MichiganTech Research Institute

Inputs to the Environmental Quality Index

Report on datasets investigated and used for calculation of the EQI

Nancy H.F. French, Benjamin Koziol, Colin Brooks,
Richard Powell, Michelle Wienert

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USDA NRCS

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Introduction

The Environmental Quality Index (EQI) was developed by Altarum/MTRI under the cooperative agreement as an index-based approach for quantifying change in environmental quality based on a variety of statewide data inputs. In the four years of the cooperative agreement, the MTRI team has pursued independent sources of environmental quality data pertinent to assessment of agricultural programs and practice effectiveness. The Year 4 report *The Environmental Quality Index Approach: Concepts, Methods, and Demonstration of the EQI Approach for NRCS Conservation Program Assessment* details the concepts behind the EQI-based program assessment method and presents the process used in finding and developing the final inputs to the EQI described in this report. Efforts to find suitable inputs concentrated on data that was geospatially defined based on remote sensing data and products and on products and data collected or modeled by agencies and organizations that collect environmental data, such as the U.S. Environmental Protection Agency (US-EPA) and the Conservation Technology Information Center (CTIC). These efforts build from MTRI's extensive experience with remote sensing and GIS, take advantage of existing well-documented data sources, and enable the EQI to eventually be applied for multiple time periods.

Table 1: EQI input sources and connection to resource concerns.

Input	Units	Source	Resource Concern or Practice
Soil condition Index			
Soil erosion	tons of sediment	EPA STEPL model (RUSLE-based)	Sheet & rill erosion
Tillage practice	% conservation	CTIC (Purdue)	conservation tillage practices (329, 344,345,346)
Crop rotation history	number of rotations	MTRI developed	Organic matter depletion
Surface water health Index			
Lake clarity	index	USGS & MTRI developed	Turbid surface water
Riparian buffers	% vegetated	MTRI developed	Riparian buffer practice (391)
Land habitat index			
Habitat improvement	acres	MTRI developed	Inadequate cove/shelter/space
T&E species	count	Mich. Natural Features Inventory (MNFI)	T&E species
Habitat fragmentation	index	MTRI developed	Habitat fragmentation
Air quality index			
NH3 emissions	kg	EPA- National Emissions Inventory	Ammonia
Particulate levels	density	MTRI developed	PM 10 level

Inputs Developed and Used in the EQI

The approach for selecting EQI inputs begins by identifying resource concerns (the concerns that are targeted with conservation practice implementations) that NRCS programs address in their prescribed practices. The effects of these practices that are observable are then measured or modeled and produced as inputs to the EQI. In Table 1, we list the measures within each of the four components of the EQI that were selected for use in the EQI with the help of the MI-NRCS staff. These were identified by considering NRCS resource concerns and discovering relevant and available information products, either measurements or model-based outputs. The EQI is used to combine these inputs into a metric that can be compared to NRCS program implementations.

These ten inputs come from a variety of sources with varying level of data preparation and analysis needed before they are used in the EQI. All of the EQI inputs used are considered to be products that are repeatable or planned to be repeated in the future so that an EQI assessment can be completed for a future timeframe and compared over time. Since program data are not available at sufficient spatial-temporal resolution to enable full potential of remotely sensed data, analysis at the county scale was decided to be the best approach for the project, and all EQI inputs described in this report were compiled at the county scale. Future EQI implementations could be done on a watershed basis, if sufficient NRCS practice data are available in the same spatial format.

Table 1 includes information on the sources of the ten EQI inputs; details for each of these are presented in this report. Three of the EQI inputs are taken from existing data sources, the CTIC conservation tillage product (CTIC 2008a), data collected by the Michigan Natural Features Inventory (MNFI; 2008) on threatened and endangered species, and the US Environmental Protection Agency's (USEPA) National Emissions Inventory report of ammonia emissions from agricultural sources (2008). The soil erosion measure is derived using the Spreadsheet Tool for Estimating Pollutant Loads (STEPL; EPA 2008), a USEPA model that uses simple, easy to use algorithms to determine sediment loads based on the USDA Universal Soil Loss Equation (USLE).

Six of the inputs used in the EQI are derived from remote sensing data and products through methods developed at MTRI. Three remote sensing-derived inputs, riparian buffers, habitat improvement, and habitat fragmentation, use land cover maps developed by the National Oceanographic and Atmospheric Administration (NOAA). These maps are complete for 1995 and 2000, and are planned for 2005 and continuing on a five-year basis. A review of the three inputs that use this NOAA dataset is presented in the Year 4 report: *Using C-CAP Land Cover Products for EQI Inputs*. The algorithm to determine crop rotation for the soil condition component was developed based on research conducted in Year 3 of this project using MODIS image data and field information collected at the Tiffin River test site (see Year 3 report: *Geospatial Algorithms for Agricultural Applications: A Review of New Advanced Technologies*); this products is described later in this report. The lake clarity product, used as one of the water health inputs, uses an algorithm developed by MTRI from Landsat images and base maps developed by the US Geological Survey (USGS; Fuller et al, 2004). Details on development of the MTRI lake clarity algorithm and products are given in the Year 4 report: *Remote Sensing of Lake Clarity*. The significance of having remote sensing-derived measures is that these products can be repeated for any time and place that appropriate remote sensing data are collected, which includes data from the past. Many data sets were considered for inclusion in the EQI that are not in the final version. These unused data sets are described in detail in the final sections of this report.

Soil Erosion

The U.S. Environmental Protection Agency's Spreadsheet Tool for Estimating Pollutant Load (STEPL) is used to estimate sediment load as the soil erosion input to the EQI. STEPL calculates nutrient and sediment loads from different land uses and the load reductions that would result from the implementation of various best management practices (BMPs) (EPA 2008). The model computes nitrogen and phosphorus nutrient loads, 5-day biological oxygen demand (BOD5) and sediment delivery based on various land uses and management practices at the watershed scale. For each watershed, the annual nutrient loading is calculated based on the runoff volume and the pollutant concentrations in the runoff water as influenced by factors such as the land use distribution and management practices. The annual sediment load (sheet and rill erosion only) is calculated based on the Universal Soil Loss Equation (USLE) and the sediment delivery ratio. The sediment and pollutant load reductions that result from the implementation of BMPs are computed using the known BMP efficiencies.

Using the STEPL model for the NRCS EQI

Within the context of the NRCS EQI, the STEPL model has been used to estimate soil erosion for the year 2005. Sediment load was calculated for each county in Michigan using inputs from the EPA STEPL Model Input Data Server. The STEPL model is designed to operate at the watershed scale; however, the scale of the NRCS EQI analysis is at the county level. To aggregate from the watershed scale to the county level, the STEPL Model Input Data Servers ability to provide data for the proportion of a watershed within a county boundary was used. Table 2 describes the sources for the input data provided by the STEPL data server. BMPs, gully and streambank erosion were not modeled. The output consisted of county-level summaries of sediment load which are aggregated and stored in a single database table which is linked to GIS county boundary polygons for visualization.

Table 2: STEPL Input Data Sources. *Data sources for each STEPL input are included in this table. All data is available online and distributed free of charge.*

Model input	Source
Land Use	USDA NRCS 1997 National Resources Inventory (NRI 2008)
Agricultural animals	USDA Census of Agriculture, 2002 (USDA 2008a)
Septic system data	National Environmental Service Center: 1992 and 1998 (NESC 2008)
Soil Hydrological Group	USDA STATSGO (USDA 2008b)

Results and Discussion

The model's output indicates that 44 of Michigan's 83 counties produce sediment loads of 10,000 tons per year or more (Figure 1 and Table 3). The highest sediment loads are concentrated within three counties, Hillsdale, Kent, and Washtenaw, with each contributing more approximately 60,000 tons or more per year. Counties with lower sediment loads, less than 10,000 tons per year, are concentrated in the northern Lower Peninsula and Upper Peninsula. However, Menominee and Ontonagon counties in the Upper Peninsula each produced over 18,000 tons of sediment per year according to the model. Also, Leelanau County, in the northwest Lower Peninsula, is ranked as the 11th highest producer of sediment load in the state at over 40,000 tons per year.

County-level sediment loads are suitable for regional analysis and comparison with other county-level data sources. However, the local variability of sediment loads within a county is not apparent at that scale. To understand the contribution of individual watersheds to county-level sediment loads, a local scale analysis was explored for Hillsdale County which exhibited some of the highest sediment loads within the state.

Table 4 describes the watersheds and their respective contribution to sediment load within the county. As illustrated in Table 4 and Figure 2, Hillsdale County contains portions of six different watersheds. Two of the watersheds bear the same name of St. Joseph. Of these two watersheds, the one to the north, with hydrologic unit code 4050001, drains areas within Indiana and Michigan, while the one to the south, with hydrologic unit code 4100003, drains portions of Indiana, Michigan, and Ohio (see Figure 2). These two watersheds comprise the largest watersheds in the county, together draining approximately 70% of the land area county and contributing 60% of the sediment load for the county (Table 4). The portion of the Tiffin watershed within the county comprises 15% of the county, yet accounts for 19% of the county's sediment load. Figure 2 illustrates the contribution of each watershed to county-wide sediment loads.

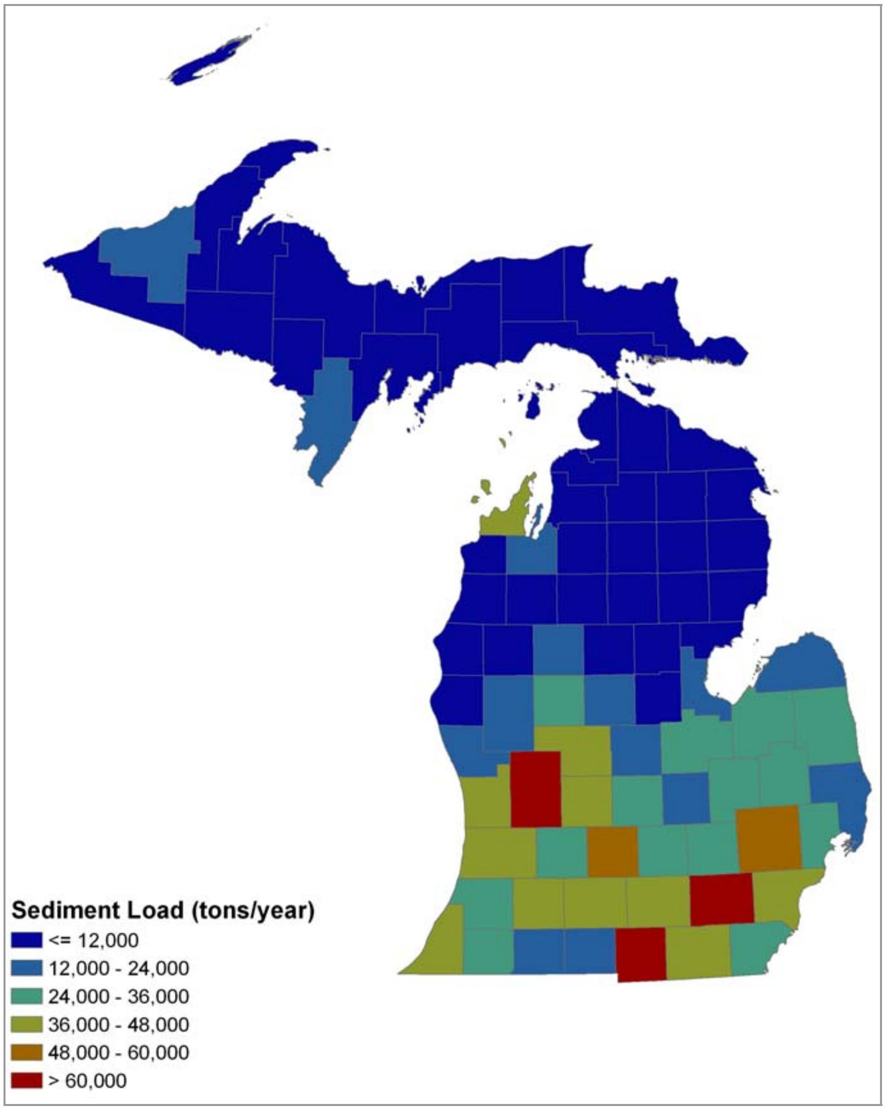

Figure 1: Sediment load by County. *Sediment load for 2005 by county as calculated by the STEPL model.*

Table 3: Sediment load by County. *Sediment load for 2005 by county as calculated by the STEPL model.*

