# Mapping Conservation Management Practices and Outcomes in the Corn Belt Using the Operational Tillage Information System (OpTIS) and the Denitrification–Decomposition (DNDC) Model

**Stephen C. Hagen** [1,*], **Grace Delgado** [1], **Peter Ingraham** [1], **Ian Cooke** [1], **Richard Emery** [2], **Justin P. Fisk** [1], **Lindsay Melendy** [1], **Thomas Olson** [1], **Shawn Patti** [1], **Nathanael Rubin** [1], **Beth Ziniti** [2], **Haixin Chen** [2], **William Salas** [1,2], **Pipa Elias** [3] and **David Gustafson** [4]

[1] Dagan Inc., Applied Geosolutions, Durham, NH 03824, USA; gdelgado@daganinc.com (G.D.); pingraham@daganinc.com (P.I.); icooke@daganinc.com (I.C.); jfisk@daganinc.com (J.P.F.); lmelendy@daganinc.com (L.M.); tolson@daganinc.com (T.O.); spatti@daganinc.com (S.P.); nrubin@daganinc.com (N.R.); wsalas@daganinc.com (W.S.)

[2] Applied Geosolutions, LLC, Durham, NH 03824, USA; remery@appliedgeosolutions.com (R.E.); bziniti@appliedgeosolutions.com (B.Z.); hchen@appliedgeosolutions.com (H.C.)

[3] The Nature Conservancy, Arlington, VA 22203, USA; pipa.elias@tnc.org

[4] Conservation Technology Information Center, West Lafayette, IN 47906, USA; gustafson@ctic.org

* Correspondence: shagen@daganinc.com

**Abstract:** Identifying and quantifying conservation-practice adoption in U.S. cropland is key to accurately monitoring trends in soil health regionally and nationally and informing climate change mitigation efforts. We present the results of an automated system used across 645 counties in the United States Corn Belt from 2005 to 2018, mapped at field-scale and summarized for distribution at aggregated scales. Large-scale mapping by OpTIS (Operational Tillage Information System), a software tool that analyzes remotely sensed data of agricultural land, provides trends of conservation tillage (defined as >30% residue cover), cover cropping, and crop rotations, while modeling by DNDC (Denitrification–Decomposition), a process-based model of carbon and biogeochemistry in soil, provides estimates of the ecosystem outcomes associated with the changes in management practices mapped by OpTIS. Ground-truthing data acquired via OpTIS mobile, a roadside field-surveying app, were used for verification in 30 counties. OpTIS results for the Corn Belt show adoption of cover crops after planting corn and soy increased from 1% to 3% of the mapped area when comparing 2006 to 2018. Comparison of trends for conservation tillage use from 2006 to 2018 shows a slight decrease in conservation tillage adoption, from 46% to 44%. Results from DNDC show these soils sequestered soil organic carbon (SOC) at an area-weighted mean change in SOC (dSOC) rate of 161 kgC/ha/year. Comparatively, in a scenario modeled without the adoption of soil health management practices, the same soils would have lost SOC at an area-weighted rate of −65 kgC/ha/year. As many factors affect changes to SOC, including climate and initial SOC in soils, modeling counterfactual scenarios at the field scale demonstrates outcomes of current soil health management in comparison to regional management practices and best management practices, with respect to SOC sequestration. Regional trends in adoption rates of conservation agriculture and resulting soil health implications are of great use for a wide range of stakeholders. We demonstrate the capability of OpTIS remote sensing to deliver robust, large-scale, multi-sensor, ground-verified monitoring data of current and historical adoption of conservation practices, and of DNDC process-based modeling to provide assessments of the associated environmental outcomes across regions in U.S. cropland.

**Keywords:** carbon sequestration; climate change mitigation; conservation tillage; cover crop; DNDC model; OpTIS; regenerative agriculture; remote sensing; soil carbon modeling; soil health

## 1. Introduction

In 2019, atmospheric $CO_2$ levels reached a level not seen at any point in the past 800,000 years [1]. $CO_2$ absorbs less heat per molecule than methane ($CH_4$) and nitrous oxide ($N_2O$), but it is more abundant in the atmosphere, therefore it contributes proportionally more (about two-thirds) of the total energy imbalance causing the Earth's temperature to rise [1]. Soils and soil management play an important role in climate change mitigation as soil carbon (C) sequestration increases the ability of soils to hold soil moisture, withstand erosion and enrich ecosystem biodiversity, while cultivation through intensive agricultural management releases soil C in the form of $CO_2$ into the atmosphere [2]. In 2015 it was estimated that soil conservation practices have the potential to sequester 20 PgC in 25 years, more than 10 percent of anthropogenic emissions [2]. Land management practices affect soil C dynamics with agricultural soils presenting both an opportunity for C storage through regenerative agriculture techniques and the potential for loss of soil organic carbon (SOC) with cultivation and soil degradation [3,4]. The importance of land management decisions to mitigate emissions from U.S. cropland has continued to increase as agricultural production grows, with 247 million acres (99 million ha) dedicated to cropland in the United States in 2019 [5]. Conservation agriculture is a suite of practices that include cover crop planting, residue and tillage conservation management, and crop rotations [6]. Understanding the historical use of these practices and implementation rates of conservation agriculture is key for conservation programs to accurately assess the effectiveness of outreach with individual landholders or at scale in counties, watersheds, or states [6]. Remote sensing is an efficient method to monitor the adoption of these C building techniques in soils, but accurate, timely and high-resolution mapping of adoption rates has been of limited geographic and temporal scope [7]. There still remains a critical need for spatially comprehensive maps of current and historical conservation agriculture adoption trends. In addition to the monitoring of conservation management techniques, modeling agricultural greenhouse gas emissions from these areas will allow stakeholders to better characterize C cycling in agricultural soils and monitor the impact of restorative agricultural practices on soil health.

Applied Geosolutions, LLC and Dagan, Inc. worked with the Conservation Technology Information Center and The Nature Conservancy and other partners to explore the history of conservation agriculture in row crops and model the associated environmental outcomes in the Corn Belt with the application of two technologies, the Operational Tillage Information System (OpTIS) and the Denitrification–Decomposition model (DNDC). This work utilized satellite data to monitor agricultural practices like no-till and the use of cover crops and paired this with biogeochemical models to estimate the impacts of management on soil C and greenhouse gas (GHG) emissions. OpTIS was used to produce spatially comprehensive maps of crop residue cover, cover crops, and crop rotations using information integrated from multiple Earth-observing satellites. Integrating data from multiple sources of Earth-observing satellites and parameterizing in an automated fashion allows for coverage of wide geographic areas at field level resolution. OpTIS-based mapping results for residue cover, cover cropping, and crop rotations were used as input to the DNDC model. DNDC is a biogeochemical modeling technology that quantifies changes in soils including GHG and C, given a range of weather, soil characteristics, and management conditions.

Remote sensing by OpTIS provides trend and snapshot data on the adoption of regenerative agriculture techniques, which is vital to managing conservation incentives and markets for ecosystem services, while DNDC simulates the effects of these practices and estimates the ecosystem and soil health benefits of conservation agriculture. In this paper, we present the results of a novel large spatial–temporal scale use of earth-observing remote sensing data to map and monitor the adoption rates of conservation management techniques, and model C dynamics associated with these conservation management practices.

## 1.1. Background of Conservation Management

Soil disturbance and residue cover management practices are key components of conservation agriculture. It has been demonstrated that conventional tillage in intensive agriculture has a large impact on water quality as soil disturbance makes soil and soil nutrients susceptible to leaching and run-off [8]. Efficacious sustainable agriculture systems rely on conservation management of residue and tillage, making use of no-till practices; planting in narrow slots or tilled strips established in the untilled seedbed of the previous crop, and reduced till practices; planting with residue left on the soil surface year-round with limited soil-disturbing activities such as using vertical tillage, chiseling, and disking [9]. Conservation tillage is a commonly-used "catch-all" term to describe numerous tilling practices that leave at least 30% crop residue on the soil surface (www.ctic.org) before planting.

Cover crop planting has demonstrated numerous benefits, including erosion control, increase in soil fertility, sequestration of organic matter, improvement in overall soil health, increase in populations of pollinators, beneficial effects on water quantity and quality, and attenuation of sediment movement and nutrient leaching [10]. Insight from U.S. farmers on the use of cover cropping highlights increased motivation in cover crop use stemming from other benefits like weed control, increased moisture retention, livestock grazing, and reduced input costs with respect to fertilizer use [11].

Incentives established by federal, state, and county or watershed government entities via cost-share programs that fund the implementation of conservation management are important as they facilitate and encourage the adoption of cover crops as well as residue and tillage conservation management for sustainable food production. For example, since 2009, funding via the Environmental Quality Incentives Program (EQIP) by the U.S. Department of Agriculture (USDA) Natural Resources Conservation Services (NRCS) has provided consecutive annual payments to allow farmers time to gain experience with operation changes to implement conservation practices [12]. These programs are essential to building a soil health legacy, as it has been demonstrated that limiting soil disturbance, maintaining residue in fields, and utilizing cover crops has the potential to increase C sequestration within agricultural soils, as shown by the monitoring of C dynamics on experimental plots [13–15].

## 1.2. Remote Sensing of Conservation Management

A review of agricultural practice mapping found the majority of cover crop and soil tillage studies are tested at small scales, often on fields or watersheds, and are highly dependent on ground data [7]. The use of satellite remote sensing in combination with farm program data can provide important information to the scientific community and inform conservation programs that seek to improve the use of conservation resources and resource protections [16]. Initial remote sensing of tillage was through limited studies to verify no-till on non-planted fields to reduce the crop canopy interference effects [17–19]. To infer tillage, indices like the Simple Tillage and Normalized Difference Tillage Index are used because they are sensitive to changes in water content, cellulose, and lignin, and can detect crop residue cover left in a field [20,21]. The use of validation with intensive transect datasets has shown that conservation tillage mapping accuracy can be as high as 95%, but the timing of imagery is critical because no-till practices can be difficult to differentiate when fields are covered with more than 30% crop foliage. Additionally, the timing of imagery in relation to the timing of management operations can be a primary cause of errors in the mapping of tillage practices with Landsat [22,23]. Recently, in a large-scale study that applied yearly mapping of no-till on soybean fields for the North Central U.S. region using the computational power of Google Earth Engine combined with a survey-based dataset on tillage practices, results show high classification accuracies, they also highlight the value of Landsat imagery and use of ground-based surveys to enable large-scale predictions [24].

