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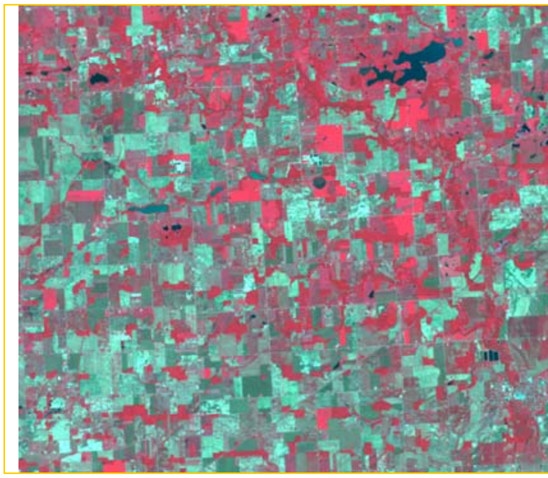

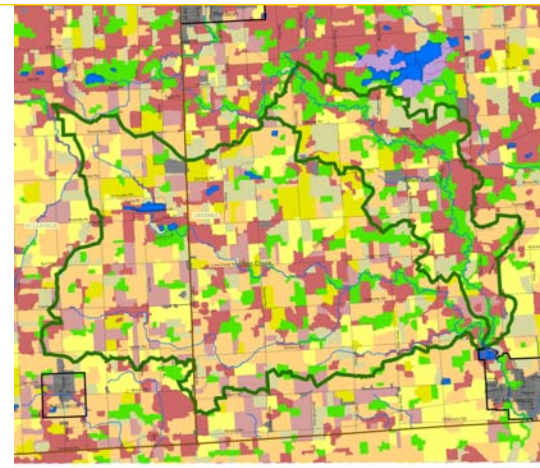

Land Use Land Cover Mapping in the Tiffin River Watershed

2004-2006

Richard Powell and Colin Brooks

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Michigan Tech Research Institute (MTRI)

3600 Green Court, Suite 100 • Ann Arbor, Michigan 48105
(734) 913-6840 (p) • (734)913-6880 (f)
www.mtri.org

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Executive Summary

We developed agriculture-focused land use and land cover maps for 2004, 2005, and 2006 for the Tiffin River watershed in southeastern Michigan, using multiple dates of satellite imagery that captured changes in crop growth over the growing season. These maps represent an improvement in land use data currently available for the region due to their focus on specific crop types, accuracy, and timeliness. Up-to-date, accurate, and agriculture-focused land cover is useful for mapping change in the landscape and for relating agricultural crop practices to water quality. For these reasons, we developed the three dates of land use / land cover for the U.S. Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS) using advanced methods described in this report.

The three dates of land cover maps were produced by MTRI analysts, who developed an innovative new technique using object-based image processing techniques and satellite data readily available to the NRCS. This new technique has the capability of classifying a variety of agricultural crop types and land uses that are not feasible with traditional pixel-based classification methods. Our object-based methods have three main benefits: 1) object-based classifications create land cover maps that more closely resemble agricultural landscapes; 2) they can differentiate different harvest methods, such as corn grain vs. corn silage; and 3) using more growing-season dates of imagery results in higher classification accuracy. Additionally, our research indicates that these new methods are less likely to incorrectly map bare fields as developed areas, and we are able to map primary crops such as alfalfa, corn grain, small grains, and soybeans with greater than 80% accuracy.

MTRI recommends that NRCS consider adopting these methods to produce regularly mapped and accurate land cover, particularly for regional and local areas of interest. For example, future projects similar to the NRCS Tiffin River study would benefit from understanding the changing patterns of particular crop types grown from year-to-year. These inputs can be also be used for water quality models. The Michigan NRCS used the 2005 land cover in its AnnAGNPS pollutant loading analysis with the Ohio NRCS. The ability to create focused land cover products with advanced methods for regional assessments and modeling would benefit the NRCS in its analyses.

Background

The accurate mapping of agricultural lands is critical in the determination of resources, assessment of environmental conditions, detection of land use change and the administration of federal agricultural programs. The phenology of agricultural crops and differences in crop management methods make agricultural landscapes dynamic in nature, presenting unique challenges for assessment through remote sensing. The interpretation of aerial photographs and other remote sensing image processing methods have been used to map agricultural land use for many years. However, these methods have several disadvantages such as the high cost and time-consuming nature of aerial photograph interpretation and the thematic class confusion of classifications based on spectral information of single pixels in a digital image.

The traditional methods of classifying remote sensing images are based upon statistical classification of single pixels in a single digital image (Lillesand and Kiefer, 2004). Recent research indicates that pixel based classification methods may be less than optimal since they do not consider the spatial relationships of landscape features (Schiewe *et al.*, 2001). Object-based classification has been identified as a method of incorporating spatial context into the classification process. This approach compliments a principle of landscape ecology that it is preferable to work with a meaningful object representing spatial patterns rather than a single pixel (Blaschke and Strobl, 2001). Object-based approaches incorporate two steps: segmentation and classification. In the segmentation phase, homogeneous image objects are derived from both spectral and spatial information (Benz *et al.*, 2001). In the classification phase, image objects are classified using established classification algorithms, knowledge-based approaches or a combination of classification methods (Civco *et al.*, 2002). We previously investigated the benefits of object-based methods for agricultural land cover mapping in a preliminary paper (Brooks *et al.*, 2006); these methods build from that earlier promising work.

Until recently, segmentation techniques for creating image objects were only available using custom algorithms in advanced mathematical software packages. Today, several commercial off-the-shelf software applications are available which specialize in image segmentation and classification such as such as Definiens AG's eCognition and Visual Learning System's Feature Analyst. In this study, we used eCognition for segmentation and classification because of its leading status in object-based classification and powerful imagery analysis capabilities, and based on our experience with using it for creating detailed and accurate land cover classifications.

Study Area

The Bean and Lime Creek watersheds (Figure 1) are two sub watersheds of the Tiffin River watershed located in southeastern Michigan, with Bean Creek forming the upper part of the Tiffin River. The Tiffin River flows into the larger Maumee River system that empties into the Lake Erie. The Maumee River is listed as impaired by the U.S. EPA as impaired for turbidity (along with other impairments) and the Tiffin River is listed as impaired for siltation and nutrients (also along with other impairments). The study area is comprised of approximately 14,000 hectares (approximately 54 square miles) of primarily agricultural land use with some small patches of deciduous forest along riparian areas. The Bean Creek part of the study area is an 8-mile stretch of the creek; above it is another 15 miles of Bean Creek and below is where the Creek generally starts being called the Tiffin River. The Lime Creek part of the study area includes that entire tributary, which also has one major drainage, Blanchard Drain, also known as Toad Creek.

The focus of this study is to develop contemporary land use / land cover maps of the study area to support the Michigan office of the USDA Natural Resources Conservation Service (MI-NRCS), particularly with its Conservation Effects Assessment Project (CEAP) Tiffin River Watershed project. The CEAP project for the Tiffin has included an AnnAGNPS study to model pollutant load, and the NRCS request a current and accurate land cover product for use as an major input. The most recent land use / land cover maps available for the study area have been the 2001 Michigan Department of Natural Resources Integrated Forest Monitoring Assessment and Prescription (IFMAP) land cover which focuses on the assessment of forest resources, and the IFMAP-derived National Oceanic and Atmospheric Administration (NOAA) Coastal Change Analysis Product (C-CAP) which is focused on change analysis, coastal uplands, and wetlands. Since the existing data products were not suitable to assist the MI-NRCS in their evaluation of farming practices in the study area, we mapped specific crop types within the study area for the years 2004, 2005, and 2006.

