MULTI-TEMPORAL AND MULTI-PLATFORM AGRICULTURAL LAND COVER CLASSIFICATION IN SOUTHEASTERN MICHIGAN

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ABSTRACT

We investigated the capabilities of multi-temporal and multi-platform remotely sensed imagery to differentiate crop types in the 14,600 ha Upper Tiffin watershed in southeastern Michigan, a primarily agricultural area. We focused on extracting signatures for corn, soybeans, wheat, alfalfa, and grasses as the major crops for the area. Input data included Landsat 5 TM, Terra/MODIS, and ASTER imagery for different parts of the 2004 and 2005 agricultural growing season. MODIS was selected to address the problems with obtaining sufficient repeat coverage of Landsat data during the growing season. We used both pixel-based and object-oriented classification techniques to assess the value of different techniques in leading to more useful agricultural land cover classifications. To contrast with these classification techniques, we predicted crop distributions using MODIS NDVI time-series profiles. ASTER data were investigated to see if its additional high-resolution bands and its multi-angle instruments could provide supplementary classification information. State and Federal agencies are active in the Upper Tiffin study area because of known problems with sediment and nutrient loading in local waterways. The Natural Resource Conservation Service (NRCS), part of the United States Department of Agriculture, used the results to understand how different land uses were affecting local water quality, and how the problems could be addressed.

INTRODUCTION

The Environmental and Emerging Technologies Division of the Altarum Institute (Ann Arbor, MI) has been working with the Michigan office of the USDA Natural Resources Conservation Service (MI-NRCS) through a cooperative agreement to help evaluate the impacts of NRCS programs and improve program management and communication. The Altarum/MI-NRCS Cooperative Agreement includes support of the Conservation Effects Assessment Project (CEAP) Tiffin River Watershed project. The MI-NRCS CEAP/Tiffin River Watershed project is a two-year project designed to assess farming practices in the Tiffin River watershed in southern Michigan (Figure 1). The MI-NRCS team is evaluating the impacts of certain waste management practices on stream water quality in Bean and Lime Creeks, two sub-watersheds of the Tiffin River, in order to formulate solutions to water quality issues.

The study area, located in the upper Tiffin River watershed of the Maumee River Basin in western Lenawee and eastern Hillsdale counties, is a primarily agricultural landscape. Being able to rapidly and accurately map specific crop types would be a useful contribution towards understanding the study area, and an important input to non-point source pollution models. We investigated multiple platforms of remotely sensed satellite imagery to create agricultural land cover maps of the study area. The three sources of imagery were the Landsat Thematic Mapper, the Moderate Resolution Imaging Spectroradiomter (MODIS), and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite systems.

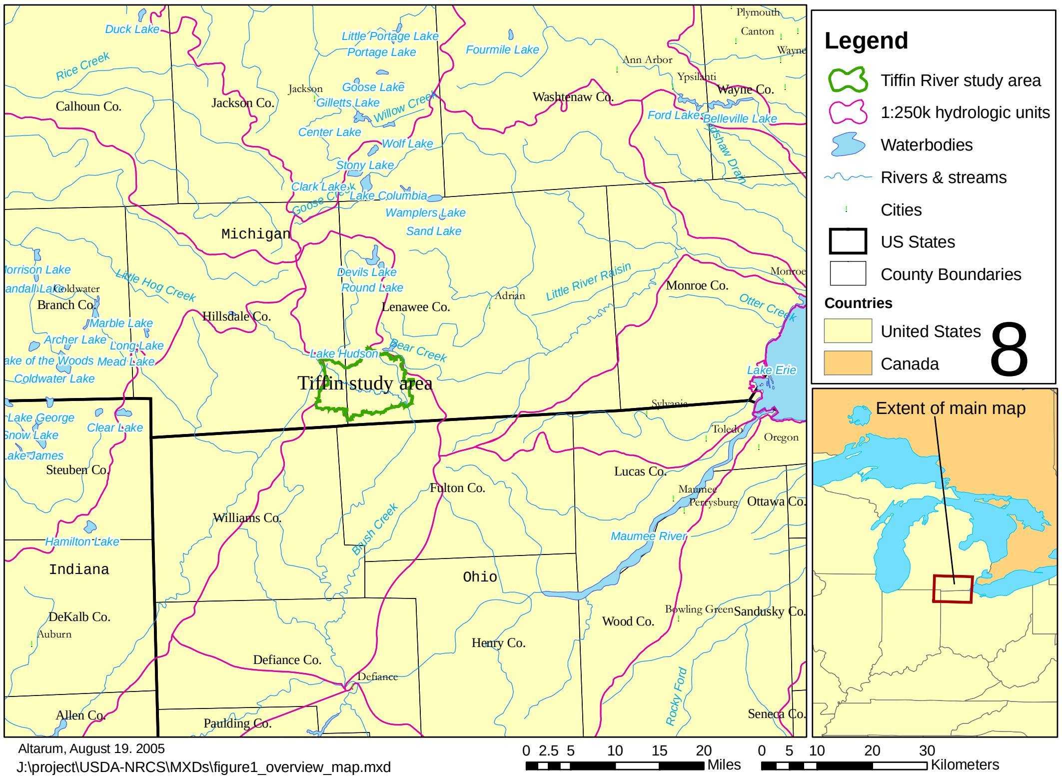

Figure 1. Location of the Tiffin study area in Southeastern Michigan.

METHODS

Tiffin Study Area Land Cover Mapping With Landsat Data

Data descriptions. Two main data sets were used to create a land cover map of the Tiffin study area. These were Landsat Thematic Mapper (TM) satellite imagery and an inventory of crop types grown in specific fields in the Bean Creek area that we tied to a Common Land Unit (CLU) GIS layer of field boundaries. This crop type data represents the reference "field data" to help create and evaluate the land cover map.

