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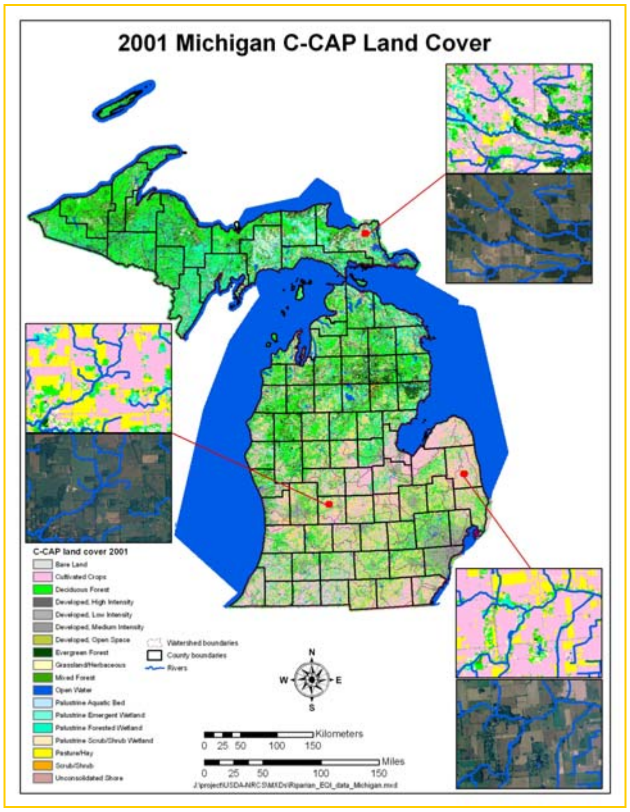

Using C-CAP Land Cover Products for EQI Inputs:

Analyzing Riparian Buffers, Habitat Improvement, and Fragmentation over Time with Satellite Imagery

Colin Brooks and Ben Koziol

May 2008

USDA NRCS

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Executive Summary

This study demonstrates that land cover products, especially those showing change over time, are key information sources for the NRCS. By having access to accurate, up-to-date, and comparable land cover layers over time, the NRCS can map habitat, study threats to rare species, calculate likely sediment loads, and assess the impacts of programs restoring forests, grasslands, wetlands, and other natural vegetation. The methods described here show that standardized, regularly produced moderate resolution land cover data layers can be used to estimate the amount of (and changes in) natural riparian vegetation, areas of habitat, and levels of habitat fragmentation in Michigan.

The main land cover product we analyzed was the Coastal Change Analysis Program (C-CAP) 1996 and 2001 spatial data layers, created by the National Oceanic and Atmospheric Administration and derived from 30-m resolution Landsat imagery. We selected those data layers because they were created with standardized methods that are being repeated every five years, with a 2006 version becoming available soon, and they cover the entire Great Lakes ecological region (along with the U.S. Pacific and Atlantic coastal states). Our analysis also shows that using different land cover layers produced with non-standardized methods, such as one produced by the state of Michigan from 1978 data, leads to incorrect conclusions of landscape change. We recommend that the NRCS take advantage of the standardized and relatively frequently released C-CAP data to evaluate land cover change and the impacts of NRCS programs, particularly at regional and local watershed scales.

The results of our land cover analyses based on C-CAP data are inputs into the Environmental Quality Index (EQI), which has been developed by the Michigan Tech Research Institute for the Natural Resource Conservation Service's (NRCS) Michigan office. We created a "Riparian Buffers" input that measured the percentage of natural vegetation (defined as forest, grassland, scrub/shrub, and non-forested wetlands) near streams for all of Michigan in 2001. We also calculated examples of percent change in riparian cover from 1978 to 1996 and from 1996 to 2001. The "Habitat Improvement" input used the C-CAP program's "change analysis" product to measure the amounts of change in and between forest, wetland, scrub/shrub, and grassland at the level of entire counties. The fragmentation analysis created a series of patch area and shape index calculations for each of the same four major land cover groupings.

Fragmentation metrics are most appropriately used at a local watershed scale, but have aggregation and noise problems when used at the county scale. Reducing the analysis unit size, permitting both thorough qualitative and quantitative consideration of the area of interest, would provide greater utility to the user. We recommend that NRCS use the fragmentation metrics when analyzing impacts of programs at local scales, such as small watersheds and study areas. Furthermore, fragmentation trends, versus the static data values created here, are perhaps the most interesting as landscape dynamics evolve under developmental processes. Fragmentation is also the most susceptible to lacking appropriate temporal data, and will become of more value as future C-CAP products become available.

The main limitation of this study was the short time period between the 1996 and 2001 dates of the C-CAP land cover data layers. However, as C-CAP products become available in the future every five years, and other regularly produced layers such as the National Land Cover Dataset are created with standardized methods, our methods will become more valuable in helping the NRCS to evalute the changing landscape and the effectiveness of its programs.

Description of the C-CAP land cover products

The National Oceanic and Atmospheric Administration's (NOAA) Coastal Change Analysis Program (C-CAP) land cover products are spatial databases depicting the vegetation and anthropogenic landscapes of the coastal United States, including the Great Lakes region, "America's freshwater coast." Two Great Lakes area spatial products were released in 2003 by NOAA, a circa 1996 land cover data layer and a circa 2001 land cover data layer, using standardized image classification methods developed by NOAA researchers and collaborators in the 1990s (Dobson et al. 1995). The dates refer to when a majority of the input Landsat satellite data scenes were from that were analyzed to create the two data layers; actual imagery dates were typically up to one to two years earlier depending on image quality. A third product, a nominally 1996-2001 land cover change product was also released in 2003 that highlighted the type of change (e.g., from agriculture into housing). The 1996 C-CAP Great Lakes layer has a published accuracy of 85%, while the 2001 version has a published accuracy of 87.7%. More information on the C-CAP data layers are available at: http://www.csc.noaa.gov/crs/lca/ccap.html and http://www.csc.noaa.gov/crs/lca/greatlakes.html

In August of 2007, NOAA released a revised version of all three Great Lakes products (1996 land cover, 2001 land cover, and 1996-2001 change) that were more consistent with C-CAP mapping methods used in other parts of the country and included a more complete list of landcover types (Nate Herold, NOAA, personal communication, 2007). This paper is one of the first publications to describe the use of these revised data. The revised data became available during the development of the EQI products using C-CAP data, and provided an opportunity to understand and demonstrate the differences made by using the updated data products. Differences seen in the amount of riparian vegetation change from 1996 to 2001 when using the original versus revised C-CAP data are highlighted in the riparian buffers section below.

C-CAP land cover products have several advantages over other potential land cover data sources. They are being produced regularly by NOAA; in addition to the 1996 and 2001 versions, a version derived from 2006 imagery is scheduled to be released in 2008, with updates intended for release every 5 years thereafter. Also, the same standardized classification methods are used for each version, meaning that land cover change (and types of land cover) can be compared between years. In contrast, the methods changed between the 1992 and 2001 National Land Cover Data (NLCD) layers, making them not directly comparable for land cover change (Wolter et al. 2006). NLCD is on an approximately 10-year update schedule, meaning that it will be much longer before additional change can be estimated. While NLCD is also derived from Landsat imagery, these features make it less than ideal for comparing land cover at two time periods. The other major recent landcover product for Michigan, the Integrated Forest Monitoring Assessment and Prescription (IFMAP) layer), is nominally 2001 (using 1997-2001 Landsat imagery), but is only available for a single time period.

Another commonly used land cover product for Michigan is the 1978 Michigan Resource Information System (MIRIS) land cover, produced largely from 1:24,000 scale aerial photography. While widely used in Michigan, its age and different production methods make it challenging to compare change over a long time period. Nonetheless, for demonstration purposes, we estimated the change in 1978 (MIRIS) to 1996 (C-CAP) land cover by creating a reasonable cross-walk table between MIRIS and C-CAP riparian vegetation cover types.

Riparian Buffers

Methods

For this analysis, we used the USGS high-resolution National Hydrography Dataset (NHD) (http://nhd.usgs.gov/) as our input streams layer. The high-resolution version was released by the USGS for the Great Lakes region only in August of 2007, so this report is one of the first to apply it to riparian analysis needs. NHD data includes geospatial information on streams, rivers, waterbodies (such as lakes and ponds) in a standardized, national format. Because of its recent release, it includes more hydrography information than other potential GIS data sources such as the Michigan Geographic Data Library's (MiGDL) Michigan streams layer.

Our focus was on producing a representative measure of the amount of natural vegetation near streams in the riparian corridor. This measure became part of the EQI's Surface Water Health Index, as the relative presence or absence of riparian vegetation can impact stream health by affecting pollutant levels, temperature, and sediment (Cooper et al. 1987, Environment Canada 2005, Goetz 2006, Lowrance et al. 1997, Osborne and Kovacic 1993, Sheridan et al. 1999).

We used the ESRI ArcMap 9.2 buffer routine to place a 100-meter distance polygon around each stream reach segment for all of Michigan's streams and rivers. This translated into a stream buffer 200-m across, which based on visual inspection of multiple sites against 2005 aerial photography, appeared to capture the typical maximum extent of riparian zones for most Michigan streams. Figure 1 shows an example of these buffers for the Upper Tiffin River (Bean Creek) area in southeastern Michigan's Lenawee County. These buffers were then "dissolved" (using the ArcMap dissolve function) into a single polygon for each unique stream identifier. This prevented double-counting of buffer areas at stream reach junctions. We then intersected this dissolved buffered streams layer with the MiGDL county boundaries layer so that each stream segment would be labeled by what county it was in. This would enable the riparian land cover totals to be summarized by County, which was needed for the data to be used as an EQI input.

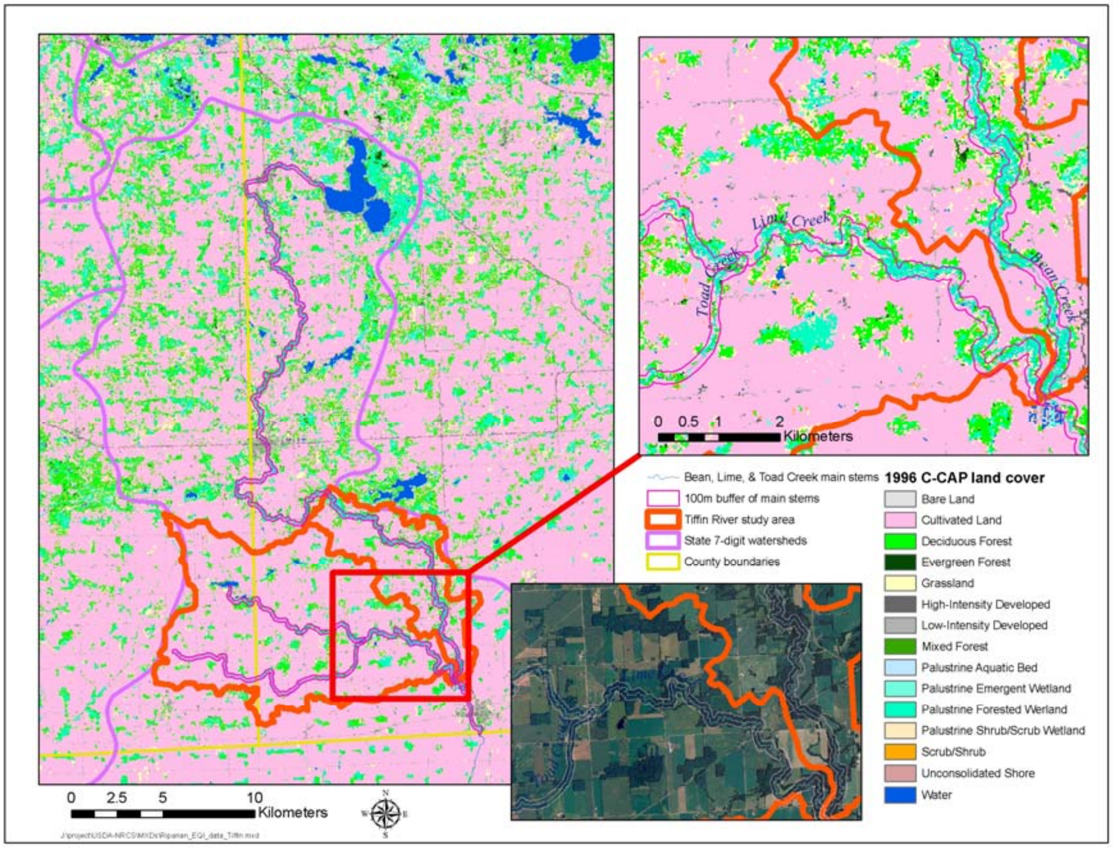

Figure 1: 1996 C-CAP land cover example for the Upper Tiffin River in Lenawee and Hillsdale Counties in southeast Michigan. *Note that the 100-m buffer on each side of the streams captures the approximate extent of riparian vegetation. The imagery insert is from 2005 NAIP imagery near the confluence of Lime Creek and Bean Creek.*

Next, we derived the area of C-CAP 2001 land cover by county within the buffered zone by using ArcMap's "Tabulate Areas" function that is available with the ESRI Spatial Analyst extension. This tool enables the rapid summation of areas by geographic unit for a multi-category layer such as landcover. We repeated this for the C-CAP 1996 land cover and the 1978 MIRIS land cover. These results were exported to Excel and made comparable using a reasonable cross-walk table (such as combining forest classes into a single class). We revised the initial analysis of comparing only percent forest at the three time periods based on input from Michigan NRCS staff who wanted the analysis to include all natural vegetation (such as grassland and scrub-shrub) in the analysis. This way, NRCS efforts to restore grasslands and other non-forested vegetation types near riparian vegetation would be included in the analysis. It was then possible to find the amount of change in landcover types from 1978 to 1996 and from 1996 to 2001, which we accomplished using Excel and the cross-walk table of landcover types to make MIRIS and C-CAP comparable.