Integration of ancillary information like field boundaries can provide useful context and increased accuracy in the classification of land cover attributes, as demonstrated by Watts and others [25]. This approach improves classifications of crops and tillage as it enables field-level rather than pixel-based classifications, and highlights the need to integrate multi-temporal imagery for

characterizing tillage intensity and rotations. Classification of agricultural land and crop type mapping at the field-scale has been shown to perform well, but findings show a need for custom creation of land use maps as seasonal or multi-year mapping made on-demand to better serve agricultural land monitoring applications [26]. Remote sensing classification techniques for winter cover crop mapping have successfully used NDVI to estimate fractional cover of winter cover crops, particularly before senescence and winter kill affect the canopy [16,27]. Similarly, biomass can be reliably estimated from NDVI at lower levels before saturation occurs [19].

Limitations on current methods for routine regional mapping of tillage practices with high-resolution data alone are due to long revisit periods and high cloud cover probabilities [28], combined with the dynamic nature of the tillage process (i.e., not every farmer in an area tills at the same time). The timing of Landsat image acquisition is limited by a 16-day repeat overpass. Sentinel 2 optical imagery from the European Space Agency provides Landsat-quality information or better, with a repeat overpass time of 5 days, with both sensors are in orbit. We designed and executed methods to generate accurate tillage maps using Landsat, Sentinel, and MODIS remote sensing imagery in an operational context. The use of multiple sensors is key because it can provide better temporal coverage, reduces the risk of catastrophic failure of the system if a single sensor is lost. Along with the integration of data from multiple satellite sensors, we integrate field boundaries to summarize pixel-based analyses of conservation agriculture at the field-level.

### 1.3. Modeling of Conservation Management

Process-based biogeochemical models, like the DNDC model, have been developed to extrapolate the measurements at specific sites and during specific periods to large regions or over extended time spans. These models play an important role in understanding nutrient cycling, predicting crop yield, and identifying outcomes of conservation management practices. The dynamic nature of DNDC and other process models allows for the simulation of interdependent processes and the scaling up of field studies focused on GHG and nutrient flux; process-based models can simulate the effects of crop management across wide areas thus reducing or eliminating the costs of field observation. In addition, these models make it possible to compare actual to counterfactual (alternative) management practices to evaluate their effectiveness for greenhouse gas mitigation or other beneficial soil health practices.

The DNDC model [29–31] was developed to simulate C and N dynamics in agroecosystems. It has been widely used to simulate soil climate, crop yields, soil C sequestration, soil N concentration, water and N leaching, and GHG emissions from both upland and wetland agricultural ecosystems during the last three decades [32–35]. DNDC runs on sub-daily to daily time steps and consists of two components. The first component, consisting of the soil, climate, crop growth, and decomposition sub-models, predicts crop growth and soil environmental factors (i.e., temperature, moisture, pH, redox potential and substrate concentration). The second component, consisting of the nitrification, denitrification, and fermentation sub-models, simulates emissions of $CO_2$, $CH_4$, $NH_3$, $NO$, $N_2O$ and $N_2$ using the soil environmental factors that are predicted by the first component. Physics, chemistry and biology dynamics, as well as empirical equations generated from laboratory studies, have been incorporated in the model to parameterize each specific geochemical or biochemical reaction [36–39].

For this study, we used the DNDC model "out of the box" as it has been extensively evaluated against datasets of SOC and GHG fluxes that were measured worldwide [32–35]. For instance, DNDC has been tested against long-term SOC field data in five sites from the USA, UK, Germany, Australia, and Canada by Li et al. [40] and by Zhang et al. [41], under conservation agriculture and cover crop practices in Italy by Camarotto et al. [42], and under diversified crop rotations in Canada by Jarecki et al. [43]. Morrow Plots, the oldest agronomic research plots in the USA, were used to validate the DNDC by both Li et al. [40] and Zhang et al. [41]; the results showed that both field and modeled data had consistent SOC dynamics, that SOC firstly decreased rapidly from 1904 to 1955 then approached equilibrium from 1955 to 1990. Jarecki et al. [43] also reported that the modeled and observed SOC were in good agreement at both sites in Canada, with differences ranging from

0.39 to 4.1 Mg C ha$^{-1}$. DNDC has also been validated against N$_2$O flux and N leaching measurement data in North America (i.e., USA and Canada), Europe (i.e., Belgium, UK), and East Asia (i.e., China, Japan, and Thailand) [44–51]. In addition, our previous study has compared the not-validated DNDC simulations of N$_2$O emissions and N leaching in the Corn Belt with 56 peer-reviewed field studies of similar interventions, and the results showed that those simulations were consistent with the meta-analysis of Midwest corn N$_2$O mitigation potential [52].

Since both SOC and N$_2$O emissions were well-validated in North America [40–48], and the "out of the box" approach has demonstrated its consistency with field studies [52], we believe that our approach and use of the model is reasonable in this case. In this study, we used the DNDC model to estimate the impacts of conservation management practices on SOC dynamics and N$_2$O emissions across 645 counties in the Corn Belt from 2005 to 2018, based on OpTIS mapping results. Our objective with this study was not to validate DNDC against field data in one or a handful of sites within the area; rather, this study aimed to assess the overall effects of conservation management on soil C and N across the whole region (i.e., the Corn Belt).

## 2. Methods

### 2.1. Study Area

The study area was created based on Land Resources Region-M (LRR-M; Central Feed; Grains and Livestock Region), an area that extends across the Corn Belt region of the United States. Counties intersecting the LRR-M were selected for the study area; in some cases, counties adjacent to but outside of LRR-M with a large corn area (>5000 acres or >2023 ha) and of substantial national interest were added; in other cases, counties with low row crop area were removed. Figure 1 shows this region encompasses 12 states, three complete statewide coverage in Iowa, Illinois, and Indiana, and nine partial coverage states for Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, Oklahoma, South Dakota, and Wisconsin.



**Figure 1.** Mapping by the Operational Tillage Information System (OpTIS) was done on 645 counties (yellow), and 2748-digit hydrologic unit code (HUC 8) watersheds (black outline). Watersheds within the Land Resources Region-M only were selected, this area covers 12 states in the Corn Belt.

*2.2. Aggregating and Reporting*

The project time period covered 2005 to 2017 crop years. In addition, we provide OpTIS results from the 2018 crop year. A crop year in this project was defined as 1 November of the previous year through 31 October of the current year (i.e., the 2005 crop year extends from 1 November 2004 through 31 October 2005).

We summarized OpTIS-mapped management practices at four geographic scales: county, crop reporting district (CRD), watershed, and state. CRD is defined by the National Agricultural Statistical Services (NASS). We defined watershed boundaries as determined by the USGS 8-digit hydrologic unit code (HUC 8) [53]. Areas selected for mapping were counties with a minimum of 75% area overlap with a HUC 8 in the study area, CRDs with at least two qualifying counties, and states with at least one reported HUC 8 contained entirely within the state. In total, we included 12 states, 274 HUC 8, 70 CRDs, and 645 counties. The input data used in OpTIS mapping and DNDC modeling are shown in Table 1.

For each management practice, we report the 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 were adjusted to the total adjusted segment area in geography—we assume that the distribution of practice classes among segments with no data are the same as those with data.

**Table 1.** Data used in OpTIS mapping of tillage practices, cover crops, and crop rotations, as well as for Denitrification–Decomposition model (DNDC) simulations of soil C, greenhouse gas (GHG) emissions, available soil moisture, and N leaching.

| Data Product | Technology | Source | Website/Access |
|---|---|---|---|
| Landsat | OpTIS | USGS/NASA | https://earthexplorer.usgs.gov/ |
| MODIS | OpTIS | NASA | modis.gsfc.nasa.gov/data/ |
| Sentinel 2 | OpTIS | ESA [54] | sentinel.esa.int/web/sentinel/sentinel-data-access |
| PRISM | OpTIS & DNDC | Oregon State University [55] | http://www.prism.oregonstate.edu/ |
| Cropland Data Layer (CDL) | OpTIS & DNDC | USDA [56] | www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php |
| MIrAD-US | DNDC | USGS | https://earlywarning.usgs.gov/fews/search |
| N deposition | DNDC | NADP [57] | http://nadp.slh.wisc.edu/ntn/ |
| Annual survey, crop yield, fertilizer, harvested acres, irrigated status | DNDC | USDA NASS [58,59] | quickstats.nass.usda.gov/ |
| Fertilizer type | DNDC | USDA ERS [60] | https://www.ers.usda.gov/data-products/fertilizer-use-and-price/ |
| Plant and harvest dates | DNDC | USDA NASS [61] | Field Crops, Usual Planting and Harvesting Dates, October 2010—Agricultural Handbook Number 628 |
| SSURGO | DNDC | USDA NRCS [62] | www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053628 |
| Atmospheric $CO_2$ | DNDC | Scripps Inst. Of Oceanography [63] | http://scrippsco2.ucsd.edu/data/atmospheric_co2/primary_mlo_co2_record |
| Crop biomass data | DNDC | Sustainable Corn Coordinated Agricultural Project (CAP) Team Research Data [64] | https://datateam.agron.iastate.edu/cscap/ |

The fundamental unit of analysis by OpTIS and DNDC was 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) [56]. CDL is a raster geo-referenced land cover map by the USDA, each 30 m pixel identifies one of 132 varieties of class types from cropland to non-cropland. We define a field segment using CDL data since 2008 and not 2005 as CDL availability is not universal prior to 2008. Crop area was lost due to the filtering of field segments to exclude fields smaller than 10 acres (4 ha) from analysis, and where fields are adjacent to roads they were 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 this "edge erosion" and minimum field size, we calculated and applied a HUC 8 area-adjustment factor to adjust the reporting size of each field segment. The adjustment factor was calculated as the total CDL pixel crop area divided by the total segment crop area within each HUC 8. The reported area of each segment within the HUC 8 was calculated as segment area times HUC 8 adjustment factor. More than 1.7 million segments were analyzed as part of this project.