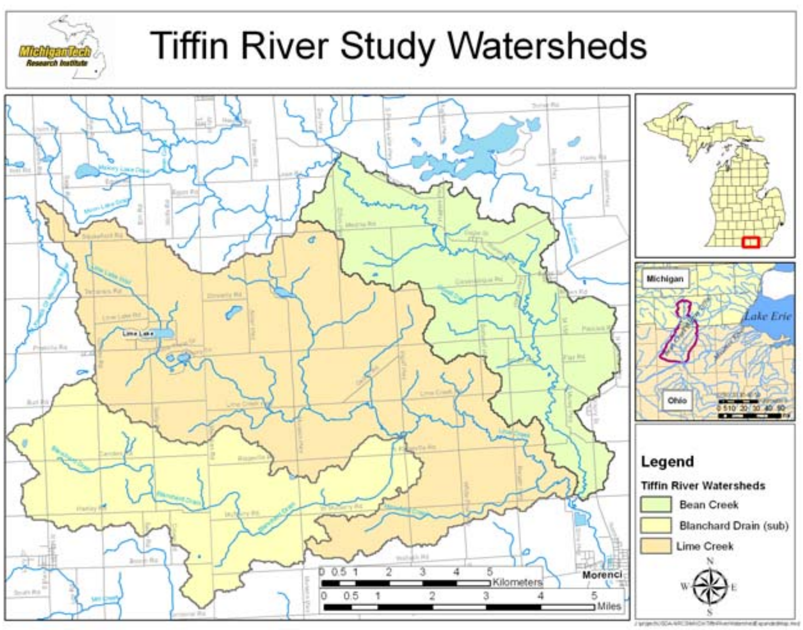

Figure 1: Bean Creek and Lime Creek Study Area. *The Study Area has two main watersheds – an 8-mile stretch of Bean Creek and all of Lime Creek; Lime Creek includes one major tributary, Blanchard Drain.*

Data

We used two primary data sets were used to map the Tiffin study area for the 2004, 2005, and 2006 growing seasons: Landsat 5 Thematic Mapper (TM) satellite imagery and an inventory of crop types grown in specific fields in the Bean Creek and Lime Creek area joined to the USDA's Common Land Unit (CLU) GIS layer of field boundaries. This crop type data represents the reference data to create and evaluate the land cover map. The crop types were inventoried by MI-NRCS, and recorded in a spreadsheet based on Common Land Unit (CLU). CLU maps delineate farm management units (fields) enrolled in Farm Services Agency (FSA) and NRCS conservation programs, and are derived from 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. The crop inventory data was combined with the CLU field boundary GIS layer by creating a unique field identifier composed of the tract number and the CLU field number. Figure 2 illustrates an example of the CLU boundaries linked to crop inventory data for the 2005 growing season.

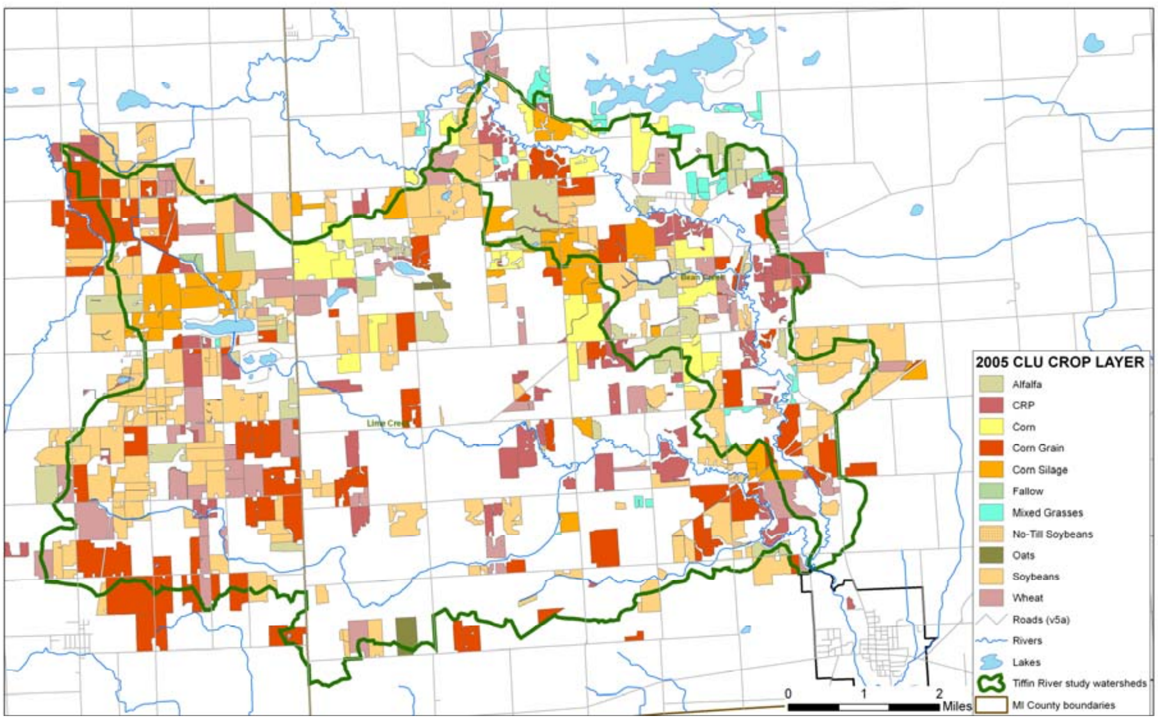

Figure 2: USDA CLU GIS data joined to 2005 crop inventory data.

Landsat TM 5 has a 30-meter spatial resolution for six reflective bands allowing for the discrimination of land cover types, such as farm fields, water, and pavement. The study area corresponds to subsets of Worldwide Reference System 2 (WRS-2) Path 20, Row 31 and Path 21, Row 31, covering northwest Ohio and southeast Michigan. For the 2004, 2005, and 2006 studies, georectified Landsat data was acquired from the OhioView data portal (OhioView.org). A review of each scene's metadata indicated that the combined root mean square error did not exceed 15 meters for any scene. A visual assessment of band to band registration within each scene, and scene to scene registration using invariant targets such as lakeshores and roadways was performed to ensure that the imagery was correctly positioned for multi-temporal analysis.

Table 1: Landsat TM 5 scenes used for 2004, 2005, and 2006 classification

Date	Landsat Scene Identifier
April 15, 2004	LT5020031000410610
August 21, 2004	LT 5020031000423410
April 18, 2005	LT 5020031000510810
May 4, 2005	LT 5020031000512410
May 20, 2005	LT 5020031000514010
June 5, 2005	LT 5020031000515610
July 7, 2005	LT 5020031000518810
August 8, 2005	LT 5020031000522010
September 9, 2005	LT 5020031000525210
May 7, 2006	LT 5020031200612700
May 23, 2006	LT 5020031200614300
June 24, 2006	LT 5020031200617500
July 17, 2006	LT 5021031200619800
August 2, 2006	LT 5021031200621400
Aug 11, 2006	LT 5020031200622300

The multi-temporal data set provides for the early, midseason, and late parts of the agricultural growing season. The use of more than one date improves the differentiation of crop types compared to from a single date (Vieira and Mather, 2000). 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. A Normalized Difference Vegetation Index (NDVI) was created for each of the image date, and used 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.,* 2003).