For the C-CAP 1996 and 2001land cover, natural vegetation included the following land cover types:

- Grassland/Herbaceous
- Deciduous Forest
- Evergreen Forest
- Mixed Forest

- Scrub/Shrub
- Palustrine Forested Wetland
- Palustrine Scrub/Shrub Wetland
- Palustrine Emergent Wetland
- Estuarine Forested Wetland
- Estuarine Schrub/Shrub Wetland
- Estuarine Emergent Wetland
- Unconsolidated Shore
- Palustrine Aquatic Bed

For the 1978 MIRIS land cover, we determined the equivalent list of classes to be:

- Broadleaved Forest
- Coniferous Forest
- Nonwooded Wetlands
- Pine or Oak Opening (Savanna)
- Shrub Rangeland
- Wetlands
- Wooded Wetlands

In reviewing the riparian buffer results, NRCS staff also asked MTRI scientists to evaluate if moderate resolution remote sensing could be used to detect applied NRCS practices, such as filter strips, grassed waterways, and constructed wetlands. Our results and discussion below provide examples of where this type of remotely sensed data appear applicable to detecting applied practices.

Results of Riparian Buffer Analysis

Table 1 shows the 1978, 1996, and 2001 "natural vegetation" totals for each time period, as well as the change from 1978 to 1996 and 1996 to 2001. Notable is the large amounts of change in the 1978-1996 period, and the relatively small amount of change from 1996-2001, as discussed below.

Table 1: 1978, 1996, and 2001 natural vegetation statistics and amounts of change in 1978-1996 and 1996-2001. *Note the relatively large amounts of changed indicated in the 1978 to 1996 analysis, and the relatively small amounts from 1996-2001. The 2001 natural area % column (in yellow) was used as the EQI input to represent the current amount of natural vegetation present in each Michigan county The area columns are included to give an indication of the relative amount of natural area present in each County.*

County	Natural Area Change (%)		Natural Area (%)			Natural Area (Ac)		
	1978-1996	1996-2001	1978	1996	2001	1978	1996	2001
Alcona	11.3%	0.5%	76.0%	87.3%	87.9%	57,176	65,715	66,118
Alger	-1.2%	0.0%	91.4%	90.2%	90.2%	75,331	74,475	74,485
Allegan	-1.9%	-0.3%	45.0%	43.2%	42.9%	42,178	40,457	40,186
Alpena	11.9%	0.9%	68.6%	80.5%	81.5%	35,214	41,343	41,820
Antrim	11.0%	-0.1%	60.3%	71.3%	71.2%	27,628	32,706	32,662
Arenac	13.6%	2.1%	46.7%	60.3%	62.4%	28,558	36,915	38,199
Baraga	0.1%	0.0%	91.5%	91.6%	91.6%	108,296	108,480	108,492
Barry	3.2%	-0.5%	54.7%	58.0%	57.5%	28,491	30,171	29,929
Bay	5.3%	0.0%	18.0%	23.3%	23.2%	13,724	17,795	17,775
Benzie	6.1%	-0.1%	74.0%	80.0%	79.9%	16,077	17,402	17,383
Berrien	8.9%	0.1%	42.9%	51.7%	51.8%	25,693	31,001	31,033
Branch	6.8%	-0.5%	35.8%	42.6%	42.1%	20,355	24,183	23,904
Calhoun	2.7%	-0.6%	56.3%	59.0%	58.3%	34,018	35,637	35,247
Cass	4.9%	0.0%	54.3%	59.2%	59.2%	17,876	19,464	19,453
Charlevoix	7.3%	0.0%	64.9%	72.2%	72.2%	23,366	25,997	26,012
Cheboygan	7.5%	-0.1%	67.4%	74.9%	74.8%	41,522	46,152	46,104
Chippewa	9.7%	0.0%	75.3%	85.0%	85.0%	88,358	100,000	99,996
Clare	7.8%	-0.4%	69.7%	77.5%	77.1%	31,702	35,262	35,074
Clinton	7.2%	-2.5%	26.2%	33.4%	30.9%	18,458	23,542	21,812
Crawford	7.1%	0.3%	86.0%	93.1%	93.5%	17,981	19,481	19,549
Delta	4.8%	0.0%	86.6%	91.5%	91.4%	71,251	75,285	75,256
Dickinson	0.4%	0.0%	90.6%	91.0%	91.0%	52,785	53,258	53,258
Eaton	10.6%	-1.9%	37.7%	48.3%	46.4%	20,551	26,350	25,338
Emmet	10.7%	-0.4%	69.3%	80.0%	79.6%	31,652	36,863	36,688
Genesee	12.5%	-0.3%	33.3%	45.9%	45.6%	24,595	33,863	33,657
Gladwin	14.5%	0.5%	59.6%	74.1%	74.6%	39,396	48,968	49,314
Gogebic	-1.1%	0.3%	92.4%	91.3%	91.5%	125,969	124,359	124,706
Grand Traverse	9.0%	0.4%	64.0%	72.9%	73.3%	19,242	21,926	22,033
Gratiot	1.7%	-0.6%	20.4%	22.1%	21.5%	15,920	17,248	16,780
Hillsdale	8.7%	0.0%	39.4%	48.0%	48.0%	23,601	28,785	28,777
Houghton	5.2%	0.0%	86.9%	92.1%	92.1%	119,911	127,118	127,146
Huron	1.8%	0.1%	15.9%	17.6%	17.7%	26,276	29,243	29,370
Ingham	13.3%	-3.8%	33.3%	46.5%	42.8%	18,392	25,732	23,642
Ionia	2.5%	-2.4%	43.7%	46.2%	43.8%	29,086	30,754	29,165
Iosco	13.8%	0.3%	63.5%	77.3%	77.6%	43,576	53,031	53,259
Iron	-0.1%	0.1%	85.8%	85.7%	85.7%	87,479	87,743	87,816
Isabella	8.2%	-0.4%	40.4%	48.6%	48.2%	22,912	27,547	27,310
Jackson	6.8%	-0.6%	59.5%	66.3%	65.7%	35,455	39,519	39,139
Kalamazoo	0.7%	-0.4%	58.2%	58.8%	58.4%	22,784	23,062	22,905
Kalkaska	3.2%	0.2%	87.1%	90.4%	90.5%	24,952	25,874	25,918
Kent	2.6%	-1.5%	51.1%	53.8%	52.2%	48,067	50,514	49,072
Keweenaw	1.3%	0.0%	89.6%	90.9%	90.9%	44,489	45,078	45,093

Table 1 (continued): 1978, 1996, and 2001 natural vegetation statistics and amounts of change in 1978-1996 and 1996-2001. *Note the relatively large amounts of changed indicated in the 1978 to 1996 analysis, and the relatively small amounts from 1996-2001. The 2001 natural area % column (in yellow) was used as the EQI input to represent the current amount of natural vegetation present in each Michigan county The area columns are included to give an indication of the relative amount of natural area present in each County.*

County	Natural Area Change (%)		Natural Area (%)			Natural Area (Ac)		
	1978-1996	1996-2001	1978	1996	2001	1978	1996	2001
Lake	10.5%	0.1%	78.7%	89.2%	89.2%	29,277	33,173	33,198
Lapeer	12.3%	0.3%	33.9%	46.3%	46.6%	30,465	41,540	41,809
Leelanau	8.6%	0.4%	56.0%	64.6%	65.0%	14,942	17,214	17,325
Lenawee	5.4%	0.0%	23.9%	29.4%	29.4%	20,104	24,666	24,657
Livingston	8.5%	-1.7%	53.0%	61.4%	59.7%	30,526	35,379	34,380
Luce	1.6%	0.1%	91.6%	93.2%	93.2%	62,462	63,526	63,563
Mackinac	3.9%	0.0%	84.8%	88.7%	88.7%	60,045	62,972	62,980
Macomb	14.3%	-0.8%	20.9%	35.2%	34.5%	14,783	24,977	24,436
Manistee	9.7%	0.7%	74.9%	84.7%	85.3%	31,426	35,506	35,796
Marquette	1.1%	0.0%	89.7%	90.8%	90.8%	158,348	160,261	160,251
Mason	12.4%	1.7%	54.1%	66.5%	68.2%	29,927	36,788	37,704
Mecosta	8.0%	1.4%	63.5%	71.5%	72.9%	39,646	44,673	45,527
Menominee	6.5%	-0.1%	82.9%	89.4%	89.3%	73,638	79,322	79,243
Midland	14.4%	0.5%	49.7%	64.1%	64.7%	34,688	44,796	45,173
Missaukee	6.4%	0.5%	73.6%	80.0%	80.5%	32,670	35,529	35,772
Monroe	8.6%	-0.2%	11.8%	20.4%	20.2%	10,063	17,610	17,429
Montcalm	4.5%	0.0%	57.3%	61.8%	61.7%	37,235	40,156	40,138
Montmorency	3.8%	0.6%	83.8%	87.6%	88.2%	33,953	35,494	35,733
Muskegon	3.2%	0.5%	55.5%	58.7%	59.2%	28,673	30,361	30,613
Newaygo	7.6%	1.9%	63.3%	70.9%	72.7%	57,570	64,470	66,158
Oakland	14.7%	-1.0%	42.5%	57.2%	56.2%	51,838	69,862	68,678
Oceana	7.3%	2.2%	62.0%	69.3%	71.5%	35,444	39,570	40,839
Ogemaw	8.0%	1.3%	65.7%	73.7%	74.9%	34,941	39,211	39,887
Ontonagon	3.3%	0.0%	89.9%	93.2%	93.3%	260,478	270,005	270,054
Osceola	17.7%	-0.2%	55.3%	73.1%	72.9%	36,036	47,597	47,497
Oscoda	6.2%	1.0%	82.3%	88.4%	89.5%	35,762	38,428	38,876
Otsego	8.7%	0.2%	77.8%	86.4%	86.7%	19,494	21,670	21,724
Ottawa	-0.1%	-0.9%	33.5%	33.4%	32.5%	26,659	26,590	25,896
Presque Isle	4.6%	1.4%	77.9%	82.5%	83.9%	29,665	31,436	31,965
Roscommon	1.6%	0.3%	77.6%	79.1%	79.4%	24,012	24,500	24,578
Saginaw	5.7%	0.0%	21.5%	27.2%	27.2%	30,169	38,138	38,128
Sanilac	6.1%	0.3%	19.6%	25.7%	26.0%	36,027	47,240	47,733
Schoolcraft	1.6%	0.0%	90.4%	92.0%	92.0%	93,395	95,072	95,048
Shiawassee	9.2%	-0.8%	22.0%	31.1%	30.4%	16,076	22,775	22,225
St. Clair	18.9%	0.5%	25.8%	44.7%	45.2%	33,880	60,440	61,165
St. Joseph	-3.2%	-0.2%	54.0%	50.8%	50.6%	23,488	22,127	22,046
Tuscola	6.2%	-0.2%	26.9%	33.2%	33.0%	36,570	45,051	44,821
Van Buren	6.1%	-0.2%	54.7%	60.8%	60.6%	35,890	39,865	39,762
Washtenaw	8.7%	-0.3%	38.8%	47.5%	47.2%	26,289	32,174	31,995
Wayne	11.2%	-2.2%	25.8%	37.0%	34.8%	18,545	28,296	26,595
Wexford	6.1%	-0.3%	80.6%	86.6%	86.4%	40,189	43,187	43,059

The ten counties with the largest amount of apparent increase in natural vegetation from 1978 to 1996 were St. Clair (+18.85%), Osceola (+17.73%), Oakland (+14.74%), Gladwin (+14.45%), Midland (+14.38%), Macomb (+14.33%), Iosco (+13.79%), Arenac (13.62%), Ingham (+13.25%), and Genessee (+12.55%). 19 counties had increases of 10% or more, highlighted in green in Figure 2. Six counties appeared to have decreases in natural vegetation from 1978 to 1996, but none were large than 5% and only one was larger than a 3% decline (St. Joseph, at -3.19%). Figure 2 shows the amount of change from 1978 to 1996 and from 1996 to 2001, while Figure 3 shows the total amount of natural vegetation in 1978, 1996, and 2001. For 1996 to 2001 using the directly comparable C-CAP land cover, no counties had greater than 5% increase or decrease. The top five counties for increase were Oceana (+2.22%), Arenac (+2.10%), Newaygo (+1.86%), Mason (+1.66%), and Presque Isle (+1.39%). The top five counties for decrease were Ingham (-3.78%), Clinton (-2.45%), Ionia (-2.39%), Wayne (-2.22%), and Eaton (-1.86%).