*2.3. OpTIS Remote Sensing*

OpTIS algorithms use multi-temporal optical satellite observations sourced from multiple platforms, including MODIS sensors on Terra and Aqua, Landsat 5, Landsat 7, Landsat 8, Sentinel 2A, and Sentinel 2B. Imagery is cloud masked and re-projected onto a 30-meter grid in Albers Equal Area projection, and precipitation from PRISM [55] is used to account for soil and crop residue moisture effects in imagery. Median plant and harvest dates are estimated at the HUC 8 level each year using a time series of MODIS NDVI observations. These dates are used to parameterize OpTIS residue cover and cover crop mapping.

2.3.1. Residue Cover

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 HUC 8 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: very low (0–15%), low (16–30%), moderate (31–50%), and high (51–100%).

2.3.2. Winter Cover

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 are compared to threshold sets at the HUC 8 scale to determine cover status. Each pixel is classified into one of two classes: (1) no winter cover—less than 30% of the field area has green cover in the winter, (2) winter cover—at least 30% of the field area has green cover in the winter. The winter cover on each field is further classified using information from CDL into winter commodities (i.e., winter wheat) or perennial (i.e., alfalfa).

2.3.3. Mapping Scale

Mapping by OpTIS is parameterized and executed at the HUC 8 watershed scale, the 8-digit USGS Hydrologic Unit Code for sub-basin level watersheds. The list of HUC 8 features included in the analysis was determined by HUC 8 boundaries that intersect the LRR-M, except where there are less than 5000 acres (2023 ha) of row crop agriculture, and additional HUC 8s were added in areas of interest near Lake Erie. Within the total of 274 HUC 8 watersheds included in the analysis, we used CDL land cover types to mask out areas with permanent grasslands and pasture, and areas converted to or from row crop agriculture during the study time period. Areas growing alfalfa or hay for fewer than six years of the study period were included in the analysis.

*2.4. OpTIS Verification Data*

Ground-level verification photo and survey data were collected at agricultural field locations across 30 regions in the Corn Belt. Initially, data collection in the spring of 2017 was done via Excel tables filled out by crop consultants during field visits in two counties, Cresco County, Iowa and Christian County, Illinois. Starting in the fall of 2017, the development team at Applied Geosolutions with funding from The Nature Conservancy launched the OpTIS Mobile app for Android and iOS platforms. Field observations were collected via OpTIS Mobile in the fall of 2017 and the spring of 2018. Ground validation was done in 43 counties in ten states in the Corn Belt (Figure 2). OpTIS Mobile was designed for roadside survey data collection by a crop consultant while minimizing errors associated with repeated data transcription from spreadsheets to a database or from tracking photo numbers, dates, and field locations. Over 90% of the field data used for validation in this project were collected using OpTIS Mobile.
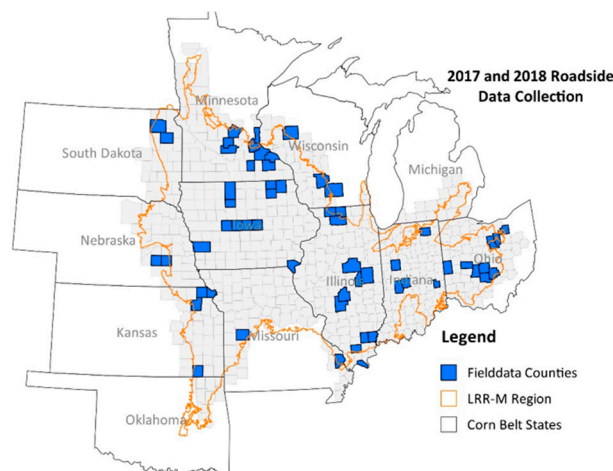


**Figure 2.** A total of 59 counties were surveyed (blue), and 30 counties were used in verification for the Land Resources Region-M (LRR-M) region (orange line) in 2017 Fall (278 fields) and 2018 Spring (1195 fields).

2.4.1. Crop Consultants

We identified independent crop consultants via the National Alliance of Independent Crop Consultants website directory (https://naicc.org/), the American Society of Agronomy website directory (https://www.agronomy.org/), and through personal references of district employees at state Natural Resources Conservation Services (NRCS), the OSU Extension at Ohio State University, and the Indiana State Department of Agriculture. Consultants were asked to visit 40 fields and conduct up to 6 repeats per season. The OpTIS team selected 15–20 of the 40 fields and consultants were tasked with identifying the remaining set of 20–25 additional fields with evidence of conservation tillage or cover cropping and adding these by digitizing them via the app (Figure 3). Requirements were to select large fields (~100 acres; 40 ha) following corn or soy crops within approximately a 30 min driving radius from their home address. The cluster of fields was 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.
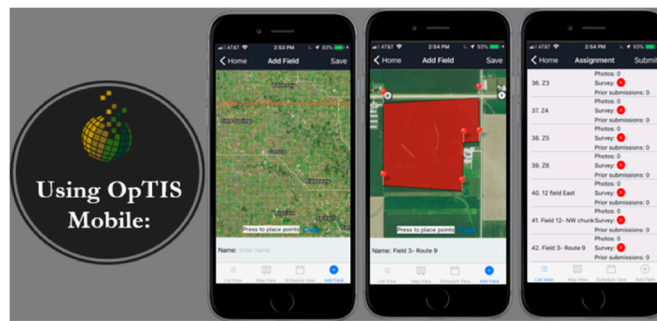
**Figure 3.** Schematic for identifying and drawing an agricultural field in the OpTIS mobile map screen.

### 2.4.2. OpTIS Mobile Surveys

To ensure consistency of data collection, we used a single generic survey in OpTIS mobile to capture observations of cover crop and tillage status. Roadside surveys included capturing crop photos, field location in the form of point coordinate from where the field was observed, as well as field boundary added manually by the data collector, observation date and time, and direction in which the observer faced to view the field from the roadside (N, S, E, W). Roadside visual estimates of green and residue cover, rounded to the nearest 5% were recorded in the surveys, as well as crop type from the previous year and the current year, if evident. Tillage practice observations including the type of tillage performed and estimated soil disturbance were collected. The presence, type, and health of the cover crop and the presence of volunteer crops or weeds were also recorded. Lastly, broad estimates of soil moisture levels and color were also gathered.

Our team implemented quality control steps on the data submitted by consultants. We reviewed and edited 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. Confirmed the photo and observation geolocation matched that of the field boundary drawn. Removed duplicate submissions (technical issues led to duplication of data. Assigned categorical answers per field for the previous and coming year's crop, tillage and cover crop. Additionally, we performed a quality check fractional green, soil, residue cover in the survey compared to visual evidence in survey photos.

### 2.5. DNDC Modeling

### 2.5.1. Inputs and Assumptions

Input data of area-weighted mean soil attributes were calculated for each segment using the NRCS SSURGO database (Soil Survey Staff, 2018). 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 SOC by dividing organic matter by 2 [65].

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 [61]. 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 United States [60]. Fertilizer rates used are based on state-based rates disaggregated to county-level based on mean reported yields [60]. 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 [66].

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 [67] 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.

### 2.5.2. 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 [58] 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 [64]. 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.

### 2.5.3. 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 from 2000 to 2004 were not included in summarized results.

### 2.5.4. Post-Processing

DNDC modeling results for daily SOC, $N_2O$, available soil water capacity (AWC), and $NO_3$ leaching were extracted from 2005 to 2017 simulated results and converted to annual values. The annual 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 is not a direct output of DNDC, however, we calculated the AWC values based on changes to SOC using equations given in Saxton and Rawls [68]. AWC was calculated as the mean daily AWC for the crop year. Spatially aggregated summaries, for the county, crop reporting district,

HUC 8, 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.

**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 CC | Second alternative scenario assumed no cover cropping |
| All ConvTill & No CC | Third alternative scenario combined the first two alternative scenarios Simulated conventional tillage and no cover cropping across all years |

## 3. Results and Discussion

Row crop fields totaling 131,605,000 acres (53,258,653 ha) 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.

In the Corn Belt as a whole, cover crops planted after corn and soy increased by 2.301 million acres (0.93 million ha) in 2018 compared to cover crop acres in 2006 (Table 4). Specifically, cover crop planting went from 1.58% (1.893 million acres; 0.766 million ha) to 3.34% (4.195 million acres; 1.70 million ha) of corn and soy acres in the Corn Belt from 2006 to 2018. Use of conservation tillage practices, defined by residue cover greater than 30% left on the field at planting, increased by 5.953 million acres (2.41 million ha), when comparing 2006 to 2018.

A range of residue cover within the residue classes was chosen to allow for consistency in matching with historical CTIC Crop Residue Management Survey data. We also report on assumed tillage practices linked with four residue levels, derived from the residue cover levels and previous year's crop (i.e., residue type). Conventional tillage—same as very low residue cover level (0–15%) for all previous year crop types. Reduced tillage, low residue—same as low residue cover (16–30%) for all previous year crop types. Reduced tillage, high residue—moderate residue cover (31–50%) where corn was the previous year's crop. 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.

### 3.1. Remote Sensing Validation

Comparison between roadside surveys and OpTIS estimates for (1) cover crop and (2) residue cover provides an understanding of the utility and limits of this satellite-based technology. We conducted validation with field verification data if there were valid remote sensing estimates for the field, defined by having a no-data fraction 0.70 or lower, and multiple field visits near the remote sensing satellite imagery acquisition dates

### 3.1.1. Cover Crops

For cover crop evaluation, we restricted the comparison further to field verification data for fields in which we had a road observation that a perennial crop or a winter commodity crop was not growing on the field. Furthermore, it was required that qualifying field surveys must have available field photos to ensure confidence in the field's status as cover cropped or not.