FIPS	NAME	Sediment Load (t/yr)	FIPS	NAME	Sediment Load (t/yr)
059	HILLSDALE	68,750.44	121	MUSKEGON	13,844.01
081	KENT	62,498.82	055	GRANDTRAVERSE	12,875.85
161	WASHTENAW	59,972.85	127	OCEANA	11,077.75
045	EATON	53,035.95	103	MARQUETTE	9,729.20
125	OAKLAND	52,658.60	009	ANTRIM	9,458.37
025	CALHOUN	45,603.92	129	OGEMAW	9,271.35
075	JACKSON	43,330.52	047	EMMET	9,122.91
139	OTTAWA	43,042.66	165	WEXFORD	7,745.44
021	BERRIEN	42,484.52	061	HOUGHTON	7,504.13
091	LENAWEE	41,086.00	041	DELTA	7,308.98
089	LEELANAU	40,655.94	043	DICKINSON	7,049.11
067	IONIA	39,891.12	105	MASON	6,689.63
117	MONTCALM	37,971.00	031	CHEBOYGAN	6,669.54
077	KALAMAZOO	37,829.31	029	CHARLEVOIX	6,364.35
163	WAYNE	37,520.77	101	MANISTEE	6,229.05
005	ALLEGAN	37,069.60	053	GOGEBIC	5,877.09
027	CASS	33,640.99	111	MIDLAND	5,748.72
087	LAPEER	33,497.93	051	GLADWIN	5,709.61
145	SAGINAW	32,386.53	001	ALCONA	5,645.60
159	VAN BUREN	31,748.91	141	PRESQUE ISLE	5,583.47
115	MONROE	31,065.95	085	LAKE	5,370.45
037	CLINTON	29,226.46	011	ARENAC	5,327.78
151	SANILAC	28,681.65	003	ALGER	5,301.79
049	GENESEE	27,635.07	019	BENZIE	5,144.76
157	TUSCOLA	26,182.30	035	CLARE	5,127.96
065	INGHAM	25,186.88	071	IRON	4,915.59
107	MECOSTA	25,139.03	033	CHIPPEWA	4,822.63
015	BARRY	24,371.02	153	SCHOOLCRAFT	4,383.88
093	LIVINGSTON	23,783.46	137	OTSEGO	4,264.92
099	MACOMB	23,405.70	069	IOSCO	4,015.75
109	MENOMINEE	19,733.30	007	ALPENA	3,572.40
023	BRANCH	19,723.71	135	OSCODA	3,556.46
131	ONTONAGON	18,509.45	113	MISSAUKEE	3,302.52
123	NEWAYGO	18,193.88	119	MONTMORENCY	2,931.72
149	ST JOSEPH	18,010.75	097	MACKINAC	2,836.64
073	ISABELLA	17,896.91	039	CRAWFORD	2,775.09
063	HURON	17,146.24	079	KALKASKA	2,579.55
133	OSCEOLA	16,853.94	013	BARAGA	2,409.62
017	BAY	16,606.76	095	LUCE	1,855.07
147	ST CLAIR	16,502.16	143	ROSCOMMON	1,836.49
057	GRATIOT	16,007.42	083	KEWEENAW	416.62
155	SHIAWASSEE	15,663.65			

Table 4: Hillsdale County Watersheds and Sediment Loads. *Results from applying the STEPL model to watershed level data.*

HUCNAME	WATERSHED HUCCODE	SEDIMENT LOAD	PERCENT LOAD	ACRES	PERCENT TOTAL
ST. JOSEPH (IN, MI, OH)	4100003	21,208	31%	154,546	40%
ST. JOSEPH (IN, MI)	4050001	19,766	29%	113,076	29%
TIFFIN	4100006	12,924	19%	57,220	15%
KALAMAZOO	4050003	11,830	17%	47,893	12%
RAISIN	4100002	1,717	3%	10,860	3%
UPPER GRAND	4050004	347	1%	4,598	1%
TOTALS:		**67,792**		**388,193**	

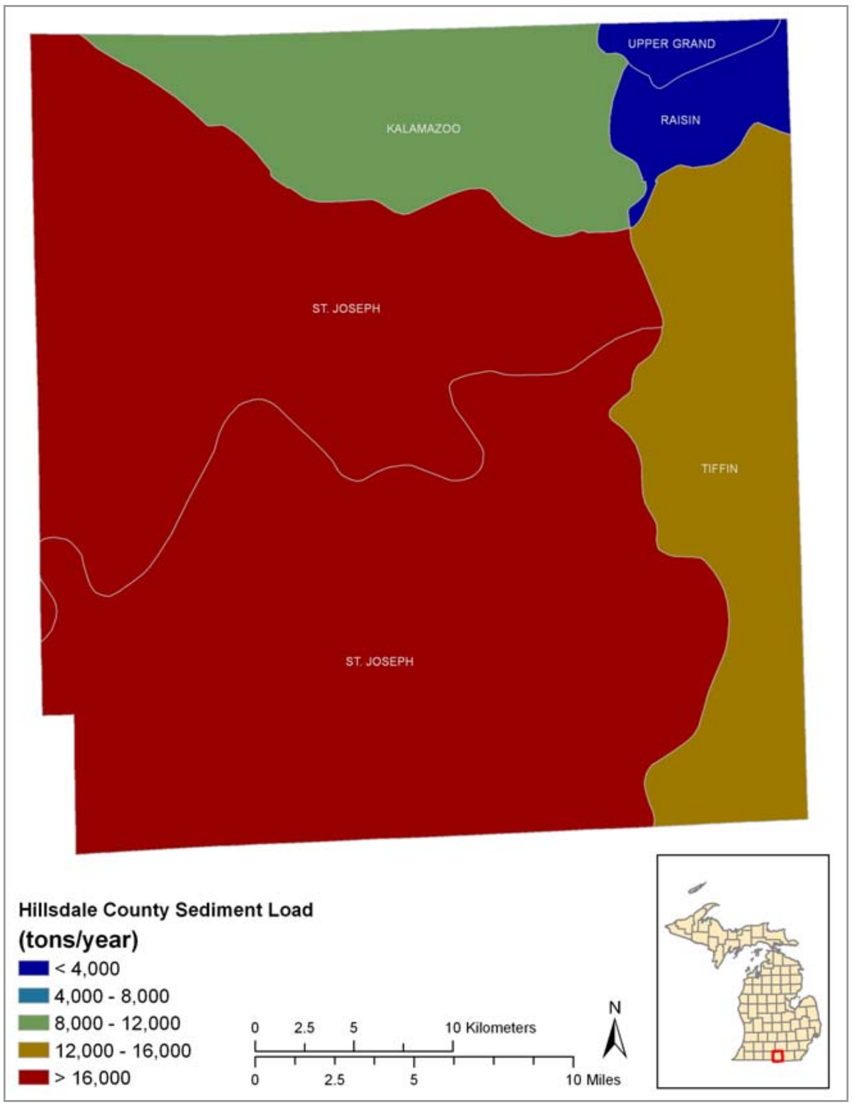

Figure 2: Sediment load by watershed within Hillsdale County.

Concluding Remarks

The U.S. Environmental Protection Agency's Spreadsheet Tool for Estimating Pollutant Load (STEPL) tool is suitable for rapidly modeling soil erosion at the county and watershed scale. The evaluation of this tool has identified several areas for future research.

The 1997 National Resources Inventory (NRI) data provided by the STEPL data input server is convenient to use, yet it is not likely to be the most suitable land use data set since it is more accurate at state and regional scales rather than county or watershed scales. The uses of more recent, higher resolution, land use land cover data may model soil erosion more accurately than the NRI data. Within Michigan, the National Oceanic and Atmospheric Administration's Coastal Change Analysis Program (C-CAP) land use land cover data set of 2001 would provide this data at a more suitable scale. A comparison of the default STEPL model output, model output using the C-CAP data, and any ground reference data would be useful for quantifying the STEPL model output for Michigan.

The estimates of soil erosion may benefit from using data from NRCS field offices to integrate gully and stream bank erosion into the model. Field office's may also benefit from modeling the potential effect of conservation practices on soil erosion by targeting areas of concern and experimenting with the model's input parameters and evaluating the model's output.

An additional avenue of investigation would be to use the model within a detailed subwatershed analysis to determine the contribution of subwatersheds to the larger watershed. For example, an analysis integrating high resolution land use and land cover data derived from aerial photographs, animal census data collected by field personnel, gully and stream bank erosion, and existing conservation practices could be applied to the model within a subwatershed delineated using Digital Elevation Models. The resulting output would accurately model the subwatershed's contribution to sediment load, and serve as a baseline for evaluating the effects of additional conservation practices on soil erosion within the study area.

Tillage Practice

Soil management practices directed at maintaining soil moisture, reducing erosion, and inhibiting nutrient leeching are important components of both sustainable agriculture and positive environmental stewardship. Conservation tillage is a crop residue management technique where surface residue is maintained following planting. In this report, a planted agricultural field utilized a conservation tillage practice if greater than 30% of the field surface area has retained crop residue. Crop residue management (CRM) is a larger ‘umbrella’ term encompassing crop-type selection to maximize residue production, use of cover crops when low residue producing crops are planted previously, and responsible tillage practices during planting. The *Tillage Practice* EQI input used conservation tillage as a measure of CRM occurring within a county. Data was analyzed and compiled for the year 2002.

As mentioned above, the principle benefit of CRM is soil maintenance: moisture retention and decreased erosion. Surface sealing decreases evaporation and dissipates the potential energy of water movement during rain and snow melt events reducing potential erosion (both sheet and rill erosion) (Unger 1990). It is estimated that as much as 60% of the annual average precipitation in the US Great Plains is lost to evaporation in the conventional (i.e. complete removal of surface residue) tillage agricultural systems (*sic*). This additional soil moisture retention may help dryland crops weather drought events and reduce the net inputs required by irrigation systems to maintain viable moisture levels (Blevins, Smith, and Thomas 1983). However, it is important to note this may have a reverse effect during periods of high precipitation possibly contributing to seed rot, delayed planting, and moisture strangulation.

Data Source

The conservation tillage data used in this study is freely distributed by the Conservation Technology Information Center (CTIC) at Purdue University (CTIC 2008b). Unfortunately, the CTIC-led effort recently lost funding and is currently awaiting news regarding its fate and future collection opportunities. Prior to this unforeseen budgeting issue, the center had collected tillage estimates from 1989 (annually through 2000) to 2004 (bi-annually through 2004). However, in 2000 there was a methodological change and data collected prior to 2000 are irreconcilable with data collected after 2000 (sic personal comm). Year 2002 conservation tillage data was chosen to coincide with the other EQI input data, most closely matching the timing of the other inputs.

Tillage data is collected using a randomized road transect survey (for a complete methodological description please consult CTIC 2007). The data collection route is designed to maximize statistical certainty for county-wide, or other bounded region, tillage estimation. Tillage estimation, measured as closely after planting as possible, is performed field-by-field using vetted residue cover counting methods (Eck, Hill, and Wilcox 1994). Crops included in the estimate of conservation tillage are listed in Table 5. EQI conservation tillage values were calculated as follows:

Table 5: List of CTIC Crop Types. The crop types to the left are used in classifying agricultural fields when conducting the residue survey.

Crop Type	
Corn	Forage
Soybeans	Permanent Pasture
Small Grains	Other Crops
Grain Sorghum	Fallow

1. Acres with tillage greater than 30% (i.e. conservation tillage) were summed by county.
2. All acres measured for tillage cover were summed by county (i.e. Total Planted Acres).
3. Percent conservation tillage acres calculated.

$$\frac{\sum(Conservation\ Tillage\ \ Acres)}{\sum(Total\ \ Planted\ \ Acres)} = (Percent\ Conservation\ Tillage)$$

Results

Results for 2002 are reported in Table 6 and a map of the results in Figure 3. Amounts of conservation tillage varied from 0 to 77 percent. Higher values, overall, were reported in the Southern Lower Peninsula – lowest values in the Upper Peninsula. Generally, the amount of tilled agricultural acres occurring in a county is related to the acres of conservation tillage observed. However, there are exceptions to this pattern. Most notably, the counties of Huron, Sanilac, Bay, Osceoloa, and Mecosta all have low conservation tillage (less than 5%), but are in the top 50% agricultural counties in the state. The ability to identify the disparities between acres planted and conservation tillage acres is a useful analysis outcome. Highlighted counties in Table 6 identify the top counties exhibiting these differences.