Methods

2004 Classification

The six Landsat 5 Thematic Mapper (TM) bands normally used for classification (all but the thermal infrared band) for the April and August images were combined with the NDVI for each date to create a 14-band input image for classification.

Leica Geosystem’s ERDAS Imagine image processing software was used to classify the 14-band Landsat composite image into a land use map. In the first step, an unsupervised pixel-based classification was performed. The classified image was compared to the 2004 Bean Creek crop type designations. The initial unsupervised classification did not identify distinct classes for areas managed under the Conservation Reserve Program (CRP) or for developed (urban) areas. CRP lands are characterized by being left fallow for multiple years, so they should result in a distinctive spectral response compared to cultivated farmland, as should developed areas. To address the issue, a supervised classification was conducted using training sites for CRP, “dense urban” (areas of impervious surfaces), 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, a “hybrid” classification was performed by integrating the 20 unsupervised classes with the supervised training sites.

To address issues with the initial classification (described in the results section), the object-based image processing software eCognition was evaluated. Since agricultural field boundaries are typically rectilinear features, the image objects identified and classified by eCognition would model the field boundaries more accurately than traditional approaches and produce a more realistic land cover map for use in the field and compared to pixel-based approaches. eCognition’s default segmentation settings for shape, color, heterogeneity, and compactness were used to create image objects. eCognition’s sample-based Nearest Neighbor classifier was used with training samples of each of the major crop types to create the classification. To increase the usefulness of the map, and maximize the accuracy of as many classes as possible, the final eCognition classification was created using additional training areas by splitting alfalfa and wheat into “growing” and “harvested” classes based on the NDVI values in April versus August.

To assess the accuracy of the classifications, 2004 crop type data that was not used for training areas was used as ground reference data. eCognition’s object-based approach was also compared with the pixel-based approach by using the same training areas from eCognition to create a completely supervised classification in ERDAS Imagine. To ensure 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 August 21, 2004 Landsat image.

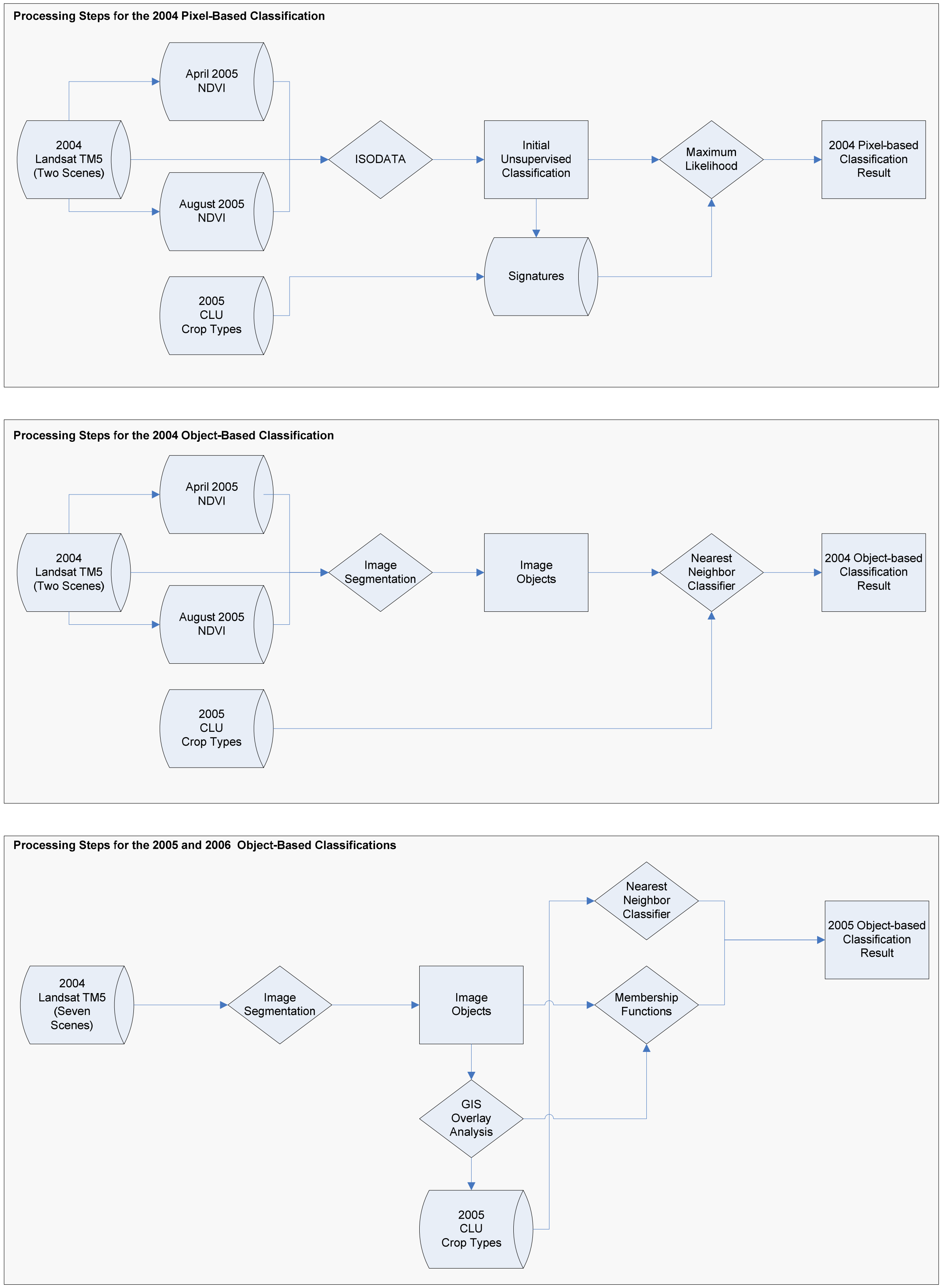

Figure 3: Classification methods for the classification projects.

2005 and 2006 Classifications

The focus of the 2005 and 2006 classifications were to use the multi-temporal data set to discriminate between crop types, and in some cases, crop harvesting methods, using rule-based membership functions available in eCognition. The six Landsat 5 Thematic Mapper (TM) bands primarily used for classification (all but the thermal band) for each of the images, forty-two bands total for 2005 and thirty-six bands total for 2006, were segmented into image objects. An overview of the classification methodology is illustrated in Figure 3.

Image Segmentation

As described previously, object-based approaches incorporate two steps: segmentation and classification. In eCognition image objects are created using user-defined scale and homogeneity parameters. The scale parameter determines the size of image objects and how different objects are from one another. The homogeneity criteria are defined by the spectral value of the image and shape of image objects. Shape is further defined by the smoothness of object borders and compactness of the resulting image objects. In this project, a relatively high scale parameter was used to capture agricultural fields as single objects. Spectral value was favored over shape, and compactness was favored over smoothness since the cultivation of agricultural fields gives them a compact form.

Calculating NDVI

In addition to other methods, the land use classification described here uses a set of rules based on the phenological growth profiles of agricultural crops. These profiles can be observed through an analysis of the Normalized Difference Vegetation Index (NDVI) over time (Sakamoto *et al.*, 2005). NDVI is an indicator for the amount of plant biomass at a location and is useful for tracking the amount of living vegetation in a field during a growing season. Higher values indicate greater amounts of vegetation while lower amounts indicate bare soils or no vegetation. For each of the Landsat scenes used in the 2005 and 2006 studies, NDVI was generated within eCognition using the application's "Customized Feature" functionality. The result was an NDVI value for each date of the Landsat imagery for every image object in each project.

