# **Op**erational **T**illage **I**nformation **S**ystem (OpTIS): A Pilot Demonstration Project Mapping Tillage Practice and Winter Cover Crops Annually Across the State of Indiana Between 2006 and 2015

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## Acknowledgements

Funds for conducting the OpTIS Indiana Pilot project were provided by the Howard G. Buffet Foundation, the USDA Climate Change Program Office, Monsanto, John Deere, Soil Health Partnership, Indiana Soybean Alliance, and Indiana Corn Marketing Council. The county-level transect data were organized and provided by Deb Fairhurst at the Division of Soil Conservation in the Indiana State Department of Agriculture, Shannon Zezula at the USDA-NRCS State Office in Indianapolis, and their colleagues in Indianapolis and in the county field offices. Technical consultation was provided by Craig Daughtry, Dorsey Plunk, Norm Widman, and Carolyn Olson at the US Department of Agriculture. Dave Gustafson was instrumental in bringing the stakeholders together to push this project forward, and Alona Bunning (ILSI Research Foundation) provided final editorial support.

*Cite report as:*
*Hagen, S, I. Cooke, C. Watts, K. Scanlon, D. Towery, and W. Salas. 2016. Operational Tillage Information System (OpTIS): A pilot demonstration project mapping tillage practice and winter cover crops annually across the state of Indiana between 2006 and 2015. Submitted by Applied GeoSolutions and the Conservation Technology Information Center.*

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# 0.0 EXECUTIVE SUMMARY

The goal of this pilot study was to comprehensively test and document the ability of the Operational Tillage Information System (OpTIS) algorithms to consistently map tillage practices and cover crops across a large area (the state of Indiana) and through time (2006 to 2015). This goal was met via three objectives: 1) collection and organization of the system input and transect data sets for comparison; 2) application of the OpTIS algorithms to generate maps of crop residue cover and cover crops for the state of Indiana from 2006 to 2015; and 3) comparison of OpTIS maps to transect estimates. While the maps have been created and validated at the farm-field level, they were converted to the county and watershed level for additional validation and distribution. The privacy of individual producers has been protected by distributing resulting maps at the county and watershed scale.

This study is responsive to multiple U.S. government needs and objectives, including the United States Department of Agriculture's (USDA) goal to ensure our lands are conserved, restored, and made more resilient to climate change (Strategic Goal 2 in USDA Strategic Plan FY 2014-2018), the USDA/National Resource Conservation Service's (NRCS) Soil Health Initiative, and the Environmental Protection Agency's (EPA) responsibility to report accurate estimates of greenhouse gas emissions (GHGs) to the UNFCCC. Our study directly aligns with Objective 2.2 in the USDA Strategic Plan to Lead Efforts to Mitigate and Adapt to Climate Change, Drought, and Extreme Weather in Agriculture and Forestry. The study conducted here has been aimed at directly improving the USDA's ability to track the adoption of conservation tillage and cover cropping, together with the associated climate change mitigation potential. Improved data on the adoption of conservation tillage practices and cover cropping resulting from this technology is available to provide valuable input into updated versions of reports such as the "USDA Agriculture and Forestry GHG Inventory: 1990-2008" – Technical Bulletin 1930 (USDA/OCE).

In April 2015, Secretary of Agriculture Tom Vilsack announced the launch of the USDA's Building Blocks for Climate Smart Agriculture and Forestry. One of the ten building blocks is Soil Health, which promotes the use of NRCS conservation practices that enhance soil carbon stocks, including no-till and cover cropping. The program targets an annual GHG reduction of between 4 and 18 MMT Co2eq/yr by 2025. OpTIS products are useful for setting the current baseline and tracking increased adoption of these conservation practices to evaluate success in meeting the targets.

When OpTIS estimates are compared to consistency-checked field observations of crop residue cover and tillage practice, we see a high rate of agreement (e.g., approximately 80% of measured variance in field-observed residue cover is explained by OpTIS estimates). When compared to transect data from all pilot counties, OpTIS typically explains around 40% of the variance in transect-estimated residue cover. These results indicate that factors other than OpTIS shortcomings significantly contribute to disagreement between OpTIS and the transect estimates. Similar results are noted for OpTIS winter cover crop maps, although substantially fewer transect estimates are available for comparison given that collection began in 2015. Based on the results from this pilot study, it is likely that the OpTIS tool will be a valuable asset in estimating tillage practices and cover crops across the U.S.

# 1.0 INTRODUCTION AND BACKGROUND

Agricultural row crops occupy over 200 million acres of land in the United States (USDA-NASS, 2012). The major row crops in the US by acres are corn, soybeans, winter wheat, spring wheat, cotton, sorghum, barley, and rice. In 2012 these crops totaled 238 million acres. Other major non-row crops totaled 69.5 million acres (USDA/NASS, 2012). Decisions regarding the implementation of tillage practices and cover cropping in these agricultural areas have a significant effect on productivity and environmental outcomes, including soil erosion, water quality, and carbon sequestration. Row crops are produced using a range of tillage management practices that can be generally categorized as conventional tillage (< 15% crop residue), reduced tillage (crop residue between 15 and 30%), and conservation tillage (> 30% crop residue) (CTIC, 2000), although there are regional differences in the way tillage practices are defined. The conservation tillage management techniques (e.g. mulch-till, ridge-till, strip-till, and no-till) involve leaving crop residue from the previous year to cover the soil while planting next year's crop. When compared to conservation tillage practices, conventional tillage can result in higher rates of soil erosion, loss of organic matter, higher evapotranspiration, higher sediment loading, and increased rates of carbon dioxide released to the atmosphere. Conventional tillage practices also have a greater impact on water quality than conservation tillage because when tilled, soil and nutrients in the soil are more susceptible to leaching and run-off (Uri et al., 1999).