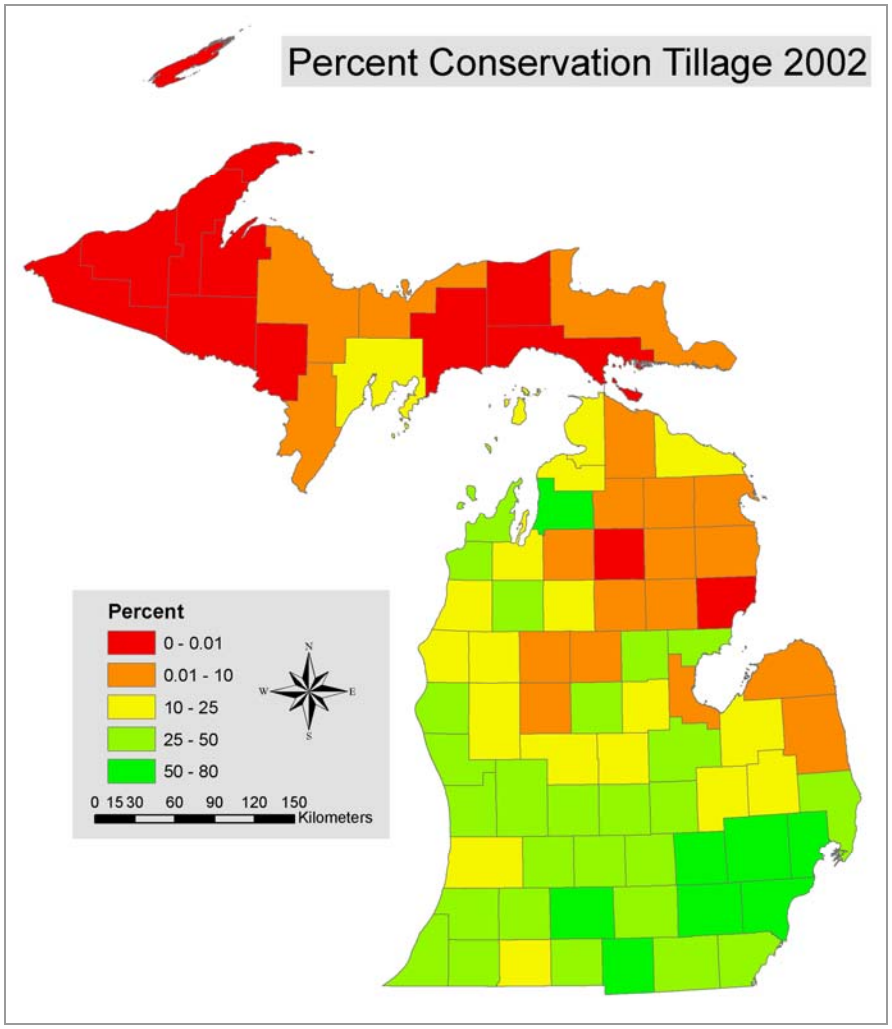

Figure 3: Percent Conservation Tillage by County for 2002. *Statewide conservation tillage appears to correlate with agricultural intensity, this pattern appearing in the Upper Peninsula and Northern Lower Peninsula.*

Table 6: Tabular Conservation Tillage Results by Count for 2002. *Counties highlighted in yellow showed conservation tillage and planted acres normalities – high planted acres with low conservation tillage.*

County Name	Percent Conservation Tillage	Total Planted Acres	County Name	Percent Conservation Tillage	Total Planted Acres
ALCONA	0.42%	7435	LAKE	17.82%	1790
ALGER	9.02%	3660	LAPEER	17.56%	127264
ALLEGAN	23.00%	150714	LEELANAU	25.68%	6600
ALPENA	1.16%	21390	LENAWEE	47.89%	271747
ANTRIM	62.66%	23300	LIVINGSTON	77.68%	56501
ARENAC	26.35%	56195	LUCE	0.00%	3185
BARAGA	0.00%	4652	MACKINAC	0.00%	2248
BARRY	45.30%	97180	MACOMB	58.68%	44502
BAY	1.87%	141878	MANISTEE	16.87%	14467
BENZIE	36.04%	6854	MARQUETTE	1.99%	5030
BERRIEN	37.42%	122956	MASON	19.24%	29680
BRANCH	37.77%	162780	MECOSTA	4.96%	38364
CALHOUN	53.68%	156521	MENOMINEE	2.23%	31445
CASS	44.64%	143622	MIDLAND	24.22%	65750
CHARLEVOIX	24.91%	9515	MISSAUKEE	19.78%	21923
CHEBOYGAN	1.76%	5120	MONROE	40.35%	239385
CHIPPEWA	1.37%	4371	MONTCALM	18.59%	171230
CLARE	7.93%	17590	MONTMORENCY	1.55%	6597
CLINTON	46.53%	199715	MUSKEGON	36.88%	39305
CRAWFORD	0.00%	105	NEWAYGO	24.04%	65289
DELTA	19.84%	20035	OAKLAND	54.12%	17278
DICKINSON	0.00%	11950	OCEANA	32.65%	62550
EATON	41.98%	171742	OGEMAW	5.55%	20890
EMMET	20.20%	6610	ONTONAGON	0.00%	12925
GENESEE	20.04%	88866	OSCEOLA	7.25%	44878
GLADWIN	31.47%	24086	OSCODA	4.58%	2620
GOGEBIC	0.00%	1675	OTSEGO	2.69%	3720
GRAND TRAVERSE	17.32%	34700	OTTAWA	25.06%	76314
GRATIOT	22.97%	254250	PRESQUE ISLE	15.99%	19320
HILLSDALE	57.10%	163399	ROSCOMMON	3.33%	300
HOUGHTON	0.00%	6737	SAGINAW	38.26%	249702
HURON	4.90%	410685	SANILAC	9.30%	359783
INGHAM	38.99%	146411	SCHOOLCRAFT	0.00%	3815
IONIA	38.28%	182605	SHIAWASSEE	34.27%	174083
IOSCO	0.00%	26128	ST. CLAIR	33.66%	127006
IRON	0.00%	7821	ST. JOSEPH	21.84%	165550
ISABELLA	32.94%	111265	TUSCOLA	21.28%	254280
JACKSON	43.01%	110722	VAN BUREN	31.23%	78249
KALAMAZOO	39.65%	109245	WASHTENAW	65.57%	114361
KALKASKA	1.25%	7600	WAYNE	57.49%	11085
KENT	31.14%	103000	WEXFORD	28.46%	6791
KEWEENAW	0.00%	139			

Future Work

CTIC methods can be replicated due to thorough documentation and ease of implementation by any organization with sufficient processing facilities. Furthermore, it is possible to augment these field sampling methods using remote sensing-based tillage indices. For example, the Modified Soil Adjusted Crop Residue Index (MSACRI) shows promise as a Landsat-based residue discriminator (Bannari et. al 2000). Pilot research has already occurred here at MTRI investigating the potential accuracies and benefits of the MSACRI approach (Schaub et al. 2007). Refining these alternative methods would prove useful in synoptic, repeatable statewide tillage assessment. First, these techniques do not require the extensive field collections that are both time and labor intensive. Second, the classification is consistent, not affected by user-induced collection errors. Combining remote sensing and field measurements (primarily used for empirical line calibration) are valid approaches to future statewide conservation tillage measurements.

Conclusions

- Conservation tillage generally increases as agricultural activity within a county increases.
- Conservation tillage data is quickly extractable from the CTIC database and can be easily analyzed to produce tillage estimates.
- Temporal data is available to monitor trends in tillage practices. However, the uncertain future of the CTIC sponsored survey may require the application of different collection methods.
- Remote sensing combined with field collects are a promising avenue for continuing statewide conservation tillage estimates.

Crop Rotation History

The Crop Rotation History input to the EQI was recommended by NRCS staff at the EQI Experts meeting of September, 2007 (see Year 4 report: *Evaluating the Impact of NRCS Programs: New Measures and Improved Communication: Report on the EQI Experts Meeting*) as an additional part of the EQI's Soil Condition Index. By adding this input, NRCS staff thought that a value could be created that would help capture a significant impact on soil condition for Michigan.

Methods

To create the Crop Rotation input, we designed a methodology that would yield a value that showed how many times an agricultural area had changed crop types over a four-year time period. If the value was 1, then the crop had never changed over those for years; if the value was 4, then the crop had changed every year. The major input to this were summer MODIS satellite images from 2004, 2005, 2006, and 2007. We used the two 250-m pixel infrared bands to capture the crop type, processing the imagery using ERDAS Imagine. We applied a supervised classification scheme (Isodata) using ground-truth data collected with NRCS help for the Tiffin River area for 2004-2007. The result was a statewide land cover map for each of those years for Michigan, with agricultural pixels represented by alfalfa, corn, soybeans, and wheat/small grains. We also mapped forest, grass/shrubland, urban, and water areas using obvious ground-truth locations as a reference. Figure 4 shows an example of the 2007 statewide land cover map

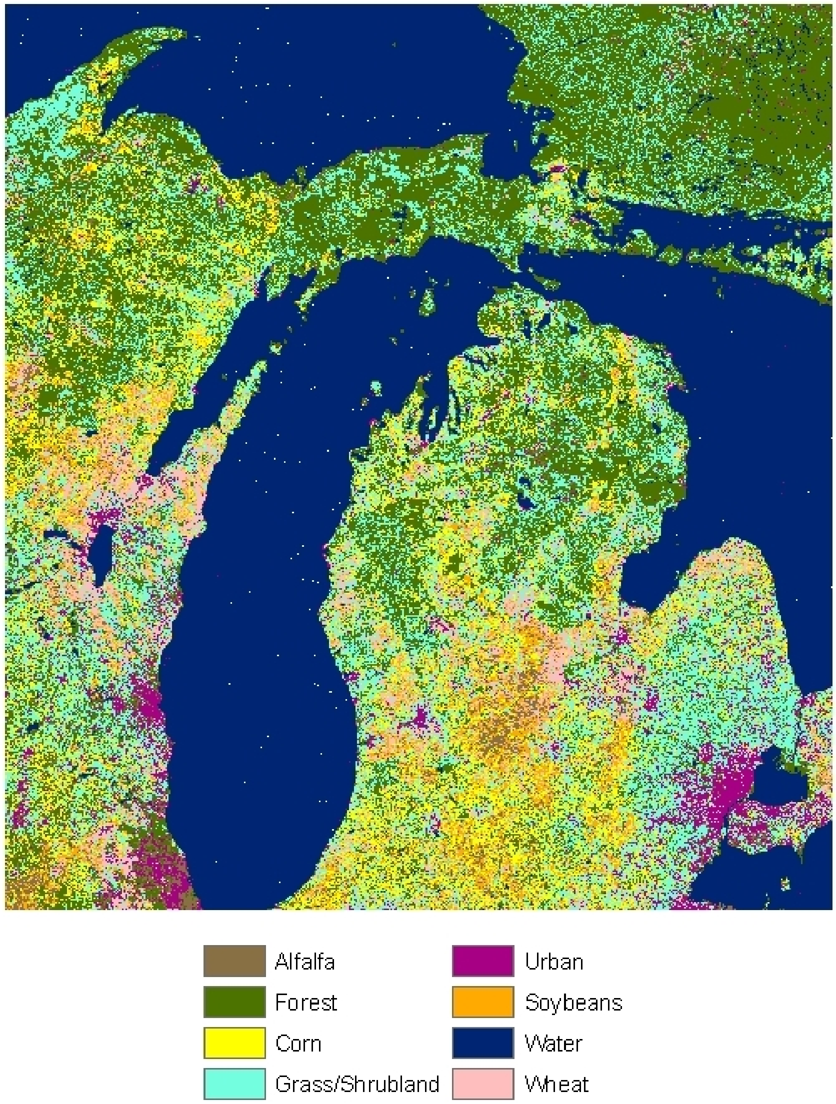

Figure 4: A statewide, agriculture-focused map created for 2007 as part of the crop rotation input. *Similar maps were made for 2004, 2005, and 2006 to measure how often crops had been rotated over the four-year period; this value would help represent the soil quality and contribute to the EQI.*

Using the Spatial Analyst extension in Desktop ArcGIS 9.2, we next extracted only those pixels that had agriculture in at least three of the four years, so that our crop rotation values would focus on actively farmed areas. For these areas, we then used the Raster Calculator part of Spatial Analyst to count how often the crop had changed over the four years. A rotation of Corn->Wheat->Alfalfa->Soybeans would be a four, as would a rotation of Corn->Wheat->Corn->Wheat. Corn for four summers in a row would be a value of one.

Results

Figure 5 shows our calculated rotation value at the pixel scale for all of Michigan. We then averaged these values for each Michigan County using the Zonalstats command, which created "average number of rotations" value shown in Figure 6. For the final input value, we scaled these so that an average number of rotations value of one had a Quality Value of one, would an average number of rotations value of four had a Quality Value of 100. When calculated, all values had average number of rotation values from 1.375 to 2.25, as shown in Figure 6. Parts of the agriculturally-dense "Thumb" region, southern Michigan, and central Michigan tended to have higher rotation values, while northern Michigan and the Upper Peninsula generally have lower rotation values.

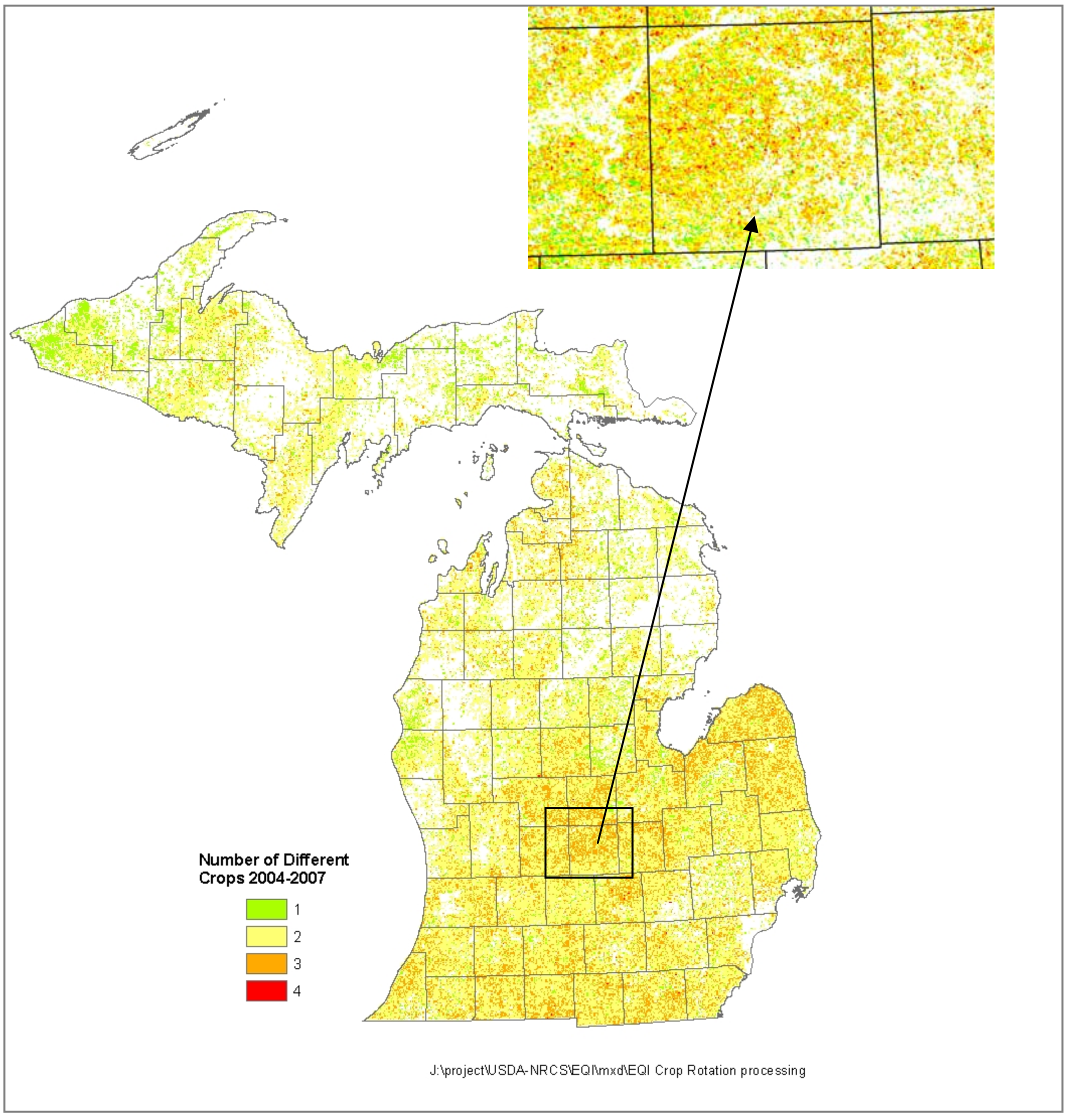

Figure 5: Number of changes in crops grown on a per-pixel basis from 2004 to 2007. *A value of 1 means the same crop was grown four years in a row; a value of four means the crop changed every year from one year to the next.*