Determine Phenology of Crops and Natural Vegetation

The image objects created in eCognition are exported from the application as a GIS vector layer with the NDVI values for each month as attributes for each object. The layer is then imported into a GIS along with the CLU crop type reference data, each Landsat TM scene and other GIS layers to assist with visualization such as transportation and hydrology layers. An overlay analysis is conducted to relate the crop type reference data with the NDVI values over time. This data is then exported into a tabular format for further analysis.

Establish Decision Rules for Classifier

The tabular data containing crop type reference data related to the NDVI time series data is imported into Microsoft Excel and separated by crop type. Descriptive statistics are generated for each crop type identifying the descriptive statistics of the NDVI values for each crop type in the time series. The mean values are plotted on a line graph to visualize and further analyze the distribution of NDVI values and crop types over the time series. The visualization reveals the patterns of crop phenology that can be used to create decision rules that define which thematic class to assign to an object. For example, Figure 3 illustrates the NDVI values for known winter wheat fields across the growing season. The characteristic early spring green-up followed by early summer senescence of winter wheat is captured by the unique trend of NDVI values from April to July. This trend can be expressed as a logical statement in a decision rule to classify image objects as winter wheat fields.

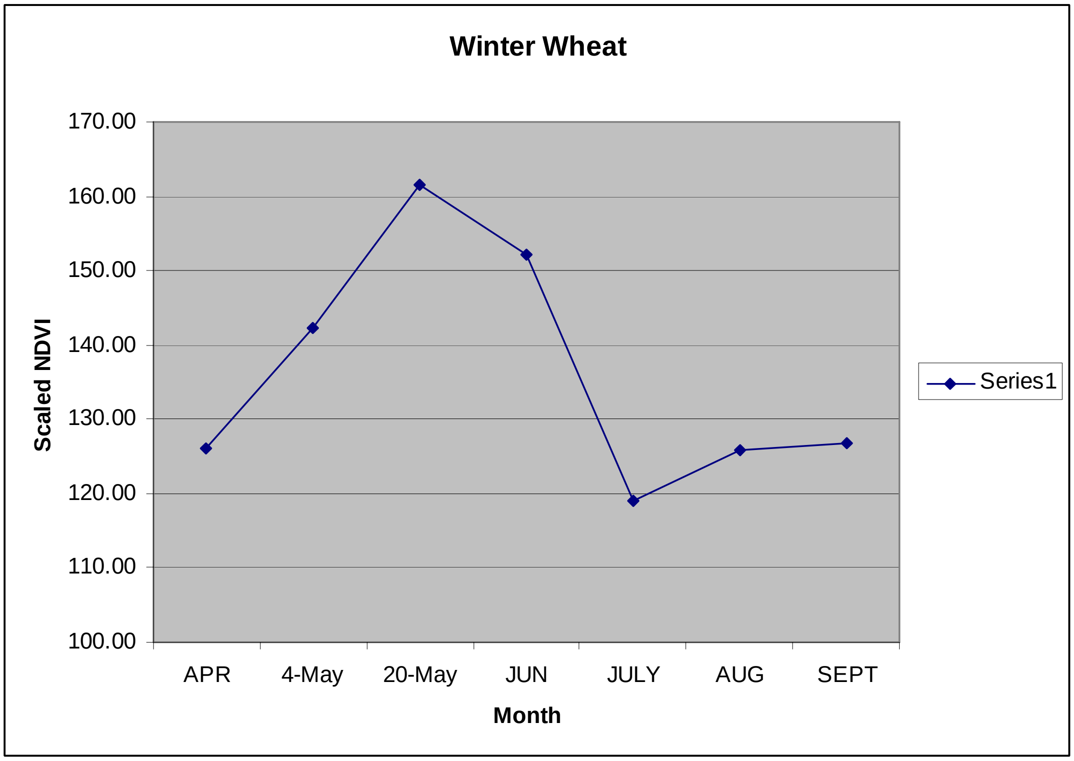

Figure 3: Phenological growth profile of winter wheat fields in southern Michigan 2005

Creating a Class Hierarchy

The crop reference data and analysis of NDVI values are used to identify the land cover classes for the classification. The analysis stage is significant since it provides some insight into the feasibility of mapping some agricultural land uses. For example, the crop type reference data distinguished between corn harvested for grain and silage. The NDVI analysis indicated that earlier harvest of corn silage is expressed by the difference in NDVI values between the crops in September (Figure 4) when considering the NDVI values across the entire growing season. This led to the separation of the corn class into Corn Grain and Corn Silage classes. Similarly, the NDVI analysis indicated that fields classified as Mixed Grass and Conservation Reserve Program (CRP) could not be distinguished separately leading to the development of a single CRP/Mixed Grass class. Once all of the land cover classes were identified, those classes along with other important non-agricultural classes were created in eCognition’s Class Hierarchy tool.

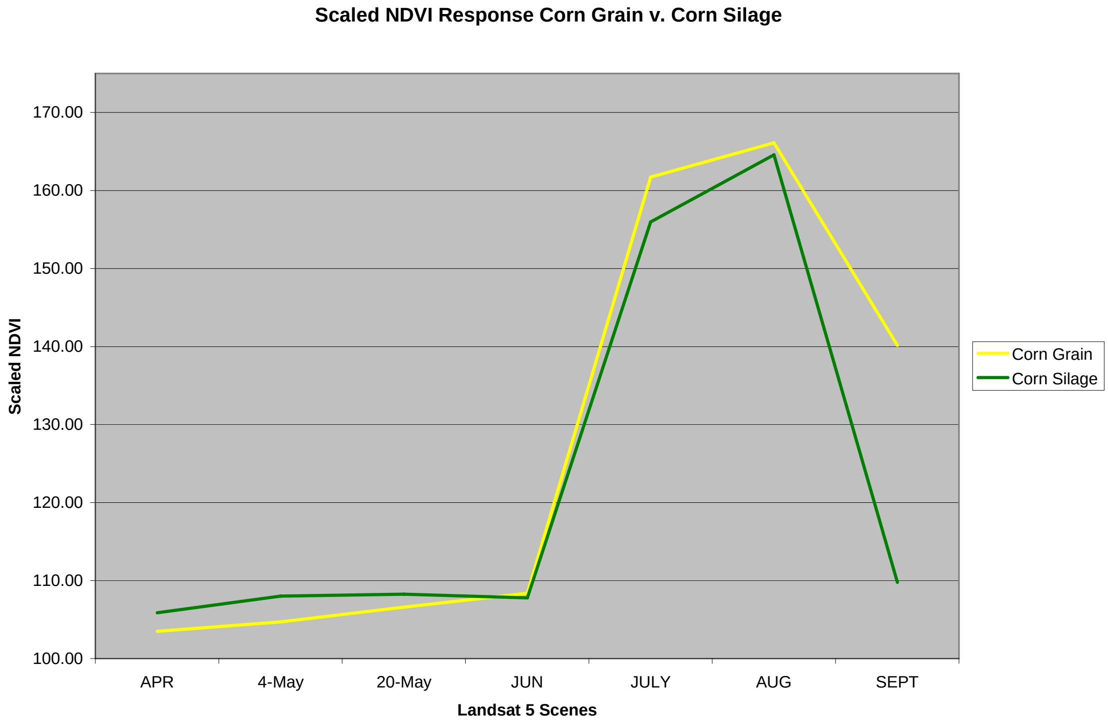

Figure 4: Phenological growth profile of Corn Grain and Corn Silage fields.

