Mapping Conservation Practices and Outcomes in the Corn Belt

Final Report

10 September 2019

A collaborative project between Applied Geosolutions LLC, Dagan, Inc., The Nature Conservancy, and the Conservation Technology Information Center, 2019

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I. Introduction

In collaboration with The Nature Conservancy and The Conservation Technology Information Center (CTIC), Applied GeoSolutions and Dagan, Inc mapped agricultural conservation practices and the associated environmental outcomes across the Corn Belt from 2005 to 2018. This project implements two technologies. The Operational Tillage Information System (OpTIS), a remote sensing tool that uses earth-observing satellite data to document the adoption of soil health practices. And, the Denitrification-Decomposition (DNDC) model, a process-based model of carbon and nitrogen biogeochemistry in soil, to estimate the outcomes associated with changes in management (Gilhespy et al. 2014).

As part of this mapping effort, the OpTIS team organized the collection of field observations of practices across the Corn Belt for use in validating the satellite-based estimates. Crop consultants in 30 regions across the Corn Belt were hired and asked to use OpTIS Mobile, a mobile app developed by Applied Geosolutions with funding from The Nature Conservancy. The mobile app guided the data collectors through the roadside survey process and uploaded the survey results and photographs directly into a database deployed and maintained by Applied GeoSolutions.

II. Study Area

The area analyzed for this project is defined by the extent of the Land Resources Region-M (LRR-M; Central Feed; Grains and Livestock Region) (Figure 1). As mapping by OpTIS is parameterized and executed at the HUC 8 (Hydrologic Unit Code for subbasin level having 8 digits) watershed scale, the main criteria for inclusion in the analysis started with HUC 8 boundaries that intersect the LRR-M. The initial set of watersheds intersecting the LRR-M was modified to include additional adjacent areas of interest near Lake Erie and exclude watersheds low in agricultural land cover. We identified a total of 274 HUC 8 watersheds for inclusion in the analysis.

Aggregation for reporting of results is done at various spatial units, including counties, crop reporting districts (CRD), states, and HUC 8 watersheds. Counties where at least 75 % of the area overlapped with a HUC 8 watershed in the study area were included in county reporting (Figure 1). For CRD reporting, CRDs where at least two counties overlapped with HUC 8s were included. And for state reporting, each state with at least one reported HUC 8 watershed contained entirely within the state was included. Reporting was done on a total of 12 states, 70 CRDs, and 645 counties.

Figure 1. OpTIS mapping was done for a total of 645 counties (yellow) in and around the Land Resources Region-M (grey line) in the Corn Belt.

III. Methods and Assumptions

The project time period covers the 2005 to 2017 crop years in their entirety. In addition, we provide OpTIS results from the 2018 crop year. A crop year in this project is defined as 1 November of the previous year through 31 October of the crop year. For example, the 2005 crop year extends from 1 November 2004 through 31 October 2005.

The fundamental unit of analysis in this study is a field segment defined as a contiguous set of 30-meter pixels with the same crop history between 2008 and 2017, based on crop classification data from the Cropland Data Layer (CDL). Field segments with < 10 acres are discarded from the analysis. Fields that border roads are often 'eroded' as a result of the effects of half-pixel shifts common to image registration from year-to-year. To account for crop area lost due to the edge erosion and minimum field size, a HUC 8 area-adjustment factor is calculated and applied to adjust the reporting size of each field segment. The adjustment factor is calculated as total CDL pixel crop area divided by total segment crop area within each HUC 8. The reported area of each segment within the HUC 8 is calculated as segment area times HUC 8 adjustment factor. More than 1.7 million segments were analyzed as part of this project.

A. OpTIS Mapping of Agricultural Practices

1. Inputs and Assumptions

OpTIS generates estimates of residue cover, tillage practices, cover crops, and days of cover (by residue and living green vegetation) at the sub-field scale, which are then summarized at the field segment scale for input to DNDC modeling. Data are sourced from MODIS sensors on Terra and Aqua, Landsat 5, Landsat 7, Landsat 8, Sentinel 2A, and Sentinel 2B. These observations are cloud masked and reprojected onto a 30-meter grid in Albers Equal Area projection. Cropland Data Layer (USDA-NASS CDL, 2019) is used to identify field segments and crop rotations. Precipitation from PRISM (PRISM Climate Group, 2019) is used in the OpTIS algorithms to account for soil and crop residue moisture effects.

Median plant and harvest dates are estimated at the HUC8 level each year using a time series of MODIS NDVI observations. These dates are used to parameterize the residue cover and cover crop mapping, but not as input to DNDC.

Areas of permanent grasslands and pasture were removed from the analysis. Areas growing alfalfa or hay for fewer than six years of the study period were included in the analysis. Areas identified as being converted to or from row crop agriculture during the study time period were excluded from the analysis.

We summarized OpTIS-mapped practices (residue cover, tillage, and cover crop classes) at four geographic scales: county, crop reporting district, state, and HUC8 watersheds. For each practice, we report area by previous crop year's crop type category (corn, soybeans, small grains, and other). Thus, the total area summary for each practice for each previous crop is the sum of the adjusted area of all segments in the geographic unit with those practices and previous crops. Area summaries are adjusted to the total adjusted segment area in a geography - we assume that the distribution of practice classes among segments with no data are the same as those with data.

2. Residue and cover crop mapping

Residue cover fraction is estimated in every available image for each location using the Normalized Difference Tillage Index (NDTI) and the Crop Residue Cover Index (CRC), parameterized at the HUC8 scale. The time series of residue cover fraction at the pixel level is then analyzed for patterns and consistency, returning a residue cover fraction value together with a certainty level at the time of planting at the 30-m pixel scale. For residue cover, the mean of all 30-meter pixels with a valid estimate within the field segment is calculated and reported. The residue cover percentage at the field scale is categorized into one of four levels of residue cover:

1. 0 to 15% - very low
2. 16 to 30% - low
3. 31 to 50% - moderate
4. 51 to 100% - high

Ranges of residue within the residue classes were chosen to allow for consistency in matching with historical CTIC Crop Residue Management Survey data. We also report on assumed tillage practices linked with these residue levels, derived from the residue cover levels and previous year's crop (i.e. residue type):

1. **Conventional tillage**— same as very low residue cover level (0-15%) for all previous year crop types;
2. **Reduced tillage, low residue**— same as low residue cover (16-30%) for all previous year crop types;
3. **Reduced tillage, high residue**— moderate residue cover (31-50%) where corn was the previous year's crop;
4. **No-till**— moderate residue cover (31-50%) where any crop except corn was the previous year's crop and high residue cover (51-100%) for all previous year crop types

Winter cover is estimated with a time series of the Normalized Difference Vegetation Index (NDVI), extending from November through July of each crop year. Timing and intensity of greenness is compared to thresholds set at the HUC8 scale to determine cover status. Each pixel is classified into one of six classes:

1. No cover
2. Commodity crop (winter wheat)
3. Spring emergent
4. Winter kill
5. Full cover
6. Not enough data to estimate

For winter cover, the field segment is determined to be covered if 30% of the row crop pixels with a valid estimate within the field segment are classified as covered (winter cover classes 2, 3, 4, and 5 listed above). The type of cover is determined from the most common cover class.

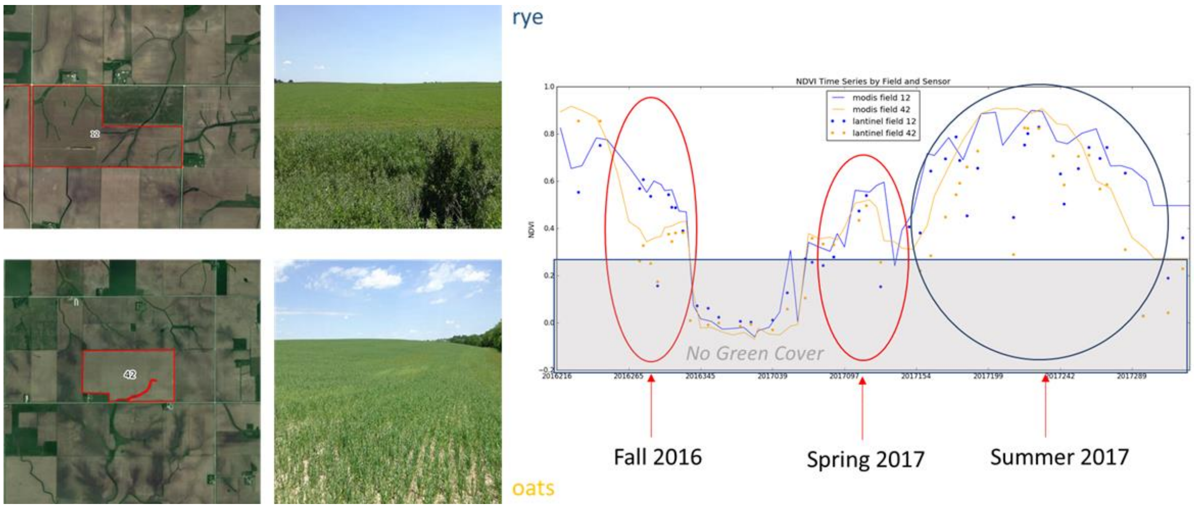


Figure 2. Demonstration of OpTIS estimates of winter cover. The algorithm works using a time series of Normalized Difference Vegetation Index (NDVI) as an estimate of green cover through the fall, winter, and spring.