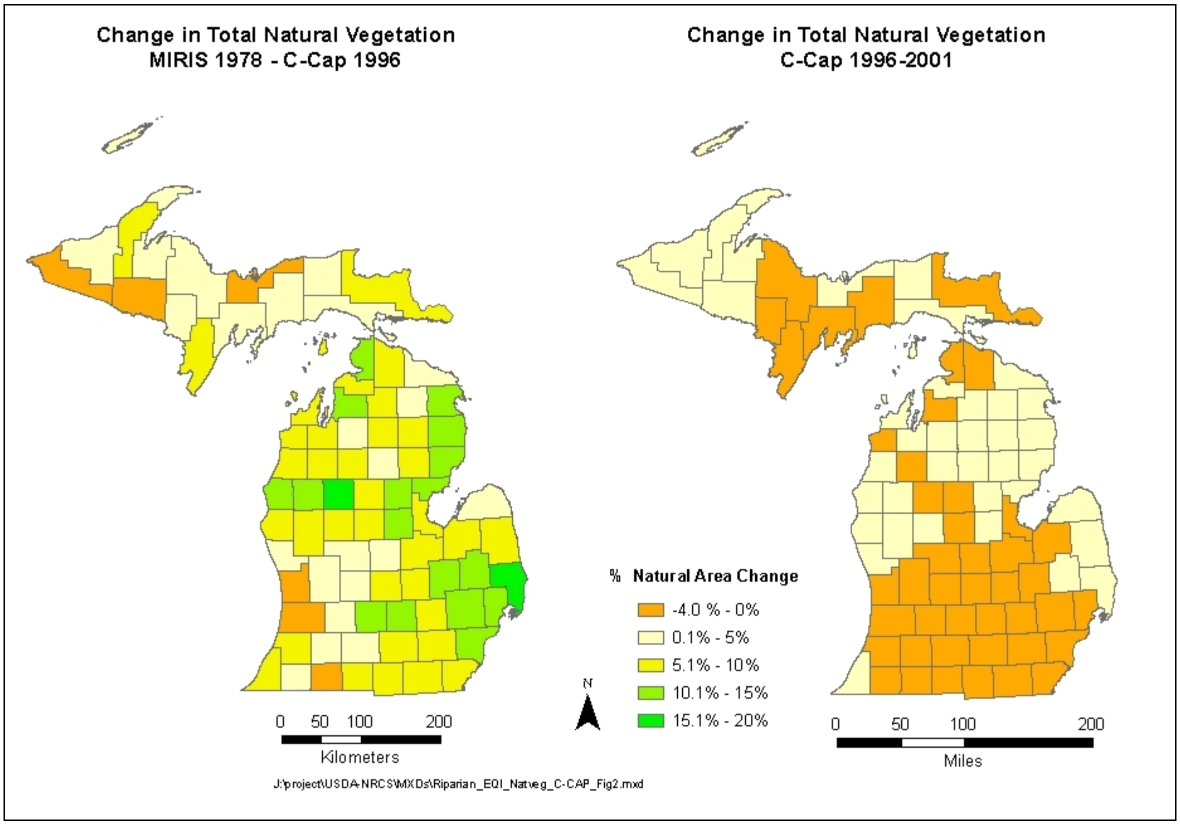

Figure 2: Percent changes in natural vegetation from 1978 to 1996 and from 1996 to 2001 using 1978 MIRIS, 1996 C-CAP, and 2001 C-CAP landcover. *Note the relatively large amount of change indicated from the 1978-1996 period by comparing MIRIS and C-CAP, while the 1996-2001 change was relatively small with no counties exceeding +/- 5%.*

Analyzing the amount of changes in specific land cover types between 1978-1996 and 1996-2001 is illustrative of the strengths and limitations of using and comparing the C-CAP and MIRIS data layers. For example, most of the counties with large supposed increases in natural vegetation from 1978 to 1996 come from dramatic increases in amount of wetland and decreases in the amount of developed land. For example, Arenac County went from 0% wetland to 24.4% wetland and from 21.1% developed to 6.4% developed, while Ingham County went from 4.5% wetland to 26.7% wetland and 21.8% developed to 7.5% developed. Clearly this is an indicator of the difference in classification schemes and image interpretation methods, not from actual land cover change. Were the 1978 and

1996 land cover layers produced with the same methods and goals, we would anticipate obtaining a more realistic analysis of change. The 1996-2001 C-CAP change analysis is indicative of this: In Ingham County, developed areas increased from 7.5% to 7.8% of the County and cultivated areas increased from 28.2% to 30.2%; in Oceana County, cultivated land decreased from 22.4% to 19.8% of the County; in Wayne County, forested land decreased from 28.2% to 27.3% of the County. All of these changes are believable and are indicative of the strength of using directly comparable land cover layers.

For the current (early 2000) version of the EQI, it is the 2001 percent natural vegetation that we are using as the EQI input, which is the third map in Figure 3. The working assumption is that the higher the percentage of the natural vegetation within riparian areas, the higher the environmental quality. For example, riparian cover can provide, in the form of increased forest, shading for streams (Abel and Allan, 2002) and control of sediment flow (Sheridan et al. 1999). As longer-term trend data become available from future land cover data layers, this input could be replaced with the percent change calculation, with higher increases in natural vegetation equaling a higher environmental quality.

As this study has been one of the first to use the revised C-CAP data for land cover change analysis, it is noteworthy to see differences in the two sets of data. In the original dataset, the amount of change from 1996 to 2001 for percent forest varied from -2.84% to +3.52%; in the revised dataset it ranged from -1.39% to + 0.70%. This indicates that the newer, revised data set records less change during the five year time period, most likely because of NOAA's use of their more consistent methods with more complete listings of land cover types.

The ability to track change means that NRCS can also estimate other land cover trends of interest. For example, between 1996 and 2001, Cheboygan County lost 858 acres of riparian forest, Emmet County lost 512 acres, Roscommon County lost 309 acres, Presque Isle lost 344 acres, and Macomb County lost 599 acres (these were the top five counties by percentage loss of riparian forest). This trend analysis can be repeated for any land cover type included in C-CAP, and also at other scales. Section 4, "Habitat Improvements", demonstrates this below at a County scale.

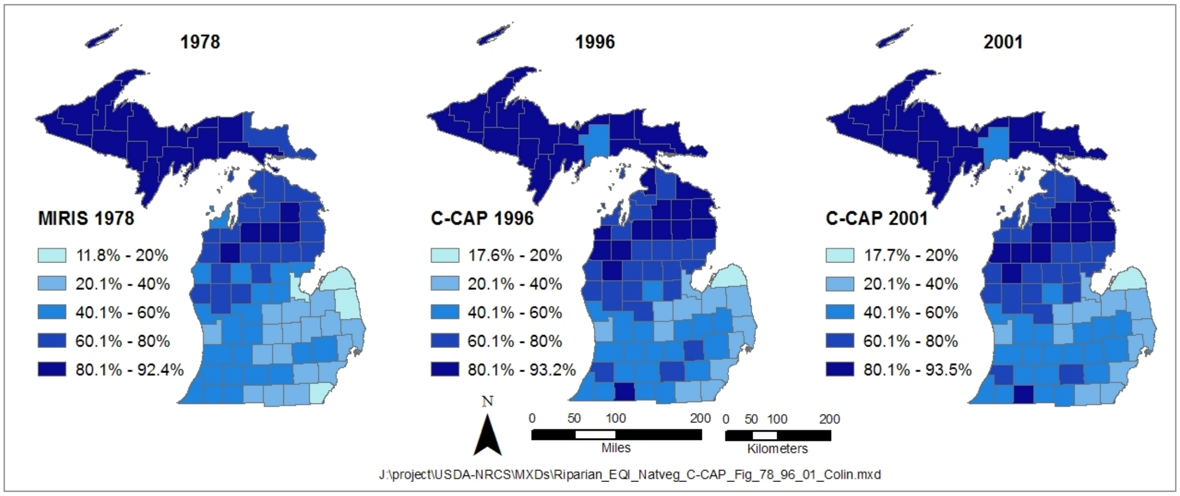

Figure 3: Percent of riparian zones in natural vegetation in 1978, 1996, and 2001 by county. *The 2001 figure on the right showing percent natural vegetation is the current EQI riparian buffer input, and was selected to show the "current" level of natural vegetation.*

Discussion & Summary of Riparian Buffer Analysis

The methods developed here for riparian buffers show promise for using C-CAP data to monitor land cover change. Currently, the relatively short five-year gap of the C-CAP data limits the potential to make major conclusions about the causes of and trends in land cover change. However, with the C-CAP land cover mapping program being funded by NOAA to release updated versions every five years, these riparian buffer methods could track change over the longer term, which could more effectively capture the impacts of NRCS conservation programs on the riparian landscape. Future versions of the NLCD land cover, which the USGS plans to release approximately every ten years using consistent methods, would also help with riparian monitoring. Dedicated mapping by an agency or group to fill in mapping needs in the interim is another possibility.

Potential future next steps for this research exist. One would be to utilize the 2006 C-CAP data when it becomes available from NOAA, which could happen later in 2008. Decadal change (1996-2006) could then be analyzed using our methods, which we anticipate should detect larger trends in land cover change. Using the change in land cover, rather than the amount of natural vegetation in a single time period, may be a replacement EQI input that is more likely to capture impacts of NRCS programs, especially for agricultural counties. MTRI could help intensively investigate areas of relatively large increases or decreases in natural vegetation for the causes of those changes, including seeing if levels of NRCS program implementation were related to these changes.   Accomplishing a rigorous mapping of applied practices could help the NRCS in definitely answering the question of where moderate resolution imagery can help meet its land cover tracking needs.

Habitat Improvements

Land cover holds great influence over human and animal activity. However, presently it is nearly impossible to discuss land cover without discussing anthropogenic influence on its development and evolution. Land cover is not simply the type of plants present at a location, but includes all aspects of surficial activities and structures: houses, pavement, forests, farms, etc. Habitat is not encompassed by all types of land cover. The EQI is concerned with assessing habitat using a universal, generalized method informed by remotely sensed data and focuses on those land cover types most important to healthy habitats for both plants and animals.

In addition to static land cover images for 1996 and 2001, C-CAP also released a change analysis product (see http://www.csc.noaa.gov/crs/lca/gl_change_summary.html). Each pixel has a code referencing each possible transition combination. Change is evaluated using a technique called cross-tabulation which maps each pixel change to its corresponding “to-from” category (i.e. Forest to Grassland). The product released by C-CAP is 30-meter resolution raster dataset with each pixel assigned one of 548 possible land cover transitions.

Since the change product was pre-calculated by C-CAP, data processing by MTRI analysis was greatly simplified (see Figure 4 for processing diagram). A Michigan county layer and the change product were intersected creating individual raster layers for each county. Processing scripts then extracted the data from raster format into a tabular database where land cover transitions were reclassed into the major land cover categories (i.e forest, wetland, grassland, scrub/shrub). The final database contains the amount of acres lost or gained by county for each land cover between 1996 and 2001. These data were then normalized to calculate the percentage land cover change for each major land cover class.

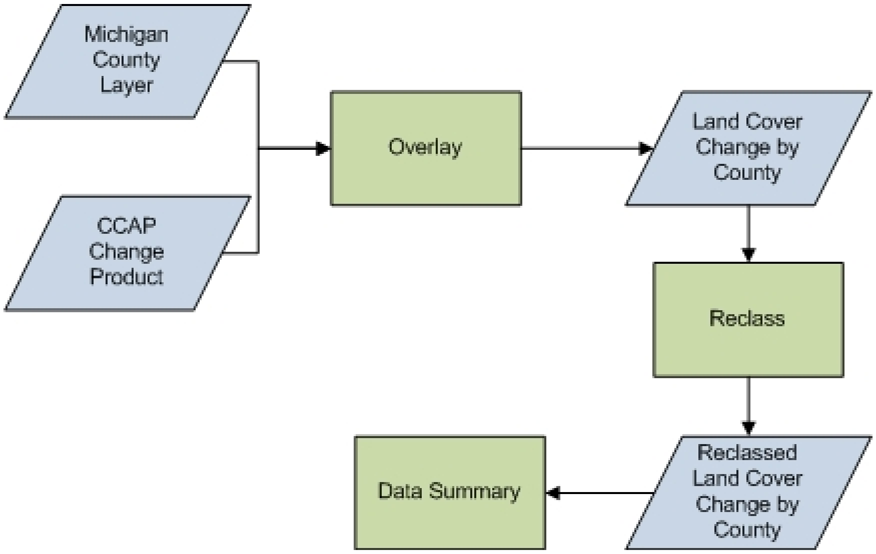

Figure 4: Data processing diagram for Habitat Improvement input. *The result is the amount of change between 1996 and 2001 for forest, wetland, grassland, and scrub/shrub at the County scale.*

Results of Habitat Improvement Analysis

Results from the habitat change analysis are displayed below in Figure 5, with each map corresponding to a different land cover type. Table 2 contains descriptive statistics for land cover change in each county.