Through funding from the USDA-Small Business Innovation Research (SBIR) program, Applied GeoSolutions demonstrated the feasibility of mapping tillage practices and cover crops with remotely sensed observations in several regions of the United States and designed a prototype system called the Operational Tillage Information System (OpTIS) that provides information about the spatial and temporal dynamics of tillage practices and cover crops across a wide region. Recently, the team made progress in refining the algorithms and expanding the areas of coverage. As part of the Indiana Pilot Project, the team expanded the system to cover the state of Indiana, and has now fully evaluated the consistency of the tillage and cover crop information produced with the system against information gathered via tillage transect surveys.

## 1.1 Relevance of information on tillage practice, crop residue cover, and winter cover crops

Accurate, timely, and spatially comprehensive information about the dynamic state of tillage practices and cover crops across a large region are valuable for several purposes.

### 1.1.1 Conservation Technology Information Center (CTIC) and the traditional windshield survey

From 1989 to 2004, the Conservation Technology Information Center (CTIC) worked with the USDA-NRCS and local soil and water conservation districts to conduct a crop residue management survey of tillage practices across the nation. In doing so, this group assembled the only wide-region time series data regarding the implementation of tillage practices in the United States. This data collection effort was highly valuable, but suffered from several shortcomings. The data collection process was expensive and time consuming, largely due to the manpower required to conduct these on-the-ground, "windshield" surveys. The results from the survey provided a sub-sampling of implemented tillage practices, as opposed to wall-to-wall observations. The national survey has not been conducted since 2004. As a result, there is currently an ongoing search for a systematic and cost-effective method for documenting tillage practices over a large region.

### 1.1.2 National Resource Conservation Service (NRCS) and conservation districts' collection and use of these data

Under its most recent Strategic Plan Framework, the United States Department of Agriculture (USDA) states its intention of "managing and protecting America's public and private lands working cooperatively with other levels of government and the private sector." The USDA National Resource Conservation Service (NRCS) works with private land owners to increase the productivity of land while protecting the soil, water, and air. The NRCS supports conservation practices that save producers money and improve the environmental health of the United States. Conservation tillage and cover crops can save farmers money by increasing organic matter in the soil, reducing fertilization, fuel, and time costs, improving soil health, and reducing runoff and erosion.

Local and state governments use information regarding tillage practices and cover crop installation to help soil and water conservation districts establish program priorities and to evaluate progress in achieving county or statewide goals. The National Agriculture Statistics Service (NASS), the arm of the federal government tasked with cataloguing the current state of agriculture in the U.S., collects some cover crop information as part of its mission to "provide timely, accurate and useful statistics in service to U.S. agriculture." Spatially comprehensive maps will allow the conservation teams to accurately assess the effectiveness of education and conservation programs, allowing them to eliminate unsuccessful programs and focus on those with demonstrated success.

### 1.1.3 Private industry's use of these data

The agricultural industry, including companies such as Monsanto, The Mosaic Company, and John Deere, use information regarding tillage practices for research, development and market strategy.

### 1.1.4 USDA Climate Change Program Office's (CCPO) use of these data

The Climate Change Program Office (CCPO) is responsible for developing and coordinating the USDA's strategic responses to climate change. One of the most important terrestrial pools for carbon (C) storage and exchange with atmospheric carbon dioxide ($CO_2$) is soil organic carbon (SOC). Cultivation has resulted in active C being oxidized and released into the atmosphere as $CO_2$. In the U.S., as much as 50% of the original SOC on cropland has been lost due to land clearing and tillage. This combination of C loss has resulted in the inability of the soil to function to its potential (less moisture holding capacity, increased runoff, less nutrient cycling, increased soil compaction, etc). The two management strategies which can increase the active organic matter (OM) on cropland soils are minimal soil disturbance and planting a cover crop between cash crops. However, one cannot merely evaluate yearly practices. Active SOC takes years to form but can be lost quickly with multiple tillage passes. The USDA NRCS Soil Health effort is gaining attention with farmers because it is about "improving the soil" (OM is a key part) and making the soil more resilient to climate change. Although past efforts have somewhat quantified the amount of tillage occurring on cropland, this has been a one-year snapshot. Implementing minimal tillage disturbance (no-till) and cover crop adoption on the same parcel over a period of years will provide the information needed to document the amount of carbon being sequestrated on U.S. cropland.

### 1.1.5 Water quality trading markets

Difficulties in tracking the use of cover crops and the implementation of conservation tillage practices can limit their use in water quality trading markets that are being implemented across the country. For these credits to be valid, the best management practices (BMPs) that are implemented must be new to the farm (additional). For this reason, farmers must submit documentation that establishes their baseline of conservation use, usually over a period of years, to show that the proposed BMPs are new to their operation. Currently, the market has had to employ a patchwork of methods for baseline documentation. For cover crops, farmers must submit an EQIP Conservation Activity Plan that identifies the need for cover crops based on on-site inspection and evaluation, and documents previous presence or absence of cover crops. In some instances, farmers may have some receipts of cover crop seeds or cost-share funding. Since most farmers do not keep records of their practices, they are asked to submit Farm Service Agency maps in combination with FSA-578 forms (e.g., crops and acreage data). The market could benefit from reliable maps of historical cover crops and tillage practices to establish baselines of usage.

Some regions are spending significant public funds to encourage the use of cover crops to improve water quality, and need documentation to demonstrate the effectiveness of the outlay. For example, Maryland spends $18 million per year to subsidize the planting of cover crops in the Chesapeake Bay Watershed (Maryland Agricultural Water Quality Cost-Share Program [MACS], 2016). While the additional acreage of cover crops produced through this program is fairly well constrained, the amount of nutrients kept out of the Bay as a result of this program is not well known.

## 1.2 Review of remote sensing in agriculture and estimating crop residue and cover crops

### 1.2.1 History of NDVI and RS for mapping agriculture

For more than 40 years, data from satellites have been used to map vegetation characteristics across large areas, often with a focus on agriculture. Collected by space-borne optical sensors, reflectance measured in different portions of the electromagnetic spectrum can be used to calculate difference ratios, such as the Normalized Difference Vegetation Index (NDVI), that are then linked with biophysical characteristics, such as vegetation greenness and productivity. Some of the first studies to match satellite reflectance to crop characteristics identified NDVI as a useful index for estimating fraction of absorbed photosynthetically active radiation (FPAR) (Wiegand et. al., 1991, Baret. et al., 1991). One early study using satellite data to monitor vegetation identified significant relationships between NDVI and plant productivity and used this relationship to create a management tool for the government of Niger (Wylie et al., 1991).