Table 1. Data used in OpTIS mapping of tillage practices, cover crops, and crop rotations, as well as for DNDC simulations of soil carbon, greenhouse gas emissions, soil available water capacity, and N leaching.

Data	Technology	Agency	Source
Landsat	OpTIS	USGS/NASA	www.usgs.gov/land-resources/nli/landsat/landsat-data-access
MODIS	OpTIS	NASA	modis.gsfc.nasa.gov/data/
Sentinel 2	OpTIS	ESA	sentinel.esa.int/web/sentinel/sentinel-data-access
PRISM	OpTIS & DNDC	Oregon State University	www.prism.oregonstate.edu/
Cropland Data Layer	OpTIS & DNDC	USDA	www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php
MIrAD-US	DNDC	USGS	earlywarning.usgs.gov/USirrigation
N deposition	DNDC	NADP NTN	nadp.slh.wisc.edu/ntn/
annual survey, crop yield, fertilizer, harvested acres, irrigated status	DNDC	USDA NASS	quickstats.nass.usda.gov/
Fertilizer type	DNDC	USDA ERS	https://www.ers.usda.gov/data-products/fertilizer-use-and-price/
plant and harvest dates	DNDC	USDA NASS	Field Crops, Usual Planting and Harvesting Dates, October 2010 - Agricultural Handbook Number 628
SSURGO	DNDC	USDA NRCS	www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053628

atmospheric CO2	DNDC	Scripps Inst. of Oceanography	scrippsco2.ucsd.edu/data/atmospheric_co2/primary_mlo_co2_record
Crop biomass data	DNDC	Sustainable Corn Coordinated Agricultural Project (CAP) Team Research Data	https://datateam.agron.iastate.edu/cscap/

B. DNDC Modeling

1. Inputs and Assumptions

Input data of area-weighted mean soil attributes were calculated for each segment using the NRCS SSURGO database. Attributes for soil were derived by extracting representative values for clay (as a proxy for soil texture), organic matter, bulk density, and pH, the four soil parameters required for input to DNDC. Organic matter was converted to soil organic carbon (SOC) by dividing organic matter by 2 (Pribyl, 2010). Soil available water capacity (AWC) was calculated on a daily basis using equations for field capacity and wilting point from Saxton and Rawls, 2006. AWC was calculated for the top 10cm - inputs include SSURGO-derived clay and sand fractions and DNDC-simulated daily SOC.

Seventeen major crops were simulated: corn, cotton, rice, sorghum, soybeans, sunflower, spring wheat, winter wheat, other small grains, rye, oats, alfalfa, other hay/non alfalfa, sugarbeets, dry beans, potatoes, and peas. Minor crops were not included in this list and were simulated as "other crops". Crop planting and harvesting dates were based on usual planting practices (NASS 2010). Hay crops (alfalfa and other hay) were cut twice in their first crop year and four times in any subsequent year.

Crops were fertilized with urea-ammonium nitrate (UAN), the most common fertilizer type used in the US (NASS 2010). Fertilizer rates used are based on state-based rates disaggregated to county-level based on mean reported yields (NASS 2010). In addition, fertilizer rates were adjusted to within-county, soil-specific rates as part of our calibration process (see "crop parameter calibration" below). Fertilizer was applied on plant date unless USDA-specified data indicated that more than one application was typical. For corn, 20% fertilizer was applied at planting and 80% fertilizer 45 days after planting. For other crops, we distributed N applications based on typical regional practices. When following an N-fixing crop, fertilizer rates were reduced by 15% based on an analysis of data extracted from the ISU Corn Nitrogen Rate Calculator.

Crop residue was assumed to remain on the soil surface following harvest. In the case of harvested grain, this comprised 100% of the non-grain above-ground biomass. Cover crops were terminated and 100% of the above ground biomass was left in place. In the case of cut perennial crops (alfalfa or hay) 85% of the above-ground biomass was removed at each cut— at the end of each growing season, whatever senesced material remained was left on the soil surface.

Tillage practices were simulated based on OpTIS-mapped data. Spring tillage was implemented 5 days prior to planting. Fall tillage was implemented 5 days after harvest. Conventional tillage was simulated with a 20 cm moldboard (top-soil inversion); reduced tillage was simulated with a 10 cm disk (top-soil mixing); no-till was simulated with no soil disturbance.

Irrigation and flooding were also accounted for. Where rice was planted, we assumed a continuously flooded growing season and flooded the segment 30 days after planting and drained the segment 21 days prior to harvest. We used USGS MiRAD data to identify segments that are typically irrigated. For irrigated segments, we used DNDC's irrigation index function to apply water weekly based on 95% of plant demand.

2. Crop Parameter Calibration

Crop parameters regarding yield were calibrated to approximate yield patterns over time. For each crop in each county, we calibrated to county-level yield based on NASS 2010 reporting. An automated process was used that iteratively adjusted crop parameters, including maximum biomass, relative biomass fractions, and carbon-to-nitrogen ratios of grain, leaf, stem, and root. Ranges for these parameters were constrained using field-measured data from the USDA Corn CAP program. Calibration of crop parameters was done for 5-year timeframes to approximate changing variety selections over time.

An automatic calibration routine was applied to re-distribute fertilizer within the county to generate soil-specific N rates. This redistribution minimized over-application of N on richer soils and under-application on poorer soils, thus reducing the probability of unrealistic N losses (as either N_2O on rich soils or NO_3 leaching on coarse soils) or low yield on poor soils.

3. Management Simulations

To compare the simulated effects of OpTIS-mapped management to less-optimal soil health management, four scenarios were run (Table 2). During the simulation runs, for each crop, auto-calibration was run to pre-generate crop parameters and soil-based fertilizer rates. An 18-year simulation from 2000 to 2017 was run for each segment for each scenario. The 2000 to 2004 timeframe was run for all four scenarios using 2005 to 2009 OpTIS-mapped management output to initialize SOC and ensure that all scenarios started with the same soil conditions on the first day of the 2005 crop year. Results for 2000 to 2004 were not included in summarized results.

Table 2. Four scenarios run to simulate effects of OpTIS-mapped management to less-optimal soil health management. Model simulations were simulated by county and proceeded as follows:

DNDC Management Scenarios	
OpTIS-mapped	"actual" distribution of soil health management practices in the study area
All ConvTill	first alternative scenario assumed conventional tillage all the time
No CoverCrops	second alternative scenario assumed no cover cropping

All ConvTill & No Cover Crops	third alternative scenario combined the first two alternative scenarios and simulated conventional tillage and no cover cropping across all years

4. Post-processing

DNDC modeling results for daily SOC, N_2O, soil available water capacity (AWC), and NO_3 leaching were extracted from 2005 to 2017 simulated results and converted to annual values. The annual change to SOC (dSOC) for any crop year was calculated as last day SOC minus first day SOC for the top 50 cm of the soil profile. Annual total N_2O and NO_3 leaching were calculated as the sum of daily losses over the crop year. AWC was calculated as mean daily AWC for the crop year. Spatially aggregated summaries, for county, crop reporting district, HUC8, and state-level, were calculated as area-weighted mean values using adjusted segment area. Mean annual values at aggregated scales represent the 2005 to 2017 mean.