Creating the Class Membership Functions

The decision rules for the various crop types identified with the descriptive statistics are used to express class membership functions within eCognition's class hierarchy tool. The minimum and maximum values are used to define range functions for each NDVI data set for each agricultural crop type within the class hierarchy. For example, class membership functions for the Corn Grain class based on the May, June and July NDVI values and describes increasing NDVI values for those three months. These functions, grouped with the class's other functions from the time-series, comprise a rule-set that is used to classify image objects.

Configuring the Nearest-Neighbor classifier

The nearest-neighbor classifier is applied to all of the classes, both agricultural and non-agricultural, in the eCognition class hierarchy using the spectral values of each band of Landsat data as the feature space. Then, a GIS vector layer containing a subset of the crop type reference data is imported into eCognition and imported as training area samples to "seed" the nearest neighbor classifier. Samples for non-agricultural classes such as Water, Forest and Developed (urban) are specified using eCognition's "sample editor" by visually identifying the imagery and assigning the corresponding object to the class as a sample.

Classification

At this point in the process, each agricultural land cover class has both a set of membership functions capturing the time-series of NDVI values and samples from the crop type reference data while non-agricultural classes are identified by samples. The classification function is performed and the results inspected visually within eCognition. The classification process is performed iteratively with steps refining the process according the output result. For example, objects that appear to be CRP/Mixed Grass based on visual assessment of the imagery may be incorrectly classified as Forest requiring refinement of the Forest samples and reclassification of the image.

Results and Discussion

According to the CLU-based field data collected and organized as described in the methods section, the primary crop types in the Bean Creek and Lime Creek study area are 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, since it is tracked by the NRCS as a possible type of cover for a field. CRP and Mixed Grasses are aggregated into a single class since CRP fields are generally covered by a mix of grass and herbaceous vegetation. The crop type inventory for the 2005 growing season differed from the 2004 inventory in that the harvesting method for corn fields (silage or grain) was recorded by MI-NRCS field technicians. The crop type inventory for the 2006 growing season differed from the previous years in that a smaller number of reference sites were used and that corn harvesting method (silage or grain) was not specified by MI-NRCS field technicians. The reference sites that were available for 2006 consisted of larger fields (100 acres or larger) with some fields located outside the Bean and Lime Creek watersheds, but still within the Upper Tiffin Watershed.

The accuracy of the classification projects described in Table 2 and within the following pages uses an error matrix, a table which displays statistics for assessing image classification accuracy by showing the degree of misclassification among classes. Within the error matrix, users, producers, and overall accuracy are used to describe the accuracy of the classification. User’s accuracy describes errors of commission which result when an object is committed to an incorrect class. Producer’s accuracy is a measure of the accuracy of a particular classification scheme. It shows what percentage of a particular ground class was correctly classified. The producer's accuracy details the errors of omission. Overall accuracy consists of the number of incorrect observations divided by the number of correct observations for all thematic classes. Overall accuracy allows the accuracy of the different classification techniques applied to the same study area and data sources to be compared.