Landsat TM has 30-meter resolution for six reflective bands allowing for discrimination of land cover type, such as farm fields, water, and urban pavement. For this study, we were able to obtain two cloud-free Landsat 5 images of the study area from the "Ohioview" data portal (http://www.ohioview.org/), with one image from April 15, 2004, and other from August 21, 2004 (Figure 2). These were selected to coincide with the date of the CLU-based crop type reference data. Our study area corresponds to Landsat path 20, row 31, covering northwest Ohio and southeast Michigan. We used Landsat data from the Ohioview site because the images are already orthorectified, significantly reducing the amount of time it takes to have the imagery in a usable and correctly positioned format, and because Ohioview focuses on posting relatively cloud-free imagery.

We used 2004 Landsat images to correspond with available 2004 crop-type inventory data for the Bean Creek watershed study area, a large part of the eastern third of the study area. The 2004 crop types were inventoried by Michigan NRCS, and recorded in a spreadsheet based on Common Land Unit (CLU). CLU maps delineate farm management units (fields) under FSA and NRCS conservation contract and are derived from the Farm Services Agency (FSA) aerial photographs and farm records. The NRCS has been digitizing the CLU fields into GIS format and releasing them on a draft basis county-by-county in Michigan and other states. We combined the crop inventory data with the CLU field boundary GIS layer by creating a unique field identifier composed of the tract number and the CLU field number. We were able to match 374 crop fields to the CLU spatial layer using the unique ID.

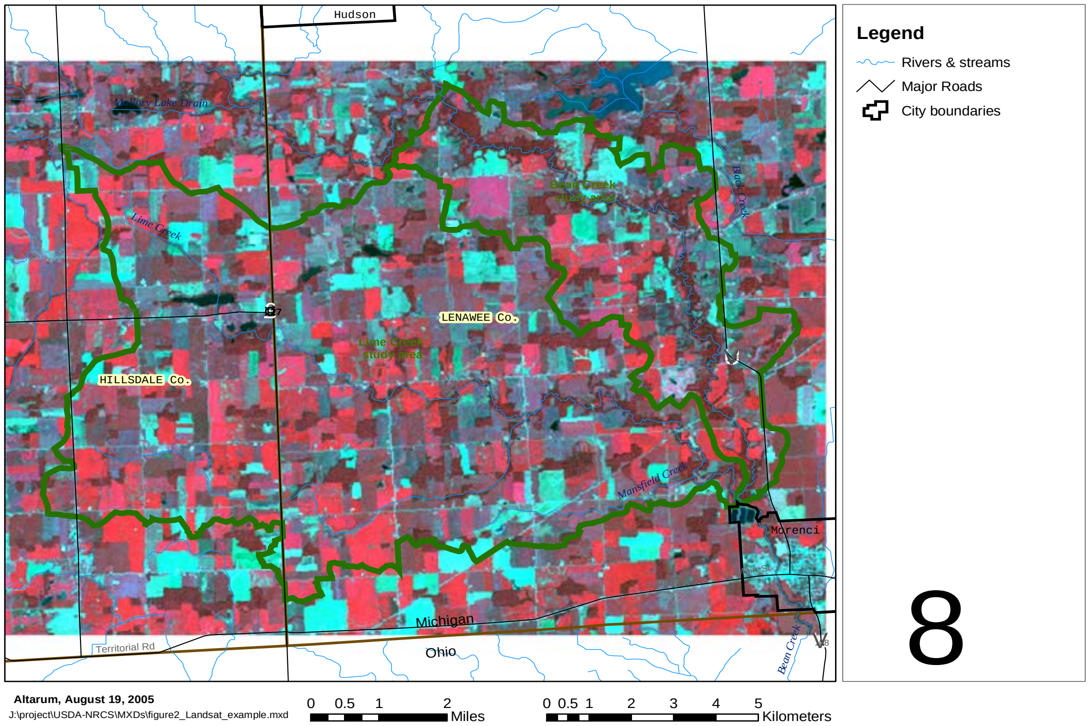

Figure 2. Landsat image example of the study area, for 8/21/2004, in false-color infrared display.

The 4/15/2004 and 8/21/2004 image dates give us data for the early and late parts of the agricultural growing season. Our hypothesis was that having more than one date would allow us to differentiate crop types better than creating a land cover map from a single date. For example, crops that might look similar in August because they were near harvest time might have different amounts of growth cover in April, and some fields that were bare in April might look significantly different from each other by August. We also created a Normalized Difference Vegetation Index (NDVI) for each of the two dates, and used them as additional "bands" of data for analysis. NDVI helps to indicate what areas in a satellite image have a large amount of growing, "green" vegetation and which areas are lacking in vegetation (Jensen, 2000). It is particularly useful for measuring the increasing amount of biomass in a farm field during the growing season (Yang et al., 2004). We combined the six main Landsat 5 Thematic Mapper (TM) bands normally used for classification (i.e., all but the thermal band) along with the NDVI for each date to create a 14-band input image for classification.

Initial classification. We used Leica Geosystem's ERDAS Imagine image processing software to classify the 14-band Landsat composite image into land cover maps. At first, we used an "unsupervised" classification strategy using 20 classes for a subset of the Landsat image corresponding to the Tiffin study area. We compared the segmented image to the 2004 Bean Creek crop type designations to assign cover type names to the classes. The initial unsupervised classification did not create distinct areas for farmland managed under the Conservation Reserve Program (CRP) or for urban areas. CRP lands are characterized by being land left fallow for multiple years, so they should result in a distinctive spectral response compared to actively cultivated farmland, as should urban areas. To address the issue, we ran a supervised classification using training sites for CRP, "dense urban" (areas that are mostly paved), and neighborhoods (areas that have a mixture of streets, trees, and grass-covered yards in the small towns located in and near the Tiffin study area). Finally, we created a "mixed" classification by combining the 20 unsupervised classes with the supervised training sites.