C. Ground Truthing

1. OpTIS Mobile

Ground-level data obtained through photos and surveys were collected at agricultural field locations across the Corn Belt. Initially, data collection in the spring of 2017was done via data tables filled out by crop consultants upon field visits for Cresco County, Iowa and Christian County, Illinois. Starting in the fall of 2017, the development team at Applied Geosolutions launched the OpTIS Mobile app for Android and iOS platforms. OpTIS Mobile was designed for roadside survey data collection by a crop consultant while minimizing errors associated with repeated data transcription from spreadsheets to database, or from tracking photo numbers, dates, and field locations (Figure 3). Over 90% of the field data used for validation in this project were collected using OpTIS Mobile.

OpTIS Mobile surveys gather the following information:

- Photos, location, date, time, and the direction the photo was taken
- Visual estimate of green and residue cover, rounded to the nearest 5%
- Crop type from the previous year and the coming year, if evident
- Tillage practice, type of tillage, and estimated soil disturbance
- Presence and health, and type of cover crops
- Presence of volunteer crops or weeds
- Broad estimates of soil moisture level and color
- Field boundaries added manually by the data collector

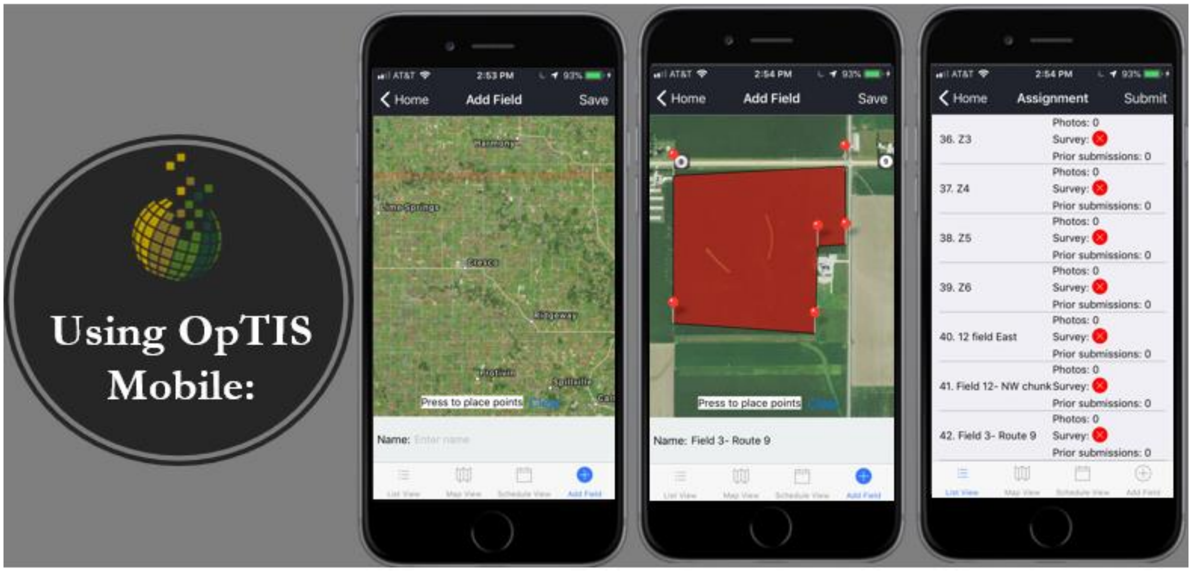


Figure 3. Schematic for identifying and drawing a field in the map screen of OpTIS Mobile app. Fields added are saved in a list of fields to be surveyed.

2. Field Data Collection

Independent crop consultants were identified via the National Alliance of Independent Crop Consultants (NAICC) website directory, the American Society of Agronomy website directory (https://www.agronomy.org/), and through personal references of district employees at state Natural Resources Conservation Services, the OSU Extension at Ohio State University, and the Indiana State Department of Agriculture. Crop consultants were asked to visit 40 fields in total. The OpTIS team selected 15 to 20 fields and crop consultants were tasked with identifying a set of 20 to 25 additional fields digitized using the app when they encountered cover cropped fields. Requirements were to select large fields (~100 acres) following corn or soy crops within approximately a 30 min driving radius from their home address. The cluster of fields were scouted via the OpTIS Mobile on their mobile devices every two to three weeks starting from March through the planting season and again post-harvest. At every visit they were asked to estimate ground cover in terms of green vegetation, residue cover, and bare soil visible from the roadside. Categorical questions were updated as they saw evidence in the fields at the time of the scheduled re-visits.

Field observations were collected via OpTIS Mobile in the fall of 2017 and the spring of 2018 (Figure 4). Ground validation was done across 43 counties in ten states in the Corn Belt, in areas that fall within the Land Resource Region M.

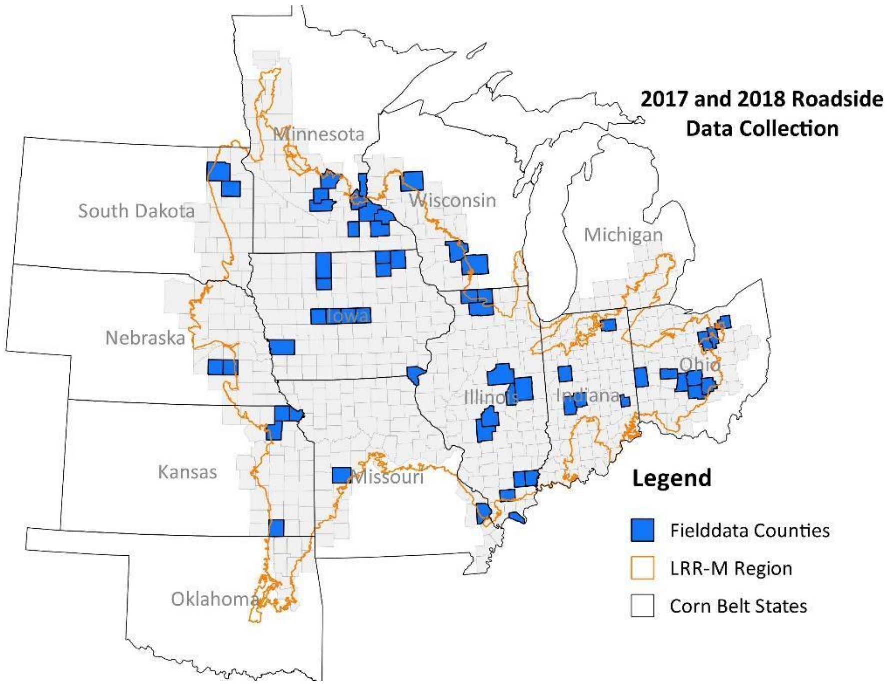


Figure 4. A total of 59 counties were surveyed (blue) in the LRR-M region (orange line) in 2017 Fall (278 fields) and 2018 Spring (1,195 fields).

3. Field Data Quality Control

To ensure consistency of data collected we used a single generic mobile app survey to capture observations in cover crop and tillage changes. In addition, our team implemented a quality control process on the data submitted by collectors. The process was as follows:

- Review and edit the field boundaries as entered by the data collector against imagery and Cropland Data Layer data to increase the chances that the boundaries contain only information from a single field
- Ensure the photo and observation match the field boundary drawn – compare the photo, photo location, and the field boundary
- Remove duplicate submissions
- Assign categorical answers per field for the previous and coming year's crop, tillage and cover crop
- Quality check fractional green, soil, residue cover in survey compared to visual evidence in survey photos

IV. Results

Row crop fields totaling 131,605,000 acres were analyzed with OpTIS and DNDC for this project. A field-level comparison of the OpTIS results to the road-side surveys is presented here, with additional county-level comparison results to the AgCensus and other remote sensing-based mapping efforts. We also report on OpTIS and DNDC data trends across the Corn Belt.

A. Remote Sensing Validation

Roadside surveys and satellite-based estimates of conservation practices were compared to provide the team and the community with a clear understanding of utility and limits of this satellite-based technology. The results from OpTIS were compared to roadside survey results for **(1)** cover crop and **(2)** residue cover.

1. Cover crop

For cover crop evaluation, we restricted the comparison to fields for which we had:

1. valid remote sensing estimate for the field in that year (no-data fraction less than 0.70)
2. indication that a perennial crop or a winter commodity crop was not growing on the field, according to the data collector
3. multiple well-timed field visits and photos to ensure confidence in the field's status as cover cropped or not

The above restrictions resulted in observations for a set of 961 fields, for which 24% were determined to have a cover crop and 76% no cover crop. The confusion matrix shows that the accuracy of the remote sensing is 87.9% and the kappa statistic is 0.63.