Forest land cover did not change substantially during the analysis period. The greatest loss (4%, or 2,146 acres) occurred in Wayne County with the greatest gain (almost 2%, or 498 acres) in Bay County (Table 4 in Appendix B shows the acreage gains or losses for each County). Grassland change has highly skewed results. Ingham County registered a 78% loss, which is a decrease of 12,292 acres of grassland. Table Oceana County, the highest gain, is 18%. Generally, counties that lost forest cover gained grasslands. The reliability of the outlying change values (i.e. Ingham County) is questionable, and we do not recommend relying on the grassland or scrub/shrub change values. It is possible errors occurred in NOAA's original cross-tabulation and perhaps in the original classification. Variability in scrub/shrub land cover range from a 20% loss in Clinton County to a 58% gain in Ogemaw County. Northern Michigan generally increased in scrub/shrub cover with decreases occurring in southern counties. The state had fairly consistent gains in wetland cover except for insubstantial losses in three Upper Peninsula counties. While these percentages changes were small, they reflect a realistic level of change in wetlands over a 5-year period. For example, Arenac County's 1.7% increase in wetland translates into a gain of 1,115 acres over 5 years. Based on this analysis, we recommend using the forest and wetland change variables as reliable indicators of land cover change.

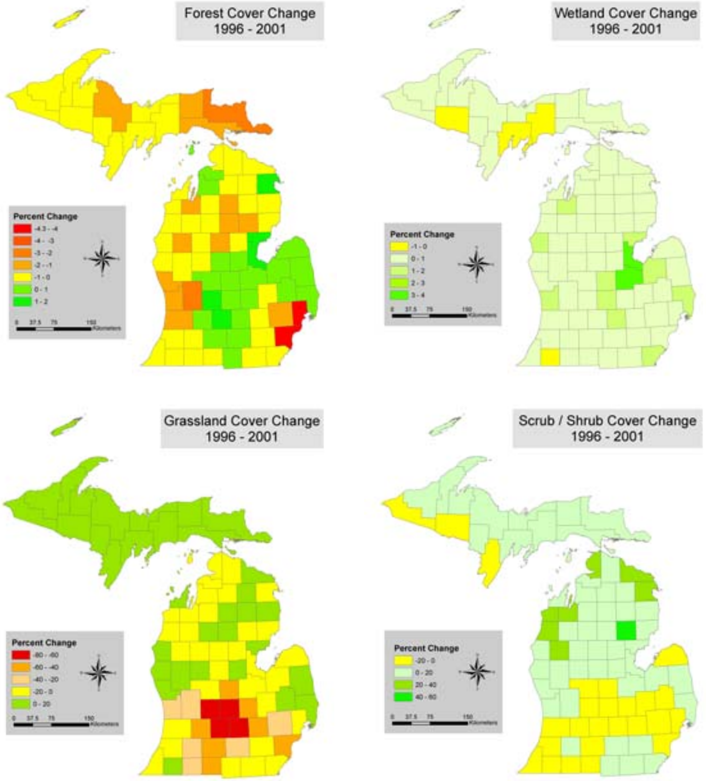

Figure 5: Change in major land cover classes from 1996 – 2001. *Using the C-CAP land cover layers, percentage change in acres can be calculated for the five-year time period. Note reforestation occurring in some agricultural southern counties and the corresponding trends between forest and grassland cover change.*

Table 2: Percent change in land cover from 1996 – 2001 for forest, grassland, scrub/shrub, and wetland. *These values serve as reference for Figure 9, and as four of the Land Habitat Index EQI inputs.*

County	Percent Change				County	Percent Change			
	Forest	Grassland	Scrub/ Shrub	Wetland		Forest	Grassland	Scrub/ Shrub	Wetland
ALCONA	-0.15	5.03	1.85	0.24	LAKE	-1.78	-0.51	20.61	0.67
ALGER	-0.31	2.36	2.16	0.08	LAPEER	0.04	1.96	-0.03	0.54
ALLEGAN	-1.13	-6.33	-0.11	0.56	LEELANAU	-0.34	3.55	9.84	0.92
ALPENA	1.56	-2.78	23.44	0.38	LENAWEE	-0.08	-4.68	0.58	0.19
ANTRIM	0.03	-9.00	11.24	0.39	LIVINGSTON	-0.55	-43.38	-1.26	0.81
ARENAC	1.38	3.34	15.07	1.73	LUCE	-1.86	9.23	4.97	0.30
BARAGA	-0.69	6.44	17.75	0.25	MACKINAC	-1.82	10.92	3.40	0.24
BARRY	0.58	-45.92	-8.85	0.97	MACOMB	-4.20	-3.15	-5.80	0.58
BAY	1.63	-18.16	16.54	3.39	MANISTEE	-0.77	-1.58	20.03	1.00
BENZIE	-0.28	-9.91	27.42	0.73	MARQUETTE	-1.24	15.05	3.27	0.31
BERRIEN	-0.22	-3.58	-0.60	0.39	MASON	-0.64	11.12	11.99	1.08
BRANCH	-0.16	-48.57	-14.68	0.66	MECOSTA	-0.01	13.20	6.95	0.85
CALHOUN	0.69	-50.49	-9.45	0.86	MENOMINEE	-0.35	2.09	-3.34	0.01
CASS	-0.22	0.35	-0.98	-0.08	MIDLAND	0.41	0.26	2.45	0.54
CHARLEVOIX	0.00	-4.99	5.24	0.24	MISSAUKEE	-0.74	1.53	8.12	0.45
CHEBOYGAN	-0.96	-5.94	17.23	0.32	MONROE	-0.59	-16.61	2.41	1.63
CHIPPEWA	-2.97	15.30	2.70	0.41	MONTCALM	0.44	-8.57	-0.42	0.70
CLARE	-1.92	-0.11	4.98	0.47	MONTMORENCY	-0.67	8.62	9.29	0.33
CLINTON	0.91	-67.20	-20.05	1.48	MUSKEGON	-1.45	8.36	4.83	0.85
CRAWFORD	-1.69	5.34	6.31	0.40	NEWAYGO	-0.29	11.51	6.36	0.69
DELTA	-0.71	5.12	2.85	-0.04	OAKLAND	-1.92	-22.66	-0.42	0.45
DICKINSON	-0.41	4.34	2.11	0.11	OCEANA	-0.12	18.31	8.59	0.96
EATON	1.57	-60.14	-0.89	0.95	OGEMAW	-1.87	-9.89	58.50	0.75
EMMET	-0.82	-18.18	28.77	0.34	ONTONAGON	-0.15	5.10	0.83	0.13
GENESEE	-0.43	-13.53	-0.20	0.64	OSCEOLA	-0.10	-5.88	3.50	0.61
GLADWIN	-0.03	-0.48	8.03	0.46	OSCODA	-0.44	9.55	6.98	0.43
GOGEBIC	-0.04	7.06	-13.63	0.24	OTSEGO	-0.62	-2.22	13.18	0.27
GRAND TRAVERSE	-1.10	-10.35	23.56	1.62	OTTAWA	-1.89	-27.97	1.21	1.42
GRATIOT	0.38	-41.12	-13.90	1.36	PRESQUE ISLE	-0.07	5.68	20.79	0.68
HILLSDALE	0.02	-2.79	0.94	0.19	ROSCOMMON	-1.93	1.38	13.93	0.36
HOUGHTON	-0.14	1.98	2.12	0.05	SAGINAW	0.39	-18.60	3.20	3.11
HURON	0.61	-7.79	-0.13	0.91	SANILAC	0.36	9.33	1.21	0.23
INGHAM	0.93	-78.22	-3.98	1.03	SCHOOLCRAFT	-0.99	3.77	0.28	-0.03
IONIA	1.03	-64.89	-17.92	0.93	SHIAWASSEE	0.78	-48.33	-1.21	0.67
IOSCO	-0.47	-0.01	8.26	0.32	ST. CLAIR	0.04	7.99	1.37	1.59
IRON	-0.44	17.56	-7.56	-0.01	ST. JOSEPH	-0.11	-32.97	-5.39	0.67
ISABELLA	0.46	-10.14	2.68	0.51	TUSCOLA	0.13	-7.43	0.40	1.00
JACKSON	0.58	-27.56	1.43	0.55	VAN BUREN	-0.47	-2.36	-2.80	0.22
KALAMAZOO	-0.04	-38.82	0.66	0.70	WASHTENAW	-0.47	-10.12	0.85	0.43
KALKASKA	-0.61	-2.15	18.23	0.46	WAYNE	-4.29	-40.84	-0.10	0.59
KENT	-2.21	-38.90	0.47	0.71	WEXFORD	-0.61	-5.51	15.20	0.74
KEWEENAW	-0.05	4.41	0.18	0.07					

Discussion of Habitat Improvement

Land cover is not only the result of multiple biophysical processes, but the interaction of these biophysical processes with the surround abiotic template. The abiotic template is described by Brown (2003) as: "Human use and management of land, i.e., how people relate to a landscape as a source of livelihood, shelter, recreation, and/or industry, are powerful forces shaping patterns and dynamics in human-occupied landscapes." The implicit link between land cover and human activity means observed changes undoubtedly had influencing abiotic inputs. The goal of the EQI is not to fully model socioecological systems, but describe an objective environmental state. However, it is important to understand the confounding factors affecting gains and losses in important habitat cover.

Considerable variability in change quantities occurs between land cover. However, some of these changes do appear correlated. For example, the loss of observed forest cover in the Upper Peninsula is mirrored by an increase in grassland (see Figure 6). Patterns such as this are visible in the majority of the transitions. Land cover changes appear dynamically linked – trends in land use and succession may partially explain the observed trends. Between 1970 and 2000, the amount of land in agriculture declined in Michigan with an associate increase in forested lands (Brown et al. 2005; Brown 2003). It is possible the increasing grassland in northern counties is related to increased grazing. The increasing scrub / shrub land cover in northern Michigan is likely early successional forests occurring as the generalized reforestation trend moves towards the Upper Peninsula.

It is also important to note these results come from, essentially, a single data point. Hence, the trajectory of these changes may not remain consistent were a second or third time period added. As is the case with many spatial data problems, the wealth of data is often overshadowed by temporal limitations. Data generation projects, such as NOAA's C-CAP, offer potential sources for consistent temporal data.

Incorporating a more dynamic component through more in-depth spatial investigations or data delivery systems for end-user customization increases the potential knowledge gleaned from the product. For example, Chippewa County in the Upper Peninsula lost approximately five percent of its forest cover between 1996 and 2001 (~1300 acres). Using the county as the analysis unit as opposed to pixel-to-pixel mapping in a spatially explicit change detection limits the ability to identify 'hot spots' of change. What land cover transitions forced forest loss? Our riparian analysis, for example, shows that about three-fifths (780 acres) of Chippewa County's forest loss occurred in the riparian zone. Furthermore, were the transitions concentrated or spread evenly throughout the county? If the losses were isolated, habitat loss could be alleviated with targeted mitigation. However, a homogenous loss implies the need for broader habitat management strategies.

Conclusions for Habitat Improvement

- Reforestation occurred in southern Michigan with slight decreases in northern counties. Isolated counties exhibited relatively rapid deforestation in southeastern Michigan. Urbanization likely drove the deforestation in the southeast while change possibly increased grazing practice in the north caused the forest reduction.
- Grassland and forest change appear highly correlated – a loss in grassland is often associated with an increase in forest. Grazing increases, residential development, and fallow agricultural land are possible explanations for these trends.
- Wetland land cover showed relatively little change over five years. This implies wetland mitigation efforts have been successful.

- Scrub/shrub cover increased in northern Michigan. The increase may be a signal of succesional regrowth, indicating forest recovery.
- Forest change and wetland change appear to be the most reliable categories of change in the C-CAP 1996-2001 change product, and we recommend that the NRCS use those as indicators of change. With the release of the 2006 C-CAP, the NRCS will be able to further track changes in these land cover types. Scrub/shrub and grassland change show larger amounts of change than would be likely in a 5-year period, and we do not recommend using them to track change.
- Spatially explicit change mapping could identify sources and losses of habitat cover as well as the distribution of the losses and gains.
- The summary approach demonstrated here (i.e. summary by county) is a useful first step in identifying broad-scale trends. Utilizing all C-CAP land cover categories would provide a more thorough description of habitat change.