Object oriented classification. To address problems with the initial classification (described in the results section), eCognition, a new image processing application from Definiens Imaging was used. eCognition uses an object-based approach to classify features in digital images. Unlike traditional methods, this method uses spatial context in addition to spectral values to classify images (Benz et al., 2004). The application derives spatial context by segmenting the image into a hierarchal network of objects based upon user-defined criteria such as shape, color and heterogeneity (eCognition User Guide, 2004). Each object is aware of its relation to other objects within the hierarchy. Statistical information about the objects and their context can be used with a traditional sample-based Nearest Neighbor classifier, a fuzzy logic rule-base or a combination of the two methods to classify the image.

Since agricultural field boundaries are largely square or rectangular features, we hypothesized that the image objects identified and classified by eCognition would model the field boundaries more accurately than traditional approaches and produce a "cleaner-looking" land cover map for use in the field and in models.

Object-based approaches incorporate two steps: segmentation, which defines the image objects, and classification. eCognition's default segmentation settings for shape, color, heterogeneity, and compactness were used to create the network of image objects. eCogntion's sample-based Nearest Neighbor classifier was used with representative areas of each of the major crop types as training sites to create the classification. To increase the usefulness of the map, and maximize the accuracy of as many classes as possible, we created the final eCognition classification using additional training areas by splitting alfalfa and wheat into "growing" and "harvested" classes based on the NDVI values in April versus August.

Accuracy assessment and additional comparisons. To assess the accuracy of the classifications, we used the 2004 crop type data that was not used for training areas as our reference or "truth" data. We also made a comparison of eCognition's object oriented approach with the pixel-based approach by using the same training areas from eCognition to create a completely supervised classification in ERDAS Imagine. To make sure that using two dates of imagery was not causing confusion between land cover classes rather than helping separate them out, the same training areas were used in an eCognition classification based solely on the 8/21/04 Landsat image.

MODIS Data Analysis

Given the limited availability of cloud-free Landsat imagery for our study area, we investigated additional sources of remote sensing data that could help us with agricultural land cover mapping. The Moderate-Resolution Imaging Spectroradiometer (MODIS) sensor is available on a pair of NASA satellites, "Terra" and "Aqua" which provide twice-daily coverage of Michigan. Though it collects 36 spectral bands, it has coarser spatial resolution, with 250 to 500-meter pixels in visible/near-infrared wavelengths versus 30-meter pixels for Landsat. The frequent satellite overpasses combined with the large number of spectral bands and wealth of standardized data products makes MODIS an excellent candidate for our studies (Lindsey and Herring, 2001; Sakamoto et al. 2005).

The major crop types in the Tiffin study area exhibit unique phenological cycles that may be observed with multiple dates of satellite imagery, specifically with the Normalized Difference Vegetation Index (NDVI), which is known to correlate with biomass and the leaf-area index (Yang et al., 2004). We used the MODIS 250-m Vegetation Index product (MOD13Q1) to create a time-series of NDVI values for test plots representing the major crops and natural land cover types during the growing seasons of 2004 and 2005. This MODIS product is created on 16-day cycles using the best available reflectance data on a pixel-by-pixel basis during each 16-day period.

The major land cover types considered for this analysis were forest, grasslands-forbs, water, corn, wheat, soybeans, and alfalfa. In 2005, one oats field site was added to the analysis. Test sites for crops and CRP (i.e., grasslands-forbs) units were selected from the CLU layer furnished by the NRCS, as described previously. Test sites for forests and water classes were extracted directly from Landsat imagery. Due to the large pixel size of MODIS, we selected test sites that were generally 500m x 500m or larger to avoid pixel mixing. During the preliminary work in 2004 only two test sites per cover class were tested. In 2005 we used a minimum of four test sites for each class, excluding oats and water, which were uncommon in the study area. Ground photographs were also taken at the test sites in 2005, approximately on 16-day intervals, to use as references to spectral values obtained from the imagery.

Based on the phenological differences among most of the land cover types, we developed and tested algorithms to generate a classification for the Tiffin study area using MODIS NDVI data for 2005 (DOY 81 through DOY 273). Early in the analysis phase it became apparent that it was impossible to distinguish corn from soybeans based on crop phenology alone, even though they are readily separated spectrally in Landsat TM imagery, so for this investigation we combined the two crops into a single class, corn-soybeans. To validate the classification we again referred to the USDA-NRCS CLU data and Landsat imagery to create 151 validation points, centered in large land cover units. Test sites used to develop the phenological curves were not included in this analysis.

ASTER Data Analysis

With its superior spatial resolution and collection of 14 spectral bands, ASTER offers some advantages to Landsat TM data (Apan et al., 2002). To determine whether ASTER could augment our attempts at crop identification we downloaded eight archived images from the LP DAAC from 2000 through January 2005. We also submitted an ASTER Data Acquisition Request (DAR) to collect ASTER imagery for the Tiffin study area at 16-day intervals during the 2005 growing season. Through this request we were successful in obtaining an ASTER scene on June 29, 2005.

A unique feature of the Terra/ASTER sensor is the ability to collect nadir and oblique views of a target during the same overpass using its infrared instruments (bands 3N and 3B, respectively). To determine whether some crops might show differential reflectances in the two view angles, we co-registered the 3N and 3B bands from the June 2005 image and calculated a 3B to 3N ratio for the scene. Because we lacked field data for 2005 at the time of this analysis, two of us (Brooks and Schaub) conducted a field trip to the study area with a USDA-NRCS representative on September 21, 2005. We believed that ASTER's ability to detect crop residue through its nadir and oblique bands could be particularly helpful for mapping crop types (Daughtry et al., 2005).

RESULTS

Landsat-derived Land Cover Maps

According to the CLU-based field data collected and organized as described in the methods section, the primary crop types in the Bean Creek area in 2004 were alfalfa, corn, soybeans, wheat, mixed grasses, and fields in the Conservation Reserve Program (CRP). CRP was included as a crop type, even though it is a land-use designation, because it is tracked by the NRCS as a possible type of cover for a field. Table 1 shows the area totals for the NRCS data for the Bean Creek area.

The initial land cover classification using a mixed unsupervised and supervised approach had an accuracy of approximately 55% when compared to the CLU reference crop type data. The classification also had the typical "salt and pepper" look that results from the computer assigning each 30 by 30-meter pixel to the land cover type in the training set that it statistically resembles without regard to the neighboring pixels.