Table 3. Confusion matrix table for classification of cover crops. Green cells indicate the number of fields with agreeing classification of cover crops between remote sensing and reference (field) data (termed true negative and true positive). White cells indicate the number of fields with disagreeing remote sensing classification and reference data, these are termed false negative and false positive.

Cover Crop Classification from		**Field Data**	
		No	**Yes**
Remote Sensing	**No**	706	92
	Yes	24	139

Below are results from comparisons, highlighting the information collected and the comparison procedure.

False negative: Photos of field id 57-448 show cover crop green-up in April 2018 (Figure 5). Cover crop is identified by the field observer, but pixels mapped by OpTIS are 0% cover cropped. It's possible that the green cover observed in the field might be extensive weed cover, rather than a cover crop. The field observer classified this field as having cover crop but marked the cover type 'Unknown'.

Figure 5. Roadside photos taken of field id- 57-448 in Missouri observed from 4/4/2018 to 6/6/2018. The crop observed for 2017 is corn, 2017-2018 winter shows evidence of cover crop type that was not identifiable by the data collector, and 2018 crop is soybean.

True negative: Roadside photos of field id 70-443 indicate there was no presence of a cover crop, and OpTIS also determined there was 0% cover cropping (Figure 6). The photos in December, March, and May indicate no sign of cover crop emergence.

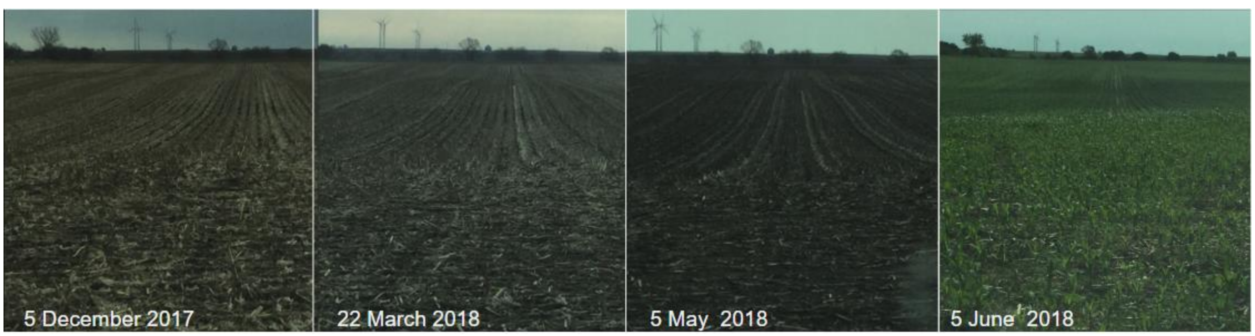


Figure 6. Roadside photos for field id 70- 443 in Iowa observed from 12/5/2017 to 6/5/2018. The 2017 crop was corn, 2017-2018 winter shows no cover crop, 2018 crop was corn.

2. Residue Cover

For residue cover evaluation, we restricted the comparison to fields for which we had:

1. valid remote sensing estimate for the field in that year (no data fraction less than 0.70)
2. multiple well-timed field visits and photos to ensure confidence in the field's residue cover status at the time of planting;

The agreement between OpTIS and field observations is 42.3%. In contrast to the cover crop evaluation, we have four classes rather than two, and misclassification can range from relatively small differences (e.g. OpTIS reports 14% residue while field observer reports 20%) to large (e.g. OpTIS reports 10% residue, field observer reports 90%). We used a weighted kappa statistic to account for differences in types of misclassification. Instances where class disagreement is most severe (e.g. "Very low" is misclassified as "High") have a weight of 16 times the cost of misclassifying in adjacent classes (e.g. "Very low" as "Low") and 4 times the cost of an in-between misclassification (e.g. "Very low" as "Moderate"). The weighted kappa statistic reported on residue cover is 0.67.

In sum, the team collected 827 valid field observations of residue cover from the springs of 2017 and 2018. We compared OpTIS-estimated residue cover to roadside-estimated residue cover in several ways. First, we note that the average residue cover from OpTIS for these 827 fields is 36.9%, while the field observed mean is 41.2% - a difference of 4.3%. The Pearson's correlation between OpTIS estimated residue cover and field estimated residue cover is 0.683. Put in other terms, OpTIS explains 46.7% of the variance observed in the field residue cover. The mean absolute deviation and root mean squared error of the OpTIS estimates are 17.5 and 21.4, respectively.

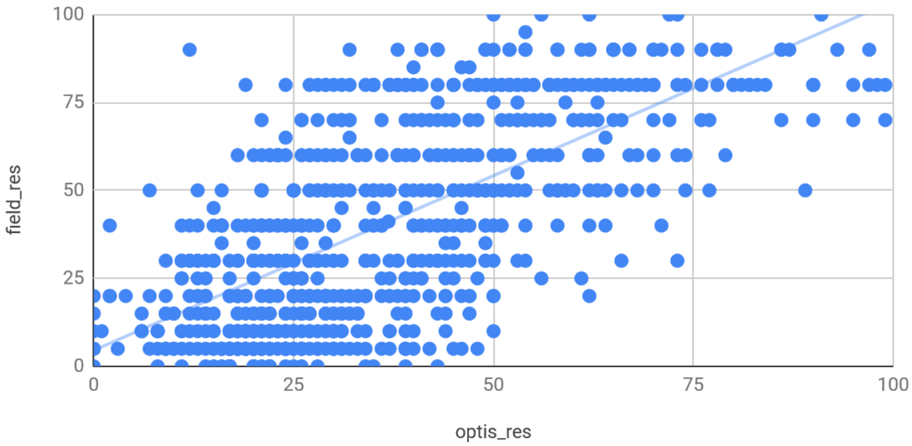


Figure 7. OpTIS and field residue cover observations has an R^2 of 0.467.

3. Misclassification and Bias

It is important to note that roadside visual estimates of residue cover are subject to error and bias. We conducted a comparison of the visual estimates of four analysts in estimating residue cover from the same set of photos taken from the roadside. We note that the Mean Absolute Deviation of these observations from four analysts across 45 fields is 12.9.

In two cases, we noted an extreme misclassification. There is an instance where a field is identified by a crop consultant as having more than 50% residue cover (no-till) was estimated by OpTIS to have less than 15% residue cover, or conventional till classification. And, a reverse case where a field survey suggests less than 15% residue while OpTIS estimated greater than 50% residue. These contradicting misclassifications represent less than 1% of the no-till and conventional tillage observations from roadside surveys and OpTIS-mapped classifications.

One of these misclassification instances is outlined below (Figure 8). The crop consultant estimated 90% residue cover in early June, as is evident from the photo from June 9, 2018. However, OpTIS-mapped estimated high residue cover until the last week of May, at which point a decrease of residue cover from 80% to 12% is identified. No apparent reason for the mismatch was discerned.

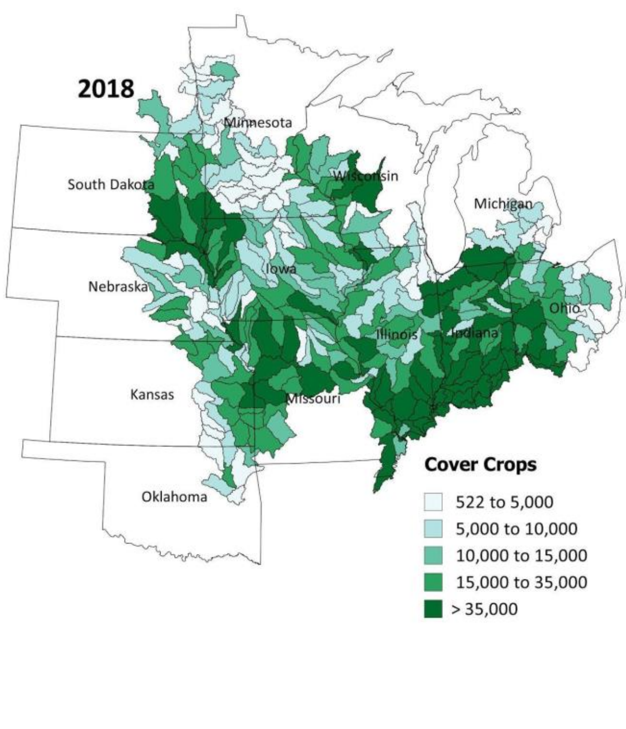
6 May 2018 9 June 2018 25 June 2018 OpTIS-mapped Residue

Figure 8. Roadside photos of field ID 86 -1751 in Missouri observed from 5/6/2018 to 6/25/2018. The 2017 crop was soybean, 2017-2018 winter shows no cover crop but extensive weed cover, and 2018 crop was soy.