Fragmentation

Landscape characterization requires that not only the relative distribution of landscape components (e.g. land cover, land use) is known, but the pattern and organization of those components are sufficiently described. Fragmentation metrics, or more generally landscape metrics, provide an empirical description of landscape pattern in a concise quantitative format. This section describes the two fragmentation metrics (i.e. patch area, shape index) used and summarizes the analysis results. We explain each calculation, enabling a fair degree of interpretability. First, the analysis process is documented followed by a description of the metric calculation. Figure 6 contains a graphic showing major analysis steps.

C-CAP land cover data from 1996 and 2001 were reclassified into four land cover classes: forest, wetland, grassland, and scrub/shrub. This dataset was then subset by county using an extract raster GIS procedure and Michigan county shapefile. C-CAP data heterogeneous with isolated land cover pixels often occurring from spectral inconsistencies affecting the original pixel-by-pixel classification. These scattered pixels, often termed ‘noise’ in remote sensing, are often removed prior to analysis (Lillesand et al. 2004). Filtering assumes homogeneity is desired, and realistic, from the dataset. When data is ordinal (i.e., discrete categories), a majority filter is commonly applied. Example input data from C-CAP are shown in Figure 7. Both images are from the same location, but the second image is from the third pass of the three-by-three, four-neighbor majority filter. This demonstrates little filter effect on overall landscape heterogeneity. Its primary function to remove isolated pixels and/or small linear feature succeeded while not detrimentally affecting data integrity.

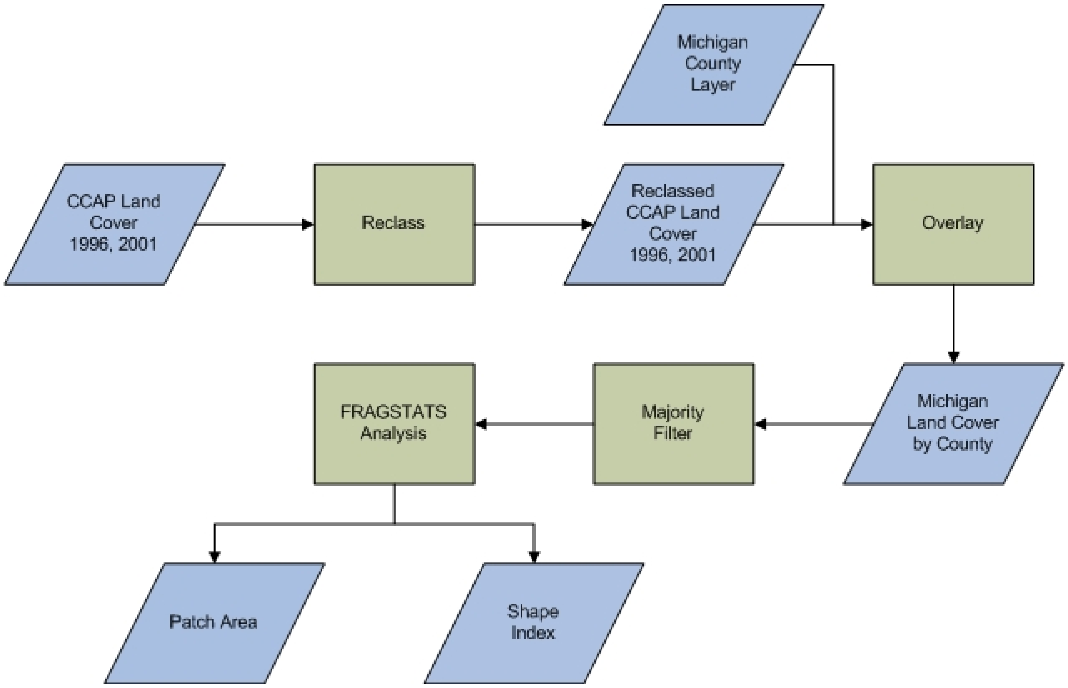

Figure 6: Data processing diagram for Fragmentation inputs. *The process involves several distinct steps resulting in calculations of patch area and shape index, which are used as EQI inputs for the Land Habitat Index component.*

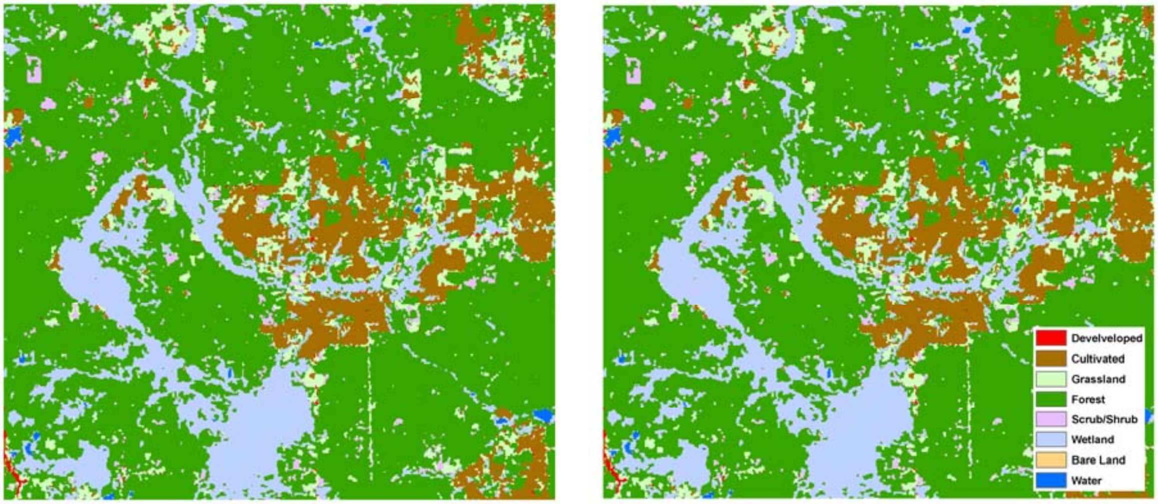

Figure 7: Example unprocessed and processed C-CAP data from northeastern Newaygo County. *The image on the left is unprocessed C-CAP data. The image on the right is following the third pass of the majority filter. Very little qualitative difference is visible in the two images – only isolated pixels have been removed with little change to no change in overall land cover pattern. This means that processed C-CAP data can be used in fragmentation analysis to create valid outputs.*

County-level fragmentation metrics were then calculated using the statistical software FRAGSTATS. FRAGSTATS is an open-source statistical program maintained by the University of Massachusetts-Amherst (FRAGSTATS 2007). Figure 6 contains a graphical representation of the analysis process. The final data includes mean patch area and mean shape index for the four land cover classes for each county by year.

The terms landscape and fragmentation metrics have been used generally. While the ultimate goal is characterization at landscape-scale, the minimum unit (data resolution aside) in landscape metrics is the patch. A patch is defined as a contiguous set of land cover cells that are, given their spatial relationship, ecologically connected. Hence, landscape and fragmentation metrics are in a real sense ‘patch’ metrics.

Diagrams depicting the calculations for each metric are in Figure 8. The patch area metric, as calculated by FRAGSTATS, divides the area of the patch by 10,000 to convert to hectares. Final output for each county is the mean patch area in each land cover class. Shape index is a slightly more complicated calculation. The perimeter of each patch is determined from the actual patch shape. Then, patch cells are reduced to its simplest form (maximally compact) and perimeter evaluated again. Actual patch perimeter is then divided by the reshaped perimeter. For example, if the patch is square, then the actual and reduced perimeters are equivalent yielding a shape index of 1. As patch structure increases in complexity, shape index values increase. Each county’s mean shape index for the four land cover classes is reported.

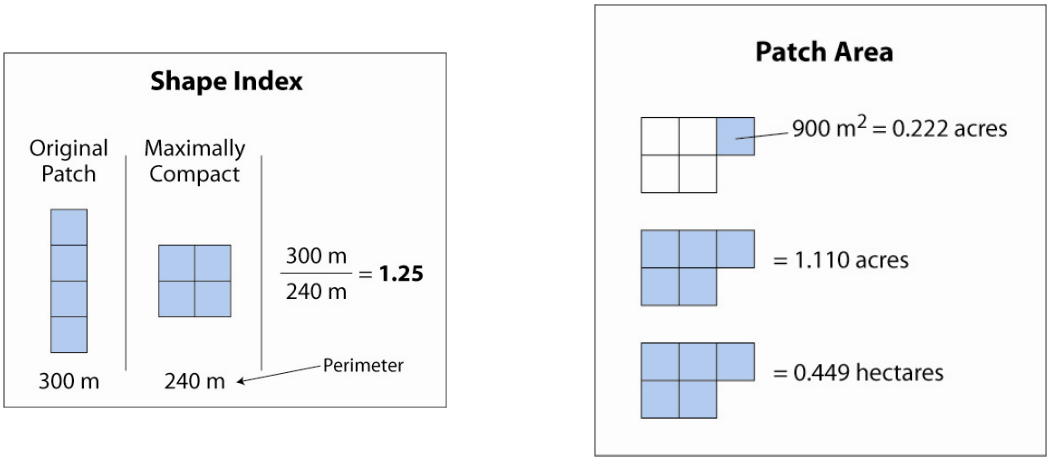

Figure 8: Graphical description of FRAGSTATS metric calculations. *The shape index represents the level of compactness of a patch of a particular land cover type. The patch area counts the number of 30x30-meter land cover cells and converts them to hectares and acres.*

Results of Fragmentation Analysis

The two figures below contain example calculations for mean patch area (Figure 9) and mean shape index (Figure 10) for forest land cover. Maps of all the analyzed land cover types are located in Appendix A.

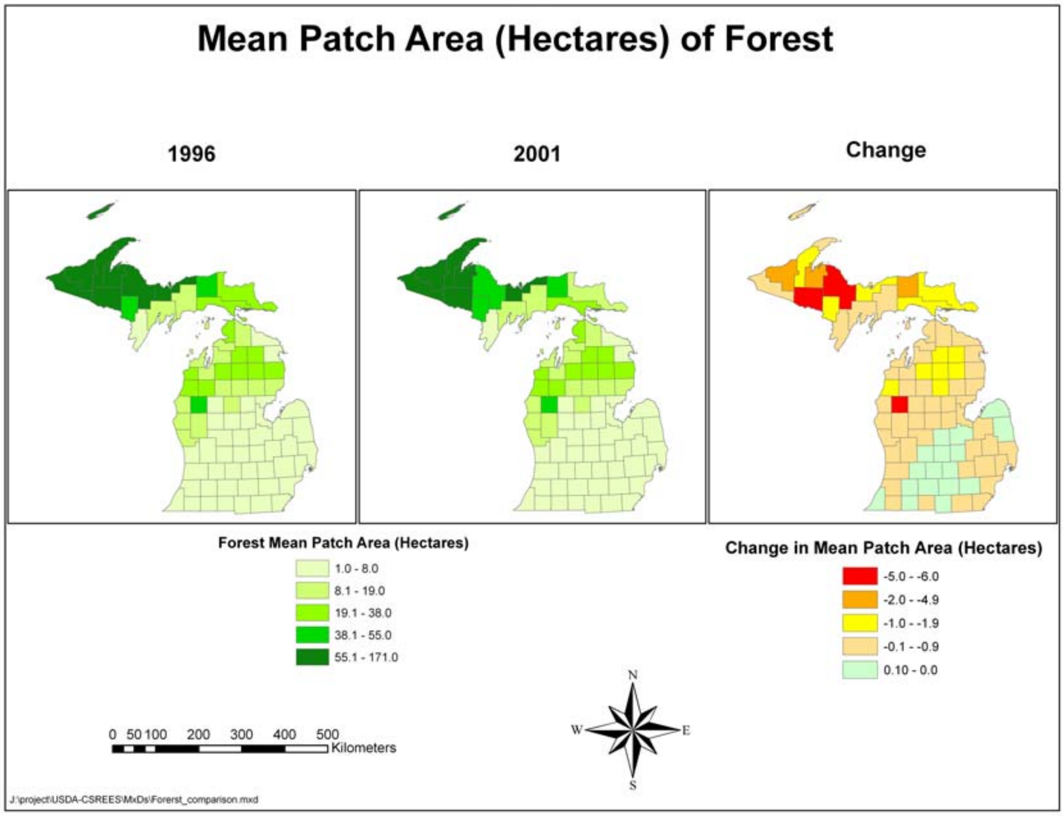

Figure 9: Mean patch area for forest land cover. *Note the larger sizes of forest patches in the Upper Peninsula and the northern Lower Peninsula. The change in mean patch area for 1996-2001 shows a decline for some counties, especially in the U.P.*