Restrictions to cover crop field data resulted in the trimming of observations to 961 fields. A confusion matrix classification of cover crops is used to describe the performance of the classification by OpTIS (or "classifier") on the field verification data. The number of correct and incorrect predictions are summarized with count values and broken by class in Table 3. The accuracy of remote sensing in identifying cover cropped fields is 87.9% and the kappa statistic is 0.63. Correctly identified classes, true-positive and true-negative, show that 24% of fields were correctly determined to have a cover crop and 76% were correctly determined to not have a cover crop.

**Table 3.** Confusion matrix of cover crop classification by remote sensing (predicted values) vs. reference field data (actual values). Green cells indicate the number of fields with agreeing cover crop classification, termed true-negative TN and true-positive TP. White cells indicate the number of fields with disagreeing classification, termed false-negative FN and false-positive FP.

| Cover Crop Classification (*n* = 959) | | Field Data (Actual Values) | |
|---|---|---|---|
| | | **Positive (1)** | **Negative (0)** |
| OpTIS (Predicted values) | Positive (1) | TP = 139 | FP = 22 |
| | Negative (0) | FN = 92 | TN = 706 |

A roadside field data example of cover crop confusion matrix false-negative class is shown in Figure 4a, the field that is cover cropped according to the field data but is estimated as not cover cropped by OpTIS. Roadside photos of field ID-57-448 show cover crop green-up in April 2018 (Figure 4a). The cover crop is identified by the field observer, but pixels mapped by OpTIS are 0% cover cropped. It is 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 a cover crop but marked the cover type "Unknown". A roadside field data example of cover crop confusion matrix true-negative class is shown in Figure 4b, the field that is not cover cropped according to the field data and is also estimated as not cover cropped by OpTIS. 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 4b). The photos in December, March, and May indicate no sign of cover crop emergence.
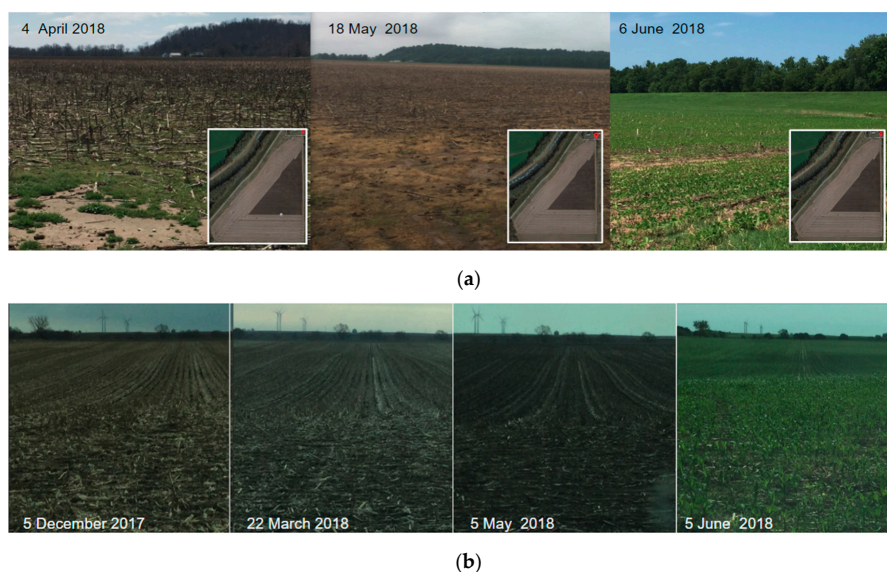


(**a**)



(**b**)

**Figure 4.** (**a**) 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; (**b**) 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.

We provide Kappa and accuracy statistics in assessing remote sensing classification as these remain the standard metric for determining categorical variability. In addition, we show cover crop classification sensitivity, specificity, precision, f-measure, and false-positive rate as extra metrics of accuracy (see Table 4). Sensitivity (also known as recall and producer's accuracy), represents the number of positive predictions made out of all the positive classifications, we report a sensitivity value of 0.60. Specificity measures the proportion of mapped fields correctly classified in the "no cover crop" category of a binary map [69], we report a value of 0.97. Precision evaluates the number of positive classification instances that actually belong in the positive class, we report a value of 0.86. F-measure is a measure of a test's accuracy, we report a value of 0.71. Lastly, our false-positive rate is 0.03, this is the ratio between the number of negative events wrongly categorized as positive (false-positives) and the number of actual negative events [69].

**Table 4.** Classification metrics for OpTIS cover crop.

| Classification Metric | Formula | Value |
|:---:|:---:|:---:|
| Sensitivity | TP/TP + FN | 0.60 |
| Specificity | TN/TN + FP | 0.97 |
| Accuracy | TP + TN/total | 0.88 |
| Precision | TP/TP + FP | 0.86 |
| | 2 * Sensitivity * Precision/Recall | |
| F-measure | + Precision | 0.71 |
| False-Positive Rate | 1-Specificity | 0.03 |

### 3.1.2. Residue Cover

Additional quality control of field observations was done on residue cover evaluation. We restricted the comparison to fields for which we had available field photos to ensure confidence in the residue cover status at the time of planting.

Quality control resulted in 827 valid field observations of residue cover from 2017 spring and 2018 spring. 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 (Figure 5). The mean absolute deviation and root mean squared error of the OpTIS estimates are 17.5 and 21.4, respectively.
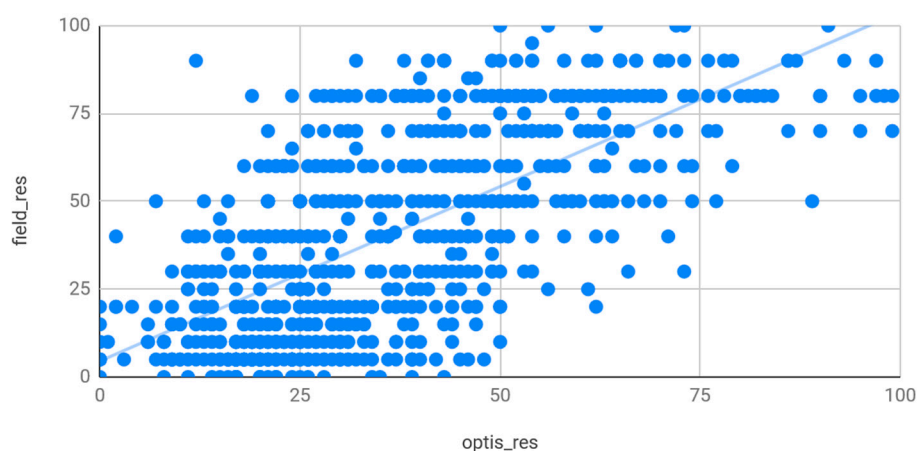


**Figure 5.** OpTIS and field residue cover observations have an $R^2$ of 0.467, $p < 0.00001$.

In contrast to the cover crop evaluation, we obtain four residue cover classes rather than two. Agreement between OpTIS and field data residue cover classification is 42.3%. Misclassification can

range from relatively small differences, for example where OpTIS reports 14% residue while field observer reports 20%, to large classification differences, for example where OpTIS reports 10% residue and field observer reports 90%. We use a weighted kappa statistic to account for differences in types of misclassification. Instances where class disagreement is most severe (i.e., "Very low" is misclassified as "High") have a weight of 16 times the cost of misclassifying in adjacent classes (i.e., "Very low" as "Low") and 4 times the cost of an in-between misclassification (i.e., "Very low" as "Moderate"). The weighted kappa statistic reported on residue cover is 0.67. In addition to kappa statistics for residue cover crop classification, a quantity disagreement of 0.12 and allocation disagreement of 0.17 are shown as quantified by Pontius and Millones [70].

### 3.1.3. Misclassification and Bias

It is important to note that roadside visual estimates of residue cover are subject to reporter 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), but was estimated by OpTIS to have less than 15% residue cover, or conventional till classification. Furthermore, there was a reverse case where a field survey suggested 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 6). The crop consultant estimated 90% residue cover in early June, as is evident from the photo from 9 June 2018. However, OpTIS-mapped estimated high residue cover until the last week of May, at which point a decrease in residue cover from 80% to 12% is identified. No apparent reason for the mismatch was discerned.
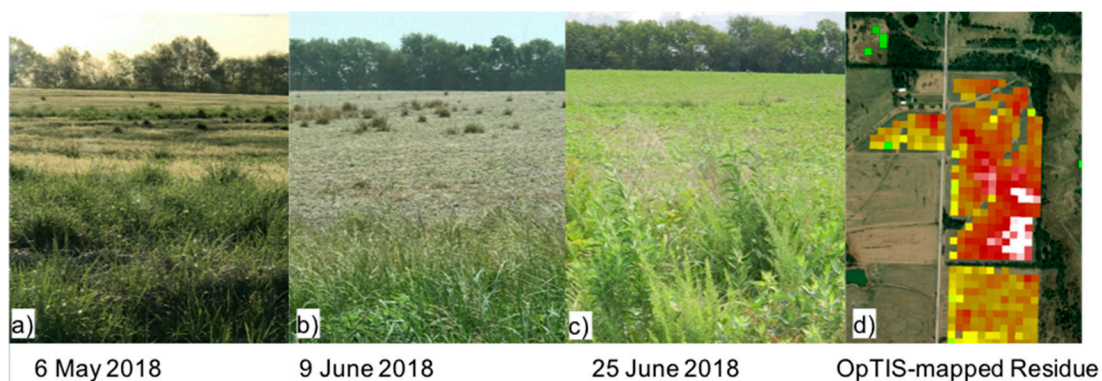


**Figure 6.** Roadside photos of field ID 86–1751 in Missouri observed from (**a**) May 6, 2018, (**b**) June 9 2018, and (**c**) June 25, 2018. The 2017 crop was soybean, 2017–2018 winter shows no cover crop but extensive weed cover, and 2018 crop was soy. (**d**) OpTIS-mapped spring residue for the same field.

### 3.2. OpTIS Corn Belt Conservation Mapping Results

In the Corn Belt as a whole, cover crops planted after corn and soy increased. Specifically, cover crop adoption encompassed 3% of the mapped area (3.88 million acres; 1.57 million ha) in 2018 compared to 1% of the mapped area (1.96 million acres; 0.79 million ha) in 2006 (Table 5 and Figure 7). When looking at total acres of cover crops compared 2018 to 2006 by state, most states show increased cover crop planting, with Iowa, Indiana, and Illinois leading the change in adoption with up to a 300% higher total number of acres than the rest of the area mapped (Figure 8a).