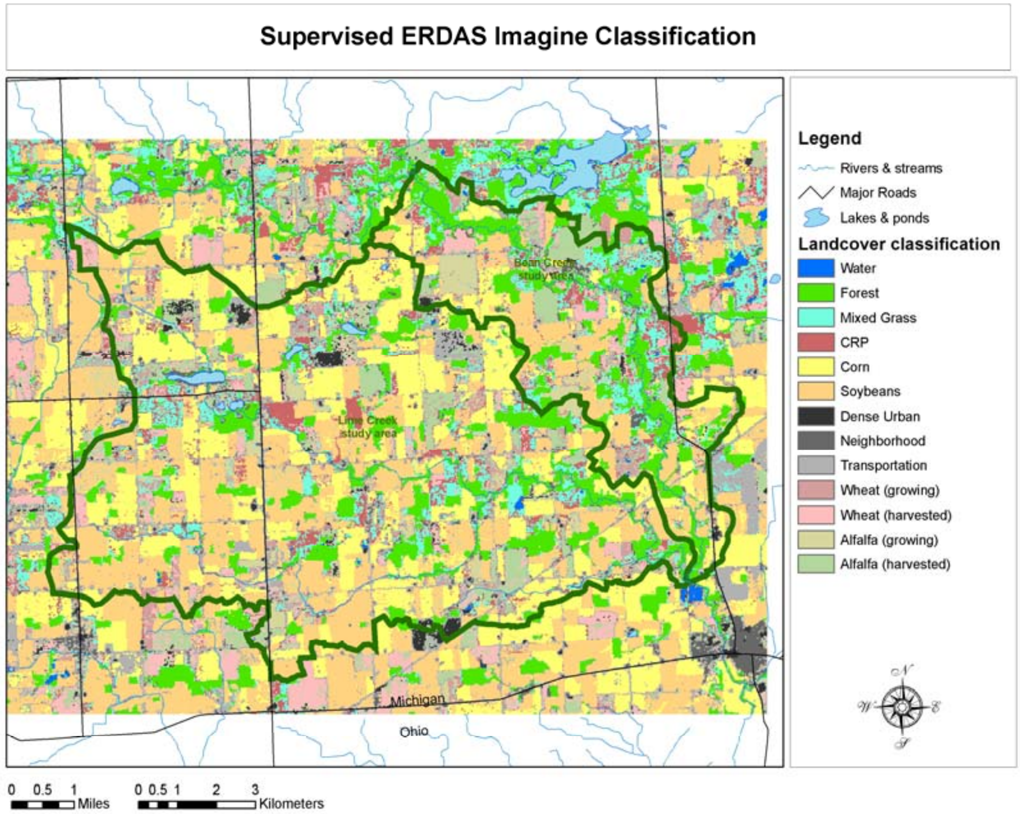

Figure 5: 2004 Pixel-based classification

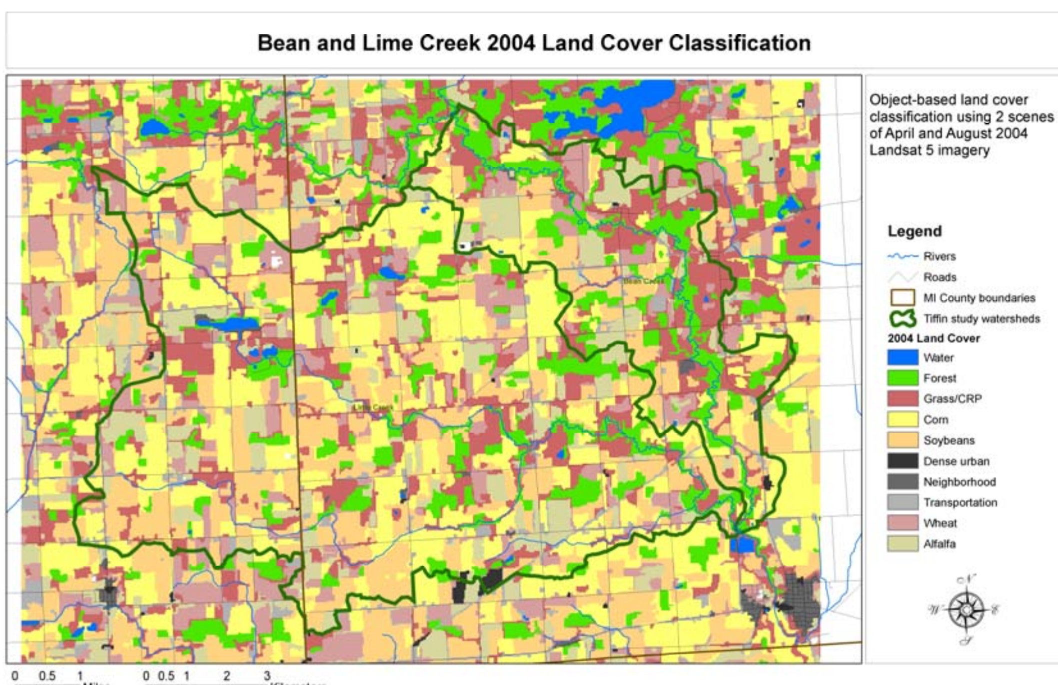

Figure 6: 2004 Object-based classification

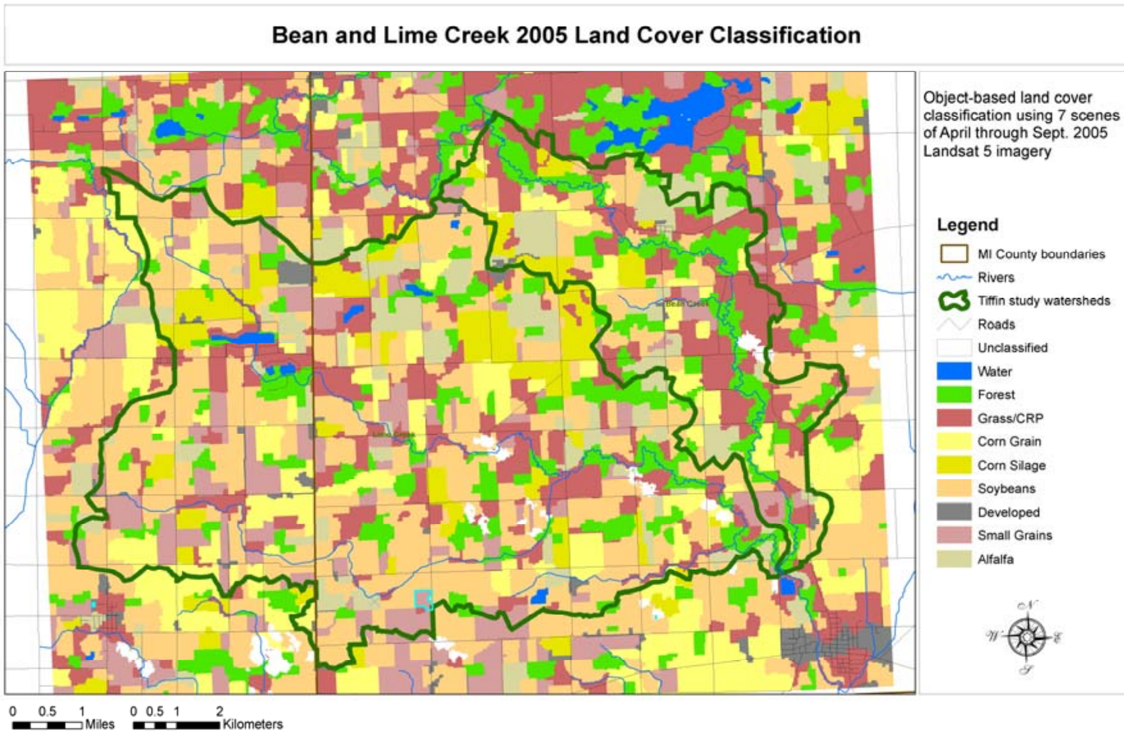

Figure 7: 2005 Object-based classification

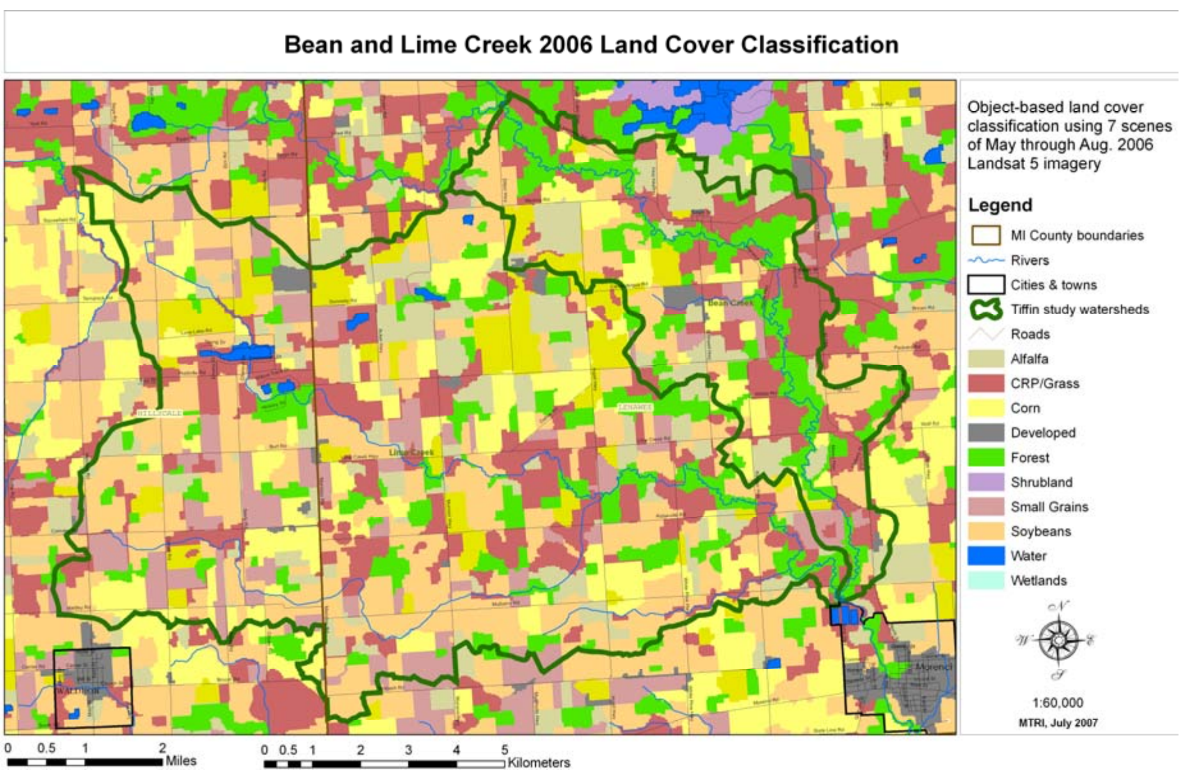

Figure 8: 2006 Object-based classification

Table 2: Error matrices for land use classifications

2004 Traditional pixel-based ERDAS classification

	Alfalfa	CRP/ Mixed Grasses	Corn	Soybeans	Wheat	Other	Total	Producer's Accuracy
Alfalfa	107	14	3	18	16	34	192	55.73%
CRP/Grass	9	238	3	14	40	45	349	68.19%
Corn	7	40	453	33	20	64	617	73.42%
Soybeans	9	21	19	338	17	47	451	74.94%
Wheat	12	9	1	3	51	12	88	57.95%
Total	144	322	479	406	144	202	1697	
User's Accuracy	74.31%	73.91%	94.57%	83.25%	35.42%	Overall accuracy: 69.95%		

2004 Nearest-Neighbor based eCognition classification

	Alfalfa	CRP/ Mixed Grasses	Corn	Soybean	Wheat	Other	Total	Producer's Accuracy
Alfalfa	115	13	2	35	19	8	192	59.90%
CRP/Grass	16	242	5	12	33	41	349	69.34%
Corn	11	44	428	85	20	30	618	69.26%
Soybeans	6	40	31	321	20	38	456	70.39%
Wheat	7	16	3	4	51	7	88	57.95%
Total	155	355	469	457	143	124	1703	
User's Accuracy	74.19%	68.17%	91.26%	70.24%	35.66%	Overall accuracy: 67.94%		