B. Corn Belt Summary

1. OpTIS Corn Belt Conservation Mapping Results

In the Corn Belt as a whole, cover crops planted after corn and soy increased by 2.301 million acres in 2018 compared to cover crop acres in 2006 (Table 4). Specifically, cover crop planting went from 1.58% (1.893 million acres) to 3.34% (4.195 million acres) of corn and soy acres in the Corn Belt from 2006 to 2018. Use of conservation tillage practices, where higher than 30% residue is left on the field at planting, increased by 5.953 million acres, when comparing 2006 to 2018.



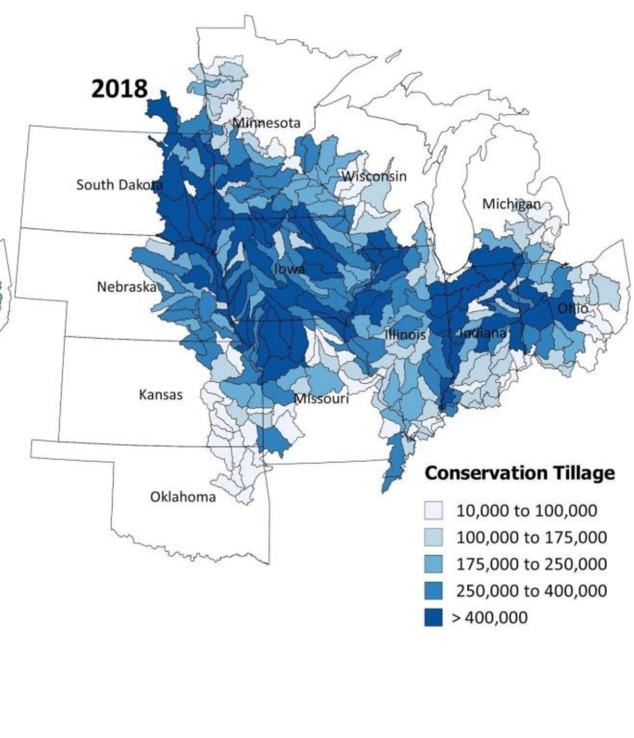


Figure 9. Conservation Tillage and Cover Crop acres across HUC8 watersheds for 2018.

Table 4. Yearly cover crops planted after soy and corn and conservation tillage acres in the Corn Belt.

Years	Cover Crop Acres	% Area of Cover Crops	Conservation Tillage Acres	% Area of Conservation Tillage
2005	1,893,988	1.58%	49,168,802	41.00%
2006	2,048,408	1.66%	55,434,967	44.90%
2007	922,791	0.77%	49,626,616	41.40%
2008	1,376,498	1.15%	59,467,349	49.90%
2009	823,177	0.69%	59,612,524	49.80%
2010	905,700	0.74%	62,026,447	51.00%
2011	1,104,235	0.90%	57,335,394	46.70%
2012	2,053,488	1.66%	60,165,458	48.70%
2013	2,461,176	1.97%	66,939,709	53.70%
2014	1,567,566	1.26%	64,525,530	51.90%
2015	1,091,400	0.88%	66,719,595	53.60%
2016	3,610,345	2.96%	54,581,100	44.70%
2017	5,047,262	4.06%	55,197,564	44.30%
2018	4,195,429	3.34%	55,122,615	43.90%

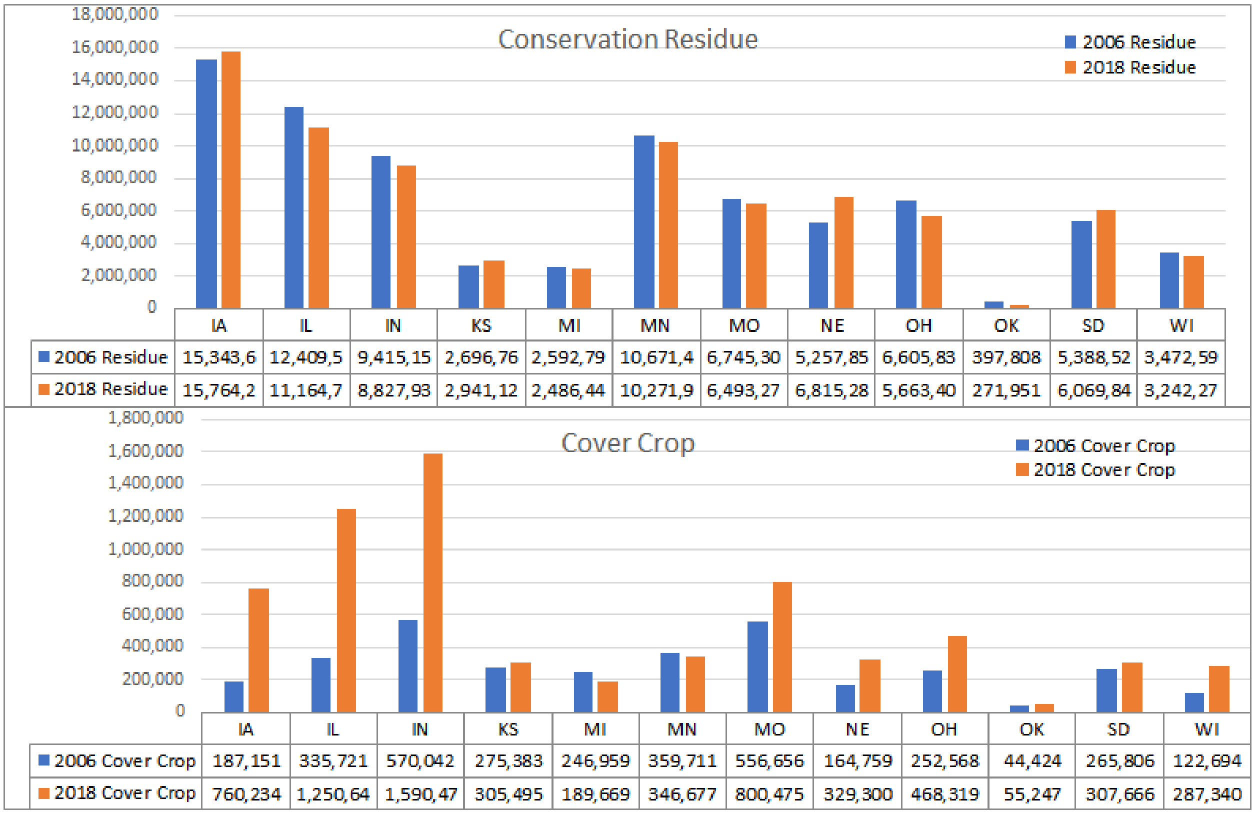


Figure 10. Comparison of statewide acres of total cover crops planted and conservation tillage practices for the years 2006 and 2018.

2. DNDC Corn Belt Results Summary: Soil Organic Carbon and Nitrous Oxide

Figure 11.A (below) shows spatial patterns of changes to soil organic carbon stocks (dSOC) by HUC8 in the US Corn Belt study area. On average, study area soils sequester SOC during the 2005-2017 timeframe - the area-weighted mean dSOC rate is 161 kgC/ha/year (weighted SD = 89 kgC/ha/year). Rates vary by HUC8 from -197 to 366 kgC/ha/year (a negative dSOC value represents a loss of SOC to the atmosphere) - most HUC8s sequester carbon on average (265 of 275 or 97%). Many factors affect changes to SOC including the distribution of crops and their management in a HUC8 (specifically in this case, a higher fraction of conservation tillage and/or cover cropping in a HUC8 will tend to increase the dSOC rate), climate, and soils, particularly initial SOC.

To demonstrate the effect of conservation practices on dSOC, we compared the OpTIS-mapped scenario with a No Soil Health Management scenario (i.e. conventional tillage all the time and no cover cropping, "no SHM"). Under no SHM, the study area would lose SOC at an area-weighted mean annual rate of -65 kgC/ha/year (weighted SD = 117) - only 38% of HUC8s sequester carbon on average (103 of 274). Figure 11.B shows differences in dSOC by HUC8 (OpTIS-mapped minus no SHM) - all differences are positive indicating that, at least at HUC8-level, on average, when soil health management practices are used, SOC sequestration is always increased. While the no SHM scenario is an extreme case and not an accurate representation of the actual distribution of management practices prior to 2005, this comparison demonstrates the benefits of SHM practices with respect to SOC sequestration as well as DNDC's ability to flexibly simulate alternative management.