### 1.2.2 Methods for identifying crop residue using remote sensing

Remote sensing data have been used to accurately map tillage practices in spatially and temporally targeted studies. Van Deventer et al. (1997) achieved high accuracy (93%) in mapping tillage practices in a region of soybean-corn rotation in Ohio using Thematic Mapper (TM) shortwave infrared bands to create Simple Tillage and Normalized Difference Tillage indices. Another approach to mapping tillage practices focuses on direct estimation of the amount of crop residues in a field using a TM-based Cellulose Absorption Index to infer tillage practices (Daughtry, 2001). Reflectances in the shortwave portion of the spectrum (1600 nm and 2100 nm) are sensitive to changes in water content, cellulose, and lignin, and have been shown to be related to crop residue cover (Daughtry, 2001). In the past ten years, ETM+ data coupled with logistic regression techniques have been very successful in mapping no-till practices with a high degree of accuracy (>95%) for a site in Montana dominated by dryland wheat (Bricklemeyer et al., 2002, 2006, and 2007). Using Landsat 5 data, Sullivan et al. (2007) compared the effectiveness of several crop residue cover indices for mapping conservation tillage practices in a watershed in Georgia. Their logistical regression approach produced accuracies as high as 78%. South et al. (2004) mapped no-till practices using a single Landsat TM footprint for a region intersecting Michigan, Indiana and Ohio with a cosine of spectral angle mapping technique (Sohn & Rebello, 2002). Validated with an intensive transect dataset, South et al. (2004) showed that conservation tillage mapping accuracy can be as high as 95%, but concluded that the time of Landsat image acquisition, limited by a 16-day repeat overpass, is critical because no-till practices are difficult to differentiate when fields are covered with more than 30% crop foliage. Bricklemeyer et al. (2006) also noted that timing of imagery in relation to timing of management operations was a primary cause of errors in their mapping of tillage practices with Landsat, and the same authors recommend using multiple image dates within a year (Bricklemeyer et al., 2007). Similar remote sensing techniques have been demonstrated for mapping winter cover crops. Hively et al. (2009) show that winter cover crop biomass can be estimated using the Normalized Difference Vegetation Index (NDVI) derived from a well-timed winter and early spring satellite images.

The integration of ancillary information, such as crop type maps, can result in increased accuracy and information extractable from remote sensing imagery. Watts et al. (2009) successfully executed a Classification and Regression Tree (CART) approach that integrates field boundary information to improve classifications of crops and tillage in Montana. The use of boundary information is advantageous, as it enables field-level rather than pixel-based classifications. This study found challenges in distinguishing no-till and conservation land when using the Landsat-based object-oriented approach. There appear to be two methodological disadvantage of the object-oriented CART approach: 1) the computational difficulty in dealing with large datasets and 2) the method's requirement that the expert users of the tool provide an interactive and sometimes arbitrary parameterization of the segmentation attributes. The study also highlighted the need to integrate multitemporal imagery for characterizing tillage intensity and rotations, which is currently lacking in tillage mapping studies.

### 1.2.3 Methods for identifying cover crops

The relationship between optical reflectance and the characteristics of winter cover crops has been demonstrated (Hively et al., 2009; Prabhakara et al. 2015). These studies have confirmed the relationship between NDVI and fractional cover, particularly before senescence and winter kill affect the canopy. Biomass can also be reliably estimated from NDVI, particularly at lower levels before saturation occurs (Prabhakara et al. 2015).

While NDVI is closely related to fractional cover of green vegetation, a plant's ability to protect the soil from erosion is determined by the total vegetation cover, including green and senescent vegetation. Some research has shown that more complex vegetation indices are sensitive to total vegetation cover (i.e. green and senescent) (Marsett et al. 2006, Hagen et al. 2012). The use of an index such as the soil adjusted total vegetation index (SATVI) might be more appropriate for mapping total vegetation cover by winter cover crops than NDVI alone.

While the relationship between NDVI and fractional green cover is clear (e.g. Prabhakara et al. 2015), the relationship between NDVI and biomass or vegetation productivity is more complicated. One factor complicating the use of NDVI as a tool for monitoring vegetation biomass is the fact that NDVI saturates and is no longer sensitive to increases in biomass above a certain threshold. This saturation results from the leaf layering and increasingly complex structure associated with higher biomass vegetation. Some studies have demonstrated that biogeochemical models using weather, soil, and management information as input can accurately estimate biomass and plant nutrient content. These studies suggest that biogeochemical models, constrained by remote sensing observations of crop canopy development, can accurately estimate biomass and nutrient uptake at accuracies beyond those achieved with remote sensing alone.

The factors limiting the operational application of optical remote sensing data to mapping winter cover crops include cloud cover, image timing, and noise from atmospheric effects or changes in soil background. For accurate assessment of cover crop attributes using remote sensing, images need to be collected at critical stages of canopy development. Often the infrequent return overpass of a single sensor, combined with high cloud cover, result in missing observations during these critical stages of development. These critical spatial and temporal sampling issues can be addressed by relying on information from a constellation of satellite sensors (including Landsat and Sentinel 2). Additionally, residual noise due to changes in atmospheric or soil background can be minimized with cloud screening, atmospheric correction, and by integrating soils information from databases such as SSURGO into the calibration process.

### 1.2.4 Limitations on current methods

Routine regional mapping of tillage practices with high resolution data (e.g. Landsat TM or ETM+) alone has been limited due to long revisit periods and high cloud cover probabilities (Allen et al. 2002), combined with the dynamic nature of the tillage process (e.g. not every farmer in an area tills at the same time). OpTIS has addressed these critical spatial and temporal sampling issues by enhancing high spatial resolution maps with temporal information from MODIS data. We have demonstrated the utility of MODIS data for mapping tillage practice over in large fields. Our research demonstrates that MODIS reflectance observations add critical information regarding tillage timing, even in regions with small field sizes (< 200 acres).