2005 Nearest-Neighbor & Membership Function eCognition classification

	Alfalfa	CRP/ Mixed Grasses	Corn Grain	Corn Silage	Soybean	Small Grains	Total	Producer's Accuracy
Alfalfa	534	16	13	18	44	39	664	80.42%
CRP/Grass	39	739	66	24	188	45	1101	67.12%
Corn Grain	5	4	1144	8	176	8	1345	85.06%
Corn Silage	58	3	27	443	65	0	596	74.33%
Small Grains	4	8	3	12	13	770	810	95.06%
Soybeans	40	20	278	62	2030	17	2447	82.96%
Total	680	790	1531	567	2516	879	6963	
User's Accuracy	78.53%	82.32%	72.54%	77.18%	78.87%	86.25%	Overall accuracy: 81.30%	

2006 Nearest-Neighbor & Membership Function eCognition classification

	Alfalfa	Corn	Soybean	Small Grains	Total	Producer's Accuracy
Alfalfa	4	0	3	0	7	57.14%
Corn	0	45	2	0	47	95.74%
Small Grains	1	0	0	15	16	95.92%
Soybeans	0	2	47	0	49	93.75%
Total	5	47	52	15	119	
User's Accuracy	80.00%	95.74%	90.38%	100.00%	Overall accuracy: 93.28%	

The initial 2004 land cover classification (Figure 5) using a pixel-based unsupervised (ISODATA) and supervised approach had an accuracy of approximately 70% when compared to the 2004 CLU reference crop type data (Table 2). This classification also contained the typical "salt and pepper" look that results from the algorithm assigning each 30 by 30-meter pixel to a land cover type in the training set that it resembles statistically without regard to its spatial context.

To improve the accuracy results and overcome the "salt and pepper" look of the 2004 map, which is not coincident with what is actually found in the landscape, an object-based classification using eCognition (Figure 6) was performed. The eCognition classification, used the sample based nearest-neighbor method with the application's default homogeneity criteria for creating image objects, and resulted in an accuracy of approximately 68% (Table 2). The overall accuracy of the supervised classification, which used the same training sets used in the object-based classification, was similar. However, the pixel-based classification misclassifies many more farm fields as one of the urban, neighborhood, or transportation classes, as seen in the central and western parts of the study area near Lime Creek (Figure 5).

The 2005 land cover classification (Figure 7) was developed using object-based methods with seven different Landsat 5 scenes. Customized homogeneity criteria were used for creating image objects. The image objects were classified using a combination of the sample-based nearest neighbor classifier and fuzzy logic membership functions. The technique resulted in an overall accuracy of approximately 81% compared to the 2005 CLU reference crop type data (Table 2).

The 2005 map, developed with Version 4 of the eCognition software, failed to produce image objects where a cloud mask was applied to the August Landsat scene, even though coincident image data was available for the other scenes. This limitation prevented the classification of approximately 45 hectares of land. The unclassified area, approximately one-third of one percent of the entire study area, is not significantly large enough to compromise the accuracy assessment.

The 2006 land cover classification (Figure 8) is also an object-based classification which used six different Landsat TM scenes and a combination of the sample-based nearest neighbor classifier and fuzzy logic membership functions with custom homogeneity criteria for creating image objects. Due to the nature of the 2006 CLU reference data, this classification and accuracy assessment focused on specific crop types (corns, soybeans, etc.), rather than agricultural land uses such as CRP lands. This produced a crop type map with an accuracy of 93%.

The initial 2004 and 2005 classifications were performed on the immediate area surrounding the Bean and Lime Creek watersheds. The 2006 classification was performed on the immediate area surrounding the extent of the Tiffin River watershed within the state of Michigan and mapped approximately 473 square miles of land in Hillsdale and Lenawee Counties (Figure 9). Techniques developed in the 2005 and 2006 were applied to the larger Tiffin River watershed area of interest (Figure 10)

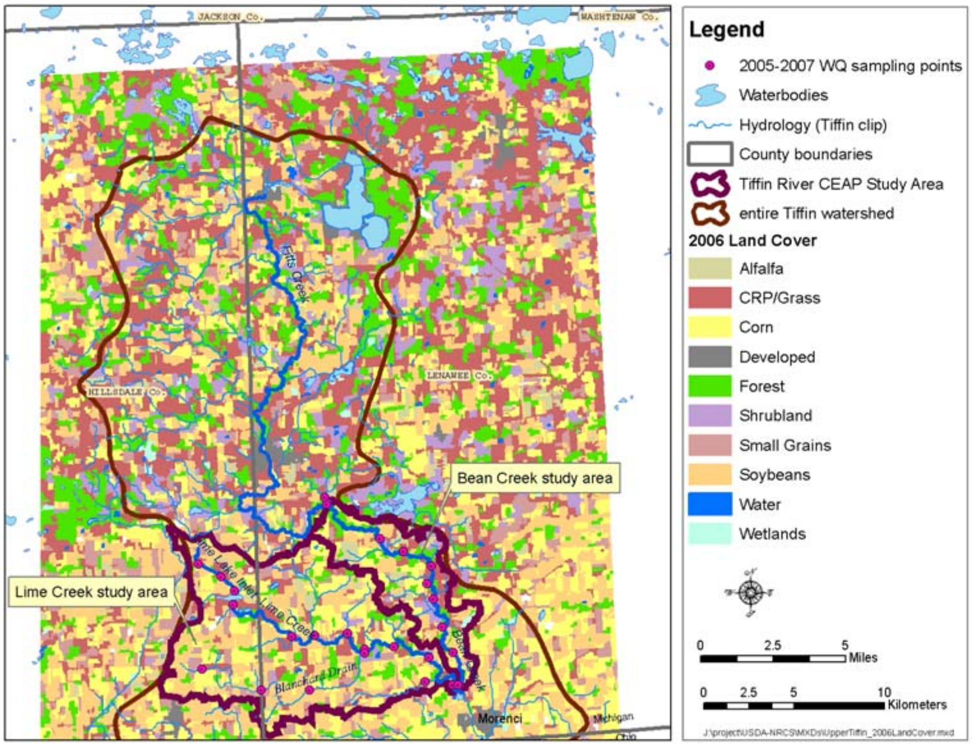

Figure 9: 2006 classification of the Tiffin River watershed within Michigan.