Table 1. Area of major crop types in the Bean Creek watershed study area based on NRCS crop type designations

2004 crop type	Number of fields	Total hectares	Percent of total
Alfalfa	31	471.5	16.4%
Corn	59	830.6	29.0%
CRP	78	387.2	13.5%
Mixed Grasses	62	221.2	7.7%
Soybeans	64	734.0	25.6%
Wheat	20	224.3	7.8%
Total	314	2868.8	

To overcome the poor accuracy results and the "salt and pepper" look, we performed an object-oriented classification with eCognition. The initial eCognition classification has an overall accuracy of 65.3%, although some classes, such as corn, were mapped relatively well. The result of the error analysis is displayed as an error matrix (Table 2, Section A). In the table, the columns are the land cover types created by the image processing software, while the rows for each section are the crop types from the CLU reference crop type field data. From a column perspective, each land cover type from the classification has the actual area, in hectares, according to the CLU reference data. For example, in Section A, the alfalfa type on the land cover map was really 12.33 ha of CRP/Mixed Grasses, 103.59 ha of soybeans, 141.03 ha of alfalfa, 11.16 ha of corn, and 6.21 ha of wheat, according to the CLU data, for an overall user's accuracy of 51.4%. The "Other" class consists of areas mapped as water, forest, neighborhoods, and transportation. We did not evaluate the accuracy of those classes because we were primarily concerned with accurately mapping different crop types, and because they were not land cover types included in the CLU reference data. The CRP and mixed grasses classes were merged into a single class for accuracy assessment because they frequently been confused in earlier versions of the classification, which is understandable considering they both consists of a grassy cover growing in fields that have been set aside from intensive farming operations. An error matrix includes an analysis of "Producer's Accuracy" and "User's Accuracy" (see Congalton, 1991).

The accuracy of the final eCognition classification, where alfalfa and wheat were separated into growing and harvested classes (Figure 3), was 68.0%, with all the agricultural classes except wheat having user's accuracies above a relatively satisfactory 70% (Table 2, section B). The overall accuracy of the supervised classification using the same training sets that were used in the object-oriented classification was almost identical at 69.8% (table 2, section C), compared to the final eCognition accuracy of 68.0%. However, the supervised ERDAS classification miss-classifies many more farm fields as one of the urban, neighborhood, or transportation classes, as can be seen in the central and western parts of the study area around Lime Creek (Figure 4).

Table 2. Error matrices for land cover classifications

Section A:	Initial eCognition classification								
	2004 crop	Alfalfa	CRP - Mixed Grasses	Corn	Soybeans	Wheat	Other	Total	Producer's Accuracy
Reference	CRP - Mixed Grasses	12.33	261.01	5.04	10.35	24.84	41.22	354.79	73.6%
Data	Soybeans	103.59	50.94	31.41	305.47	19.17	38.34	548.92	55.6%
	Alfalfa	141.03	18.81	1.71	20.79	48.96	8.46	239.77	58.8%
	Corn	11.16	47.07	454.06	58.86	17.28	29.52	617.95	73.5%
	Wheat	6.21	23.76	2.61	3.60	51.12	7.11	94.41	54.1%
	Total	274.33	401.59	494.83	399.07	161.37	124.65	1855.84	
	User's Accuracy	51.4%	65.0%	91.8%	76.5%	31.7%			65.3%
									Overall accuracy
Section B:	Final eCognition classification								
	2004 crop	Alfalfa	CRP - Mixed Grasses	Corn	Soybeans	Wheat	Other	Total	Producer's Accuracy
Reference	CRP - Mixed Grasses	16.11	242.38	5.04	11.70	32.94	41.22	349.39	69.4%
Data	Soybeans	5.85	39.96	31.41	321.13	19.98	38.34	456.67	70.3%
	Alfalfa	115.20	12.60	1.71	35.19	19.26	8.46	192.42	59.9%
	Corn	10.80	43.56	428.41	84.87	20.34	29.52	617.50	69.4%
	Wheat	7.47	15.75	2.61	3.60	51.12	7.11	87.66	58.3%
	Total	155.43	354.25	469.18	456.49	143.64	124.65	1703.65	
	User's Accuracy	74.1%	68.4%	91.3%	70.3%	35.6%			68.0%
									Overall accuracy
Section C:	Traditional pixel-based ERDAS classification								
	2004 crop	Alfalfa	CRP - Mixed Grasses	Corn	Soybeans	Wheat	Other	Total	Producer's Accuracy
	CRP - Mixed Grasses	9.36	237.70	3.42	13.59	39.96	45.36	349.39	68.0%
	Soybeans	9.45	21.24	19.35	337.60	17.28	47.25	452.17	74.7%
	Alfalfa	107.10	14.04	3.33	17.64	15.84	34.47	192.42	55.7%
	Corn	7.47	39.60	453.25	33.12	19.80	64.26	617.50	73.4%
	Wheat	12.24	8.82	1.26	2.61	50.85	11.88	87.66	58.0%
	Total	145.62	321.40	480.61	404.56	143.73	203.22	1699.15	
	User's Accuracy	73.5%	74.0%	94.3%	83.4%	35.4%			69.8%
									Overall accuracy
Section D:	Classification using only August image								
	2004 crop	Alfalfa	CRP - Mixed Grasses	Corn	Soybeans	Wheat	Other	Total	Producer's Accuracy
	CRP - Mixed Grasses	19.62	190.35	68.76	12.15	10.71	57.87	359.47	53.0%
	Soybeans	182.07	35.46	23.85	271.99	21.69	29.79	564.85	48.2%
	Alfalfa	142.47	36.45	11.97	21.06	22.59	13.50	248.05	57.4%
	Corn	9.45	101.52	294.40	7.92	10.35	42.57	466.21	63.1%
	Wheat	6.39	53.64	3.33	2.25	16.29	6.12	88.02	18.5%
	Total	360.01	417.43	402.31	315.37	81.63	149.85	1726.60	
	User's Accuracy	39.6%	45.6%	73.2%	86.2%	20.0%			53.0%
									Overall accuracy