OpTIS algorithms are designed to address two critical issues: 1) satellite data are useful in mapping crop residue cover and tillage practice over wide areas, in a way not possible with ground measurements alone, and 2) the reliance on any single satellite for mapping tillage practice is not practical due to individual limitations in spatial and temporal resolutions and because satellites have limited life-cycles and are frequently replaced. To overcome limitations often encountered with single satellites, we have designed OpTIS to take advantage of data from multiple satellite sensors.

We have designed and executed methods to generate accurate tillage maps using Landsat, AWiFS, Sentinel, and MODIS remote sensing imagery in an operational context. The use of multiple sensors is key because it (a) can provide better temporal coverage, (b) reduces the risk of catastrophic failure of the system if a single sensor is lost, and (c) is flexible and allows users tradeoffs in spatial and temporal resolution of their tillage and cover crop products.

### 1.2.5 Future remote sensing products coming soon and how they affect OpTIS

Sentinel 2 optical imagery from the European Space Agency (ESA) are now available. These data provided Landsat-quality information or better, with a repeat overpass time of 5 days, once both sensors are in orbit. Sentinel 1 C-Band SAR imagery from ESA, with a repeat overpass of 5 days and ability to image through clouds, is also available now. C-band SAR imagery has been used in Europe to map changes in surface roughness resulting from tillage practices. Moving forward, these data will limit or reduce the need within the OpTIS system to gap fill with the coarse resolution MODIS imagery.

## 1.3 Accuracy of current data products available and accuracy of data required by end users

Statistics regarding tillage practices and cover crops at county and regional scales have been collected via a "cropland roadside transect survey" (CTIC, 2008) that has been modified to include visual estimates of cover crop presence and species made from the road (i.e. "windshield surveys"). However, these surveys are incomplete. The focus of these transects has been crop residue and tillage practice. Few of the transects collect cover crop information, making it difficult or impossible to understand historical trends. Additionally, the data collected are sub-sampled transects through counties, often measuring less than 10% of the fields within a county. The identification of tillage practices and cover crops is sensitive to the timing of the surveys. While the transects typically occur in the spring when tillage practice is most easily identified, ideal timing for the identification of cover crops can often be in the fall or early winter. This timing will vary year-to-year, county-to-county, and even farm-to-farm. The installation of cover crops or the adoption of conservation tillage by a farmer depends on the crop, soil type, topography, enrollment in the Conservation Reserve Program and the willingness of the farmer to change farming practice.

Data from the transect survey are often collected from a vehicle while moving quickly, often at more than 40 mph. The quick assessment conducted by the team in the vehicle can lead to mistakes or disagreements in several ways:

A. Occasionally, the transect point falls on or near a field boundary, making it challenging for the team to identify the correct field for the transect survey. This is not terribly problematic when collecting data for the traditional survey, because effects on the statistical sample will be minimal. However, when these data are compared to estimates from a satellite, this field confusion is quite problematic.

B. It is often challenging to assess field average residue cover level accurately while standing in a field. Assessing the level of crop residue cover from a quickly moving vehicle to an accurate percentage level can lead to significant uncertainty or error.

C. The timing of the transect survey can introduce significant additional uncertainty. For residue cover it is important that the survey is conducted in the spring after the farmer has tilled but before the crop canopy obscures view of the surface. For cover crops, a late fall transect is best. Not every transect is conducted at an optimal time, resulting in additional uncertainty in the transect results.

### 1.4 Description of the team and pilot project

The team assembled to complete the Indiana Pilot Project includes experts in remote sensing, computer science, and conservation agriculture from Applied GeoSolutions, based in Durham, New Hampshire, and the Conservation Technology Information Center (CTIC), based in West Lafayette, Indiana. The Indiana State Department of Agriculture, the USDA-NRCS office based in Indianapolis, and Soil and Water Conservation District team members contributed critical data and expertise to the project. A technical advisory team from the USDA provided feedback and shared experience over the course of the project. Dan Towery provided consistent input and guidance regarding conservation tillage in the region.

## 2.0 APPROACH AND METHODS EMPLOYED WITHIN THE OPTIS SYSTEM

### 2.1 Data sets

We have designed and executed methods to generate accurate tillage and cover crop maps using Landsat and MODIS remote sensing imagery in an operational context. The use of multiple sensors is key because it (a) can provide better temporal coverage, (b) reduces the risk of catastrophic failure of the system if a single sensor is lost, and (c) is flexible and allows users tradeoffs in spatial and temporal resolution of their tillage and cover crop products.

#### 2.1.1 Landsat observations

For more than four decades, Landsat sensors have been imaging the earth from space, providing critical information about agriculture, forestry, and other natural resources. The sensors used here, from Landsat 5, 7, and 8, provide spectral reflectance information in multiple bands, or wavelengths, at a 30-m spatial resolution (Tables 1-3). The repeat overpass time for these sensors is 16 days. Landsat 5 and 7 were in orbit, offset by eight days, between 2000 and 2011, when Landsat 5 malfunctioned. Between late 2011 and early 2013, Landsat 7 was alone in orbit, until Landsat 8 was launched in February 2013 – again offset from Landsat 7 by eight days.