**Table 5.** Yearly cover crops planted after soy and corn and conservation tillage acres in the Corn Belt.

| Years | Cover Crop Acres | Cover Crop Ha | % Area of Cover Crops | Conservation Tillage Acres | Conservation Tillage Hectares | % Area of Conservation Tillage |
|---|---|---|---|---|---|---|
| 2005 | 2,065,432 | 835,869 | 2% | 48,707,764 | 19,711,762 | 42% |
| 2006 | 1,963,643 | 794,675 | 2% | 55,116,662 | 22,305,408 | 46% |
| 2007 | 784,100 | 317,321 | 1% | 48,887,840 | 19,784,638 | 42% |
| 2008 | 1,693,953 | 685,533 | 1% | 59,514,473 | 24,085,177 | 51% |
| 2009 | 853,474 | 345,396 | 1% | 59,201,973 | 23,958,710 | 51% |
| 2010 | 799,084 | 323,385 | 1% | 60,671,511 | 24,553,424 | 51% |
| 2011 | 1,156,283 | 467,941 | 1% | 56,769,756 | 22,974,406 | 47% |
| 2012 | 1,908,452 | 772,340 | 2% | 58,823,578 | 23,805,576 | 49% |
| 2013 | 2,383,074 | 964,417 | 2% | 65,479,475 | 26,499,180 | 54% |
| 2014 | 1,620,402 | 655,768 | 1% | 63,432,404 | 25,670,742 | 52% |
| 2015 | 1,050,637 | 425,187 | 1% | 66,168,899 | 26,778,187 | 55% |
| 2016 | 3,456,192 | 1,398,702 | 3% | 53,860,483 | 21,797,039 | 45% |
| 2017 | 4,872,734 | 1,971,968 | 4% | 54,391,780 | 22,012,052 | 45% |
| 2018 | 3,888,410 | 1,573,618 | 3% | 54,202,762 | 21,935,557 | 44% |
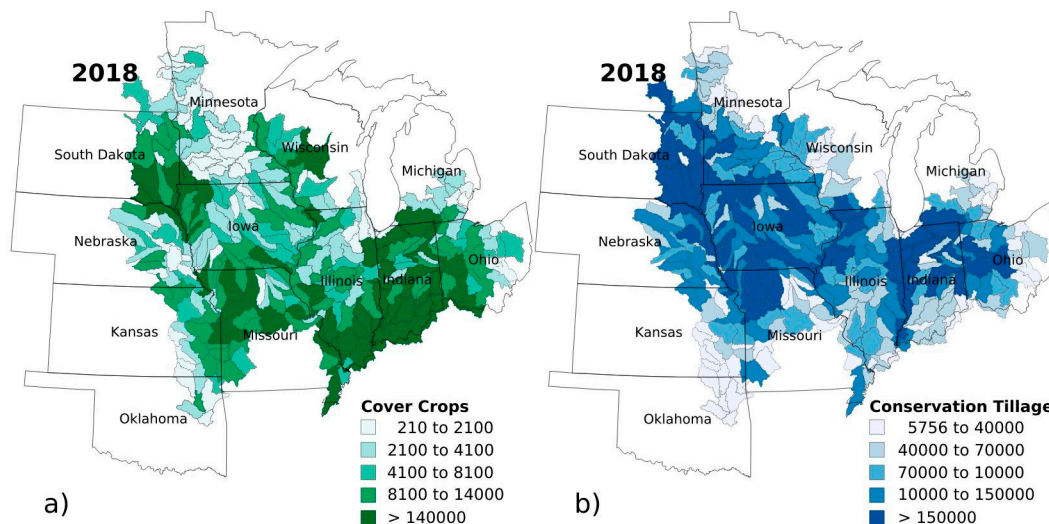


**Figure 7.** (**a**) Cover crop hectares and (**b**) conservation tillage hectares across HUC 8 watersheds for 2018.

The use of conservation tillage practices, where higher than 30% residue is left on the field at planting, remained relatively steady when observing all years 2005 through 2018 (Figure 8). There is a decrease in the area mapped from 46% in 2018 to 42% in 2006, but when looking at total acres of conservation residue by state, there are smaller percent differences in the number of acres in conservation tillage, with the largest proportional changes in Oklahoma showing a decrease of 32% in the mapped area in 2018 compared to 2006, while Nebraska shows a 30% increase in the same time period (Figure 8b).

*3.3. DNDC Corn Belt Conservation Mapping Results*

Spatial patterns of dSOC stocks by HUC 8 in the Corn Belt study area are shown on Figure 9a. 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 HUC 8 from −197 to 366 kgC/ha/year (a negative dSOC value represents a loss of SOC to the atmosphere)—most HUC 8 s sequester C on average (265 of 275 or 97%). Many factors affect changes to SOC including the distribution of crops and their management in a HUC 8 (specifically in this case, a higher fraction of

conservation tillage and/or cover cropping in a HUC 8 will tend to increase the dSOC rate), climate, and soils, particularly initial SOC.
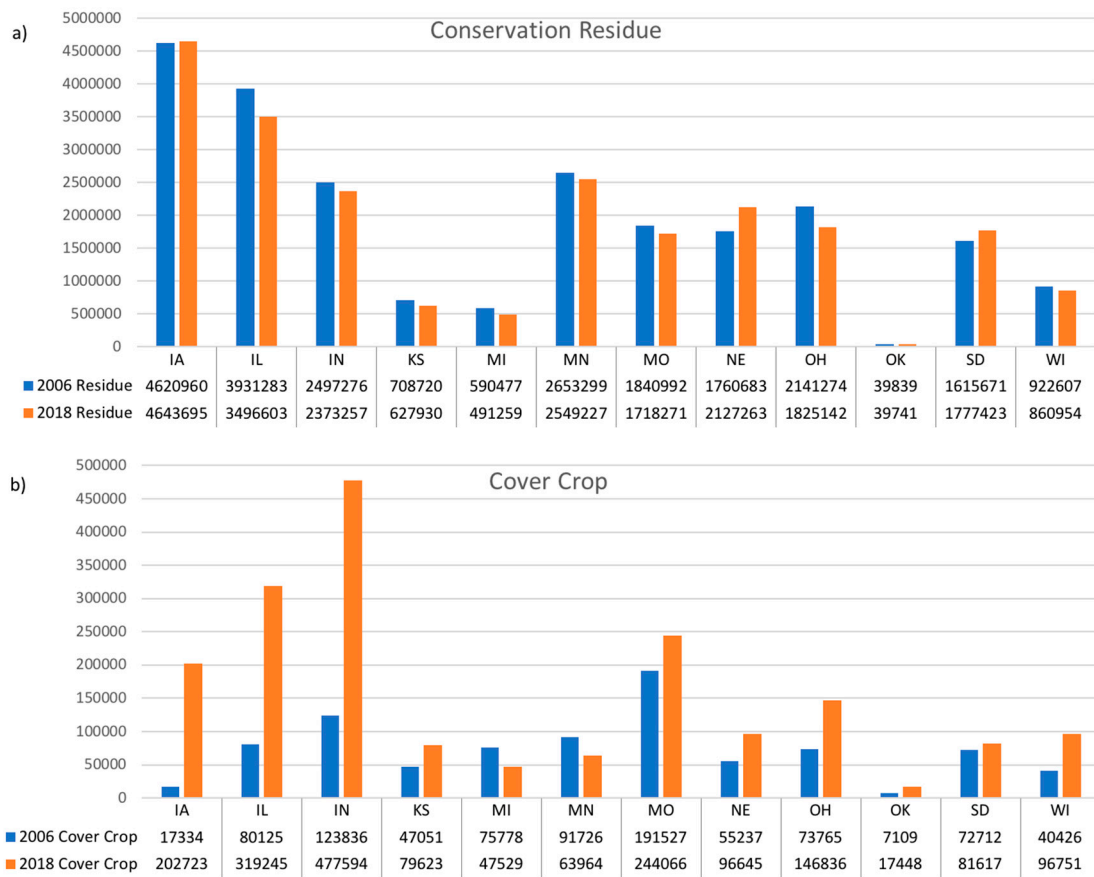


**Figure 8.** Comparison of statewide hectares of (**a**) conservation tillage practices and (**b**) total cover crops planted for the years 2006 and 2018.
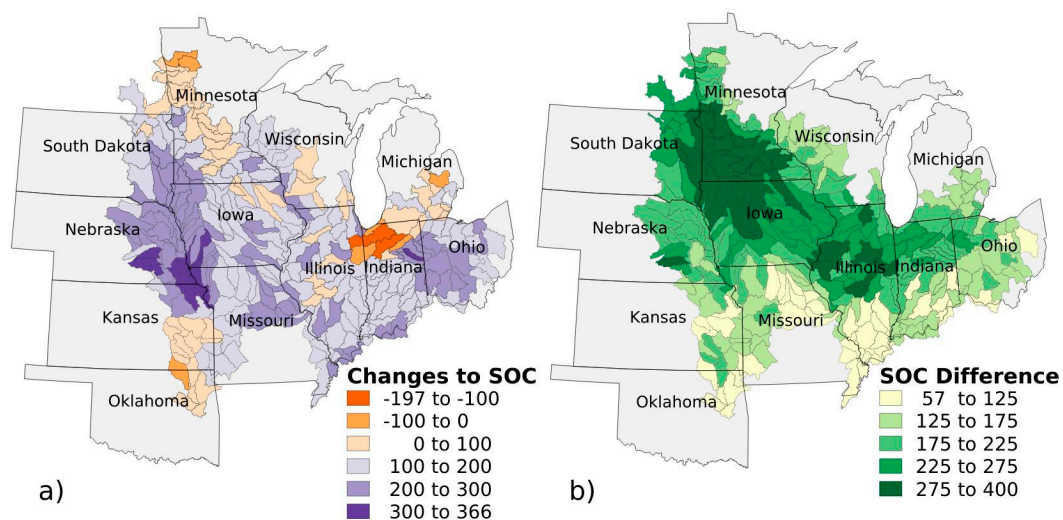


**Figure 9.** (**a**) Area-weighted mean annual dSOC stock rates (kgC/ha/yr) by HUC 8 from 2005 to 2017 simulated with OpTIS-mapped management practices (negative dSOC values represent a loss of soil organic carbon (SOC)); (**b**) Additional mean annual SOC accumulation (kgC/ha/yr) from OpTIS-mapped management by HUC 8 (compared to no soil health management practices scenario).