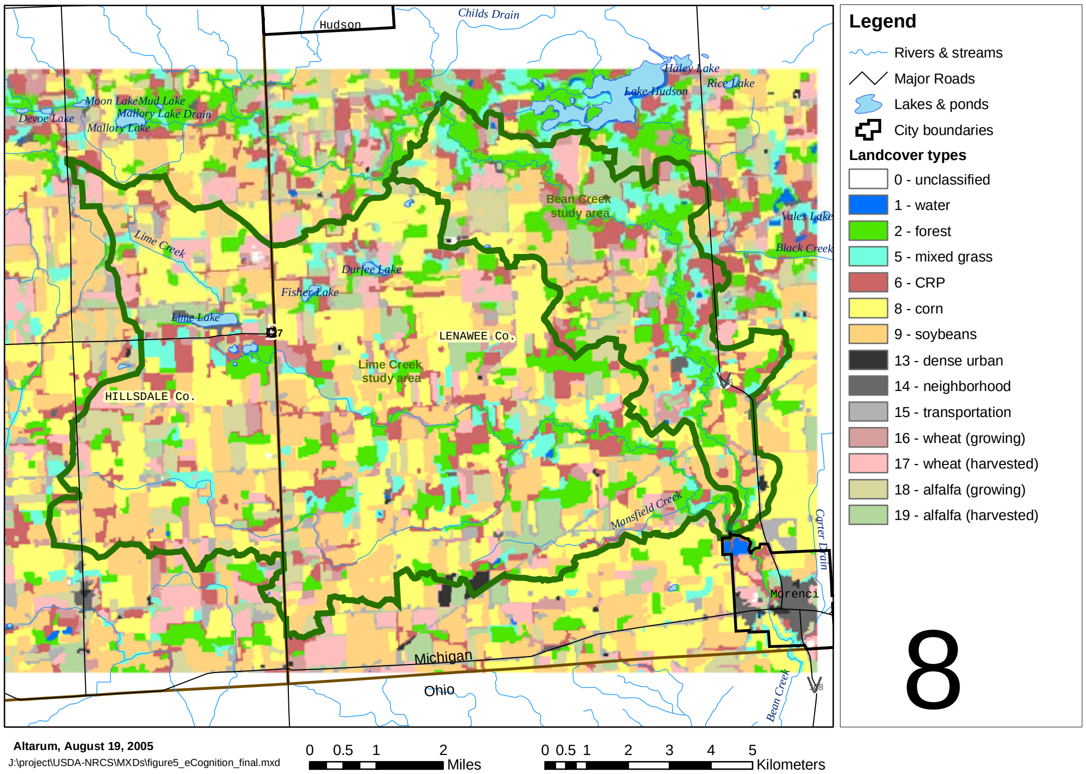

Figure 3. Object-Oriented eCognition Classification.

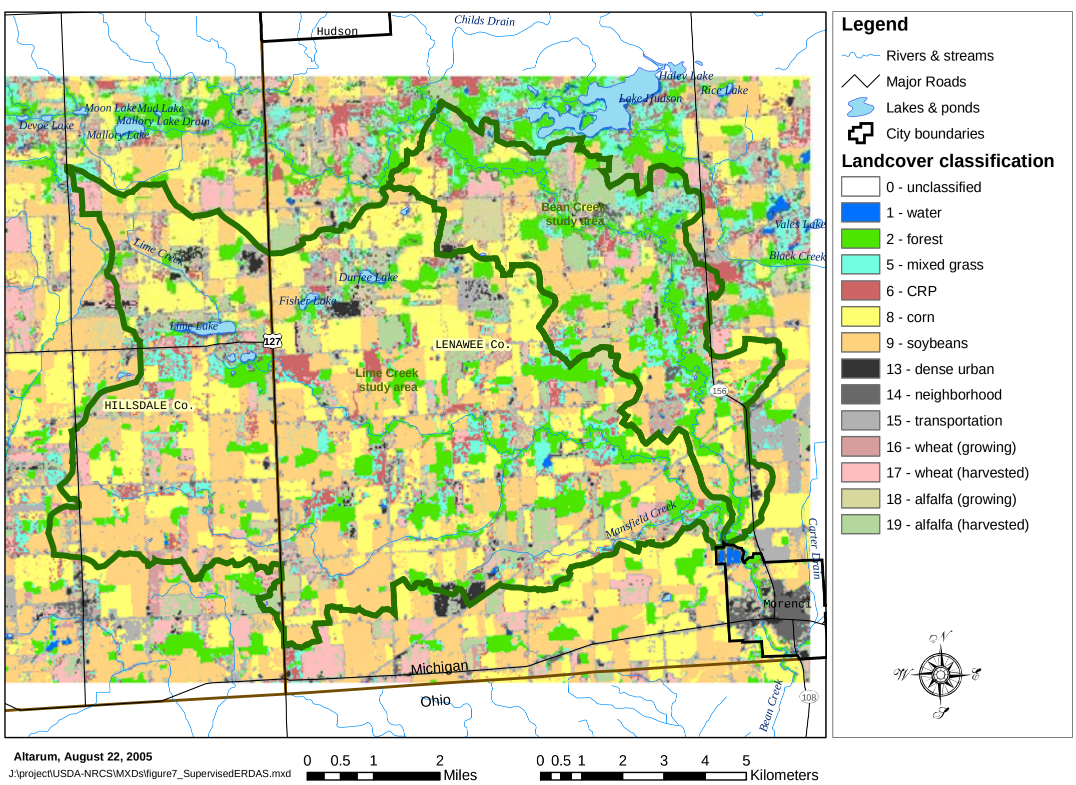

Figure 4. Supervised ERDAS Imagine Classification.