**Table 1: Landsat 5**

| Landsat 5 | Wavelength (micrometers) | Resolution (meters) |
|---|---|---|
| Band 1 | 0.45-0.52 | 30 |
| Band 2 | 0.52-0.60 | 30 |
| Band 3 | 0.63-0.69 | 30 |
| Band 4 | 0.76-0.90 | 30 |
| Band 5 | 1.55-1.75 | 30 |
| Band 6 | 10.40-12.50 | 120* (30) |
| Band 7 | 2.08-2.35 | 30 |

**Table 2: Landsat 7**

| Landsat 7 | Wavelength (micrometers) | Resolution (meters) |
|---|---|---|
| Band 1 | 0.45-0.52 | 30 |
| Band 2 | 0.52-0.60 | 30 |
| Band 3 | 0.63-0.69 | 30 |
| Band 4 | 0.77-0.90 | 30 |
| Band 5 | 1.55-1.75 | 30 |
| Band 6 | 10.40-12.50 | 60 * (30) |
| Band 7 | 2.09-2.35 | 30 |
| Band 8 | .52-.90 | 15 |

**Table 3: Landsat 8**

| Bands | Wavelength (micrometers) | Resolution (meters) |
|---|---|---|
| Band 1 - Coastal aerosol | 0.43 - 0.45 | 30 |
| Band 2 – Blue | 0.45 - 0.51 | 30 |
| Band 3 – Green | 0.53 - 0.59 | 30 |

| | | |
|---|---|---|
| Band 4 – Red | 0.64 - 0.67 | 30 |
| Band 5 - Near Infrared (NIR) | 0.85 - 0.88 | 30 |
| Band 6 - SWIR 1 | 1.57 - 1.65 | 30 |
| Band 7 - SWIR 2 | 2.11 - 2.29 | 30 |
| Band 8 – Panchromatic | 0.50 - 0.68 | 15 |
| Band 9 – Cirrus | 1.36 - 1.38 | 30 |
| Band 10 - Thermal Infrared (TIRS) 1 | 10.60 - 11.19 | 100 * (30) |
| Band 11 - Thermal Infrared (TIRS) 2 | 11.50 - 12.51 | 100 * (30) |

Landsat provides information in wavelengths and at a spatial resolution appropriate for mapping field-level crop residue and cover crops. Therefore, it is the foundational data set used here for mapping. The data are acquired via the USGS's EarthExplorer system (http://earthexplorer.usgs.gov/). We acquired all available Landsat imagery for the state of Indiana between 2006 and 2015 with cloud cover less than 70%. This included data from 11 path/rows and over 2,000 images in total.

### 2.1.2 MODIS observations

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a NASA sensor aboard two separate satellite systems. These systems together provide high temporal frequency optical reflectance observations in seven spectral bands at a nominal 250- and 500-m spatial resolution. Here, we rely on two derived Level-3 products delivered via the NASA Land Processes Distributed Active Archive Center (LPDAAC; https://lpdaac.usgs.gov/). MCD43A4 and MCD43A2 provide 500-m composites of nadir BRDF-adjusted reflectance and BRDF-Albedo Quality, respectively. The reflectance estimates are provided in the following wavelengths:

**Table 4: MODIS**

| BAND # | RANGE nm |
|---|---|
| 1 | 620–670 |
| 2 | 841–876 |
| 3 | 459–479 |
| 4 | 545–565 |
| 5 | 1230–1250 |
| 6 | 1628–1652 |
| 7 | 2105–2155 |

The first MODIS sensor was launched in early 2000. We use data composites from two MODIS tiles (h11v04 and h11v05) that cover the state of Indiana every 8 days between 2006 and 2015.

Surface reflectances from coarse resolution MODIS products (e.g. MCD43A4) are sufficient for mapping cover crops, tillage practice, and tillage timing when fields are large (>200 acres). Additionally, MODIS reflectance observations contribute information for identifying tillage timing even when fields are smaller (< 200 acres) and MODIS pixels contain reflectance observations from multiple fields.

#### 2.1.3 PRISM precipitation

The PRISM Climate Group at Oregon State University (http://www.prism.oregonstate.edu/) integrates climate observations from monitoring networks across the country within a modeling framework to produce comprehensive estimates of weather variables on a regular spatial and temporal grid. The products used here are delivered at the daily time step at a resolution of approximately 4,000 m. The precipitation data is used in conjunction with the optical imagery to identify areas in the image of recent precipitation, which may have high soil moisture content and altered soil albedo.

#### 2.1.4 Field observations

The USDA state office in Indianapolis provided to the team the raw transect observations from the tillage surveys conducted in 2009, 2011, 2013, and 2015 in six counties (Allen, DeKalb, Decatur, Knox, Ripley, and Tippecanoe). We acquired an additional transect from Hendricks County in 2015. These data include the GPS coordinate taken on the road along the transect together with the conservationist's estimates of the following: present crop, previous crop, tillage practice, slope %, residue cover fraction, and whether the site was flood or rain damaged. The data collected during the 2015 survey included additional information on cover cropping (presence, quality, and a confidence level). The cover crop survey was collected in the Fall of 2014 and Spring of 2015.

#### 2.1.5 SSURGO soil data

SSURGO soil data from the USDA was acquired and processed for Indiana. Soil albedo and percent clay fraction maps were created. In the final application of the system, these layers were not included, as they did not improve system performance.

### 2.2 Pre-processing steps

At Applied GeoSolutions, we have developed and implemented an open-source software system for acquiring, processing, and managing geospatial data. The Geospatial Image Processing System, or GIPS (http://dx.doi.org/10.5281/zenodo.48142), runs in a Linux operating system environment. It is composed of a C++-based image processing library with a user-friendly wrapper written in the Python language, and a

Python-based data management system. Much of the geospatial data pre-processing described in this section is conducted with GIPS.

### 2.2.1 Cloud masking

Clouds and the associated shadows need to be identified and masked in Landsat imagery because the reflectance from the land surface is obscured or severely distorted in these areas. Our automated system for processing Landsat includes two algorithms for cloud masking: a) a modified implementation of a cloud and cloud shadow screening system called Automatic Cloud Cover Assessment (ACCA; Irish et al. 2006), applied to Landsat 5 and 7 data; and b) for Landsat 8, the Quality Assessment Band (Band BQA). These screens provide an indication of which pixels are affected by clouds or cloud shadows, and these pixels are removed from consideration for use in the primary OpTIS algorithms.