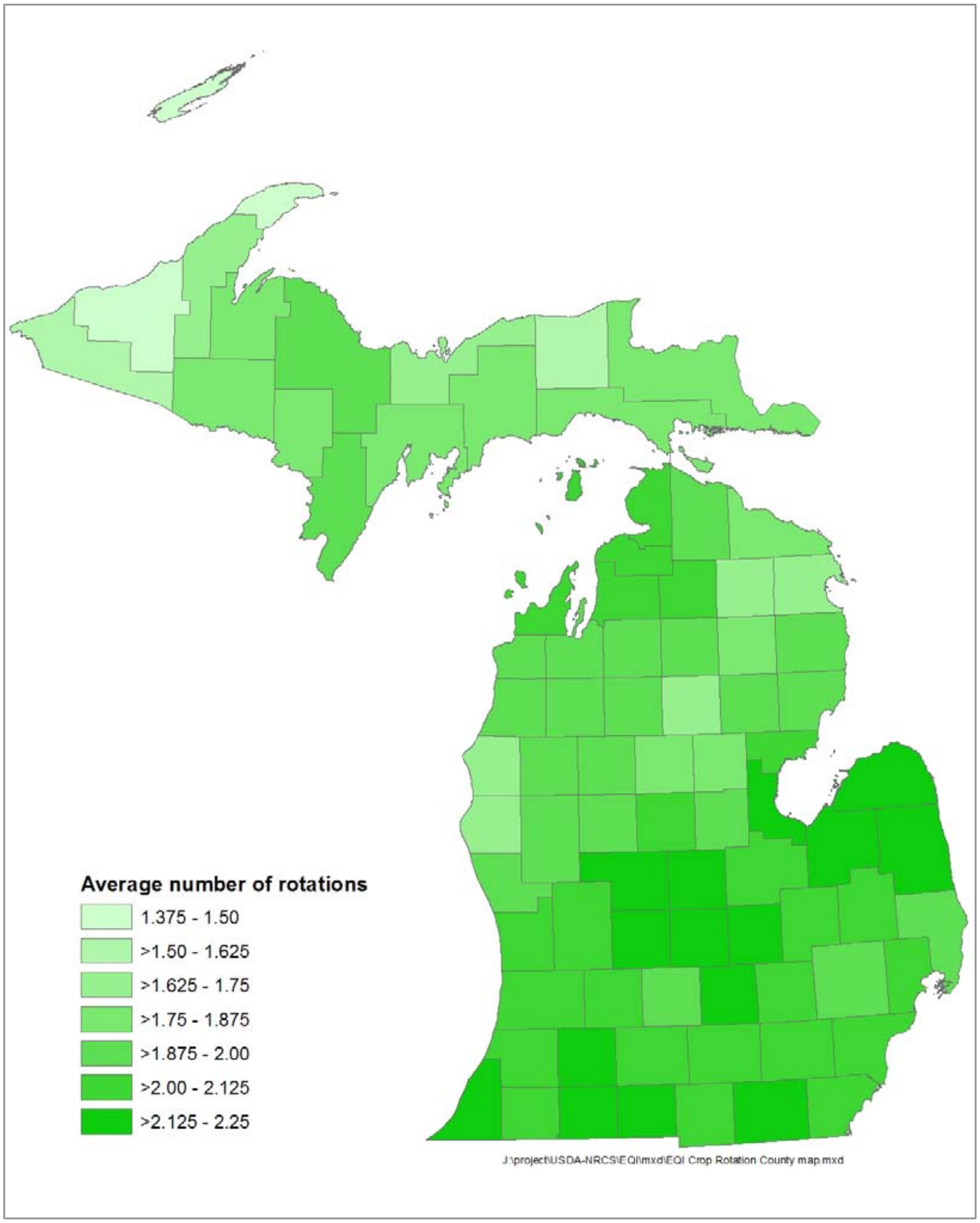

Figure 6: Average number of rotations calculated at a County scale. *Some areas such as the "Thumb" counties tended to have higher number of rotations than other parts of the state, which could lead to higher soil quality.*

Discussion and Recommended Next Steps

The results shown here demonstrate that it is possible to calculate a crop rotation value that can be used as an EQI input. We have several recommendations to improve this demonstration analysis in order to create a more representative indicator of environmental quality, including:

- Divide rotation patterns into different levels of environmental impact; a rotation of Corn->Wheat->Corn->Wheat may not be as good for the environment as a more diverse one such as Corn->Wheat->Alfalfa->Soybeans.
- Add in ground truth data from other agricultural areas, such as the sugar beets growing regions in the Thumb (such as Huron County) and the grape growing regions of the northwestern Lower Peninsula (such as Leelanau County).
- Use multiple growing season MODIS images from April through October to capture the changes in crop phenology, which should improve classification accuracy, and takes advantage of the daily overpasses of MODIS.
- Investigate the potential to use higher-resolution but still frequently gathered satellite imagery such as Landsat, AWiFS, and CBERS to create a more representative indicator of field rotations.

The methods used in developing the initial crop rotation EQI input demonstrates a way to represent the frequency of crop rotation for all agricultural areas in Michigan. The additional steps outlined would lead to a more accurate, representative, and potentially higher-resolution crop rotation index, which would improve future versions of the EQI.

Lake Clarity

Water quality of large lakes in Michigan for the years of 1985 and 2005 were evaluated by expanding upon traditional methods of water quality assessment using remote sensing imagery. MTRI researchers assessed water clarity from satellite imagery by modeling the relationship between in-situ Secchi disk transparency data and lakes 20 acres or larger captured in moderate resolution Landsat satellite imagery. This relationship can be used to evaluate water quality by classifying the lakes according to their trophic state using a documented relationship between visible-light satellite imagery data and water clarity.

Thorough documentation of this input is located in the Year 4 report: *Remote Sensing of Lake Clarity*.

Riparian Buffers, Habitat Improvement, and Habitat Fragmentation

Three environmental quality measures assessing aquatic and terrestrial habitat condition were calculated using remotely sensed C-CAP land cover data developed by NOAA. The riparian buffers analysis quantified natural vegetation within 100-meters of streams. Habitat improvement measured percent natural vegetation cover. Fragmentation evaluated land cover pattern by applying metrics measuring the shape and size of homogenous natural vegetation patches.
Thorough documentation of this input is located in the Year 4 report: *Using C-CAP Land Cover Products for EQI Inputs: Analyzing Riparian Buffers, Habitat Improvement, and Fragmentation over Time with Satellite Imagery*.

Threatened and Endangered Species

As an input to the EQI we used maps derived from data provided through the Michigan Natural Features Inventory (MNFI) showing presence/absence of federally listed endangered and threatened, species in Michigan. Documentation of this dataset is located in the Year 1 report: *Distribution of Endangered, Invasive, and Special Concern Species in Michigan*. In conversations with MI-NRCS experts, it was decided that the federally listed species were best as a metric for the EQI. NRCS targets conservation activities to help alleviate pressures and improve conditions for endangered and threatened species. This input allows this concern to be represented in the EQI. Aditionaly, this data is reliably archived and will be available for future EQI-like assessments. Consideration of including the presence and absence of invasive species was also discussed. This idea was dropped due to a low confidence in this data set as it is currently available.

Ammonia Emissions

The National Emissions Inventory (NEI) modeled ammonia emissions for the year 2002 (NEI 2008). These data are freely distributed and available for download via their website. Emission estimates are calculated using county-level livestock population, manure management trains (MMTs), and species-specific “emission factors.” Livestock considered in the model include beef, dairy, swine, poultry, sheep, goats, and horses. A MMT is defined by the U.S. Environmental Protection Agency (USEPA) as:

> “…an animal confinement area (e.g., housing, drylot, pasture); components used to store, process, or stabilize the manure (e.g., anaerobic lagoons, solid separators); and a land application site where manure is applied as a fertilizer source.” (USEPA 2008)

Emissions factors were defined following an extensive literature review. Livestock population, MMTs, and emissions factors were then combined in a forward model to produce the county-level ammonia estimates with units of kilograms per year.

Table 7: Ammonia Model Inputs. *Data sources used by the NEI for the development of the ammonia emissions model are listed in the table below.*

NEI Model Inputs	Data Source
Livestock Population	National Agricultural Statistics Service (NASS)
Emission Factor	*literature review*
Manure Management Train (MMT)	*USEPA developed in-house*

A map of ammonia emission estimates can be found in Figure 7 with tabular results reported in Table 8.

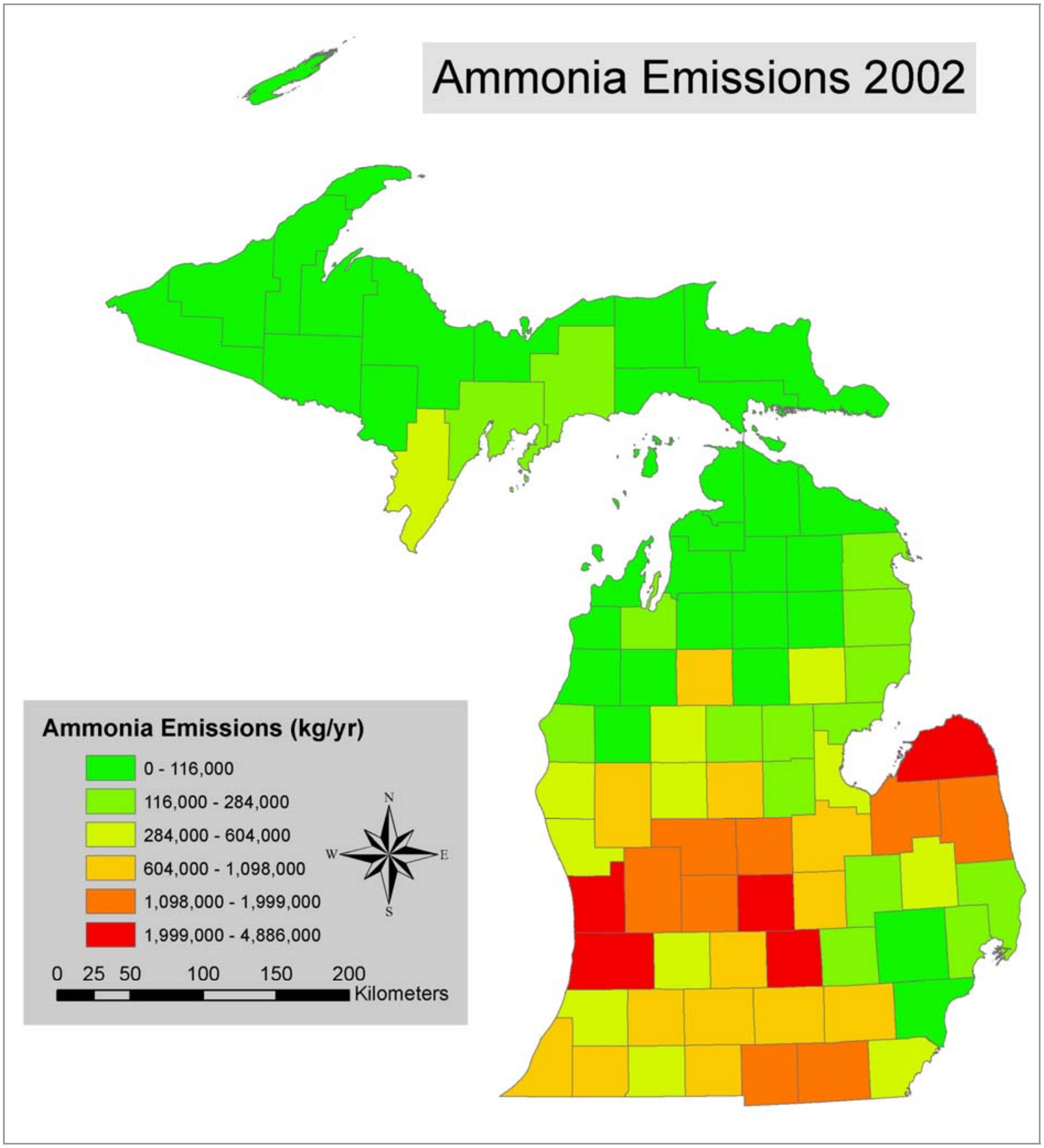

Figure 7: Ammonia Emissions 2002. *County-level estimates of ammonia emissions were downloaded from the NEI for 2002.*