To demonstrate the effect of conservation practices on dSOC, we compared the OpTIS-mapped scenario with a "No Soil Health Management" ("No SHM") 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 kgC/ha/year), only 38% of HUC 8 s sequester C on average (103 of 274). Figure 9b shows differences in dSOC by HUC 8 (OpTIS-mapped minus no SHM)—all differences are positive indicating that, at least at HUC 8-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.

Mean annual nitrous oxide ($N_2O$) emissions from OpTIS-mapped management are shown in (Figure 10a). Area-weighted mean annual $N_2O$ emissions in the study area are 1.6 kgN/ha/year (weighted SD 0.51 kgN/ha/y)—HUC 8-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.
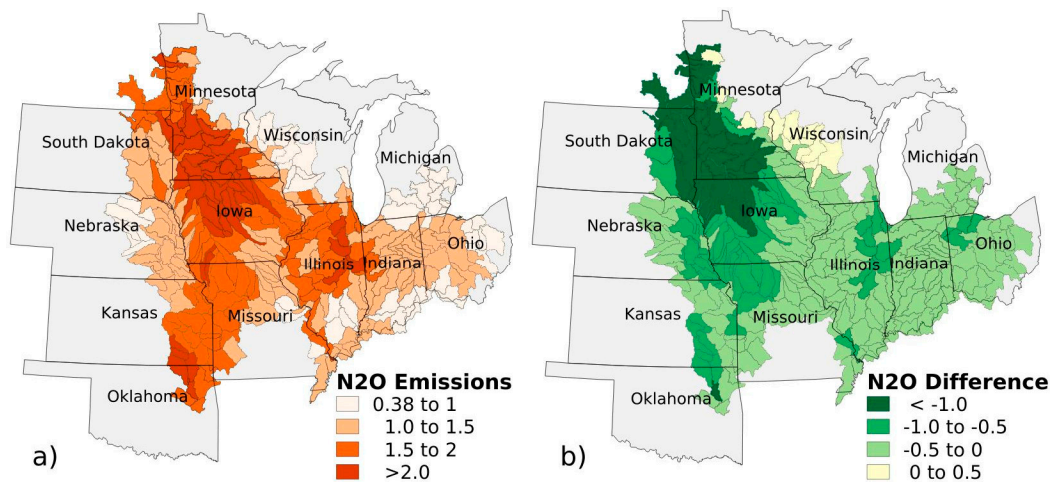


**Figure 10.** (**a**) Area-weighted mean annual $N_2O$ emissions (kgN/ha/yr) from 2005 to 2017 by HUC 8 in the Corn Belt, simulated with OpTIS-mapped management practices. (**b**) Difference between OpTIS-mapped management and no SHM scenario $N_2O$ emission rates (kgN/ha/yr) between 2005 and 2017 by HUC 8.

As we did for dSOC, we compared the OpTIS-mapped scenario to the no SHM scenario (Figure 10b). 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 HUC 8s (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 $N_2O$.

### 3.4. 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 11).
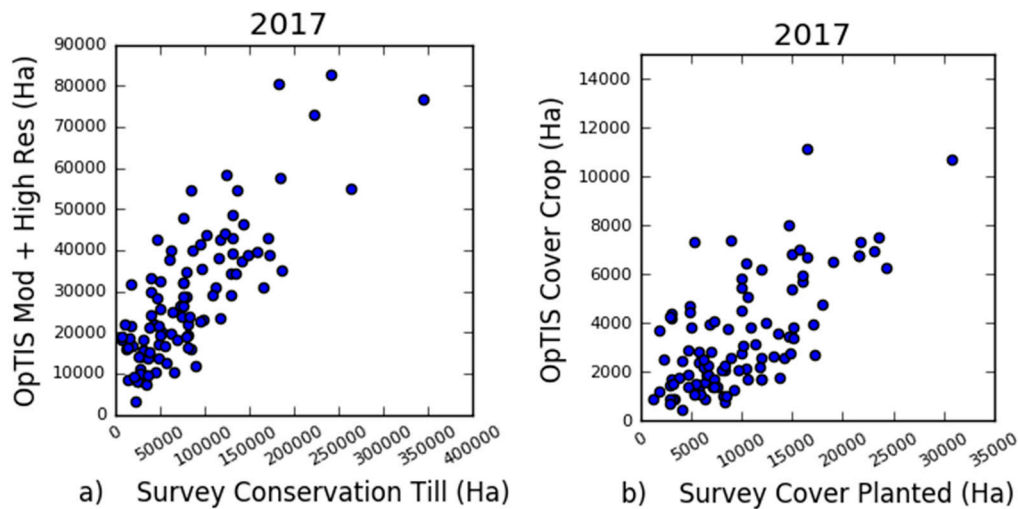
**Figure 11.** (**a**) OpTIS mapped conservation tillage correlates well with AgCensus reported conservation tillage—0.80 correlation coefficient; (**b**) OpTIS mapped cover crops correlate moderately well with AgCensus reported cover crops—0.67 correlation coefficient.

It is important to note that OpTIS and the AgCensus take different approaches to estimate the 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 12). The two sources of estimates are significantly correlated in both years. Maps of 2017 to 2018 show a clump of outliers where OpTIS provides low cover crop estimates of less than 5000 acres or 2023 hectares, while EWG provide significantly higher cover crop estimates of 10,000–20,000 acres or 4046–8094 hectares. Overall, OpTIS estimates correlate closely with assessments from other sources, but some significant county-level differences exist and should be explored.
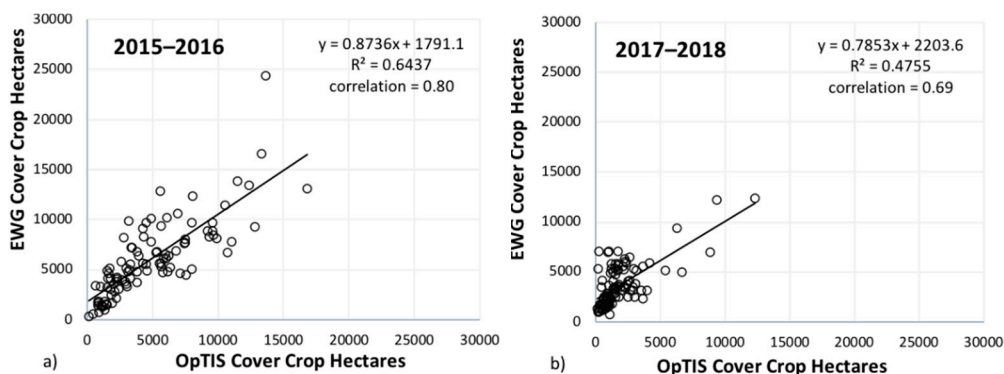


**Figure 12.** Comparison of county-level cover crop hectares for Iowa in (**a**) 2015 to 2016 and (**b**) 2017 to 2018 as estimated by OpTIS (*x*-axis) and the Environmental Working Group (EWG) (*y*-axis).

*3.5. Follow-on Research and Applications*

Detailed spatial and temporal information on the use and outcomes associated with soil health management practices, namely conservation tillage and cover cropping, will help improve the understanding of crop resilience and biodiversity, and support burgeoning ecosystem service markets. For example, there is recent research using satellite-based estimates to understand the effect of conservation practices on yield [71]. Additional analysis of patterns of prevented planting together with historical rates of conservation practice adoption could provide insights into the role management plays in crop resilience. Further, broad-area conservation practice adoption information could be used to support the expanded application indices of sustainability [72]. While the research results presented here are not intended to act as an inventory of soil carbon sequestration or greenhouse gas emissions, further calibration and validation of the tools employed here will facilitate their use for such applications.

## 4. Conclusions

The purpose of this project, the first of its kind, was to fully apply OpTIS and DNDC as a system to monitor the level of adoption of soil health practices and use mapped estimates to model the associated ecosystem impacts of soil health and greenhouse gas emissions at high spatio-temporal resolution. We show results across 1.8 billion acres (0.72 billion ha) with field-level results for a span of 13 years in states in the Corn Belt region of the United States.

The adoption of cover crops is increasing. Cover crops planted after corn and soy over the winter increased by nearly 2 million acres (0.81 million ha) between 2016 and 2018. The increased usage of cover crops was limited initially during this monitoring period with acceleration in the adoption rate in recent years.

Use of conservation tillage practices, in which residue is left on 30% or more of the agricultural field, remained steady for corn and soybeans, the average being 44.4 percent across the Corn Belt in 2018, and 45.5 percent in 2006.

Data-driven estimates of conservation agriculture and soil health effects can support accelerated efforts to improve soils and environmental outcomes by (a) informing soil and water conservation districts in establishing priorities and evaluate progress in achieving county or statewide goals; (b) providing environmental agencies at the national and state levels information to track progress towards meeting the water quality goals; (c) allowing stakeholders throughout the agriculture and food system supply chain to better understand market trends in the adoption of cover crops and specific tillage systems that impact environmental sustainability, such as greenhouse gas emissions and soil C sequestration; (d) helping regional and national agricultural offices evaluate and compare the effectiveness of conservation programs across large regions; and (e) reducing transaction costs associated with monitoring and verifying ecosystem services with burgeoning markets. While the types of information provided via technologies like OpTIS and DNDC will not improve soil health and environmental outcomes alone, they are likely to be a key tool in efforts to bring about positive changes.