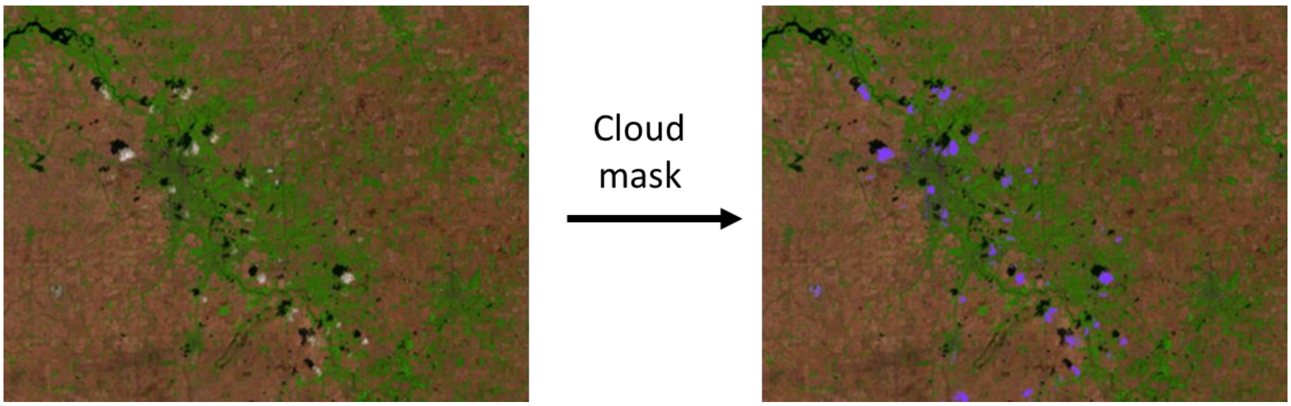



**Figure 1: Landsat 8 example of BQA masking.**

Occasionally, these automated algorithms fail to identify clouds. During the quality assessment stage of processing, these areas are identified by a team member, digitized, and removed from further processing.

The MODIS products are composites assembled from multiple cloud-free observations within a 16 day window. Because the overpass frequency is daily, missing data is less of an issue in the MODIS time series. However, there are instances of reduced quality or missing data, as indicated in the MCD43A2 quality bands.

### 2.2.2 Conversion of reflectance to indices

The cloud-free 30-m Landsat and high-quality MODIS 500-m reflectance observations are used to calculate remote sensing-based indicators of vegetation greenness and crop residue cover. The indices used here include:

**Table 5: Vegetation and tillage indices used in OpTIS**

| Index | Formula | Source |
|---|---|---|
| NDVI | (NIR - RED) / (NIR + RED) | Tucker 1979 |
| NDTI | (SWIR1 - SWIR2) / (SWIR1 + SWIR2) | Daughtry et al. 2006 |
| CRC | (SWIR1 - BLU) / (SWIR1 + BLU) | Sullivan et al. 2008 |

where NDVI is the Normalized Difference Vegetation Index, NDTI is the Normalized Difference Tillage Index, CRC is the Crop Residue Cover index, BLU is blue reflectance, RED is red reflectance, NIR is near infrared reflectance, and SWIR1/SWIR2 are reflectance from the shortwave infrared portion of the spectrum (1.6 and 2.2 micrometers, respectively).

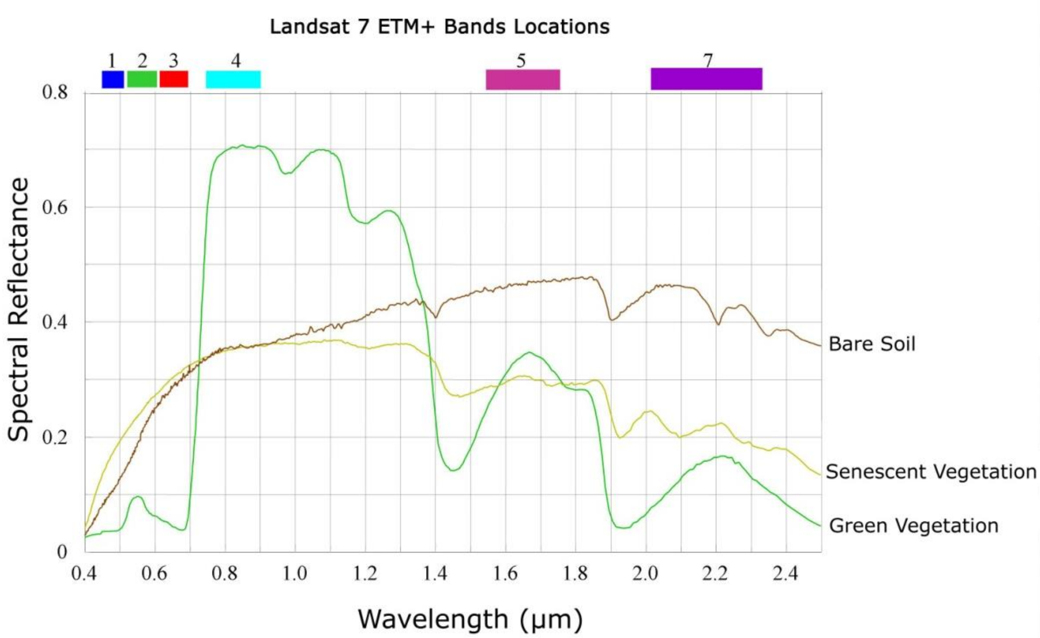



**Figure 2: Senescent vegetation is distinct from soil and green vegetation, particularly in the shortwave infrared portion of the spectrum (L7 bands 5 and 7). These bands are used within the tillage indices implemented here.**