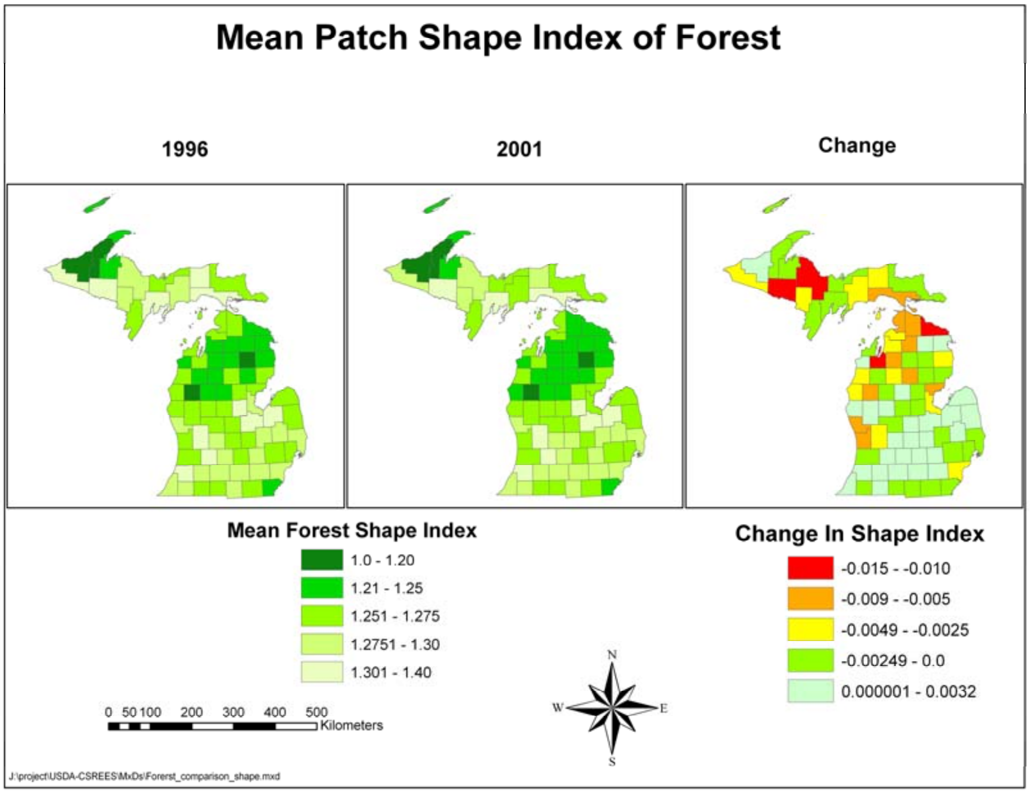

Figure 10: Mean shape index for forest land cover. *In general, counties in the U.P. and northern Lower Peninsula tend to be more compact (i.e., less linearly-shaped). A few U.P. and L.P. counties appear to be becoming less compact (red areas).*

Overall, fragmentation patterns tend to follow population density gradients that are coupled with development and agriculture. For example counties in the northern Lower Peninsula and Upper Peninsula have lower shape index values (see Figure 10). However, the pattern is not consistent with some heavily forested counties (i.e. Gogebic and Iron). This is an excellent example of the non-parametric patch averaging issues discussed below. It appears the benefits of these statistics occur in counties with similar land cover, demographics, etc. Comparing fragmentation between counties with significantly different overall land cover is not advised, considering the Gogebic / Iron example. Agriculture counties in southern Michigan are examples where comparison is valuable. Generally, fragmentation metrics prove most useful in places where context is well defined and external factors are controlled. In other words, in order to use fragmentation metrics effectively, appropriate questions and scales must be applied by agencies and researchers using the data.

It is important to note the small degree of change between 1996 and 2001 in the metrics. This is also related to averaging, but in addition can be attributed to the short duration between the land cover datasets. A significant acreage change in a cover type does not necessarily correlate with a change in the counties fragmentation patterns. Further observations are required to confirm if these dynamics remain constant, accelerate, or slow.

Discussion of Fragmentation

These metrics help quantify the vulnerability of landscape patches to external disturbance (Environment Canada 2005). Both measures combined describe the size and shape of the land cover classes, something that pure areal quantities do not describe. While not the case here, given the need to minimize index inputs to maximize interpretability, it is often the case that fragmentation studies employ many additional metrics (Lausch & Herzog 2002). However, these metrics provide adequate information on the shape and size of landscape patches and often considered principle inputs to any fragmentation study.

With only a five year period between images, change in land cover fragmentation statistics likely did not occur on a scale readily visible to the moderate spatial resolution of the products (i.e. 30-meter). These concerns could be addressed by using data with higher spatial resolution, isolating subtle changes not readily visible to the lower spatial resolution sensor. Furthermore, aggregation at the county level leads to the inevitable 'smoothing' from many patches averaging out isolated changes. Hence, the relatively static state of both mean patch area and shape index during the analysis period is unsurprising. By adding additional image years, more insight into representative changes in land cover pattern and structure would emerge. Limiting this approach is the difficulty in obtaining statewide historic land cover with consistent classification methods both in terms of sensor used and technique employed. However, the C-CAP products used in this analysis are planned by NOAA to be created every five years, with the 2006 version already in production. Additionally, future versions of the NLCD should be produced approximately every 10 years using standardized methods. This means methods developed here could be used in the near future to track impacts of land cover change.

From Figure 11, a high degree of patch variability is clearly visible. The final output for each metric is the average of all patches. Figure 15 demonstrates potential problems when using the mean. The large patch significantly shifts the mean resulting in a value uncharacteristic of true patch configuration. While an extreme example, with actual size distribution being more parametric, these effects are undoubtedly present in these data. Furthermore, the relevance and environmental importance of larger and small patches are not included in the metric calculation. For example, a size-weighted mean and shape index would reduce the influence of multiple small patches.

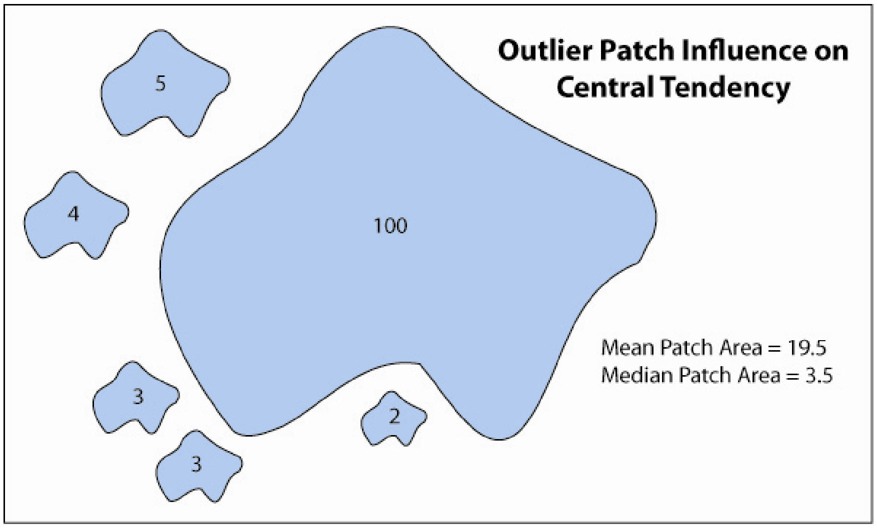

Figure 11: Influence of Patch Size Distribution. *The above figure illustrates the effects of patch size distribution on central tendency. Heavily forested counties in the Upper Peninsula are affected by these outliers as these counties often contain many small forest patches.*

Mapping fragmentation measures by county provides a useful initial assessment of the habitat matrix. The limitations mentioned above (i.e. lack of serial data, smoothing) are real and hinder the interpretability of the final product. Adding additional dates would help confirm trends in change patterns. Additionally, including the metrics in context-specific studies could yield information more valuable for the user. For example, small analysis units (e.g. sub-watershed, single farm unit) would restrict data noise and simplify interpretation. Using counties facilitates confirmation of already known statewide ecological patterns – primarily the effects of agriculture and population on land cover. This analysis has also confirmed that a single date is insufficient to determine trends. Once additional data is added to the study, monitoring ecologically important habitat will be more feasible.

Conclusions for Fragmentation

- Fragmentation metrics offer valuable information when the right question is asked and the proper analysis unit utilized. If specific habitat cover requirements are defined (e.g. patch area), the outputs statistics have more applicability to the 'real-world' ecological condition.
- Fragmentation metrics are highly susceptible to statistical inconsistencies. Counties with large, well-formed forest patches are heavily impacted by this problem.
- Fragmentation trends do not follow land cover trends discussed in Section 4: Habitat Improvement. Favorable fragmentation statistics correlate with dominant land cover types in the regions with some notable exceptions. In addition, the degree of variability observed in habitat change is not present in the fragmentation data – again, a product of patch smoothing.
- Improving the temporal resolution of the land cover data (i.e. additional dates) would allow conclusions to be drawn regarding any fragmentation trends in the dataset. Furthermore, this could lead to queries as to the origin of the fragmentation. For example, are the causes of fragmentation within a county related to increases in agriculture or development?

Evaluation of Moderate Resolution Remote Sensing for Detecting Applied Practices

To determine the viability of moderate resolution satellite imagery such as Landsat 5 to detect past practice implementation, the NRCS past practices database was compared against various types of imagery using ArcMap 9.2. Knowing the tract in which the practice was carried out, we were able to locate the parcel within the imagery using the USDA's Common Land Unit (CLU) layers and then proceed with a visual analysis of the area to determine if the practice in question could be detected. We obtained various results, depending on the type of practice reviewed and the accuracy of the information obtained from the NRCS database.

With reliable input data and an application area of sufficient size, it is possible to visually identify filter strips, grassed waterways and wetland creation using moderate resolution satellite imagery. Figures 12, 13, and 14 give examples of these applications as seen in the National Agriculture Imagery Program's (NAIP) 2005 aerial photography as well as Landsat 5 satellite imagery obtained for the same year.

Figure 12: Filter Strip Implementation, Tract No. 13245, Clinton County Michigan; Landsat TM 5 (Bands 4, 3, 2). *The filter strip is discernable in both the high-resolution NAIP image, and the Landsat image that can be used to map large multi- county areas.*

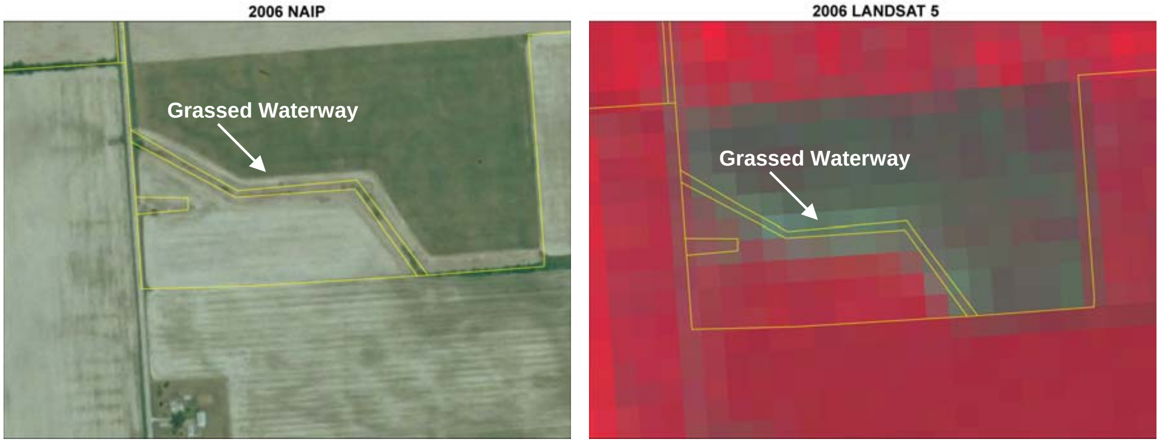

Figure 13: Grassed Waterway Implementation, Tract No. 1475, Lenawee County Michigan; Landsat TM 5 (Bands 4, 3, 2). *The grassed waterway, implemented in 2005, is visible in both the 2-meter resolution 2006 NAIP imagery and the color-infrared 2006 Landsat image.*

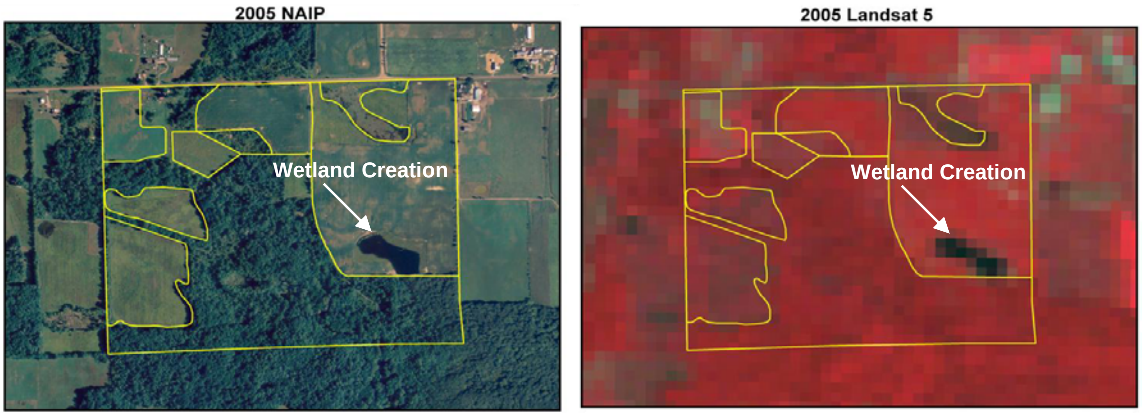

Figure 14: Wetland Creation Implementation, Tract No. 2590, Hillsdale County Michigan; Landsat TM 5 (Bands 4, 3, 2). *The created wetland (a farm pond) is readily visible in the Landsat image.*

We also determined that it is possible to visually identify conservation cover when the location of the practice implementation is known (Figure 15). However, it is likely that imagery analysis techniques could confuse conservation cover implementations with the surrounding existing landcovers, especially when those covers consist of grasses and small shrubs.