Table 8: Ammonia Emissions by County 2002. *Notice the dramatic differences between agricultural and non-agricultural counties. The Northern Lower Peninsula and Upper Peninsula have significantly lower emissions than the Southern Lower Peninsula.*

County Name	Emissions (kg/year)	County Name	Emissions (kg/year)
Alcona	116364	Lake	52491
Alger	49346	Lapeer	524195
Allegan	3687129	Leelanau	110273
Alpena	196426	Lenawee	1165792
Antrim	95830	Livingston	255469
Arenac	283587	Luce	7781
Baraga	63416	Mackinac	83474
Barry	520148	Macomb	204219
Bay	603723	Manistee	38837
Benzie	39096	Marquette	56567
Berrien	805377	Mason	199103
Branch	997659	Mecosta	475199
Calhoun	877741	Menominee	424971
Cass	882398	Midland	151143
Charlevoix	62756	Missaukee	655286
Cheboygan	85665	Monroe	582440
Chippewa	105714	Montcalm	1171681
Clare	224221	Montmorency	71582
Clinton	1999296	Muskegon	475449
Crawford	50300	Newaygo	874997
Delta	245594	Oakland	76986
Dickinson	65691	Oceana	377602
Eaton	851940	Ogemaw	525551
Emmet	81756	Ontonagon	48755
Genesee	212536	Osceola	348351
Gladwin	146355	Oscoda	99837
Gogebic	4276	Otsego	68132
Grand Traverse	184768	Ottawa	3274970
Gratiot	1455696	Presque Isle	107942
Hillsdale	1399389	Roscommon	4208
Houghton	40622	Saginaw	1097971
Huron	4885307	St. Clair	248685
Ingham	3849168	St. Joseph	360896
Ionia	1865446	Sanilac	1606549
Iosco	237157	Schoolcraft	226784
Iron	18678	Shiawassee	675447
Isabella	808074	Tuscola	1304633
Jackson	731729	Van Buren	394146
Kalamazoo	754086	Washtenaw	672406
Kalkaska	36940	Wayne	100243
Kent	1320165	Wexford	101111
Keweenaw	4104		

Particulate Levels

Atmospheric particulate matter is composed of fine (i.e. smoke, aerosols) and coarse (i.e. dust, water vapor) materials. As light passes through these particulates, it is absorbed, scattered, and reflected, its intensity altered from the original source. Remote sensing takes advantage of this atmospheric disturbance, quantifying the degree to which light intensity is altered as it passes through the atmospheric column. The air quality measure utilized in this portion of the EQI is called *atmospheric optical depth* or AOD. This measure provides a proxy to assess particulate matter concentrations though not providing precise quantitative measures of those concentrations.

Background on AOD

AOD is a transparency measure used in optics to evaluate the disturbance effect a medium has on light intensity. To put it simply, AOD can be thought of as the ratio of light intensity incident on an object to the light intensity upon exiting the object. Hence, there is a linear relationship between disturbance along a path and AOD value. That is, as AOD increases the amount of disturbance also increases. (The actual calculation is slightly more complicated, but this approximation is sufficient for our purposes.) In the context of remote sensing, it is often the desire of image analysts to remove atmospheric effects to better observe and interpret the Earth's surface. The goal of AOD remote sensing is to isolate atmospheric disturbance to provide an empirical measure of its optical depth.

Calculating AOD Using Remote Sensing

Remote sensing data was obtained from the MODIS (Moderate Resolution Imaging Spectrometer) satellite. MODIS is a hyperspectral sensor (36 spectral bands from 0.4 micrometers to 14.4 micrometers) with a spatial resolution varying with band from 250 meters to one kilometer (MODIS 2008). MODIS has a daily return interval. AOD arrives from NASA as a derived product (identified as a Level 2 product by NASA) – the calculation complete and only requires a modest amount of processing before that data is in a usable format. For an in-depth description of the MODIS algorithm, please consult (Liang, Zhong, and Fang 2006).

An example output from the MODIS AOD algorithm is located in Figure 8. Two observations are immediate: (1) the data is very sparse and (2) the spatial resolution is very coarse. In regards to data sparsity, the algorithm has very strict quality control procedures. Basically, all the pixels 'missing' in this image contained clouds or sufficient atmospheric haze to exceed uncertainty expectations for the calculation. Coarse spatial resolution originates from the sensor design and bands included in the AOD algorithm. Data is resampled to match the lowest spatial resolution of the inputs, in this case the middle-infrared band (1-km). These algorithmic limitations led to the bi-monthly averaging. Daily MODIS outputs often covered a small percentage of Michigan counties requiring multiple daily images to provide sufficient coverage. After daily images were combined, the county averages were all calculated with a minimum of 50 values except for Keweenaw County.

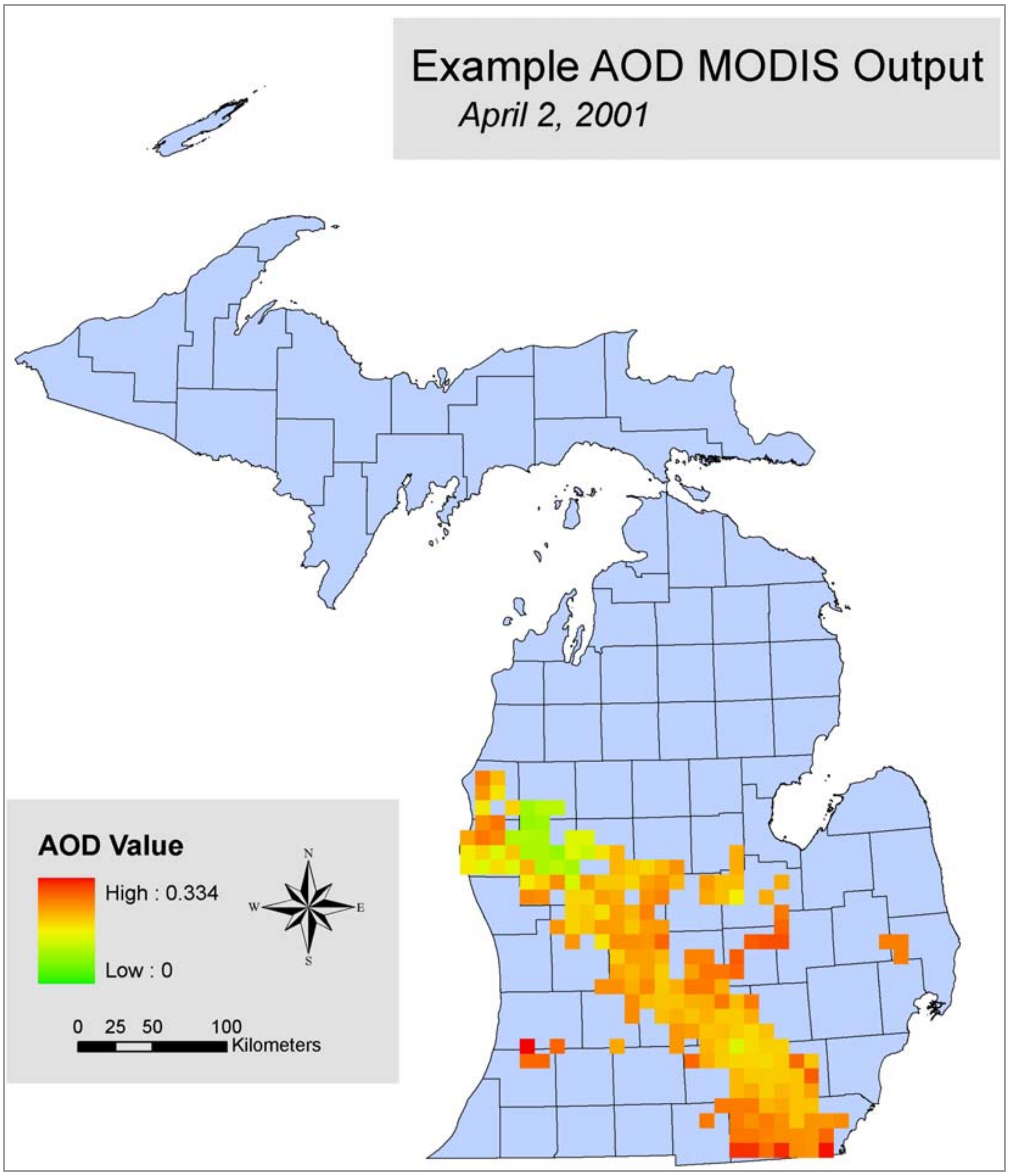

Figure 8: Example AOD MODIS output from April 2001. *Note the data scarcity and coarse spatial resolution of the output. These sampling problems required time-averaging of MODIS outputs to calculate county-wide AOD estimates. Recall that higher AOD values represent areas of higher atmospheric disturbance.*

Methods

Three years (2001, 2001, and 2003) of AOD data were downloaded for the months of April and May (NASA 2008). These data are daily collects of AOD over the state of Michigan. In addition, a comparison dataset for the (October and November) was also downloaded. The daily MODIS data was then subset by county and loaded into a database with each MODIS pixel having a date and county association. For each year, the AOD values for each two-month period were averaged by county. Statistical comparisons, to be discussed below, used Matlab as the analysis software. A data processing diagram is located in Figure 9.

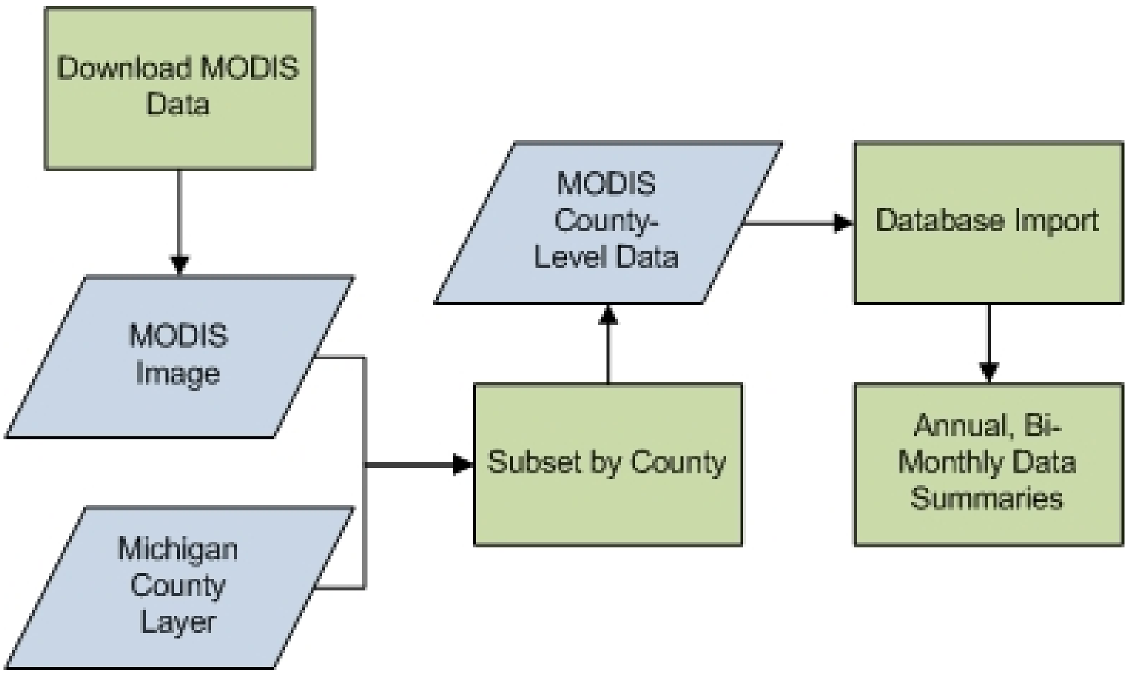

Figure 9: AOD Data Processing Diagram. *This flowchart described that analysis process progressing from the original data download to final summation in the database.*

Results

Analysis results in tabular form are located in Appendix A with graphical depictions found in Figure 10.