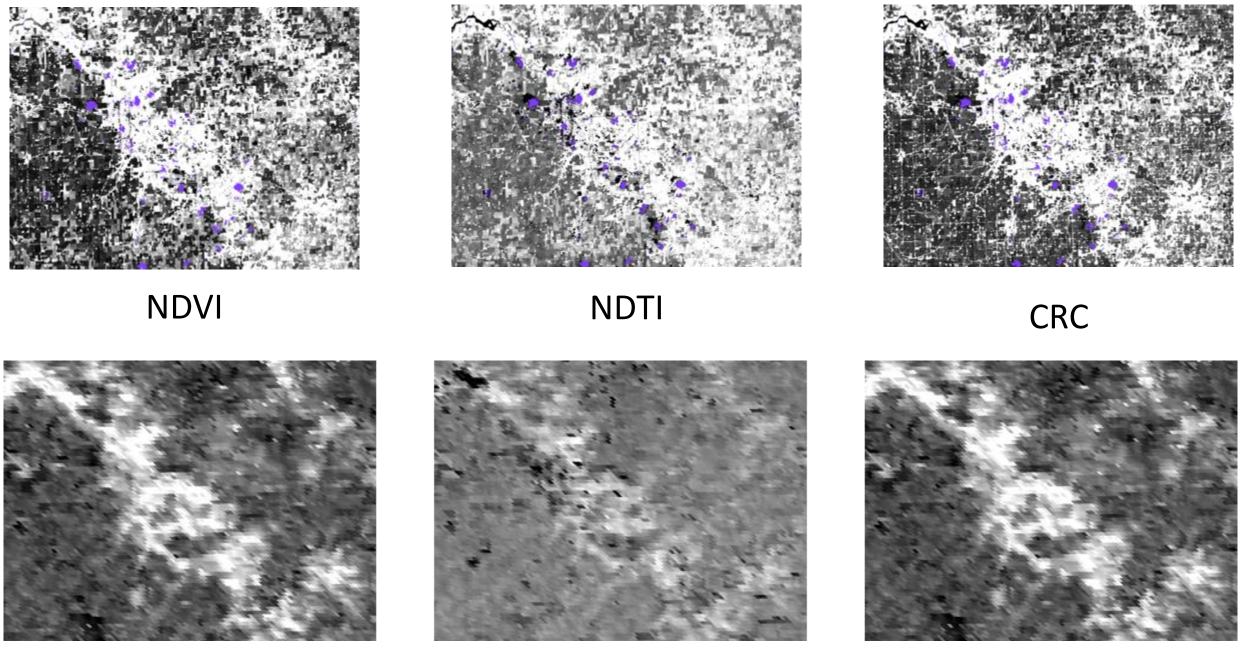



**Figure 3: Landsat (top) and MODIS (bottom) vegetation and tillage indices for a sample region (white is high and black is low index value. The difference in spatial resolution is apparent.**

### 2.2.3 MODIS gap-filling

MODIS (MCD43A4) data are delivered at regular 8-day intervals and rely on observations gathered within a 16-day moving window to provide nadir-corrected surface reflectance. When sufficient cloud-free observations are not available in the 16-day window, no estimate of surface reflectance is provided for the pixel. Therefore, our team developed and implemented a method for gap-filling MODIS data. Data gaps are filled with a weighted average of observations from the preceding and following 8-day composite, the composite from the same day of year in the preceding and following year, and the average observed reflectance at that day of year from all years. The weights are determined via the inverse observed standard deviations generated from the residuals calculated from estimates generated in the described method for all pixels *with* valid observations and the actual observed value.

### 2.2.4 Precipitation calculations

Precipitation is estimated for each satellite image used in OpTIS. For Landsat, total precipitation over the three days preceding the date of image collection is calculated. For MODIS, total precipitation within the 16-day moving window associated with each composite is calculated. These precipitation totals are originally compiled at the 4,000-m scale and then up-scaled so that each satellite-based pixel (30-m for Landsat and 463-m for MODIS) has a precipitation value associated with it. Areas receiving significant precipitation before or during the satellite observation period are identified using this method and parameterized separately.

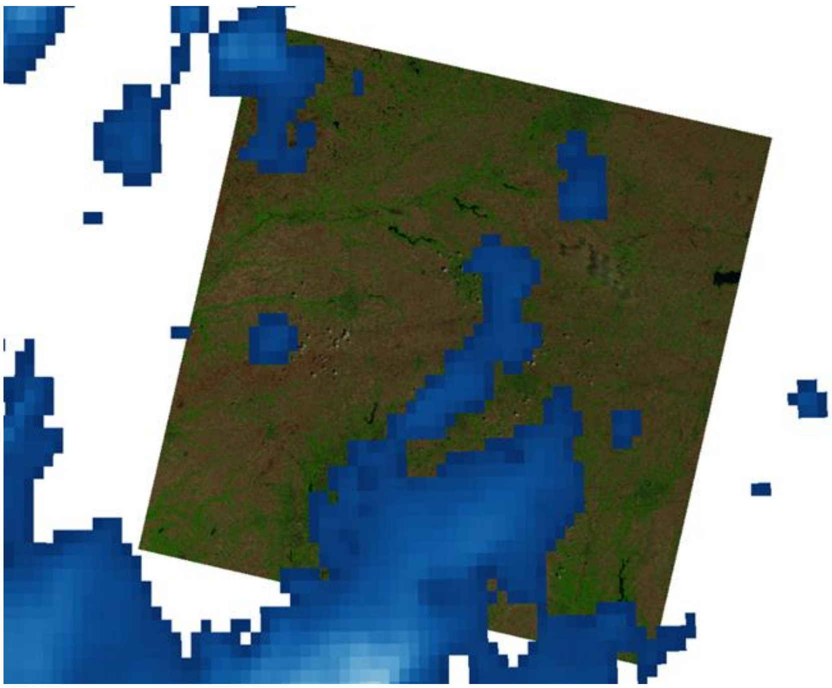


**Figure 4: Precipitation intensity in the 3 days prior to the image acquisition is indicated by the blue to white. Zero precipitation is transparent.**

### 2.2.5 Preparation of the field observations

To compare the satellite-based observations of residue cover and cover crops to ground-based estimates, our team worked with the tillage transect data provided by the Indiana Department of Agriculture in Indianapolis, working in conjunction with the USDA-NRCS state office in Indianapolis. During this iterative process, our team converted the coordinates provided in the tillage transect survey report into a shapefile and ingested these coordinates into a Geographic Information System (GIS). High resolution imagery from Google Earth, including both the most recent NAIP data and data from high resolution optical satellites, were opened in the GIS and placed under the coordinates from the transect. Using the transect coordinates located on the road, the look direction indicated by the transect team (e.g. left or right side of the road as they are traveling), and the high resolution optical data, our team digitized the farm field boundaries associated with each observation. These digitized field boundaries were subsequently sent to the Soil and Water Conservation District teams responsible for collecting the observations at the county level and feedback was provided regarding the accuracy of the digitization. During the digitization process, our team recorded two levels of our confidence in the estimate location based on: a) the distance between the transect point and the center of the field along the road and b) overall confidence that the field digitized is the one recorded by the transect team (based on factors including presence of vegetation obscuring view from the road, context of the field, etc.).