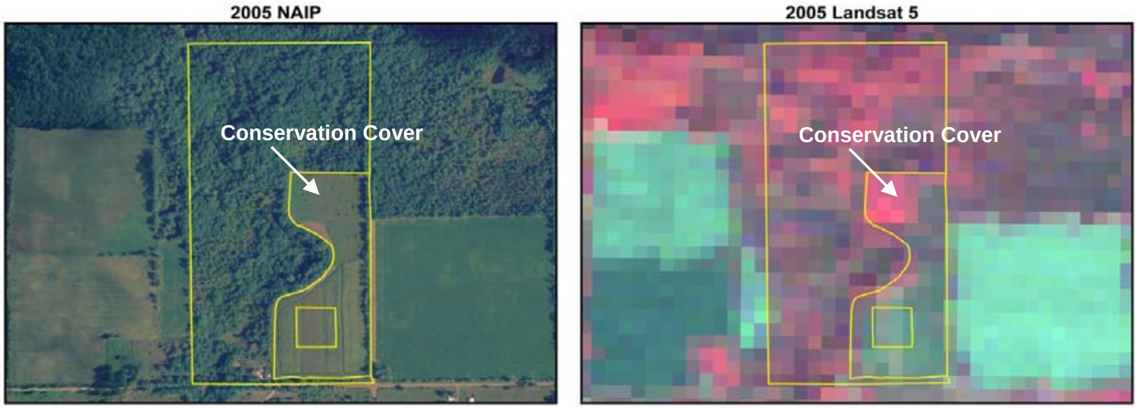

Figure 15: Conservation Cover Implementation, Tract No. 1033, Clinton County Michigan; Landsat TM 5 (Bands 4, 3, 2). *The conservation cover appears as a distinct bright area in the Landsat satellite image.*

We determined that riparian forest cover and herbaceous riparian plantings could not be visually distinguished from surrounding existing cover without more sophisticated analysis. We had similar results for contour buffer strips. Some riparian forest cover could be identified clearly when it was near streams that were surrounded by agriculture. It would take dedicated imagery analysis techniques that capture more subtle differences in spectral reflectance, such as those completed for the C-CAP project, to detect and map these riparian cover types. Table 3 summarizes where visual identification of practices worked well and did not work well.

Table 3: Evaluation of when visual identification of NRCS practices using moderate resolution Landsat imagery does and does not work well. *Riparian cover types need image analysis algorithms to capture their spectral differences from surrounding land cover types in order to be mapped accurately.*

Works well for:	Does not work well for:
Filter strips	Riparian forest cover (vs. other forest cover)
Grassed waterways	Herbaceous riparian planting
Created wetlands	Contour buffer strips
Conservation cover	

For filter strips, grassed waterways, created wetlands, and possibly for conservation cover, moderate resolution imagery such as Landsat does appear to be able to detect NRCS practices. This gives confidence that regional and national land cover spatial data layers would capture these practices as they impact the landscape. Dedicated mapping by an agency or group could help ensure that these practices were mapped accurately if they were a primary concern.

Concluding Remarks

There are several logical potential next steps for the riparian buffer analysis. The first would be to apply additional dates of land cover that used the same methods and land cover classes as existing data sets. Focusing on the change in land cover values, rather than the total amount of natural vegetation, could prove an insightful analysis that more closely tracks the environmental impact of NRCS programs. Creating a custom land cover data set that captured applied practices for multiple time periods could also help in this assessment.

Habitat changes are not homogenous through a landscape. Applying a spatial context to the land cover changes would identify the major contributing factor to the gains and losses in important habitat. For example, it would be feasible to add an additional measure tracking change from forest to agriculture or vice versa. Qualitative representation of change density (akin to “heat maps”) for these targeted transitions offer an alternative to the quantitative methods demonstrated here. Essentially, methods to identify hot spots of habitat change are an important next step proving very useful to land managers.

Barring the availability of land cover data to calculate fragmentation trends, an important step with the fragmentation data is attempting to remove the effects of averaging and noise. This could include using a different measure of central tendency (i.e. median) or adding an additional layer of processing that logically select patches based on area restrictions. Furthermore, fragmentation would prove very useful if guidelines outlining habitat shape and size recommendations became available. Guidelines could either be generic based on broad ecological assumptions, or tailored for a specific plant species, animal species, or land cover type of interest to the NRCS.

The methods developed for this study show that relatively recent, moderate resolution land cover products can be used to develop inputs assessing the amount of riparian cover, the changes in County-level habitat, and the fragmentation of Michigan’s landscape. It is also important to emphasize the generalized framework utilized in this analysis. The framework applied here can be used on many types of remotely sensed data, including higher- resolution imagery, meaning that our analysis methods are not restricted to a single product such as Landsat. These methods will become more applicable as standardized land cover products that monitor longer time periods become available. This will take advantage of the power of remote sensing to act as a “time machine” assessing past change and monitoring change into the future.

Acronym List

C-CAP	Coastal Change Analysis Program
CLU	Common Land Unit
EQI	Environmental Quality Index
GIS	Geographic Information System
IFMAP	Integrated Forest Monitoring Assessment and Prescription
LP	Lower Peninsula
MiGDL	Michigan Geographic Data Library
MIRIS	Michigan Resource Information System
MTRI	Michigan Tech Research Institute
NAIP	National Agricultural Imagery Program
NHD	National Hydrography Dataset
NLCD	National Land Cover Data
NOAA	National Oceanic Atmosphere Administration
NRCS	Natural Resource Conservation Service
UP	Upper Peninsula
USGS	United States Geological Survey

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Appendix A: Patch Area and Shape Index Results for Wetlands, Grassland, and Scrub/Shrub

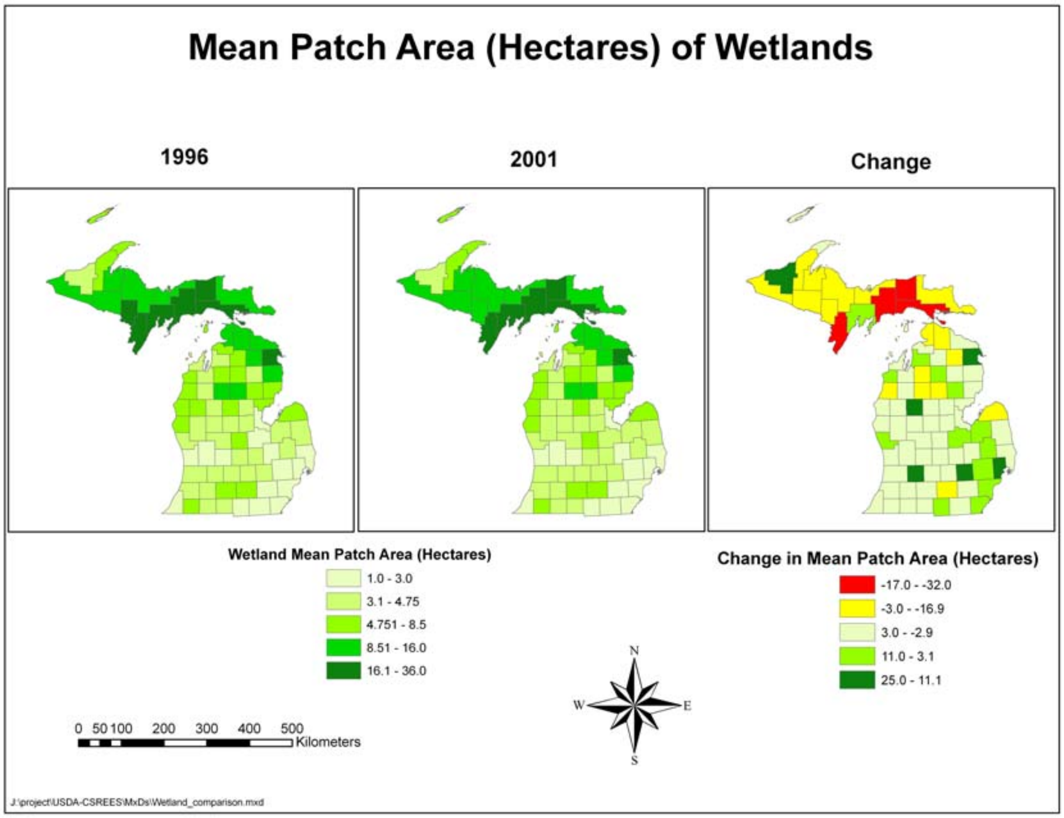

Figure 16: Mean patch area for wetlands land cover.

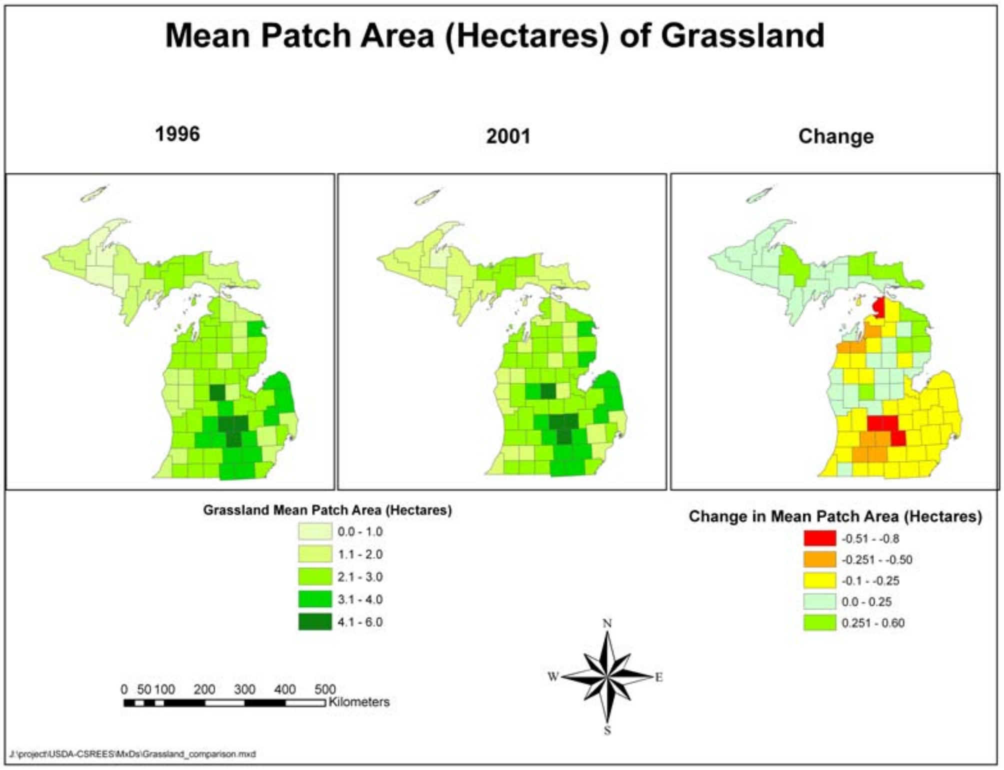

Figure 17: Mean patch area for grassland land cover.

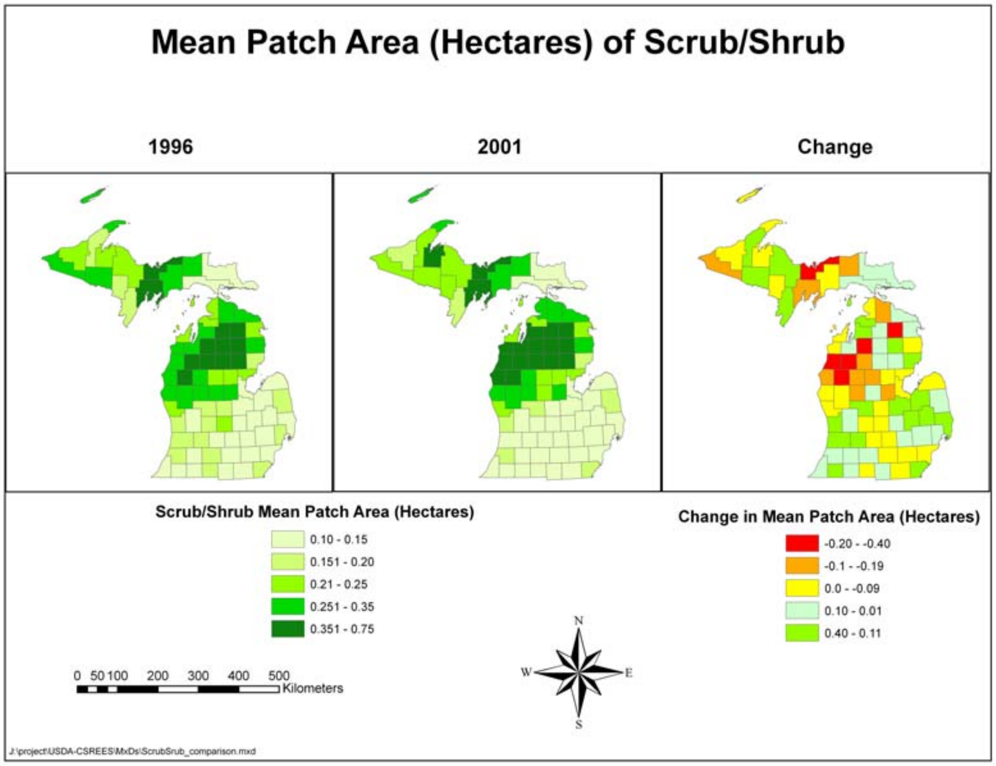

Figure 18: Mean patch area for scrub/shrub land cover.