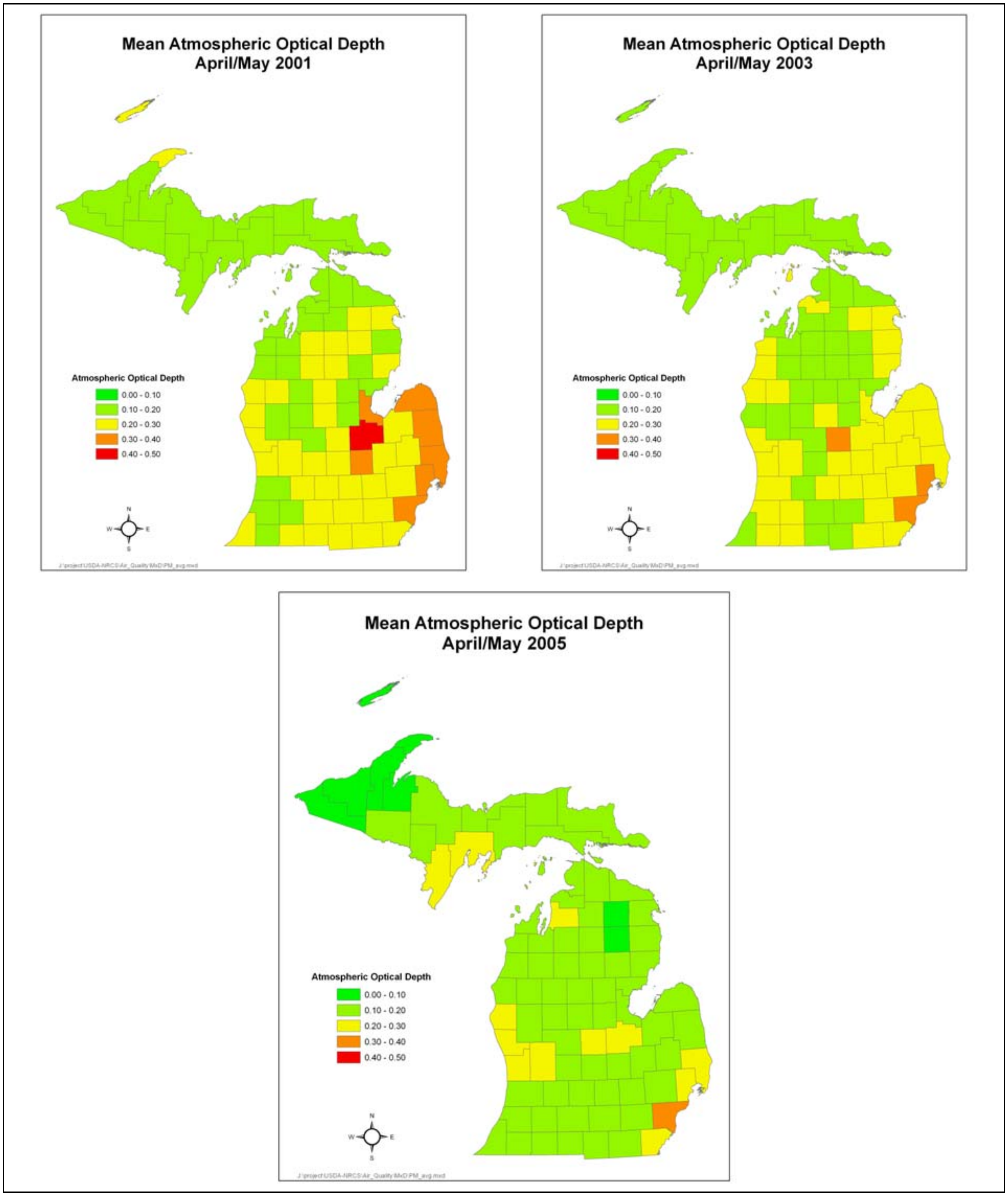

Figure 10: Graphical Results of AOD Analysis. *In 2001 and 2003, AOD averages were generally higher in southern Michigan. The trend does not hold in 2005.*

Results for this three-year analysis show moderate variability between counties. During 2005, the AOD product appears to signal a slight decrease in statewide AOD. Additionally, lower AOD values consistently appear in the Upper Peninsula, higher values concentrated near urban areas. The highest AOD average was 0.421 in Saginaw County in 2001 with the lowest reported average in Houghton County in 2005, a value of 0.074. Figure 11 is a boxplot of yearly AOD values. Again, the consistent pattern is visible as well as the slight drop in statewide AOD in 2005. This trend is further confirmed in Figure 6. Counties exhibiting greatest AOD range also 'topped the charts' in maximum and minimum statewide AOD values.

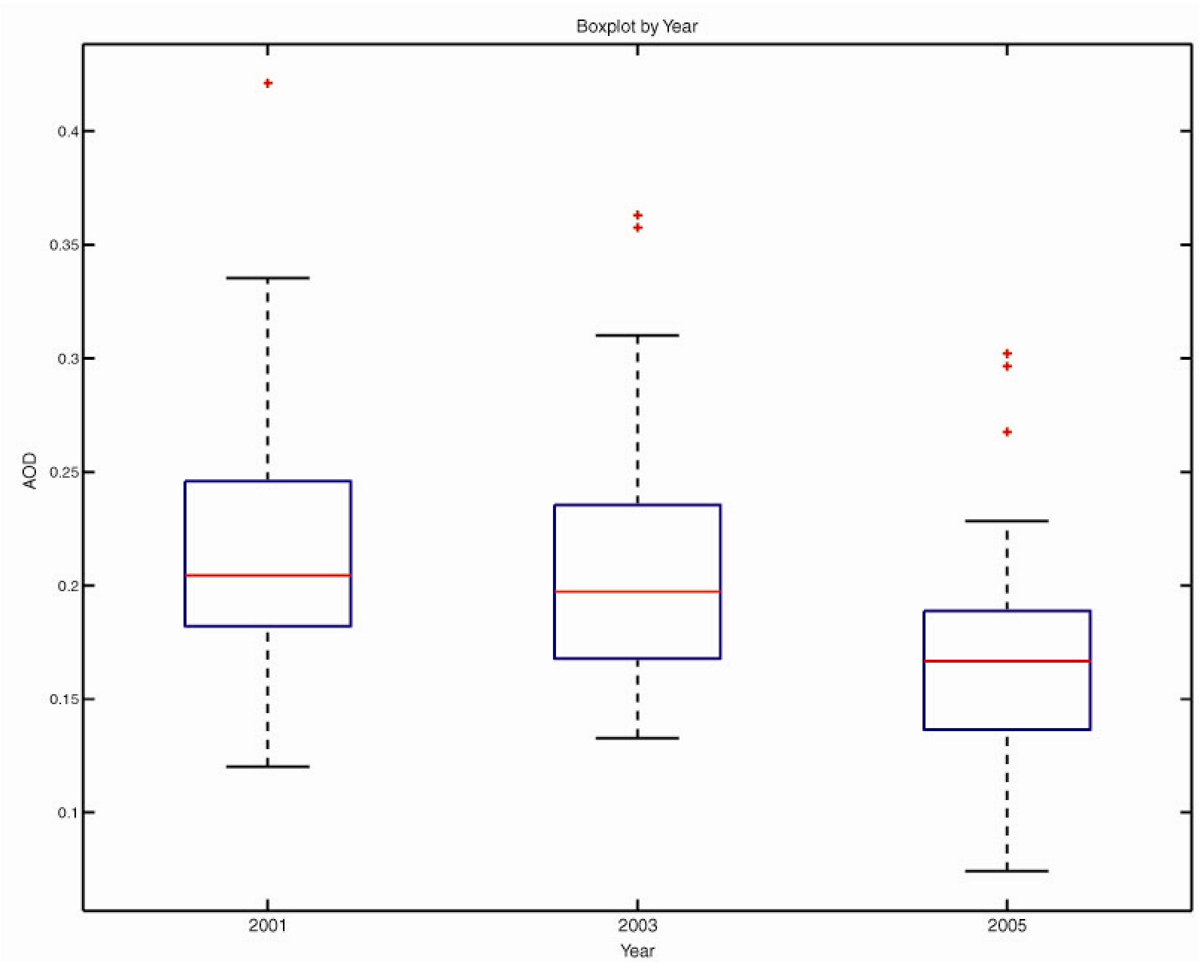

Figure 11: Boxplot of AOD Values by Year. *Statewide variability in AOD values remain constant from 2001 – 2005. Note the significant drop in 2005.*

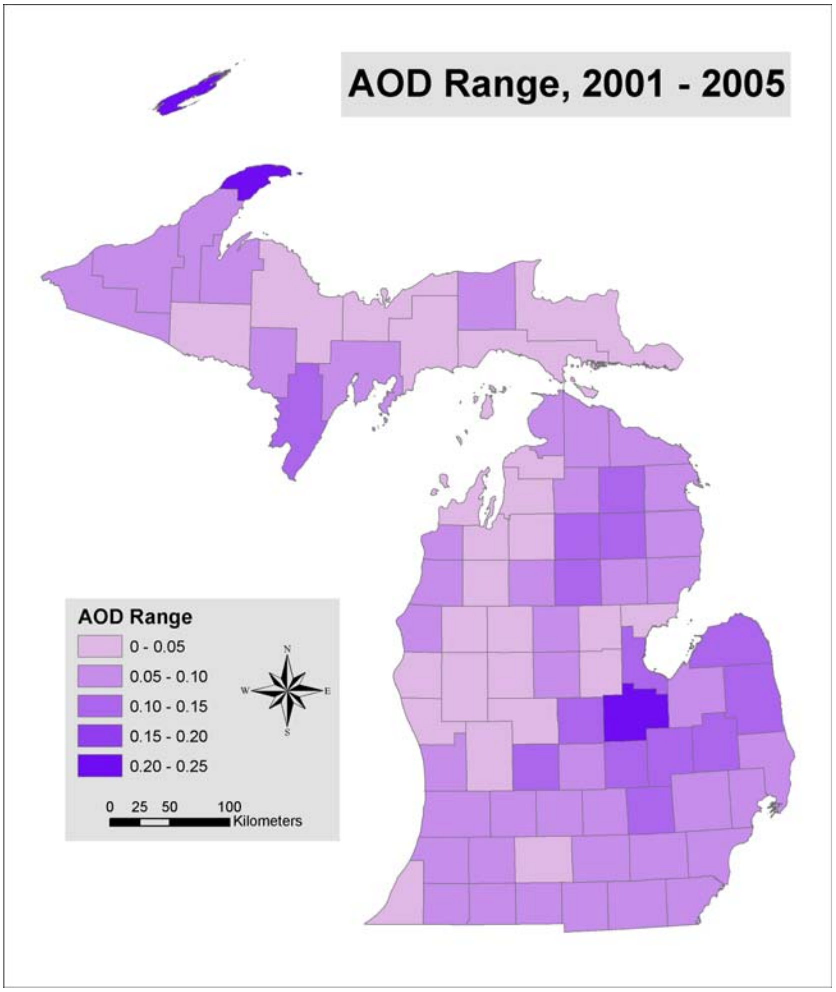

Figure 12: AOD Range, 2001 - 2005. *AOD had stable fluctuations from 2001 to 2005. The two counties (Saginaw and Houghton) with the greatest change also had the largest statewide maximum and minimum AOD values.*

Discussion

This discussion will focus on two important questions that arise from the above results:

1. Are there any patterns in AOD that relate to possible anthropogenic forcing?
2. Can AOD from MODIS be used to isolate more detailed profiles of atmospheric pollutants?

Anthropogenic Influences on AOD

Human atmospheric inputs are diffuse, arising from point and area sources – point sources being isolated emitters while area sources emit from defined regions. Developed, industrial regions usually provide the greatest concentration of point source emitters. Agricultural areas are primarily a large collection of area sources. Atmospheric contributions from these sources differ in terms of size and chemical composition, each having different spectral signatures. AOD combines the signatures of the many atmospheric pollutants into a single measure. In addition, the spatiotemporal limitations of the AOD measure due to inconsistent daily measures and sensor specifications inhibit identification of single sources.

The approach used here to identify human influence on AOD is two-fold. First, the state was divided into NRCS districts and AOD evaluated between them (see Figure 13 for region map). Second, the seasonality of AOD is evaluated using spring and fall AOD measurement. The hypothesis with both these approaches is to test the possible effects of human land use and land cover patterns on AOD. For example, it is expected that AOD values will decrease when moving north through the state as land cover changes from developed, agricultural areas to decreased development and increased forest. For seasonality, it is hypothesized that spring agricultural activities would increase AOD.

Results for the region variability analysis are presented in Appendix B. The goal of the analysis was to determine difference mean AOD between regions. An ANOVA (Analysis of Variance) is a useful statistical framework to check for difference in means when more than two groups are used. The boxplots in Appendix B for each year show a decreasing pattern in AOD from Lower to Upper Michigan. This pattern is consistent with the hypothesized relationship of AOD with decreasing agriculture, development, and population. Furthermore, all differences are significant except for Upper Michigan in 2005. In 2005, the Upper Peninsula experienced significant variability in AOD. The reasons for this variability are unclear but possibly explained by weather events or smoke. It is also possible that these measurements are statistical aberrations caused by an algorithmic malfunction.

