, 2003), again with different input combinations. The algorithm was set for 20 maximum iterations and 20 clusters to take all possible variance in the area into consideration. Only two types of unsupervised classification were completed for each single date. Inputs were the red, NIR and MIR bands with either the NDMI or the NDVI. The classes were labeled based on the majority rule (> 80% of the classified pixels indicating one crop type) and used in further hybrid classification attempts. These classifications were only completed with single-date images.

2.4.3. Hybrid Classification

Hybrid classification was completed using the maximum likelihood classifier with the results of the single-date unsupervised classification (Iso-fr-NDVI or Iso-fr-NDMI, Table 2) and either the NIR or the MIR band as inputs. Training data was again consistent with that from the supervised classifications described above. These were completed with both single-date and multi-temporal image stacks.

2.5 Accuracy Assessment

In order to determine the accuracy of all classifications, approximately half of collected points (250+ GCP points and more from water features determined from spectral response and overlay of a water GIS layer) were retained and used in post-classification analysis. This was completed by comparing classified pixels with actual reference classes via computation of the Kappa coefficient of agreement (2.5.1., Jensen, 2005), from a classification error matrix (Table 2) to give a view of overall accuracy. Kappa coefficients were also calculated for each crop within the stack to determine which stack was the most accurate. To verify the post-classification results, crop area from the classification was calculated (Number of pixels classified as “pea”/Total number of pixels classified as a crop) and compared to Figure 2.

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})}$$ *Eq. 2.5.1 Jensen, 2005*

where:

r = the number of rows in the error matrix
x_{ii} = the number of observation in row i and column i
x_{i+} = the marginal totals of row i
x_{+i} = the marginal totals of column i
N = the total number of observations.

3.0 Results and Discussion

3.1 Classification methods

Based on the post-classification analysis, the most accurate classification was the August single-date image created using supervised classification of NDMI with the red, NIR, and MIR bands. The best classification method for June was the same as for August, with a decrease in accuracy, however, of more than half. The July image was also classified best with a supervised technique, however, the NDVI (in the place of the NDMI), red, NIR, and MIR band combination was more successful.

The next best overall classification was the July/August stack (88.3% classification accuracy, 68.4% post-classification accuracy) created using hybrid classification of the MIR band with the unsupervised classification result from the NDMI and red, NIR, and MIR bands (Iso-fr-NDMI). For all two-image stacks hybrid classification provided the most accurate classification. The June/July multi-temporal stack was classified best using the unsupervised Iso-fr-NDVI and the MIR band whereas the June/August stack was classed equally well with both the unsupervised Iso-fr-NDVI with the MIR band and unsupervised Iso-fr-NDMI with the MIR band.

There was not an increase in post-classification accuracy in the three-image stack, rather a decrease (83.64% classification accuracy; 57.2% post-classification accuracy) created using the hybrid technique using the unsupervised Iso-fr-NDMI and MIR, similar to the results seen with the two image stacks. The second best classifications were the supervised technique using only the NDVI (74.1% classification accuracy, 55.9% post-classification accuracy) or using NDVI with MIR (84.61% classification accuracy, 50.67% post-classification accuracy).

Unsupervised classification was not very accurate indicating that its use alone as a means of crop classification would not be comparable to other methods (hence the results are not reported here). Nevertheless, this procedure clustered pixels of similar reflectance values within a set number of classes (pre-determined, here 20 to catch differences within crop types as well as between them) which helped determine patterns in the data. Two classifications were completed for each single image with one of the two indices and the three broad bands (red, NIR, MIR). These classifications were then used in the hybrid classifications increasing the classification accuracy by 50% and more in some cases.

It is interesting to note that single-image classifications were significantly more accurate when using spectral information with a vegetation index, yet for the stacks, the hybrid classifications worked better (Figure 4). This is due to a reduction in data redundancy and noise by normalization. In addition, as can be seen in Figure 4, the unsupervised classification creates a homogeneous raster layer that seems to filter out the small within-field disparities. This coupled with a vegetation index further reduces noise and results in more correctly classified pixels (the null-class is practically non-existent). The problem of heterogeneity at the field borders is also reduced (less variance) and these pixels are less likely to be misclassified.