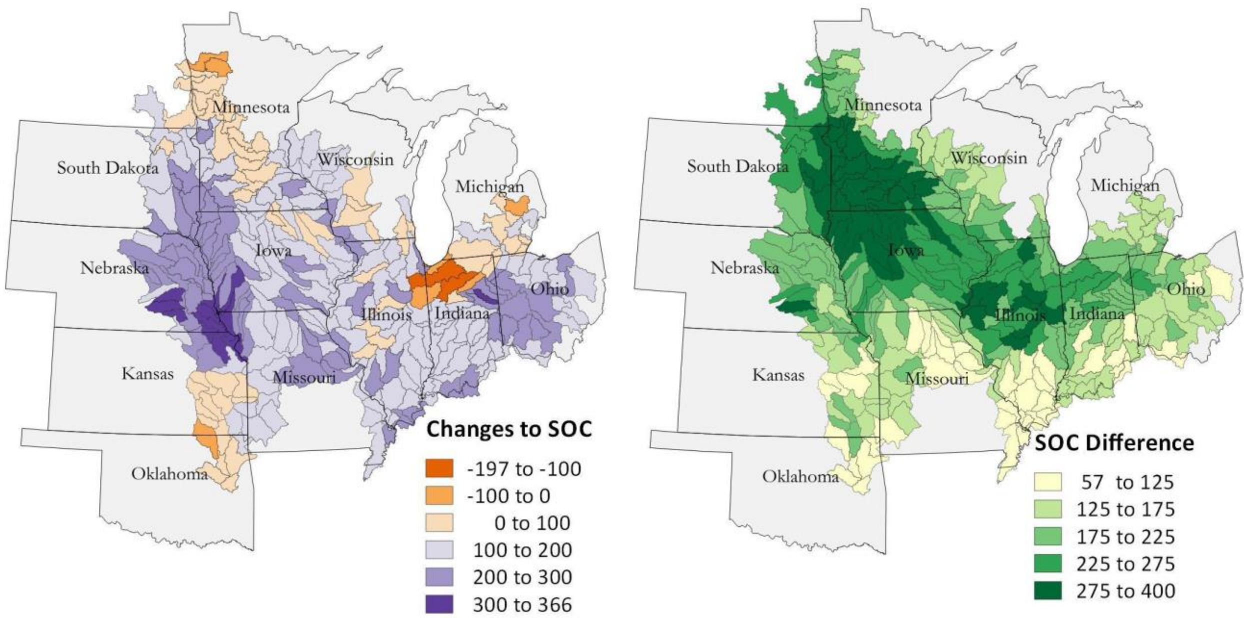


Figure 11. A) Area-weighted mean annual SOC stock change rates (dSOC, kgC/ha/yr) by HUC8 from 2005 to 2017 simulated with OpTIS-mapped management practices (negative dSOC values represent a loss of SOC); **B**) Additional mean annual SOC accumulation (kgC/ha/yr) from OpTIS-mapped management by HUC8 (compared to no soil health management practices scenario).

Mean annual nitrous oxide (N_2O) emissions from OpTIS-mapped management are shown in figure 12.A (below). Area-weighted mean annual N_2O emissions in the study area are 1.6 kgN/ha/year (weighted SD = 0.51 kgN/ha/y) - HUC8-level emissions range from 0.38 to 2.95 kgN/ha/year. The strongest predictors of N_2O rate are fertilizer N rate and soil texture although N_2O emissions are affected by numerous factors including climate (particularly typical precipitation patterns), other soil attributes (including SOC, particularly as affected by tillage), and prevalence of cover cropping.

As we did for dSOC, we compared the OpTIS-mapped scenario to the no SHM scenario (OpTIS-mapped minus no SHM - figure 12.B). Under no SHM, area-weighted mean annual N_2O emissions are 2.2 kgN/ha/year (weighted SD = 0.98 kgN/ha/y) - this scenario increases N_2O emissions for most HUC8s (262 of 274 or 96%). This increase has two likely major causes: with no cover cropping there are likely enhanced spring N_2O emissions as residual soil N tends to be higher than with cover crops; under conventional tillage N cycling tends to increase (decreased N immobilization and increased mineralization) thereby increasing N losses, particularly N_2O.

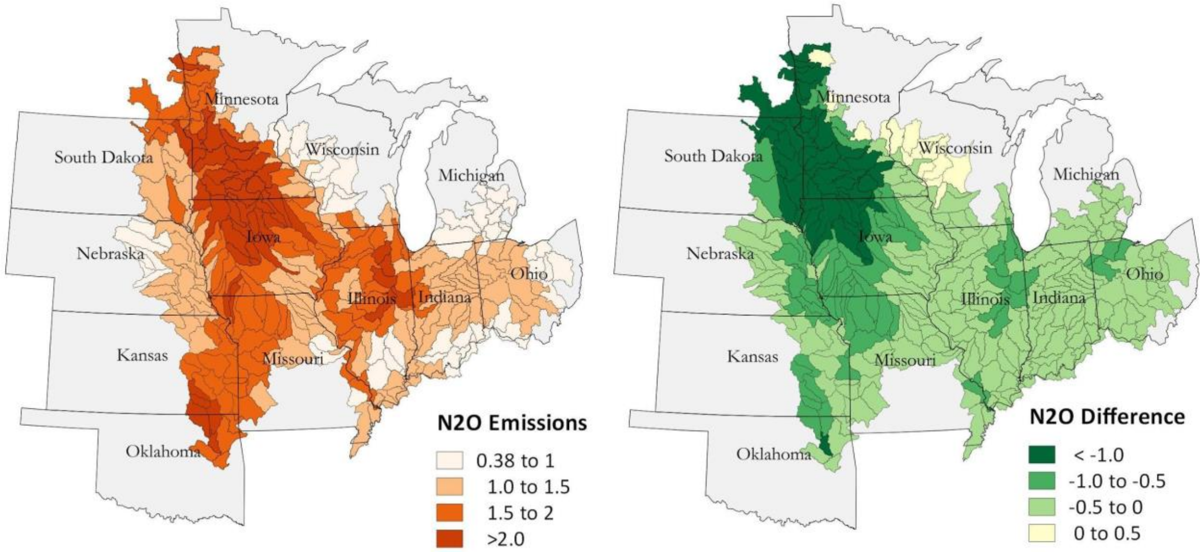


Figure 12. A) Area-weighted mean annual N_2O emissions (kgN/ha/yr) from 2005 to 2017 by HUC8 in the Corn Belt, simulated with OpTIS-mapped management practices. **B)** Difference between OpTIS-mapped management and no SHM scenario N_2O emission rates (kgN/ha/yr) between 2005 and 2017 by HUC8.

C. Iowa Summary

1. Overview

Conservation tillage remains relatively steady over the study period in Iowa, ranging from 13 m to 18 m acres. Cover crops usage begins to increase in 2014 and surges in 2016 to 2018 (Figure 13.B). OpTIS estimates of cover crop adoption will reflect weather-related impediments to crop establishment.

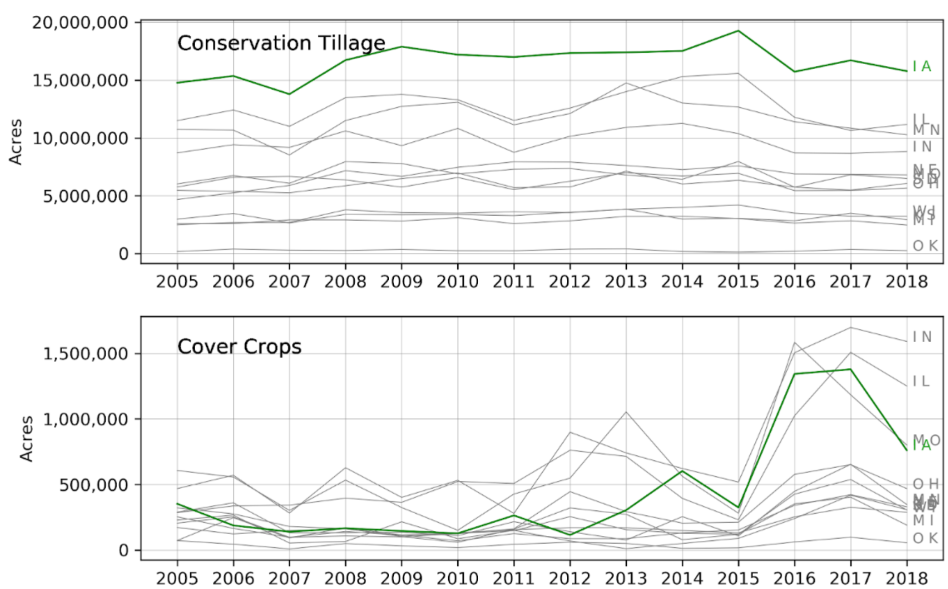


Figure 13. Implementation of conservation practices in acres from 2005 through 2018 for **A)** Conservation Tillage and **B)** Cover Crops mapped for Iowa against states in the Corn Belt.