**Author Contributions:** Conceptualization, S.C.H., P.I., I.C., J.P.F. and W.S.; Data curation, P.I, I.C., J.P.F., T.O., S.P. and N.R.; Formal analysis, S.C.H., G.D., P.I., I.C., J.P.F., L.M., T.O., N.R. and B.Z.; Funding acquisition, S.C.H., W.S., P.E. and D.G.; Investigation, S.C.H., G.D., I.C., J.P.F., L.M., T.O. and B.Z.; Methodology, S.C.H., P.I., I.C., J.P.F., L.M., T.O., N.R., B.Z. and W.S.; Project administration, S.C.H., I.C., J.P.F. and W.S.; Resources, J.P.F. and W.S.; Software, I.C., R.E., J.P.F., T.O., S.P. and N.R.; Supervision, S.C.H., P.I., I.C., J.P.F. and W.S.; Validation, S.C.H., G.D., P.I., R.E., L.M. and N.R.; Visualization, G.D., R.E., L.M. and N.R.; Writing—original draft, G.D.; Writing—review & editing, S.C.H., G.D., P.I. and H.C. All authors have read and agreed to the published version of the manuscript.

## References

1. Lindsey, R. Climate Change: Atmospheric Carbon Dioxide: NOAA Climate.gov. 2020. Available online: https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide (accessed on 31 August 2020).

2. Hayduk, D.; Satoyama, S.; Vafadari, K. *Soils Help to Combat and Adapt to Climate Change by Playing a Key Role in the Carbon Cycle*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2015; pp. 1–4. Available online: http://www.fao.org/3/a-i4737e.pdf (accessed on 20 September 2019).

3. Janzen, H.H. Janzen Soil carbon: A measure of ecosystem response in a changing world? *Can. J. Soil Sci.* **2005**, *85*, 467–480. [CrossRef]

4. Lal, R.; Follett, R.; Stewart, B.A.; Kimble, J. Soil Carbon Sequestration to Mitigate Climate Change and Advance Food Security. *Soil Sci.* **2007**, *172*, 943–956. [CrossRef]

5. Farm Service Agency (FSA). *Crop Acreage Data Reported to FSA. 2019 Crop Year 2019_fsa_acres_web_010220.xlsx*; United States Department of Agriculture Farm Service Agency: Washington, DC, USA, 2019. Available online: https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data/index (accessed on 8 August 2019).

6. United States Department of Agriculture (USDA). *USDA Strategic Plan: FY 2018—2022*; USDA: Washington, DC, USA, 2018; p. 33.

7. Bégué, A.; Arvor, D.; Bellon, B.; Betbeder, J.; de Abelleyra, D.; Ferraz, R.P.D.; Lebourgeois, V.; Lelong, C.; Simões, M.; Verón, S.R. Remote sensing and cropping practices: A review. *Remote Sens.* **2018**, *10*, 99. [CrossRef]

8. Uri, N.D. Factors Affecting the Use of Conservation Tillage in the United States. *Water Air Soil Pollut.* **1999**, *116*, 621–638. [CrossRef]

9. United States Department of Agriculture (USDA); Natural Resources Conservation Service (NRCS). Conservation Practice Standard Overview: Residue and Tillage Management (329) No-Till/Strip Till/Direct Seed. In *United States Department of Agriculture Natural Resources Conservation Service*; USDA: Washington, DC, USA, 2012; pp. 1–2.

10. United States Department of Agriculture (USDA); Natural Resources Conservation Service (NRCS). *Conservation Practice Standard Overview: Cover Crop (340)*; United States Department of Agriculture Natural Resources Conservation Service: Washington, DC, USA, 2014; pp. 1–2.

11. Conservation Technology Information Center (CTIC). *Annual Report 2019–2020 National Cover Crop Survey August 2020*; Conservation Technology Information Center: West Lafayette, IN, USA, 2020; Available online: https://www.sare.org/wp-content/uploads/2019-2020-National-Cover-Crop-Survey.pdf (accessed on 4 August 2019).

12. United States Department of Agriculture (USDA); Natural Resources Conservation Service (NRCS); Environmental Quality Incentives Program (EQIP). *Environmental Quality Incentives Program*; United States Department of Agriculture Natural Resources Conservation Service: Washington, DC, USA, 2019. Available online: https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/programs/financial/eqip/ (accessed on 19 July 2019).

13. Six, J.; Elliott, E.T.; Paustian, K. Agregate and Soil Organic Matter Dynamics under Conventional and No-Tillage Systems. *Soil Sci. Soc. Am. J.* **1999**, *63*, 1350–1358. [CrossRef]

14. Grandy, A.S.; Robertson, G.P. Land-use intensity effects on soil organic carbon accumulation rates and mechanisms. *Ecosystems* **2007**, *10*, 58–73. [CrossRef]

15. Steenwerth, K.; Belina, K. Cover crops enhance soil organic matter, carbon dynamics and microbiological function in a vineyard agroecosystem. *Appl. Soil Ecol.* **2008**, *40*, 359–369. [CrossRef]

16. Hively, W.; Lang, M.; Mccarty, G.; Keppler, J.; Sadeghi, A.; McConnell, L. Using satellite remote sensing to estimate winter cover crop nutrient uptake efficiency. *J. Soil Water Conserv.* **2009**, *64*, 303–313. [CrossRef]

17. Bricklemyer, R.S.; Lawrence, R.L.; Miller, P.R. Documenting no-till and conventional till practices using Landsat ETM+ imagery and logistic regression. *J. Soil Water Conserv.* **2002**, *57*, 267–271.

18. Van Deventer, A.P.; Ward, A.D.; Gowda, P.M.; Lyon, J.G. Using thematic mapper data to identify contrasting soil plains and tillage practices. *Photogramm. Eng. Remote Sens.* **1997**, *63*, 87–93.

19. Gowda, P.H.; Dalzell, B.J.; Mulla, D.J.; Kollman, F. Mapping tillage practices with landstat thematic mapper based logistic regression models. *J. Soil Water Conserv.* **2001**, *56*, 91–96.

20. Daughtry, C.S.T.; Doraiswamy, P.; Hunt, E.; Stern, A.; McMurtrey, J.; Prueger, J. Remote sensing of crop residue cover and soil tillage intensity. *Soil Tillage Res.* **2006**, *91*, 101–108. [CrossRef]

21. Hagen, S.C.; Heilman, P.; Marsett, R.; Torbick, N.; Salas, W.; Van Ravensway, J.; Qi, J. Mapping Total Vegetation Cover Across Western Rangelands with Moderate-Resolution Imaging Spectroradiometer Data. *Rangel. Ecol. Manag.* **2012**, *65*, 456–467. [CrossRef]

22. Bricklemyer, R.S.; Lawrence, R.; Miller, P.R.; Battogtokh, N. Predicting tillage practices and agricultural soil disturbance in north central Montana with Landsat imagery. *Agric. Ecosyst. Environ.* **2006**, *114*, 210–216. [CrossRef]

23. Bricklemyer, R.S.; Lawrence, R.L.; Miller, P.R.; Battogtokh, N. Monitoring and verifying agricultural practices related to soil carbon sequestration with satellite imagery. *Agric. Ecosyst. Environ.* **2007**, *118*, 201–210. [CrossRef]

24. Azzari, G.; Grassini, P.; Edreira, J.I.R.; Conley, S.; Mourtzinis, S.; Lobell, D.B. Satellite mapping of tillage practices in the North Central US region from 2005 to 2016. *Remote. Sens. Environ.* **2019**, *221*, 417–429. [CrossRef]

25. Watts, D.B.; Runion, G.B.; Balkcom, K.S. Nitrogen fertilizer sources and tillage effects on cotton growth, yield, and fiber quality in a coastal plain soil. *Field Crop. Res.* **2017**, *201*, 184–191. [CrossRef]

26. Azzari, G.; Lobell, D. Landsat-based classification in the cloud: An opportunity for a paradigm shift in land cover monitoring. *Remote. Sens. Environ.* **2017**, *202*, 64–74. [CrossRef]

27. Prabhakara, K.; Hively, W.D.; Mccarty, G.W. Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *39*, 88–102. [CrossRef]

28. Allen, R.G.; Tasumi, M.; Morse, A.; Trezza, R. A Landsat-based energy balance and evapotranspiration model in Western US water rights regulation and planning. *Irrig. Drain. Syst.* **2005**, *19*, 251–268. [CrossRef]

29. Li, C.; Frolking, S.; Frolking, T.A. A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. *J. Geophys. Res. Space Phys.* **1992**, *97*, 9759–9776. [CrossRef]

30. Li, C.; Frolking, S.; Frolking, T.A. A model of nitrous oxide evolution from soil driven by rainfall events: 2. Model applications. *J. Geophys. Res. Space Phys.* **1992**, *97*, 9777–9783. [CrossRef]

31. Li, C.; Frolking, S.; Harriss, R. Modeling carbon biogeochemistry in agricultural soils. *Glob. Biogeochem. Cycles* **1994**, *8*, 237–254. [CrossRef]

32. Gilhespy, S.L.; Anthony, S.; Cardenas, L.; Chadwick, D.; Del Prado, A.; Li, C.; Misselbrook, T.; Rees, R.M.; Salas, W.; Sanz-Cobena, A.; et al. First 20 years of DNDC (DeNitrification DeComposition): Model evolution. *Ecol. Model.* **2014**, *292*, 51–62. [CrossRef]

33. Giltrap, D.L.; Li, C.; Saggar, S. DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. *Agric. Ecosyst. Environ.* **2010**, *136*, 292–300. [CrossRef]

34. Giltrap, D.; Yeluripati, J.; Smith, P.; Fitton, N.; Smith, W.; Grant, B.; Dorich, C.D.; Deng, J.; Topp, C.F.; Abdalla, M.; et al. Global Research Alliance N 2 O chamber methodology guidelines: Summary of modeling approaches. *J. Environ. Qual.* **2020**, *49*, 1168–1185. [CrossRef]

35. Yeluripati, J.B.; Del Prado, A.; Sanz-Cobena, A.; Rees, R.M.; Li, C.; Chadwick, D.; Tilston, E.; Topp, C.F.E.; Cardenas, L.M.; Ingraham, P.; et al. Global Research Alliance Modelling Platform (GRAMP): An open web platform for modelling greenhouse gas emissions from agro-ecosystems. *Comput. Electron. Agric.* **2015**, *111*, 112–120. [CrossRef]