MODIS results

The results of the MODIS time-series analysis showed, as expected, that most land cover types had unique characteristics in their NDVI time-series curves (Figure 5). Forests greened-up early and had a high NDVI (~0.8-0.9) until the end of the growing season. Grasslands-forbs plots had a similar pattern to forests, though with lower NDVIs. Water usually demonstrated typical near-zero NDVI values with occasional, brief spikes in NDVI, possibly due to aquatic vegetation. Multiple cropping of alfalfa was evident by large fluctuations in NDVI during the year. Wheat showed a two-peaked NDVI, where the first peak in late May represented mature wheat and the second peak in August represented secondary plant growth of mostly weeds after wheat harvest. Corn and soybeans were the last crops to green-up with peak NDVIs in late July for corn and mid-August for soybeans. Although data for oats were limited to one field, that test site exhibited its maximum NDVI in late May to mid-June, followed by a sharp decline in NDVI for the remainder of the growing season (~0.3 NDVI).

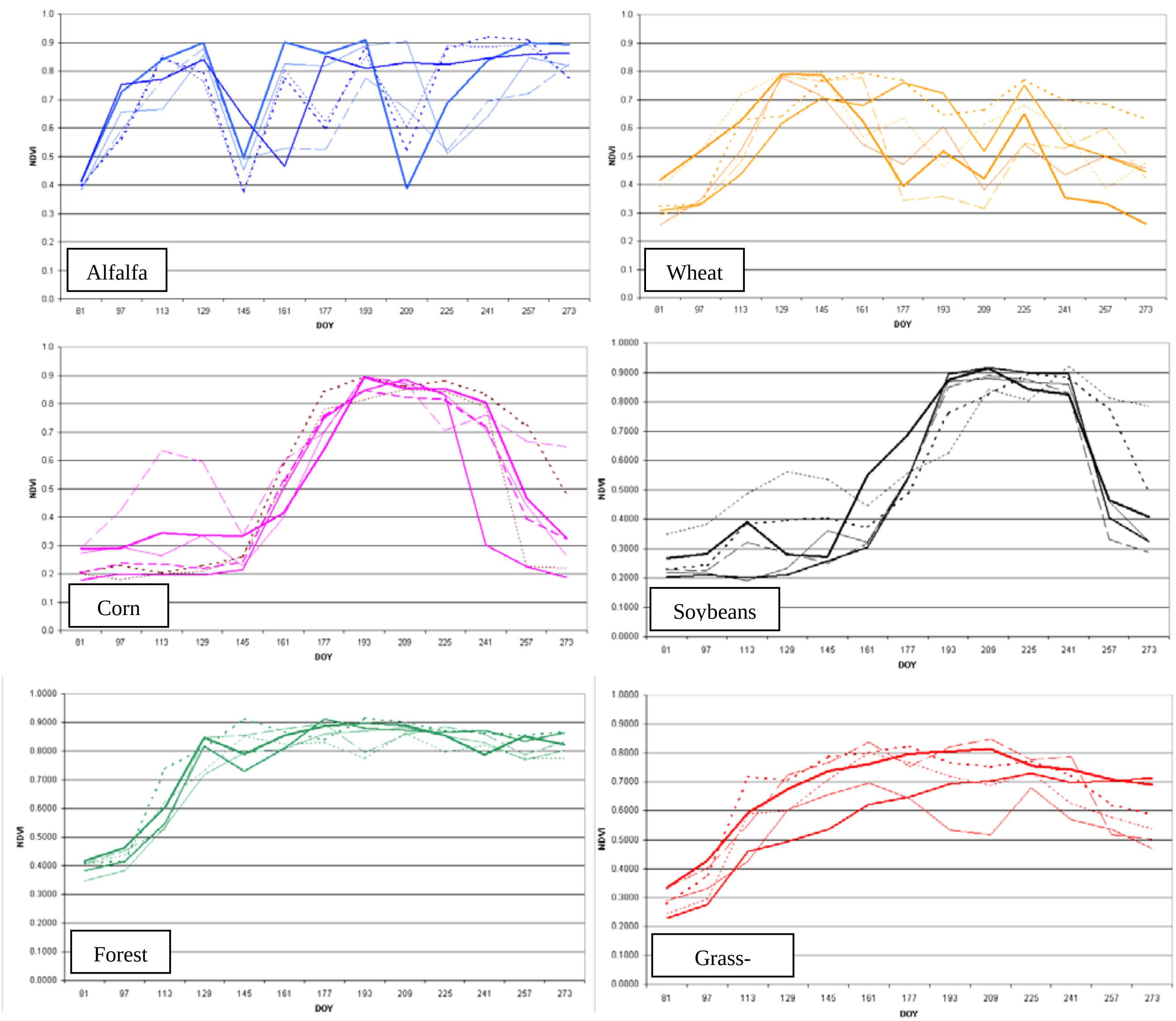

Figure 5. NDVI time-series curves for alfalfa, wheat, corn, soybeans, forest, and grasslands-forbs for the 2004 and 2005 test sites. The horizontal axis is the day-of-year (DOY) at the beginning of a 16-day MODIS cycle. Each line in a graph represents a different sample crop field.