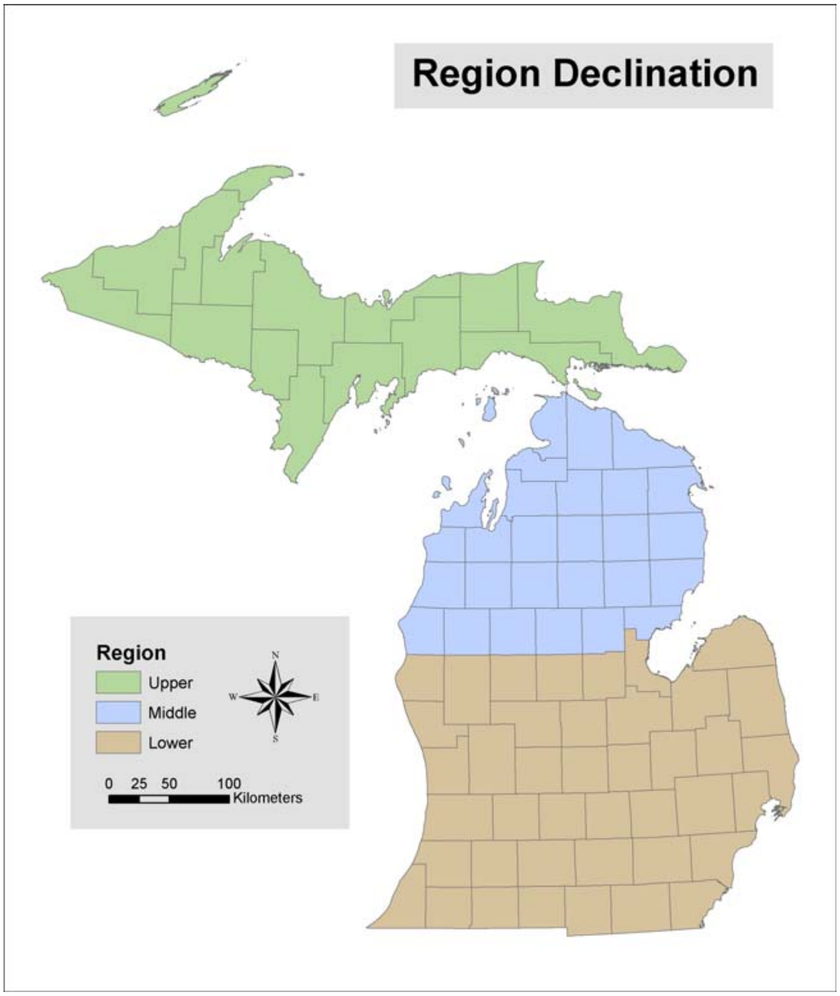

Figure 13: NRCS Districts Used for Regional Analysis. *Districts correspond well with patterns in population, agriculture, and development. These districts/regions can be used to approximate human influence on AOD.*

Seasonality differences also showed statistical differences – remember, a fall dataset was downloaded for 2001 (October and November). Seasonal difference in AOD has many contributing factors, the two primary being: (1) agricultural activity (e.g. tillage, planting) facilitates the release of additional particulate matter during April-May and (2) atmospheric haze from higher relative humidity increases AOD. The hypothesis, then, is higher AOD values during the months of April-May should be observed statewide and at the regional level. These AOD values should be higher overall in Southern Michigan, decreasing to the north. One-tailed *t*-tests were used to test the hypothesis that average spring values were higher by region. Results are reported in Table 9.

Table 9: Results of One-Tailed t-tests. *For the state and each region the calculated mean differences are statistically significant.*

Description	Spring Mean	Spring St. Dev.	Fall Mean	Fall St. Dev.	Mean Difference	p-value
Statewide	0.2155	0.056	0.0927	0.0218	0.1228	< 0.05
Lower	0.2453	0.0562	0.0978	0.0281	0.1475	< 0.05
Middle	0.2003	0.0271	0.088	0.0111	0.1123	< 0.05
Upper	0.1615	0.043	0.0869	0.0122	0.0746	< 0.05

Overall, the statistics demonstrated lower overall seasonal average AOD statewide and by region. The ‘Upper’ region had the smallest AOD difference between spring and fall. This analysis framework did not incorporate ancillary information to control for the likely influences in seasonal climatic differences affecting atmospheric transparency. Again, it is hypothesized these observed seasonal differences are attributed to (1) increased agricultural activity and (2) seasonal climate. Determining the relative strengths of these influences requires further investigation.

Improved Detail in AOD Profiles

As mentioned above, the AOD measure retrieved by MODIS is an aggregation of atmospheric disturbances that together contribute to the measured transparency. AOD, then, should have a correlates with the concentration of particulates, haze, etc. in the atmospheric column. Many studies have addressed this specific question using *in situ* measurements of particulate concentrations, pollutant volumes, etc. to statistically test for linear and non-linear relationships with AOD (Engel-Cox et al. 2004; Song, Zhang & Cai 2006). These studies have mixed results. Applying similar techniques would require significant calibration data collects with uncertain results. Problems with this method include:

1. Comparing different data scales – point collect for *in situ* measures and 1-km for remote sensing
2. Accuracy of atmospheric models contained in MODIS algorithm
3. Algorithm inconsistencies over light and dark targets

Conclusions

- Seasonal and regional differences exist in the statewide AOD distribution likely driven by agricultural intensity and climatic variability.
- Data sparsity requires monthly or bi-monthly averaging to provide county AOD values significantly limiting the temporal resolution of the data product.
- Large data archive and continued collections into the foreseeable future, temporal trends in AOD may be developed to better understand the effects of changing land use on atmospheric

Other Inputs Investigated

In searching for and development of inputs that were appropriate as EQI inputs, the MTRI team found several promising yet currently unavailable or infeasible inputs. These include measures for the soil, water, and air components of the index. The inputs which show the most potential for future use in an EQI-like assessment are described below and summarized in Table 10.

Treatment of Highly Erodible Land

In year one of the cooperative agreement, Altarum/MTRI began development of a GIS-based method to assess the amount of highly erodible land (HEL) that had come under treatment through NRCS conservation programs. HEL is designated in USDA soil maps, and NRCS programs target HEL lands for conservation practice implementations in order to most effectively impact erosion prone areas. The Year 1 report: *Case Study of Erosion Control Practices in Michigan* and Year 2 report *Analysis of Erosion Reduction Measures on Highly Erodible Land* describe in detail the approach and results of the HEL Treated product developed as an EQI input under this project. In the end, the HEL product was dropped from the EQI because the NRCS staff considered the product unreliable. While the method was deemed a valid approach for assessing where and when HEL had been treated, the data used to feed the model is considered inaccurate enough that the end product would not be reliable. In particular, HEL designation, in both the soils map and in conservation program contracts, are driven by specific needs of some states to better manage lands where erosion was a critical issue; Michigan is not one of those states, so detailed information of HEL location and treatment is not made. If changes are made in HEL mapping and recording of HEL treatments (in particular, location of HEL treatments), this method could be employed in an EQI-like assessment.

Soil Carbon Sequestration

Farming practices can have a large impact on the amount of carbon that moves between the land and atmosphere, though plant function and soil decomposition, and the hydrosphere through soil erosion. Models of the rates of carbon exchange and net carbon loss to the atmosphere are currently under development due to a new emphasis on understanding the full carbon cycle. The roll of agriculture in mitigating carbon emissions has had some attention, but is not yet ripe for use as inputs to the EQI. Research projects such as the Consortium for Agricultural Mitigation of Greenhouse Gases (CASMGS; http://www.casmgs.colostate.edu/default.asp), USDA efforts under the CEAP (Potter et al 2006) and state-level soil carbon accounting efforts, such as has been completed for Nebraska, Iowa, and Indiana by the Natural Resources Ecology Laboratory (NREL) at Colorado State University (see http://www.nrel.colostate.edu/ projects/agecosys/), will provide information on carbon sequestration that can be used in an EQI-like assessment. Inputs to the model include soil type, temperature and precipitation, and organic matter decomposition rates as well as information on carbon inputs through crop residues and farming practices such as harvest procedures and tillage practice. An assessment of soil carbon sequestration has been done for some states and is possible for any others. As this data becomes available, it can be integrated into the EQI.

In-situ Water Quality Measures

Efforts are underway to systematically collect water quality data for major watersheds within the State of Michigan (see http://www.michigan.gov/deq/ for a copy of the "Michigan Water Quality Monitoring Strategy"). A transition of the EQI method to a watershed approach would improve the utility of these data for farm practice assessment, but sensitivity to NRCS activity of data collected at the major watershed scale will need to be assessed, and may not be valid (see Year 1 report: *Statistical Case Study of the River Raisin Watershed*). In-situ water measures at the farm or small watershed scale are more likely to show farm practice impacts on water quality and these not as useful for a statewide application, such as the EQI. As in-situ quarter quality data collections become more automated and common, an assessment of the scale at which these need to be known for a statewide assessment should be made and considered for an EQI-like application.

Methane Emissions

US-EPA currently models methane emissions from agriculture under their greenhouse gas program. The major farming practices that emit methane are enteric fermentation, manure management, rice cultivation and agricultural residue burning. The EPA uses methane estimates for most of these source categories at the state level. The level of uncertainty in the estimates increases greatly at the county scale so they have not developed estimates at scales finer than a single state (see http://www.epa.gov/methane/). New research on emissions from animal feeding operations from enteric fermentation and waste management will improve these models and allow them to be spatially defined. This research is currently underway by the USDA Agricultural Research Service (ARS) in studies of trace gases under their global change program (see http://www.ars.usda.gov/research/ programs.htm). As these data are collected and integrated into farm emissions models, they should be in a very accessible form for use in an EQI-like assessment.

Table 10: Potential additional EQI inputs researched.

Possible EQI Input	Source	Current Issues	Future Potential
Treatment of HEL	USDA	Procedure to map HEL under treatment was developed under this program, but found to be inadequate due to data reliability	Good to fair– USDA would need to commit to tracking HEL treated land and improving HEL soil maps.
Soil carbon	USDA and others	Development of soil carbon dynamics maps for Michigan is beyond the scope of this project. Local-scale assessment is feasible, but difficult to scale to counties.	Very good – New research on modeling soil carbon dynamics should allow a comprehensive assessment in the near future. Soil carbon maps are complete for some states.
In-situ water quality	M-DEQ and/or US-EPA	Insufficient in-situ data is currently collected to assess for practice implementation effects.	Fair to poor – Funding for a sufficiently fine-scale measurement network is not foreseeable.
Methane emissions	US EPA and/or USDA	Currently, the US-EPA models methane emissions at the state level only. Refinements of the model are needed to make county-level estimates.	Very good –New research by USDA on emissions from animal feeding operations will improve these models and allow them to be spatially defined.

Summary & Conclusions

This report, along with two additional Year 4 reports: *Using C-CAP Land Cover Products for EQI Inputs* and *Remote Sensing of Lake Clarity,* describe in detail the origin and method for obtaining the ten EQI inputs developed under the MI-NRCS/MTRI cooperative agreement. In developing the ten inputs to the EQI, several factors needed to be considered. First, inputs need to be relevant to the assessment being made. The approach of using the NRCS resource concerns and developing the index based on NRCS program goals has provided a framework for EQI selection that results in relevant environmental measures. Second, only data that is feasible to obtain within the limitations of both method and cost, could be considered, since the purpose of this effort is to provide an assessment of conservation program impacts, which themselves have cost and feasibility limitations. Third, inputs need to be repeated data sets so that change in EQI can be measured over time. For this initial development work, MTRI found several inputs that were accessible and most likely will be available for future assessments. The project effort also identified a few potential data inputs that should be considered when a new EQI or EQI-like analysis is done.

Few of the measures found for NRCS program assessment were available from before c. 2000. Because of this, a comprehensive retrospective EQI-based assessment could not be made. For this project, however, a demonstration of conducting an EQI assessment using the Surface Water Quality EQI inputs and some limited information on NRCS implementations was complete. This demonstration assessment is reported in the Year 4 report: *The Environmental Quality Index Approach: Concepts, Methods, and Demonstration of the EQI Approach for NRCS Conservation Program Assessment*. In future EQI-based program assessments, the inputs described above, including ones that were not selected in the final EQI but have potential to be available for c. 2000 and beyond, will be of great value, since they were developed with NRCS goals and resource concerns in mind.