Table 2. Overall Post Classification Accuracy

Method	Vegetation Index	Single Image			Two images Standard Stack			Three images
		June	July	August	June/July	June/Aug	July/Aug	Standard Stack
Maximum Likelihood Classifier	2-3-4-NDVI	43.1	61.6**	68.6	43.9	38.6	23.9	11.0
	2-3-4-NDMI	43.4**	51.1	70.0**	50.0	40.8	51.5	15.8
	NDVI only	11.6	27.9	39.3	39.3	22.8	52.0	55.9
	NDVI MIR band	25.4	55.9	54.2	52.7	54.4	64.5	50.7
	NDMI NIR band	34.4	23.5	52.2	33.3	50.2	55.3	55.3
Hybrid-MLC	Iso-fr-NDVI +MIR band	27.6	59.4	59.2	64.5**	57.9	68.2	53.5
	Iso-fr-NDVI +NIR band	38.6	48.76	53.5	55.3	59.6	64.3	51.8
	Iso-fr-NDMI +MIR band	34.4	55.9	57.2	61.6	61.6**	68.4**	57.2**
	Iso-fr-NDMI +NIR band	42.1	55.9	51.5	57.7	61.6**	61.8	54.6

where Iso-fr-NDVI indicates an ISODATA unsupervised classification from NDVI-green-red-NIR as an input and Iso-fr-NDMI an unsupervised classification from NDMI-green-red-NIR as an input.
***indicates best post-classification image/stack for the set.*

3.2. Vegetation indices

Supervised classification using a vegetation index and three broad spectral bands was more useful in single images than in stacks. With this method overall the NDMI more accurately classified the area than the NDVI in 6/7 cases (Table 2). However, the differences were not very large. When using the NDMI with only the NIR band, the accuracy was higher than using the NDVI with MIR band for only June and the three image stack, otherwise the NDVI with the MIR band was substantially more accurate (the

June/July stack the accuracy increased by 40%). When using the NDVI only, the accuracy was very low for 5/7 classifications. The July/August and August NDVI only classifications were 40% to 50% higher than the other five.

Many different band combinations were used with the unsupervised clusters to determine the most optimal hybrid classification for use in this study. The four best were (in order):

1. Unsupervised classification from 2-3-4-NDMI with MIR
2. Unsupervised classification from 2-3-4-NDMI with NIR
3. Unsupervised classification from 2-3-4-NDVI with MIR
4. Unsupervised classification from 2-3-4-NDVI with NIR

From this list it is obvious that the most accurate classification techniques incorporated NDMI more than NDVI, showing the importance of the NDMI to crop studies. Additionally, five from seven (70%) of the best post-classification accuracies used the NDMI as compared the NDVI. The varying topsoil moisture (as indicated in the Saskatchewan crop reports, 2004) was indicative of crop growth, thus detecting moisture (using the NDMI) could also be integral to determining the health of these crops for use in yield prediction. However, this was a very wet year for Saskatchewan after many seasons of drought, suggesting that only this index be tested in a drier year to determine if the results are similar.

3.3 Classification validation

It was important to compare not only overall classification accuracies, but also separate accuracies per crop. Figure 3 shows the comparison of these using the best classification techniques for each single date, 2-day stack, or 3-day stack. Water was well classified in every image. The use of the three date multi-date stack increased the classification accuracy of alfalfa, oat, grass and pea. The two date (July/Aug) stack however, was able to classify barley, canola and lentils better. Summer fallow was well classified by either July or August (but not well by the July/Aug stack). Wheat was classified best by the August image. Mustard was not well classified in any image-stack.

Results from the post-classification analysis were verified by calculating the area each crop type as compared to the total area classified as agricultural land use (Table 3). These values were compared to the previous years' harvested area (Figure 2) to discern how well the classification techniques depicted reality. The single-date August image has a reasonable value for wheat (37.8% compared with 38.13%), however all other values are not as accurate. Both the June and July single-date images are inconsistent with the data from Figure 2. Of the three two-date image stacks, the June/August stack is the most similar (major crop areas are the closest). The July/Aug stack overestimates the wheat area by 10% and the canola crop by 5%. It is interesting to note that the NDVI-only 3-image-stack, although less accurate, shows more reasonable crop area estimates than that of the hybrid classification. In all cases, mustard and summer fallow were underestimated and pea were overestimated (except in the case of the single June or July images). For a visual comparison of these results, see Figure 4 below. However, the area data are from the previous year; we can't conclude the classification accuracy is low based on this comparison.