36. Li, C. Modeling Trace Gas Emissions from Agricultural Ecosystems. *Nutr. Cycl. Agroecosyst.* **2000**, *58*, 259–276. [CrossRef]

37. Li, C.; Farahbakhshazad, N.; Jaynes, D.B.; Dinnes, D.L.; Salas, W.; McLaughlin, D. Modeling nitrate leaching with a biogeochemical model modified based on observations in a row-crop field in Iowa. *Ecol. Model.* **2006**, *196*, 116–130. [CrossRef]

38. Li, C.; Salas, W.; Zhang, R.; Krauter, C.; Rotz, C.A.; Mitloehner, F. Manure-DNDC: A biogeochemical process model for quantifying greenhouse gas and ammonia emissions from livestock manure systems. *Nutr. Cycl. Agroecosyst.* **2012**, *93*, 163–200. [CrossRef]

39.　Zhang, Y.; Li, C.; Zhou, X.; Moore, B. A simulation model linking crop growth and soil biogeochemistry for sustainable agriculture. *Ecol. Model.* **2002**, *151*, 75–108. [CrossRef]

40.　Li, C.; Frolking, S.; Butterbach-Bahl, K. Carbon Sequestration in Arable Soils is Likely to Increase Nitrous Oxide Emissions, Offsetting Reductions in Climate Radiative Forcing. *Clim. Chang.* **2005**, *72*, 321–338. [CrossRef]

41.　Zhang, F.; Li, C.; Wang, Z.; Li, X. Long-term effects of management history on carbon dynamics in agricultural soils in Northwest China. *Environ. Earth Sci.* **2015**, *75*, 1–9. [CrossRef]

42.　Camarotto, C.; Ferro, N.D.; Piccoli, I.; Polese, R.; Furlan, L.; Chiarini, F.; Morari, F. Conservation agriculture and cover crop practices to regulate water, carbon and nitrogen cycles in the low-lying Venetian plain. *Catena* **2018**, *167*, 236–249. [CrossRef]

43.　Jarecki, M.; Grant, B.; Smith, W.; Deen, B.; Drury, C.; Vanderzaag, A.C.; Qian, B.; Yang, J.; Wagner-Riddle, C. Long-term Trends in Corn Yields and Soil Carbon under Diversified Crop Rotations. *J. Environ. Qual.* **2018**, *47*, 635–643. [CrossRef]

44.　Deng, J.; Li, C.; Burger, M.; Horwath, W.R.; Smart, D.; Six, J.; Guo, L.; Salas, W.; Frolking, S.; Cuo, L. Assessing Short-Term Impacts of Management Practices on N$_2$O Emissions from Diverse Mediterranean Agricultural Ecosystems Using a Biogeochemical Model. *J. Geophys. Res. Biogeosci.* **2018**, *123*, 1557–1571. [CrossRef]

45.　Deng, J.; Zhu, B.; Zhou, Z.; Zheng, X.; Li, C.; Wang, T.; Tang, J. Modeling nitrogen loadings from agricultural soils in southwest China with modified DNDC. *J. Geophys. Res. Space Phys.* **2011**, *116*. [CrossRef]

46.　Deng, Q.; Hui, D.; Wang, J.; Yu, C.-L.; Li, C.; Reddy, K.C.; Dennis, S. Assessing the impacts of tillage and fertilization management on nitrous oxide emissions in a cornfield using the DNDC model. *J. Geophys. Res. Biogeosci.* **2016**, *121*, 337–349. [CrossRef]

47.　Abalos, D.; Smith, W.N.; Grant, B.B.; Drury, C.F.; Mackell, S.; Wagner-Riddle, C. Scenario analysis of fertilizer management practices for N$_2$O mitigation from corn systems in Canada. *Sci. Total Environ.* **2016**, *573*, 356–365. [CrossRef]

48.　He, W.; Yang, J.Y.; Drury, C.F.; Smith, W.; Grant, B.; He, P.; Qian, B.; Zhou, W.; Hoogenboom, G. Estimating the impacts of climate change on crop yields and N$_2$O emissions for conventional and no-tillage in Southwestern Ontario, Canada. *Agric. Syst.* **2018**, *159*, 187–198. [CrossRef]

49.　Beheydt, D.; Boeckx, P.; Sleutel, S.; Li, C.; Vancleemput, O. Validation of DNDC for 22 long-term N$_2$O field emission measurements. *Atmos. Environ.* **2007**, *41*, 6196–6211. [CrossRef]

50.　Wang, J.; Cardenas, L.M.; Misselbrook, T.; Cuttle, S.; Thorman, R.E.; Li, C. Modelling nitrous oxide emissions from grazed grassland systems. *Environ. Pollut.* **2012**, *162*, 223–233. [CrossRef] [PubMed]

51.　Cai, Z.; Sawamoto, T.; Li, C.; Kang, G.; Boonjawat, J.; Mosier, A.R.; Wassmann, R.; Tsuruta, H. Field validation of the DNDC model for greenhouse gas emissions in East Asian cropping systems. *Glob. Biogeochem. Cycles* **2003**, *17*, 1–10. [CrossRef]

52.　Ingraham, P.A.; Salas, W.A. Assessing nitrous oxide and nitrate leaching mitigation potential in US corn crop systems using the DNDC model. *Agric. Syst.* **2019**, *175*, 79–87. [CrossRef]

53.　United States Department of Agriculture (USDA); Service Center Agencies National Geospatial Management Center. *8 Digit Watershed Boundary Dataset*; USDA/NRCS—National Geospatial Management Center: Reston, VA, USA, 2013.

54.　Drusch, M.; Del Bello, U.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; et al. SENTINEL-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sens. Environ.* **2012**, *120*, 25–36. [CrossRef]

55.　PRISM Climate Group, Oregon State University. Available online: http://prism.oregonstate.edu (accessed on 4 August 2019).

56.　United States Department of Agriculture (USDA); National Agricultural Statistics Service (NASS); Cropland Data Layer (CDL). *Published Crop-Specific Data Layer*; USDA-NASS: Washington, DC, USA, 2019. Available online: https://nassgeodata.gmu.edu/CropScape/ (accessed on 5 August 2019).

57.　NADP Program Office Wisconsin State Laboratory of Hygiene. *National Atmospheric Deposition Program (NRSP-3)*; NADP Program Office Wisconsin State Laboratory of Hygiene: Madison, WI, USA, 2020.

58.　United States Department of Agriculture (USDA); National Agricultural Statistics Service (NASS). NASS—Quick Stats. 2018. Available online: https://data.nal.usda.gov/dataset/nass-quick-stats. (accessed on 13 November 2018).

59. United States Department of Agriculture (USDA); National Agricultural Statistics Service. *Crop Production Historical Track Record*; US Gov. Print. Office: Washington, DC, USA, 2016.

60. United States Department of Agriculture (USDA); Economic Research Service (ERS). Fertilizer Use and Price Website. 2017. Available online: https://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx (accessed on 2 January 2017).

61. United States Department of Agriculture (USDA); National Agricultural Statistics Service (NASS). *Field Crops: Usual Planting and Harvesting Dates, October 2010*; Agricultural Handbook Number 628; United States Department of Agriculture National Agricultural Statistics Service: Washington, DC, USA, 2010.

62. Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. *Soil Survey Geographic (SSURGO) Database*; United States Department of Agriculture: Washington, DC, USA, 2018. Available online: https://sdmdataaccess.sc.egov.usda.gov (accessed on 15 December 2018).

63. Keeling, C.D.; Piper, S.C.; Bacastow, R.B.; Wahlen, M.; Whorf, T.P.; Heimann, M.; Meijer, H.A. *Exchanges of Atmospheric $CO_2$ and 13 $CO_2$ with the Terrestrial Biosphere and Oceans from 1978 to 2000. I. Global Aspects*; SIO Reference Series, No. 01-06; Scripps Institution of Oceanography: San Diego, CA, USA, 2001; 88p, Available online: http://escholarship.org/uc/item/09v319r9 (accessed on 5 July 2019).

64. Abendroth, L.J.; Herzmann, D.E.; Chighladze, G.; Kladivko, E.J.; Helmers, M.J.; Bowling, L.; Castellano, M.; Cruse, R.M.; Dick, W.A.; Fausey, N.R.; et al. *Sustainable Corn CAP Research Data (USDA-NIFA Award No. 2011-68002-30190)*; National Agricultural Library-ARS-USDA: Beltsville, MD, USA, 2017. [CrossRef]

65. Pribyl, D.W. A Critical review of the conventional SOC to SOM conversion factor. *Geoderma* **2010**, *156*, 75–83. [CrossRef]

66. Iowa State University. Corn Nitrogen Rate Calculator. 2019. Available online: http://cnrc.agron.iastate.edu/ (accessed on 18 February 2019).

67. Pervez, M.S.; Brown, J.F. Mapping Irrigated Lands at 250-m Scale by Merging MODIS Data and National Agricultural Statistics. *Remote Sens.* **2010**, *2*, 2388–2412. [CrossRef]

68. Saxton, K.E.; Rawls, W.J. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil Sci. Soc. Am. J.* **2006**, *70*, 1569–1578. [CrossRef]

69. Stehman, S. Selecting and interpreting measures of thematic classification accuracy. *Remote Sens. Environ.* **1997**, *62*, 77–89. [CrossRef]

70. Pontius, R.G.; Millones, M. Death to Kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. *Int. J. Remote Sens.* **2011**, *32*, 4407–4429. [CrossRef]

71. Deines, J.M.; Wang, S.; Lobell, D.B. Satellites reveal a small positive yield effect from conservation tillage across the US Corn Belt. *Environ. Res. Lett.* **2019**, *14*. [CrossRef]

72. Chae, K.; Cisney, J.; Gang, A.; Khan, K.; Lloyd, T.; Mckay, N.; Mckeen, G.; Ossanna, J.; Owen, J.; Pan, S.; et al. State Sustainability Index. 2016. Available online: https://drive.google.com/file/d/0B_41G9iz2F6PbWxjNXVaZnRqdzQ/view (accessed on 9 October 2020).

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.