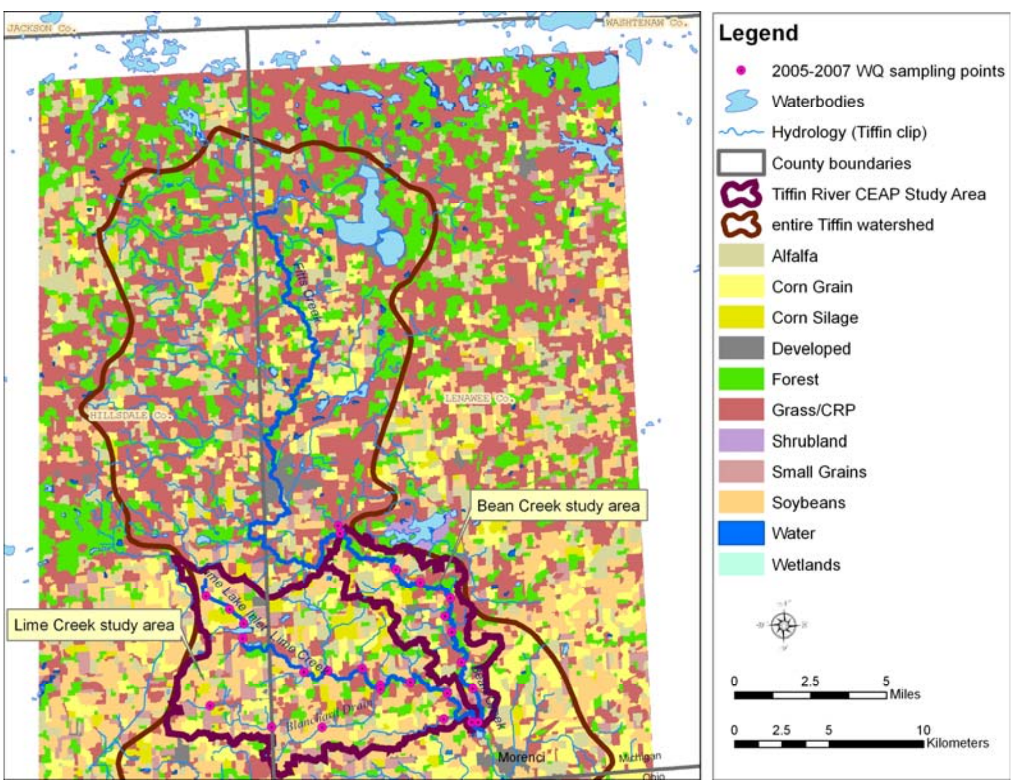

Figure 10: 2005 classification of the Tiffin River watershed within Michigan.

Figure 11 compares the pixel-based classification versus an object-based classification for a representative area of the study area using the 2004 methods that used the two available cloud-free Landsat scenes. The object-based methods have created a classification that more closely resembles fields in agricultural landscape, while the pixel-based classification has the typical noise of pixels being mixed in with other cover types. Overall, the two methods have similar accuracy. Because of the improved appearance of the object-based classification, the object-based methods provide a significant improvement in creating a useful map compared to the pixel-based methods.

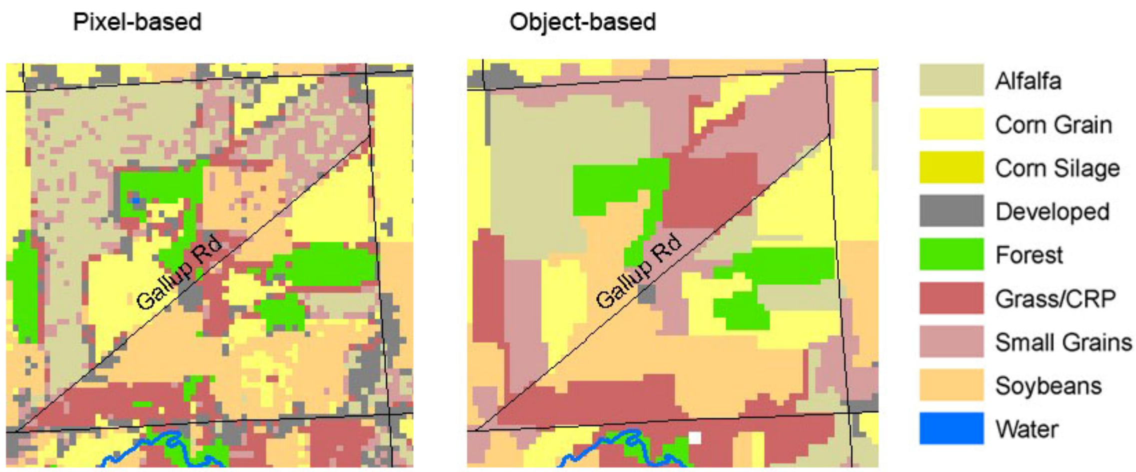

Figure 11: Comparison of traditional pixel-based classification vs. newer object-based classification for part of the Tiffin River study area

Concluding Remarks

The comparison of traditional classification methods with object-oriented classification using Landsat data indicates that an object-based classification is more likely to produce a map that closely resembles the rectilinear shape of farm fields in the study area compared to traditional techniques such as the hybrid unsupervised and supervised classification.

The results of the comparisons of the 2004 and 2005 object-based classifications indicate that more than two Landsat scenes, a moderate amount of training data, and a combination of the sample-based nearest neighbor classifier and class membership rules produce a more accurate land cover map (Table 2). The use of class membership rules demonstrated that the phenological growth profiles of agricultural crops can be derived from multi-temporal data for accurate land cover classification. Since eCognition produces a more visually pleasing product, with a similar accuracy to pixel-based methods when using a limited set of input data, the object-based approach is recommended for future studies.

The implementation of membership functions would benefit from advanced statistical techniques to identify the most effective image acquisition dates, spectral bands, and spectral band combinations to develop even more accurate object-based land cover maps. An example of this approach would be to apply Fisher's linear discriminant analysis (LDA) to the seven Landsat scenes and ground reference data used in the 2005 study. Fisher's LDA is a data mining technique that is used to determine which variables discriminate between two or more classes by evaluating successive linear combinations of training samples to maximize the ratio of between-class variance over within-class variance in an expectation of spreading the means of different classes as much as possible while keeping the within-class variation at a similar level for all classes (Yu *et al*., 1999). The variables identified by the analysis could be useful as the basis of class membership rules within eCognition. Investigations into this approach by Xu and Gong (2007) indicate that this method is appropriate for segmented image objects as well as for reducing the dimensionality of large data sets.

Most importantly, the results of this study indicate that object-based image analysis represents a significant advancement in land cover mapping. The object-based approach combines the elements of image interpretation with traditional classification and GIS analysis techniques to extract the context and morphology of landscape features within a semi-automated environment with greater accuracy than traditional semi-automated approaches.

In the future, object-based image analysis will provide a critical tool for analyzing the substantial archive of moderate resolution remotely sensed data and ever increasing amounts of data from high resolution sensors, Light Detection and Ranging (LIDAR), and Synthetic Aperture Radar (SAR) systems.

The ability of the object-based approach to analyze data at multiple scales is likely to be the focus of a considerable amount of future research in landscape ecology. Landscapes are complex systems composed of different critical levels of organization where interactions are stronger within levels than among levels, and where each level operates at relatively distinct temporal and spatial scales (Wu and Marceau, 2002). To detect significant features occurring at specific levels of organization in a landscape, two elements are required: a multiscale dataset which can identify these features and a procedure to delineate individual image-objects and identify them as scale changes (Wu and Marceau, 2002). The object-based approach provides a tool to evaluate the scale of landscape processes through multi-resolution image segmentation. Object-oriented data models developed in the discipline of geographic information science provide a framework for tracking image objects as they change in scale. Future studies could apply these tools to model interactions within agroecosystems at local scales such as crop growth and soil dynamics and riparian buffer analysis or at statewide or regional scales.

Acronym List

C-CAP	Coastal Change Analysis Product
CEAP	Conservation Effects Assessment Project
CLU	Common Land Unit
CRP	Conservation Reserve Program
EPA	Environmental Protection Agency
FSA	Farm Services Agency
GIS	Geographic Information System
IFMAP	Integrated Forest Monitoring Assessment and Prescription
LDA	Linear Discriminant Analysis
LIDAR	Light Detection and Ranging
MTRI	Michigan Tech Research Institute
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NRCS	Natural Resource Conservation Service
SAR	Synthetic Aperture Radar
TM	Thematic Mapper
USDA	United States Department of Agriculture
WRS-2	Worldwide Reference System 2

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