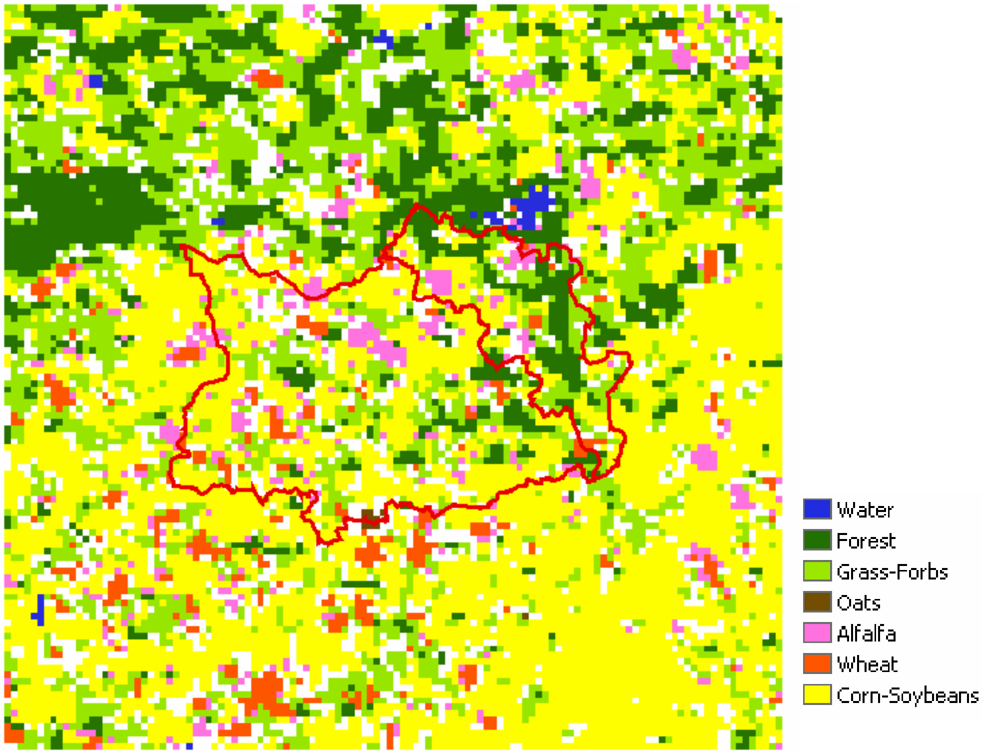

Figure 6. Land cover classification for Tiffin study area (red outline) and surrounding area based on 2005 MODIS NDVI time-series data. White cells are unclassified.

The result of the MODIS-based classification using the crop phenology approach is presented in Figure 6. We used an error matrix to present the results of the accuracy assessment to compare the accuracy of the classification with the observed validation points (Table 3). The analysis showed that this approach was approximately 80% accurate for the Tiffin study area with a kappa statistic of 0.707. The two classes that had the highest error rates were alfalfa and grasslands-forbs.

Table 3. Error matrix for the MODIS-based classification. The category 'other' represents unclassified pixels in the classification.

		Prediction										
		Alf	Corn-Soybeans	For	Grass/Forbs	Water	Wheat	Other	Total	Omission Error	Producer's Accuracy	Q
Observed	Alfalfa	8	1	1	0	0	1	2	13	38.5%	61.5%	1.158
	Corn-Soybeans	3	64	1	1	0	0	3	72	11.1%	88.9%	34.027
	Forest	2	2	24	2	0	0	1	31	22.6%	77.4%	5.945
	Grass/Forbs	0	2	2	8	0	0	1	13	38.5%	61.5%	1.336
	Water	0	0	0	1	3	0	0	4	25.0%	75.0%	0.082
	Wheat	0	0	0	3	0	9	1	13	30.8%	69.2%	0.890
	Other	0	0	0	0	0	0	0	0			0.000
	Total	13	69	28	15	3	10	8	146			43.438
	Commission Error	38.5%	7.2%	14.3%	46.7%	0.0%	10.0%	100.0%				
	User's Accuracy	61.5%	92.8%	85.7%	53.3%	100.0%	90.0%	0.0%				

Overall Accuracy	**79.5%**
Unclassified %	**5.5%**
Kappa Statistic	**0.707**

ASTER Results

Our initial examination of the scene for 2005 demonstrated variation in the 3B:3N ratio that appeared to coincide with some field boundaries (Figure 7), particularly those fields having ratio values of 1.2 to 1.3. Based on our field reconnaissance trip, we found that nine out of the 10 fields that we visited with high backscatter (i.e., 3B:3N) ratios were wheat, and one was a field that had been fallow during 2005.

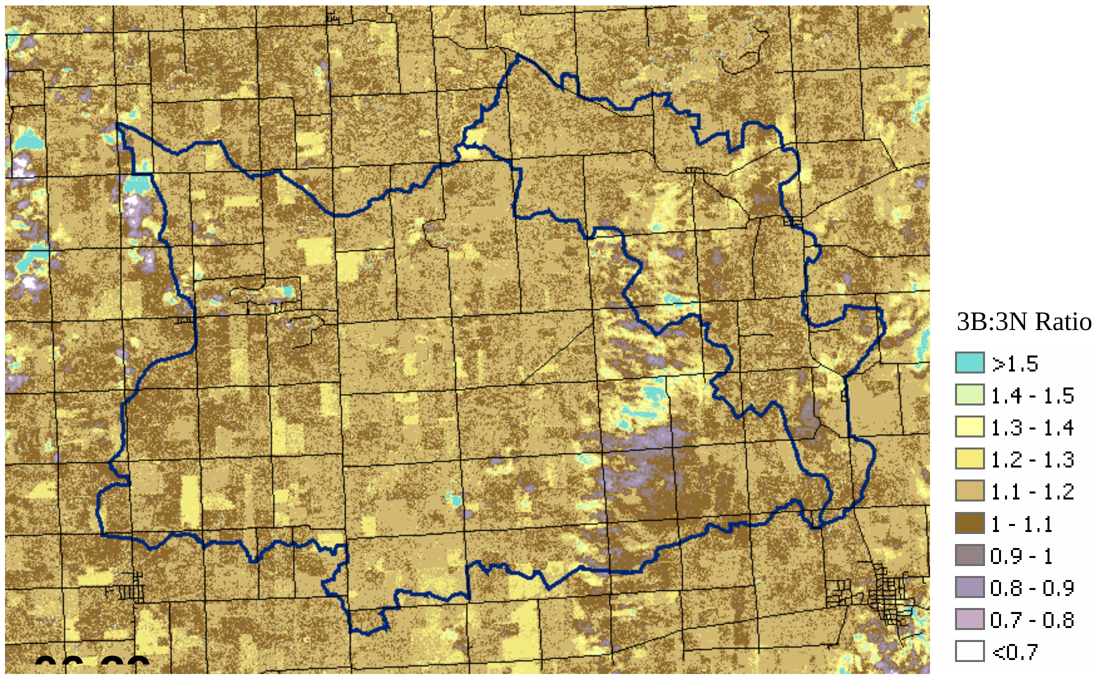

Figure 7. Ratio of 3B to 3N ASTER bands for June 29, 2005 in Tiffin study area (blue outline). Most features with 3B:3N ratios greater than 1.3 or less than 1.0 are clouds or shadows.