2. OpTIS vs. Fielddata

Comparison of OpTIS-mapped and field observations (n=308) in Iowa for residue cover show a correlation coefficient of 0.65 in Iowa (0.68 across the Corn Belt) and a weighted kappa statistic of 0.67. Winter cover by OpTIS-mapped and field observations show an 89% agreement in Iowa (88% across the Corn Belt), kappa statistic of 0.68 in Iowa (0.63 across the Corn Belt)

3. OpTIS vs. AgCensus

OpTIS mapped 840,000 acres of cover crops compared to 973,000 reported in the 2017 AgCensus (Figure 14). At the county scale across Iowa, OpTIS-mapped cover crops correlate moderately well with AgCensus reported cover crops with 0.67 correlation coefficient (see section V).

OpTIS mapped 7.1 m acres of no-till compared to 8.2 m reported in the 2017 AgCensus (Figure 14). Conservation tillage mapping by OpTIS correlates well with AgCensus reported conservation tillage with a 0.80 correlation coefficient (see section V).

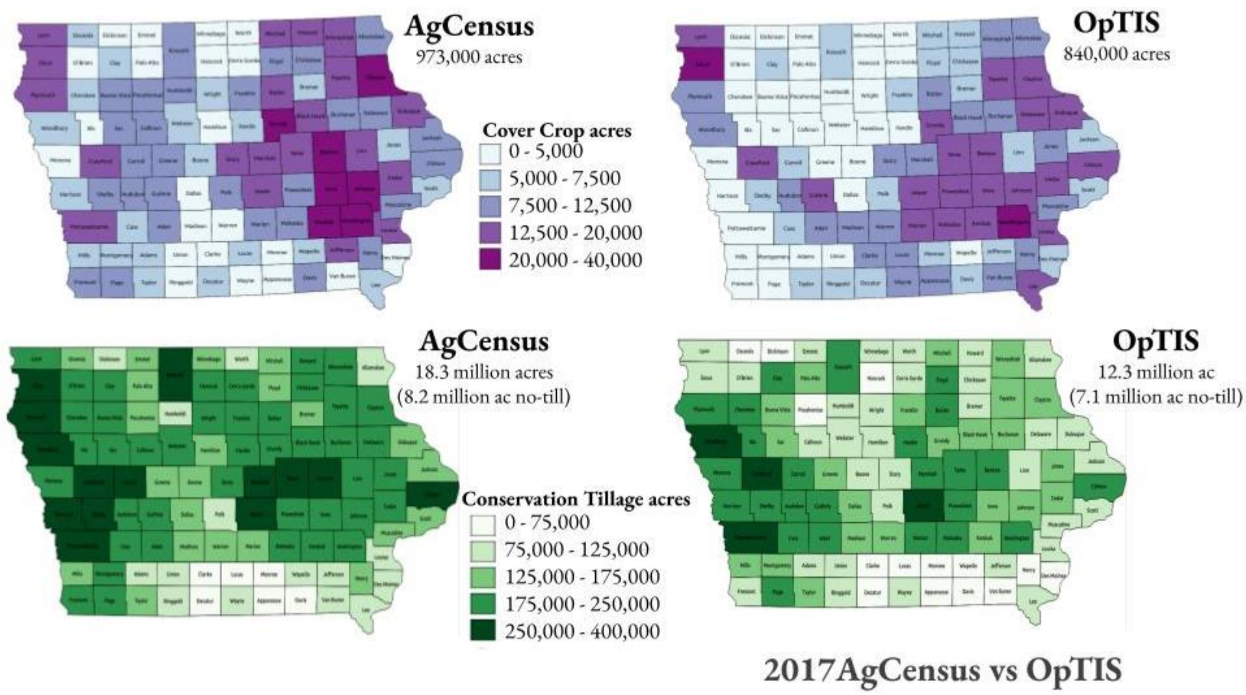


Figure 14. Comparison of AgCensus (maps on left) and OpTIs-mapped (maps on right) cover cropping (top maps) and tillage practices (bottom maps) in Iowa.

4. DNDC Iowa Results Summary: Soil Organic Carbon and Nitrous Oxide

Figure 15.A (below) shows spatial patterns in changes to SOC (dSOC) in counties in the Des Moine Lobe region. On average, these county's soils sequester SOC during the 2005-2017 timeframe— the area-weighted annual mean dSOC rate is 144 kgC/ha/year (weighted SD = 71 kgC/ha/year). Rates vary by county from 9 to 329 kgC/ha/year. When simulated with no soil health management

practices, these counties lose SOC on average (i.e. dSOC is always negative. Area-weighted mean annual dSOC is -155 kgC/ha/year, weighted SD = 44). Figure 15.B shows the spatial distribution of these differences.

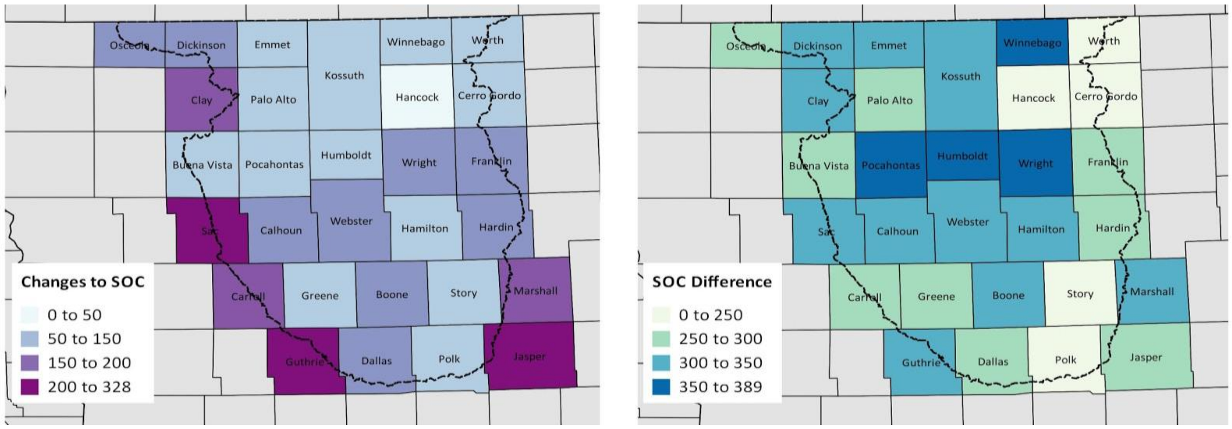


Figure 15. A) Area-weighted mean annual SOC stock change rates (dSOC, kgC/ha/yr) by county from 2005 to 2017 simulated with OpTIS-mapped management practices (negative dSOC values represent a loss of SOC); **B**) Additional mean annual SOC accumulation (kgC/ha/yr) from OpTIS-mapped management by county (compared to no soil health management practices scenario).

Area-weighted mean annual N_2O emissions for this region are 2.4 kgN/ha/year (weighted SD = 0.3) and vary from 1.5 to 3.0 kgN/ha/year (Figure 16.A). Differences in emissions between counties are likely driven by the relative assemblages of crops and soil textures (and therefore fertilizer N and residue incorporation rates) as well as the distribution of tillage regimes (given the size of the area, precipitation patterns are unlikely to have a large effect). We compared the results of the OpTIS-mapped scenario and the no soil health management scenario ("no SHM"): area-weighted mean annual N_2O emissions for no SHM are 3.6 kgN/ha/year (weighted SD = 0.7)— this scenario increases N_2O in all cases. Figure 16.B shows the distribution of county-level differences across the region.