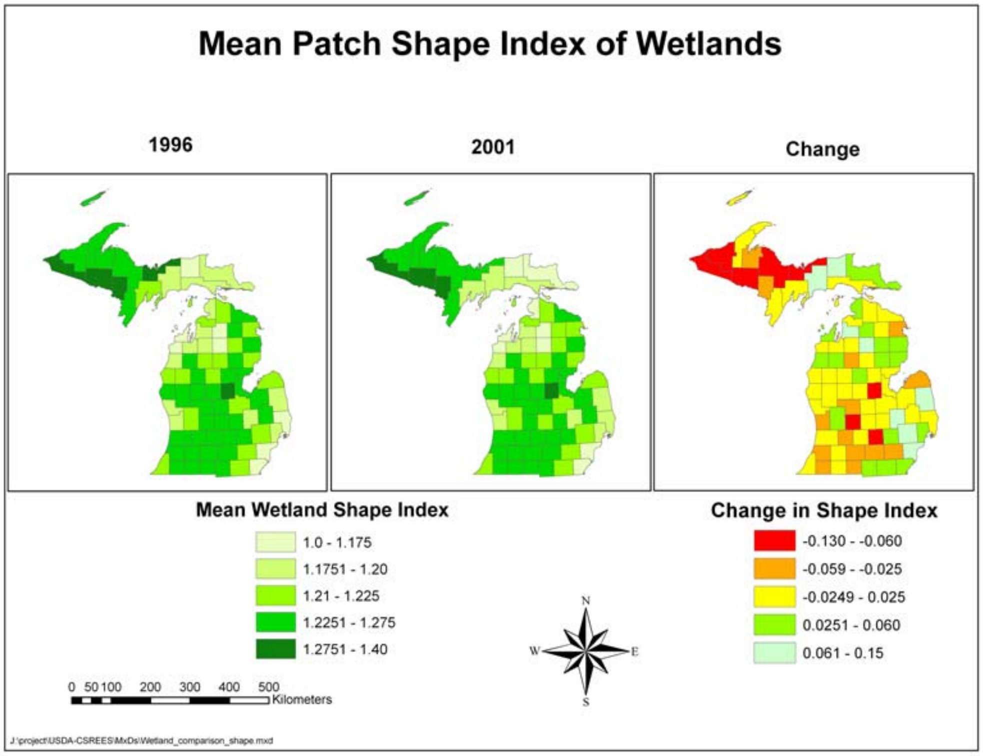

Figure 19: Mean shape index for wetlands land cover.

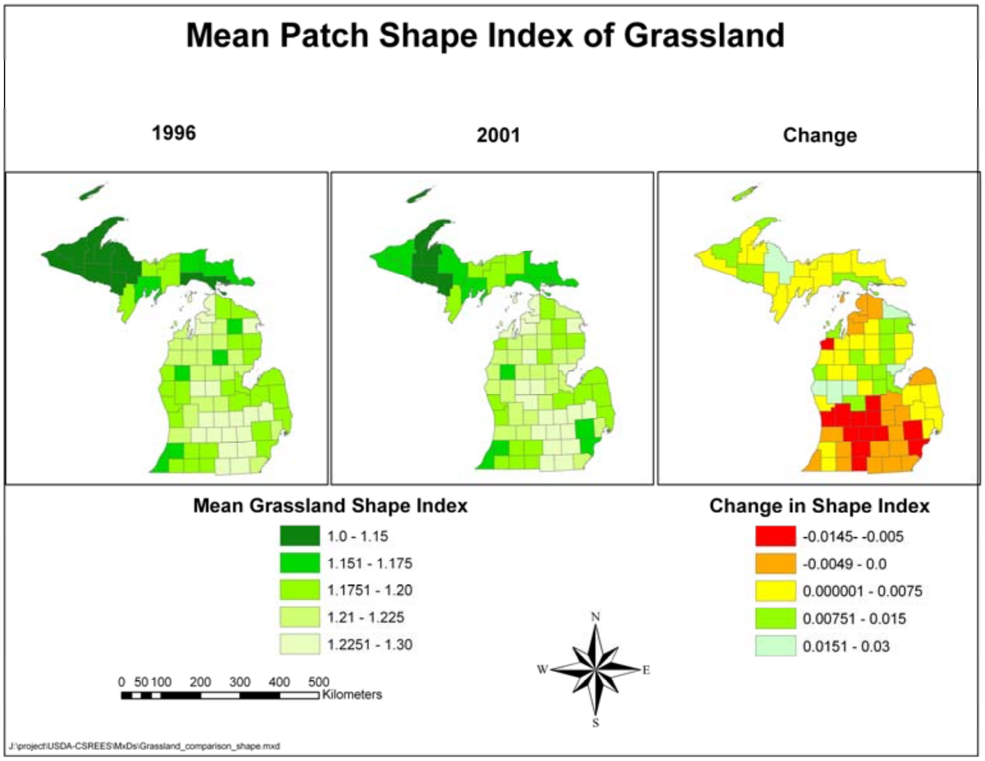

Figure 20: Mean shape index for grassland land cover.

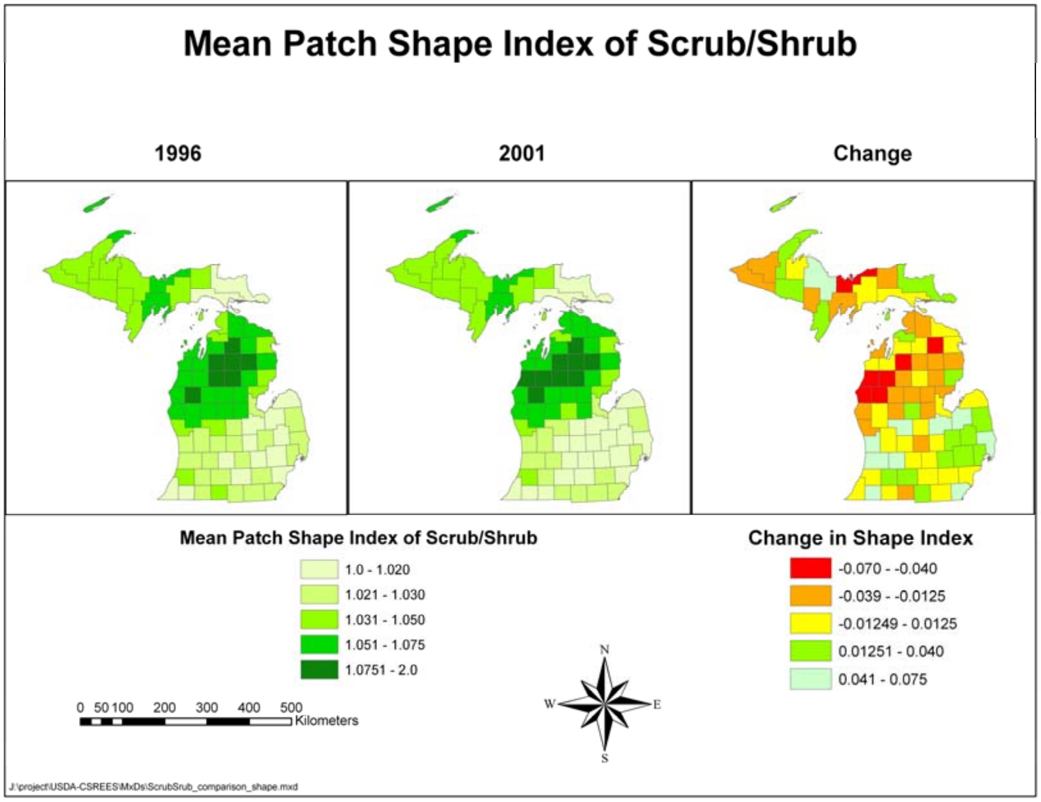

Figure 21: Mean shape index for grasslands land cover

Appendix B: Amounts of Change by County from 1996-2001

Table 4: Amounts of change by County in acres from 1996-2001 using the C-CAP "change analysis product". *Forest and wetland have relatively small amounts of change in the five year period, but grassland and scrub/shrub have amounts that are larger than would be expected over five years for many counties.*

	Change in Acres					Change in Acres			
County	**Forest**	**Grassland**	**Scrub / Shrub**	**Wetland**	**County**	**Forest**	**Grassland**	**Scrub / Shrub**	**Wetland**
ALCONA	-393	1841	218	221	LAKE	-4548	-148	3587	260
ALGER	-1198	580	256	111	LAPEER	32	248	-2	286
ALLEGAN	-1317	-1587	-12	342	LEELANAU	-354	969	745	177
ALPENA	1493	-874	1648	621	LENAWEE	-35	-285	29	74
ANTRIM	46	-3598	1302	115	LIVINGSTON	-495	-7051	-72	551
ARENAC	841	766	890	1115	LUCE	-4416	2523	371	892
BARAGA	-2779	911	1542	319	MACKINAC	-5091	3445	263	716
BARRY	569	-6802	-760	461	MACOMB	-1784	-289	-209	125
BAY	498	-2203	423	895	MANISTEE	-1456	-677	2979	489
BENZIE	-328	-2694	2246	198	MARQUETTE	-9047	6234	516	1027
BERRIEN	-140	-651	-22	137	MASON	-847	2830	1575	524
BRANCH	-47	-3705	-559	313	MECOSTA	-19	5156	974	424
CALHOUN	547	-9180	-660	655	MENOMINEE	-785	536	-269	22
CASS	-124	30	-36	-34	MIDLAND	432	60	310	454
CHARLEVOIX	5	-1296	326	133	MISSAUKEE	-1056	647	1244	366
CHEBOYGAN	-2062	-2898	2591	420	MONROE	-215	-1323	77	270
CHIPPEWA	-12811	10177	363	1615	MONTCALM	413	-2179	-36	494
CLARE	-3228	-48	647	346	MONTMORENCY	-1352	2972	1421	239
CLINTON	323	-8634	-833	488	MUSKEGON	-1875	2211	503	309
CRAWFORD	-3815	3048	1089	156	NEWAYGO	-788	4513	1315	500
DELTA	-2054	1370	374	-145	OAKLAND	-2914	-4531	-25	320
DICKINSON	-1198	613	130	169	OCEANA	-164	5686	1108	419
EATON	747	-7915	-42	372	OGEMAW	-3253	-4026	9079	473
EMMET	-1147	-7273	1938	208	ONTONAGON	-1018	898	124	89
GENESEE	-376	-2018	-13	200	OSCEOLA	-141	-2403	586	365
GLADWIN	-34	-208	1134	417	OSCODA	-1114	3451	1247	150
GOGEBIC	-191	499	-476	442	OSTEGO	-1148	-1134	2072	105
GRAND TRAVER	-1428	-4182	3116	480	OTTAWA	-1247	-3501	67	399
GRATIOT	87	-3434	-343	514	PRESQUE ISLE	-98	2321	2778	1093
HILLSDALE	9	-209	55	89	ROSCOMMON	-3102	446	1960	387
HOUGHTON	-678	281	254	50	SAGINAW	283	-2344	174	1461
HURON	214	-471	-4	413	SANILAC	234	992	78	116
INGHAM	384	-12292	-160	463	SCHOOLCRAFT	-2570	1765	33	-117
IONIA	551	-10597	-909	308	SHIAWASSEE	231	-3049	-36	236
IOSCO	-848	-2	603	263	ST CLAIR	42	1531	135	843
IRON	-2171	2842	-754	-25	ST JOSEPH	-47	-2437	-161	253
ISABELLA	306	-2853	235	228	TUSCOLA	113	-1393	25	527
JACKSON	507	-3351	96	533	VAN BURREN	-390	-441	-226	137
KALAMAZOO	-32	-5845	33	309	WASHTENAW	-442	-1257	54	245
KALKASKA	-1194	-1403	3221	234	WAYNE	-2146	-4850	-2	103
KENT	-2853	-9397	45	394	WEXFORD	-1300	-2500	2504	261
KEWEENAW	-118	88	15	58					