Acronym List

ANOVA	Analysis of Variance
AOD	Atmospheric optical depth
ARS	Agricultural Research Service
AWiFS	Advanced Wide Field Sensor
BMP	Best management practice
BOD5	5-day biological oxygen demand
CASMGS	Consortium for Agricultural Mitigation of Greenhouse Gases
C-CAP	Coastal Change Analysis Program
CBERS	China-Brazil Earth Resources Satellite
CRM	Crop residue management
CTIC	Conservation Technology Information Center
EQI	Environmental Quality Index
HEL	Highly erodible land
MDEQ	Michigan Department of Environmental Quality
MMT	Manure management train
MNFI	Michigan Natural Features Inventory
MODIS	Moderate Resolution Imaging Spectroradiometer
MSCARI	Modified Soil Adjusted Crop Residue Index
NASA	National Aeronautics and Space Administration
NASS	National Agricultural Statistics Service
NEI	National Emissions Inventory
NESC	National Environmental Service Center
NOAA	National Oceanographic and Atmospheric Administration
NRI	National Resources Inventory

RUSLE Revised Universal Soil Loss Equation

STATSGO State Soil Geographic Database

STEPL Spreadsheet Tool for Estimating Pollutant Loads

USEPA U.S. Environmental Protection Agency

USDA U.S. Department of Agriculture

USGS U.S. Geological Survey

USLE Universal Soil Loss Equation

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Appendix A

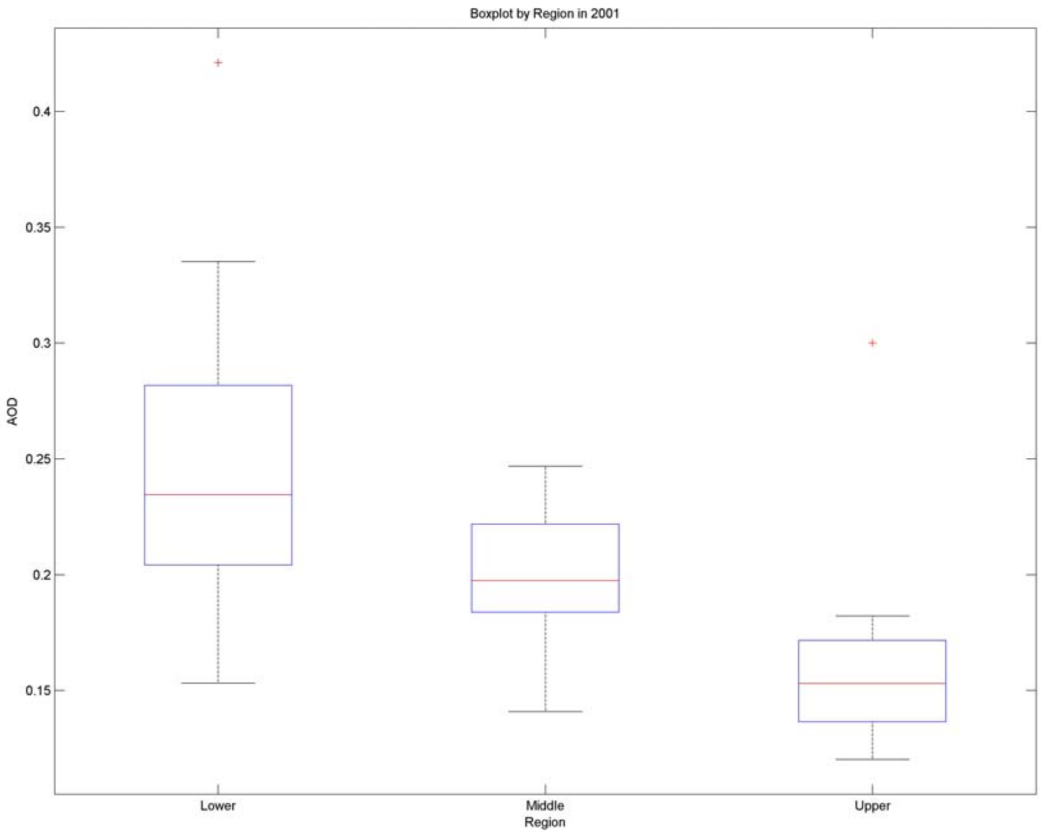
This table contains average AOD values for each county (April/May 2001-2003). AOD values for 2001 and 2003 are similar while a drop occurs in most counties in 2005.

	Mean AOD				Mean AOD		
County Name	2001	2003	2005	County Name	2001	2003	2005
Alcona	0.196	0.232	0.135	Lake	0.214	0.215	0.168
Alger	0.152	0.155	0.164	Lapeer	0.295	0.252	0.151
Allegan	0.191	0.248	0.168	Leelanau	0.183	0.193	0.189
Alpena	0.221	0.200	0.122	Lenawee	0.277	0.218	0.195
Antrim	0.200	0.184	0.202	Livingston	0.202	0.241	0.127
Arenac	0.183	0.180	0.189	Luce	0.121	0.141	0.184
Baraga	0.149	0.146	0.080	Mackinac	0.175	0.158	0.189
Barry	0.235	0.184	0.156	Macomb	0.335	0.358	0.297
Bay	0.304	0.245	0.191	Manistee	0.173	0.224	0.165
Benzie	0.143	0.203	0.189	Marquette	0.159	0.165	0.167
Berrien	0.204	0.192	0.160	Mason	0.246	0.240	0.166
Branch	0.248	0.172	0.189	Mecosta	0.167	0.179	0.136
Calhoun	0.219	0.195	0.178	Menominee	0.135	0.168	0.268
Cass	0.158	0.233	0.185	Midland	0.189	0.181	0.184
Charlevoix	0.188	0.200	0.178	Missaukee	0.232	0.163	0.132
Cheboygan	0.194	0.155	0.114	Monroe	0.254	0.263	0.211
Chippewa	0.140	0.133	0.180	Montcalm	0.189	0.199	0.167
Clare	0.222	0.172	0.124	Montmorency	0.233	0.212	0.096
Clinton	0.229	0.264	0.180	Muskegon	0.216	0.215	0.217
Crawford	0.247	0.152	0.132	Newaygo	0.188	0.197	0.171
Delta	0.182	0.148	0.228	Oakland	0.271	0.270	0.191
Dickinson	0.120	0.143	0.191	Oceana	0.214	0.198	0.214
Eaton	0.230	0.206	0.150	Ogemaw	0.199	0.162	0.130
Emmet	0.192	0.173	0.128	Ontonagon	0.160	0.171	0.082
Genesee	0.295	0.253	0.153	Osceola	0.181	0.176	0.157
Gladwin	0.141	0.177	0.157	Oscoda	0.235	0.155	0.098
Gogebic	0.153	0.169	0.092	Otsego	0.198	0.193	0.123
Grand Traverse	0.186	0.191	0.151	Ottawa	0.247	0.269	0.215
Gratiot	0.247	0.310	0.209	Presque Isle	0.191	0.167	0.124
Hillsdale	0.245	0.177	0.167	Roscommon	0.226	0.149	0.117
Houghton	0.162	0.143	0.074	Saginaw	0.421	0.285	0.215
Huron	0.315	0.236	0.186	St Clair	0.302	0.252	0.213
Ingham	0.218	0.221	0.167	St Joseph	0.215	0.256	0.180
Ionia	0.261	0.198	0.160	Sanilac	0.331	0.279	0.191
Iosco	0.201	0.203	0.138	Schoolcraft	0.182	0.184	0.168
Iron	0.134	0.154	0.116	Shiawassee	0.327	0.226	0.180
Isabella	0.203	0.227	0.161	Tuscola	0.260	0.230	0.162
Jackson	0.218	0.196	0.163	Van Buren	0.153	0.240	0.156
Kalamazoo	0.196	0.244	0.155	Washtenaw	0.227	0.234	0.176
Kalkaska	0.207	0.166	0.186	Wayne	0.324	0.363	0.302
Kent	0.236	0.245	0.216	Wexford	0.175	0.158	0.143
Keweenaw	0.300	0.141	0.080				

Appendix B

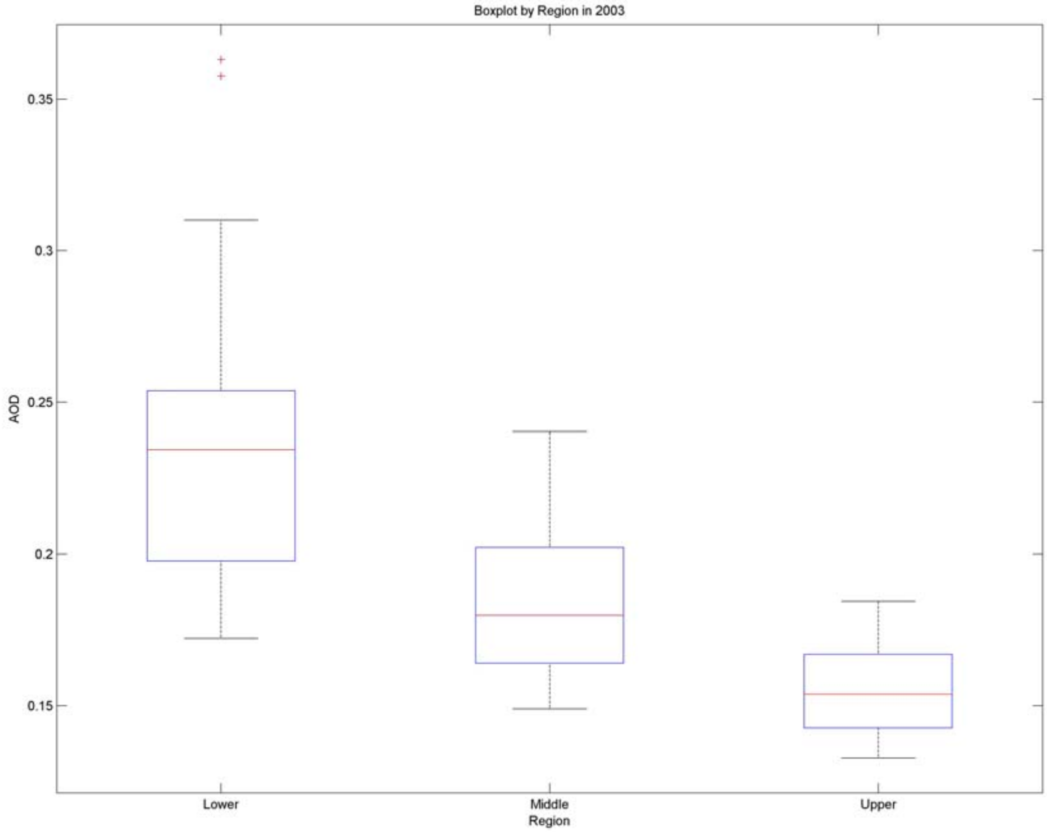
Results for the regional ANOVA analysis are presented below. For each year, boxplots and mean difference statistics are presented. Each mean difference statistic has estimated confidence intervals for the mean difference. Mean differences are not significant if the confidence intervals contain a zero (i.e. Lower CI -5, Mean Difference 4, Upper CI 13).

2001



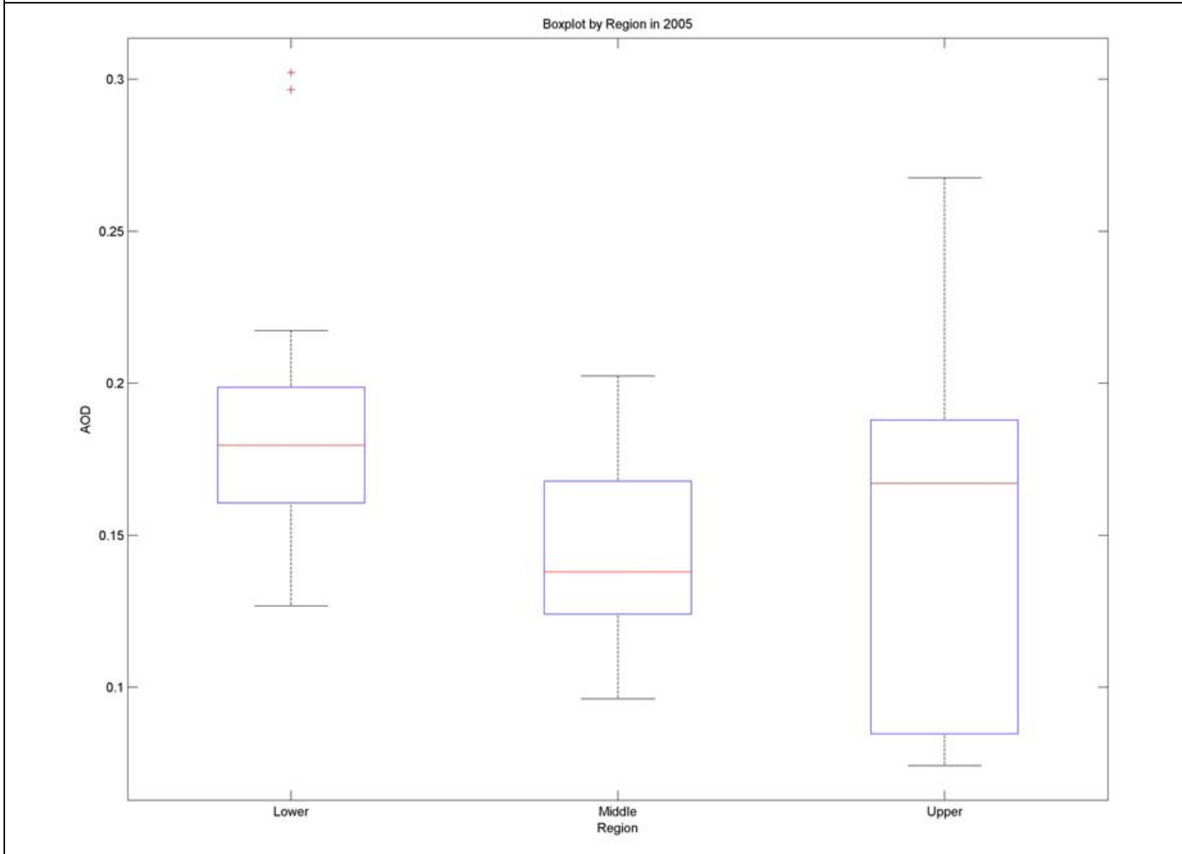
Region		Lower CI	Mean Difference	Upper CI
Lower	Middle	0.0176	0.045	0.0724
Lower	Upper	0.0504	0.0838	0.1171
Middle	Upper	0.0032	0.0388	0.0743

2003



Region		Lower CI	Mean Difference	Upper CI
Lower	Middle	0.0299	0.0503	0.0707
Lower	Upper	0.0561	0.081	0.1059
Middle	Upper	0.0042	0.0307	0.0573

2005



Region		Lower CI	Mean Difference	Upper CI
Lower	Middle	0.0143	0.0375	0.0607
Lower	Upper	0.0049	0.0332	0.0614
Middle	Upper	-0.0345	-0.0044	0.0258