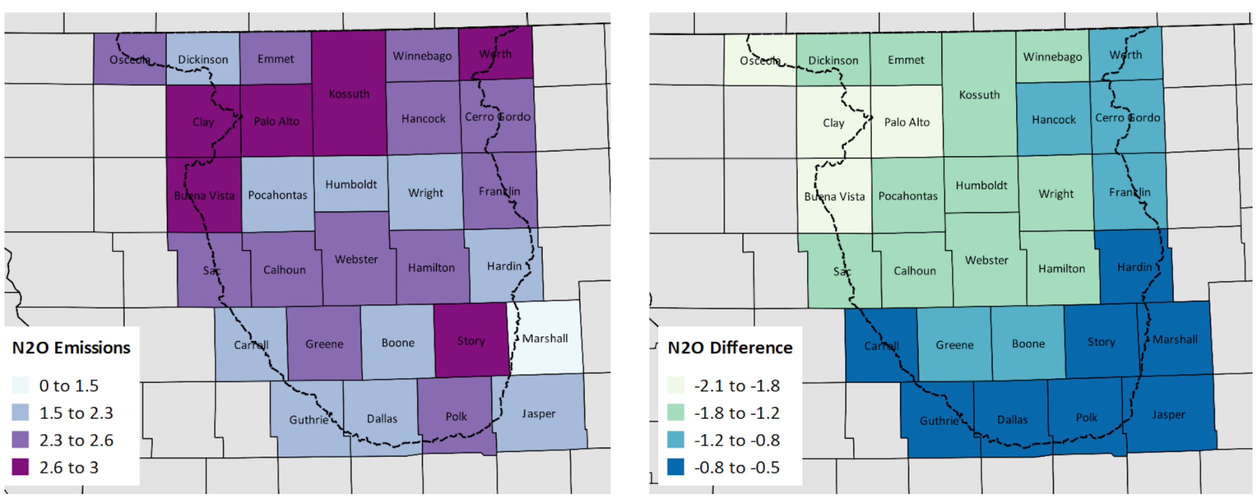


Figure 16. A) Area-weighted mean annual N_2O emissions (kgN/ha/yr) from 2005 to 2017 by county in the Corn Belt, simulated with OpTIS-mapped management practices. **B)** Difference between OpTIS-mapped management and no SHM scenario N_2O emission rates (kgN/ha/yr) between 2005 and 2017 by county.

V. Comparison with AgCensus and Other Mapping Efforts

The OpTIS mapped tillage practice and cover crop results were compared to estimates from two additional efforts at the county scale in Iowa. First, OpTIS maps of conservation tillage and cover cropping in 2017 were compared to the results of the 2017 AgCensus.

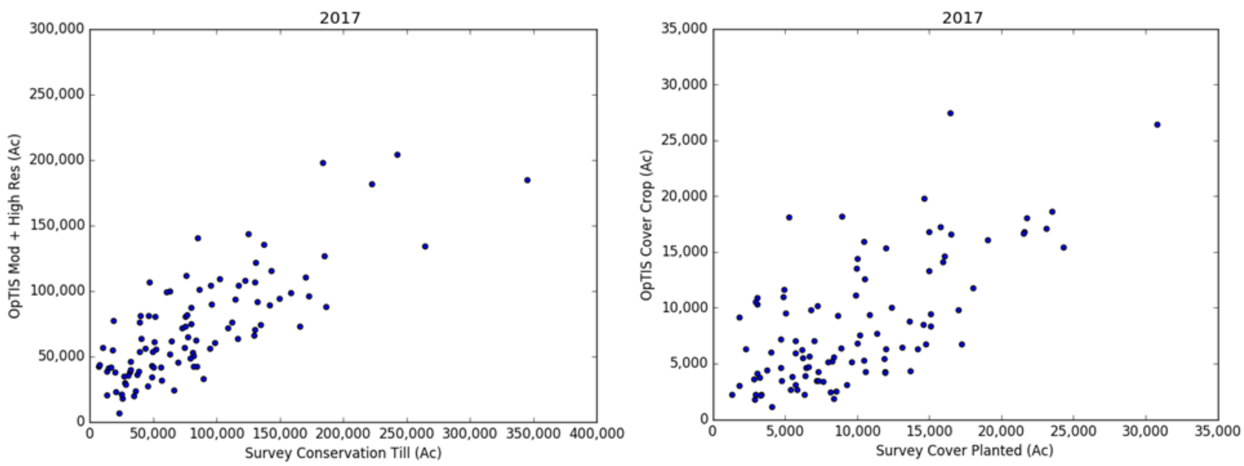
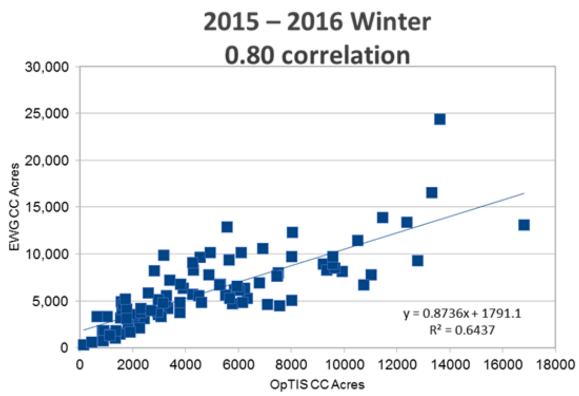


Figure 17. **A)** OpTIS mapped conservation tillage correlates well with AgCensus reported conservation tillage – 0.80 correlation coefficient; **B)** OpTIS mapped cover crops correlate moderately well with AgCensus reported cover crops– 0.67 correlation coefficient.

It is important to note that OpTIS and the AgCensus take different approaches to estimating adoption of conservation practices. OpTIS relies on data from earth observing satellites and computer algorithms, while the AgCensus relies on a complete census of growers. Therefore, OpTIS does not capture the intent of the grower, while the AgCensus might capture intent. For example, a grower can plant cover crops in the fall but a cold snap in fall and a subsequent wet spring could prevent the cover crop from establishing a full canopy. In this case, it is likely that OpTIS would not register a cover crop, while the AgCensus might.

Next, OpTIS maps of cover cropping were compared to county-level maps of cover crops produced by the Environmental Working Group (EWG) in the winters of 2015 - 2016 and 2017 - 2018.



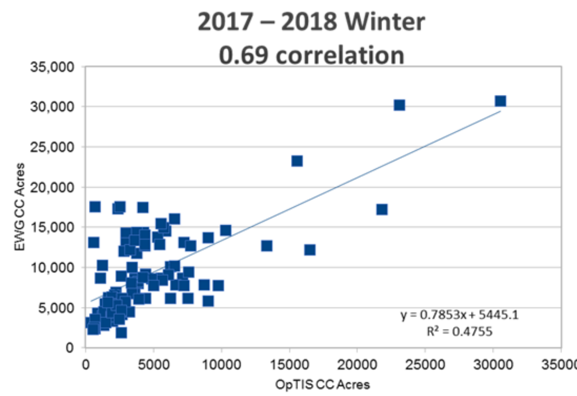


Figure 18. Comparison of county-level cover crop acreage for Iowa in 2015 - 2016 and - 2018 as estimated from two different methods: OpTIS (x-axis) and EWG (y-axis).

The two sources of estimates are significantly correlated in both years. Maps of 2017 to 2018 show a clump of outliers where OpTIS estimates low cover crop acreage (0-5,000) while EWG estimates significantly higher acreage (10,000 - 20,000).

Overall, OpTIS estimates correlate closely with estimates from other sources, but some significant county-level differences exist and should be explored.

VI. Conclusion

Farming practices have changed across the corn belt over the past decade. Conservation tillage practices continue to be implemented and expanded in some regions and the use of cover crops is growing quickly in many areas. These "soil smart" agronomic practices have a substantial effect on environmental outcomes, such as soil carbon and nitrous oxide emissions. Information from tools like OpTIS and DNDC can be used by a variety of stakeholders to better understand how row crop farming is changing and how these changes are affecting the soil, water, and atmosphere.

VII. Acknowledgments

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- Data collection for validation was conducted by more than 25 crop consultants and advisors who were identified with the help of the American Society for Agronomy's online database and through the Soil and Water Conservation Districts.

- Several organizations provided support for an OpTIS pilot project across the state of Indiana in 2015-16 through which feasibility for this corn belt study was established. This report is available at http://optis.ags.io/documents/47/OPTIS_201701.pdf.

- The Indiana Department of Agriculture provided time and support for the Indiana Pilot Project (http://optis.ags.io/documents/47/OPTIS_201701.pdf) and contributed continuing field data for multiple seasons for this project.

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