To test the hypothesis that fields with high backscatter ratios (1.15 to 1.3) are wheat fields, a set of 95 validation points representing two categories of land cover, wheat vs. non-wheat, were created using the USDA-NRCS CLU data for agricultural fields and Landsat TM for water and forests. Cloudy areas were masked from the validation process. The error matrix showed that the overall accuracy of this simple classification was 92.6% with a Producer's Accuracy of 100% and a User's Accuracy of 73.1%. One of the commission errors coincided with a field of oats, most likely due to its similarities in growth structure to wheat.

DISCUSSION

For the Landsat based classifications, particular classes proved challenging to classify correctly. As can be seen in Table 2, the wheat class continued to cause problems with only a 35.6% accuracy, even after selecting additional training areas and splitting the class into "growing" and "harvested" classes to avoid spectral confusion. Assessing the "growing wheat" versus "harvested wheat" classes separately showed that the growing wheat class was classified particularly poorly (20.1% user's accuracy), while harvested wheat was mapped somewhat better (47.9% user's accuracy). The problem with wheat appears to be related to the dates of the available Landsat imagery. In mid-April, wheat has some growth, but by the third week of August, wheat has typically been harvested for a month in southeastern Michigan, which we confirmed with NRCS and Altarum staff familiar with local crop phenology. What appears to be "growing wheat" in August is really harvested fields where weedy plants have been growing for almost a month after harvest. We believe that using satellite imagery that includes the peak periods of wheat growth would lead to a significantly higher accuracy.

Our comparison of traditional classification methods with object-oriented classification for Landsat data shows that, compared to the traditional supervised classification, the eCognition classification is much less likely to assign an urban class to a farm field. We believe that if we had 2004 crop types for the Lime Creek area, the eCognition classification would end up having a higher accuracy than an ERDAS-based classification created using the same input data. In addition, the eCognition's object-oriented approach produces a map that much more closely resembles the rectangular farm fields of the study area. Since eCognition produces a more visually pleasing product with an almost identical accuracy, we recommend the object-oriented approach for future similar studies. When one image date was taken out of the analysis, the overall accuracy dropped from 65.3% to an unsatisfactory 53.0%, clearly showing that using two dates of imagery is making a significant improvement in land cover mapping accuracy (table 2, section D).

Our investigations into the uses of phenological data as derived from MODIS NDVI and backscatter data from ASTER demonstrate how multiple remote sensing data sources can be used to improve overall land cover classification. Whereas wheat was a difficult crop to identify spectrally with Landsat TM, its unique phenological properties and high degree of backscatter allow it to be distinguished efficiently from other common crops. In contrast, the phenological curves for corn and soybeans are almost identical, making it impossible to distinguish these crops with MODIS NDVI data alone. However, they are quite different spectrally, and can be distinguished with Landsat TM.

We are now exploring the potential of using MODIS NDVI data to classify major land cover types throughout Michigan's Lower Peninsula. If successful, this will be a low-cost, repeatable method for quantifying crop areas efficiently on a broad scale.

As described in the methods section, eCogntion is capable of classifying image objects using a sample-based nearest neighbor classifier, fuzzy logic membership functions, or a combination of both methods. The project described here only used the sample-based nearest neighbor classifier. We hypothesize that overall accuracy may be improved by using eCogntion's capability to integrate a combination of both methods and to perform the classification at several levels of increasing detail to leverage the capabilities of object-oriented class inheritance (Benz et al., 2004).

CONCLUSIONS & NEXT STEPS

To help the NRCS assess farming practices in the Tiffin River watershed, we created agriculture-focused land cover classifications of the study area based on April and August 2004 Landsat imagery. The final land cover classification had an overall accuracy of 68.0%, with alfalfa, corn, and soybeans being mapped best. Problems were encountered mapping wheat because of a lack of cloud-free imagery during the peak growing season for wheat. We compared two land cover classifications software techniques, objected-oriented methods with eCognition and pixel-based methods with ERDAS Imagine. The newer object-oriented method produced mapped areas that more closely resembled agricultural fields, and had an almost identical accuracy to more traditional pixel-based methods. Using two dates of Landsat imagery created a more accurate classification compared to using a single date. The final land cover classification has been shared with NRCS for inclusion in a non-point source pollution model. We also demonstrated that different phenological growth profiles could be created using coarser-scale MODIS imagery for the major crop types, and that crop types could be predicted based on these profiles. ASTER's unique ability to provide nadir and oblique backscatter data appears to be a useful tool for distinguishing wheat from other crops.

We are continuing to pursue several avenues of investigation as part of the Altarum/MI-NRCS Cooperative Agreement. For the Landsat-based classifications, an initial survey indicated that six cloud-free Landsat 5 images of the study area are available for 2005. We will be using these in combination with a larger reference data set of 2005 CLU-based crop type data to create additional agriculture-focused land cover classifications. The 2004 land cover layer was sent to the NRCS for use in a non-point source pollution model, and we are awaiting comments on its value for this purpose. We anticipate that a higher-accuracy land cover classification based on 2005 data will prove of additional value to the NRCS.

The larger set of 2005 Landsat images will allow us to verify the MODIS phenology results with higher-resolution Landsat data. We will create a classification that fuses the strong wheat signature from ASTER with Landsat-based classes to create an improved classification. Our particular interest is to more fully exploit the capabilities of eCognition, particularly its fuzzy logic membership functions. It may be possible to use eCognition to combine the MODIS-based phenology results with the Landsat-based classification to improve accuracy. We will also be expanding the MODIS-based classifications across southern Michigan.

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