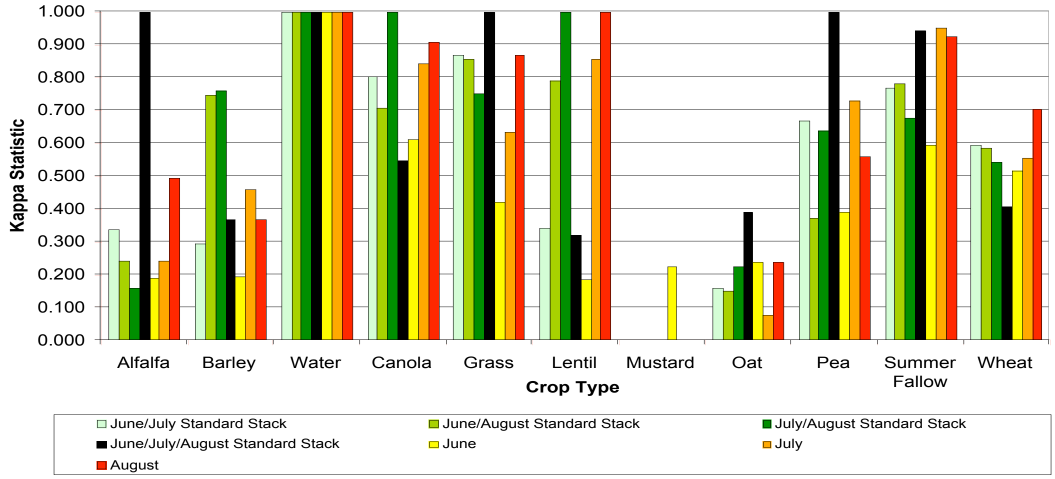

Figure 3. Comparison of Kappa Statistics for the
best classification technique for each image set (*see Table 2)*

Table 3. Percent area by crop for the best classification of each image-stack

Crop	Percent of Crop Area							
	June	July	August	June/July	June/Aug	July/Aug	June/July/Aug	
Wheat	27.72%	39.20%	37.80%	36.27%	34.55%	47.50%	47.22%	36.46%
Oat	21.56%	14.90%	9.90%	8.34%	12.04%	9.95%	7.47%	6.02%
Barley	8.38%	6.28%	10.57%	12.21%	4.44%	5.17%	4.95%	4.29%
Canola	5.77%	13.54%	13.86%	12.12%	22.06%	14.68%	17.51%	19.35%
Peas	8.58%	12.58%	19.43%	12.66%	14.12%	10.41%	10.29%	16.65%
Alfalfa	6.90%	5.34%	1.25%	6.67%	5.13%	3.76%	1.92%	2.80%
Lentils	9.64%	0.62%	0.58%	2.97%	0.73%	0.46%	0.40%	3.35%
Mustard	0.55%	0.03%	0.67%	0.05%	0.26%	0.24%	0.03%	0.98%
Summer Fallow	10.90%	7.52%	5.95%	8.70%	6.67%	7.84%	10.22%	10.09%
CLASSIFICATION METHOD	**MLC-2-3-4-NDMI**	**MLC-2-3-4-NDVI**	**MLC-2-3-4-NDMI**	**Iso-fr-NDVI+MIR**	**Iso-fr-NDMI + MIR**			**NDVI-only**

3.4 Optimal scene combination

The August single-image was resulted in the best classification, indicating the necessity of its use in remote sensing for crop delineation in Saskatchewan. As most crops were sown in early June, reached maturity at the beginning of August, and were harvested in late August early September, one could hypothesize that the highest level of greenness for these crops ranged from the end of July to the end of August. The aforementioned could also explain why the July-August image stacks are better able to classify between different crop types (Tables 2 and 3, Figure 3) than the June-August or June-July image stacks. On the other hand, due to a late start to the growing season, all crops were behind schedule (as indicated in the study area crop reports, 2004) suggesting that in "normal" years two July images (early and late) may work as well as the July-August stack. These results support those reported by Murakami, *et. al.* (2001), Arikan (2004), and Van Niel and McVicar (2004).

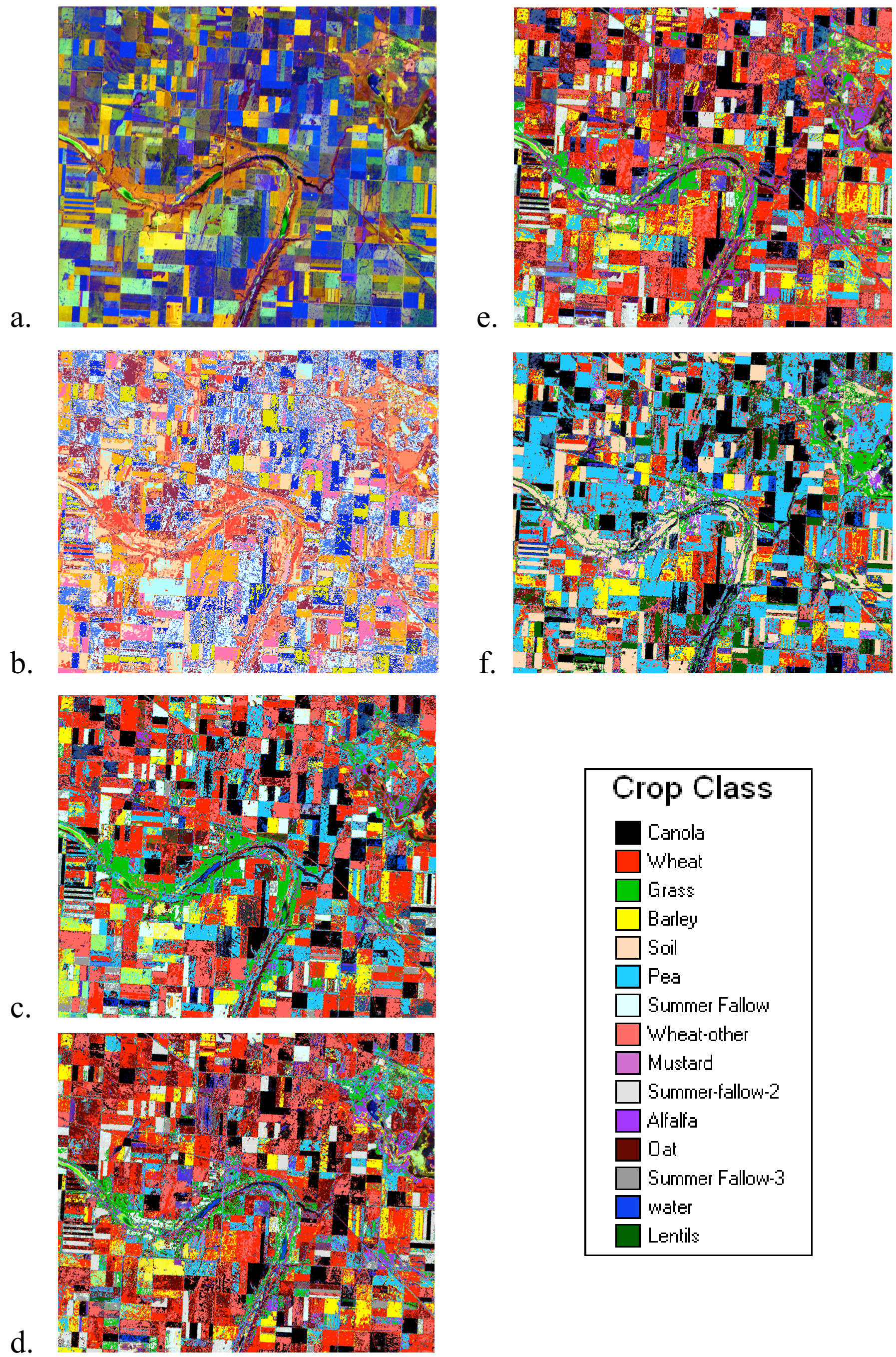

Figure 4. **a.** Original false colour composite (4,2,3); **b.** Isodata unsupervised classification for August; **c.** Supervised classification 2-3-4-NDMI for August; **d:** June/Aug hybrid classification; **e**: July/Aug hybrid classification; **f.** June/July/Aug Supervised NDVI-only.

The supervised June-July-August three-image stack (NDVI-only method) better quantified the crop percentage for the area (Table 3), indicating that overall classification accuracy was more important than post-classification accuracy. Other classifications (single and two date) expressed wheat as a percentage of crop land as very low (~29%) or 10% too high. Those that were more accurate in their wheat area estimation were, however, too low in the canola and other major crop coverages. Summer fallow was accurately classified, but was 10% too low by crop area. This may be due to the increased variance within this crop class. Fields classed as summer fallow were barren, weedy, or showed traces of the previous years' crop (such as canola or wheat with which it was often misclassified).

5.0 Summary and Conclusions

In summary, SPOT 4 20 m data sets are expensive, but have a high enough spectral, spatial, and temporal resolution to be able to classify crop areas with an overall accuracy of 90% for a single August image using supervised classification. Hybrid classification for two and three stacks is a viable way to reduce data redundancy and increase classification accuracy for the short growing season in Scott, Saskatchewan. The best two-way stack (July-August) was more accurate than the three-image stack indicating that 3 images may not be required for accurate delineation of all crops. However, due to the delayed growing season in 2004, future years may show that two July images may work best for classification purposes. Future research should focus on the use of standard iterative stack classification with object based techniques and testing these methods across soil boundaries to determine the value of the research completed here.

In order for large area crop classification to be feasible one must be able to replicate results in different areas across eco-regional or soil boundaries. The results from this research indicate that these classification techniques should be tested in other soil and eco-regions of Saskatchewan to determine if they work equally well there. In addition, future research should include using multi-date iterative stacking techniques, i.e. classify crops using the best image for that crop (as indicated in Figure 2) and compile together the separately classified layers using processes indicated by Van Niel, *et al* (2004).

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7.0 References

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