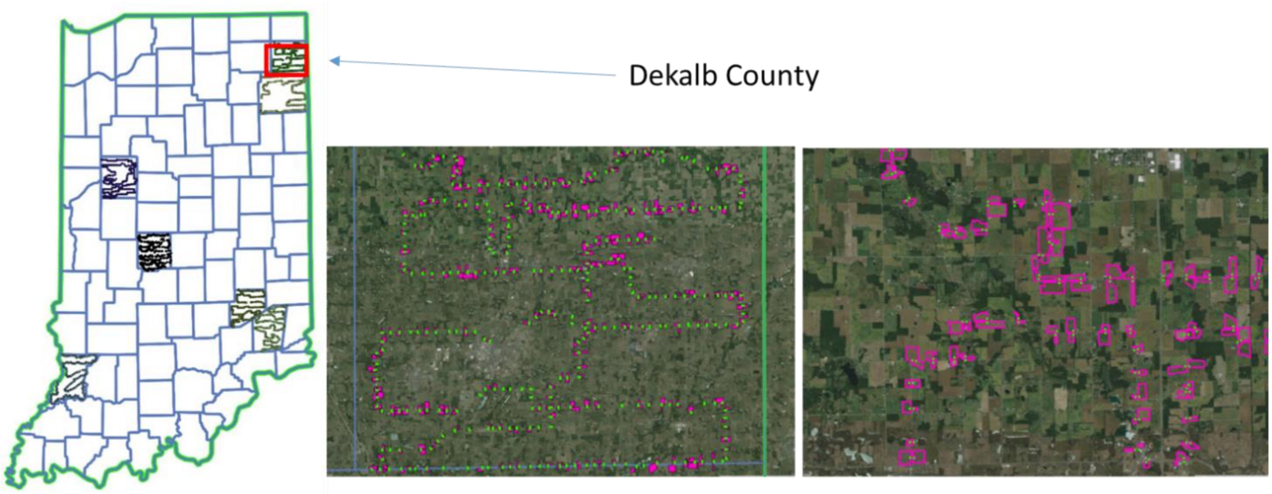



**Figure 5: Tillage transect data were collected and provided from seven counties in Indiana. These point data were related to fields via digitization.**

## 2.3 Primary Algorithms

### 2.3.1 Crop Residue Cover Estimates

Our algorithms for mapping tillage practices rely on fractional estimates of crop residue cover. There is a linear relationship between satellite-based residue cover indices NDTI and CRC and the field-measured residue cover.

While this relationship is typically consistent and strong within a particular image (within a consistent atmosphere and sun-sensor geometry), the parameters of the linear relationship (i.e. the slope and the intercept) can change significantly between images. Therefore, our approach relies on an image-by-image calibration at the watershed scale.

This approach results in a uniquely calibrated estimate of residue cover within each watershed in each individual Landsat or MODIS image for both NDTI and CRC. The residue cover estimates derived from NDTI and CRC are integrated via a weighted average to produce a residue cover estimate for each pixel in each image, calibrated at the watershed scale. A time series of residue cover estimates generated in this way is input into a decision tree to produce an estimate of post-tillage residue cover and certainty for a season. In generating final estimates of cover and certainty for a season, the decision tree takes into account the timing of image input and the temporal pattern of residue cover observed.

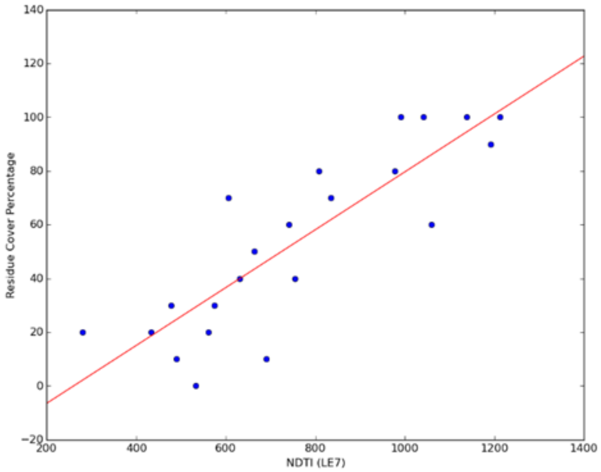



Image date: 2012-04-13
Field observation date: 2012-04-24
Field photos (n = 22)

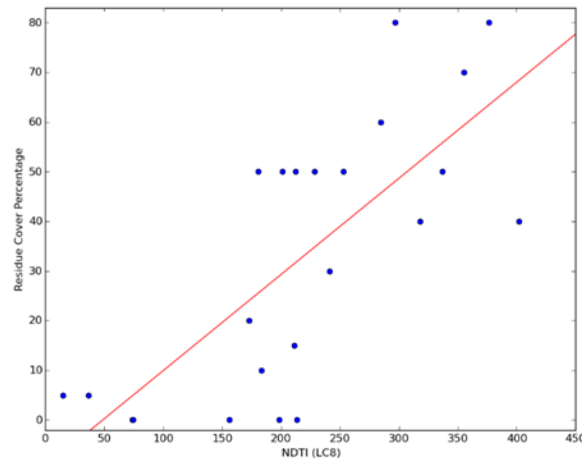



Image date: 2013-05-26
Field observation date: 2013-05-30
Field photos (n = 22)

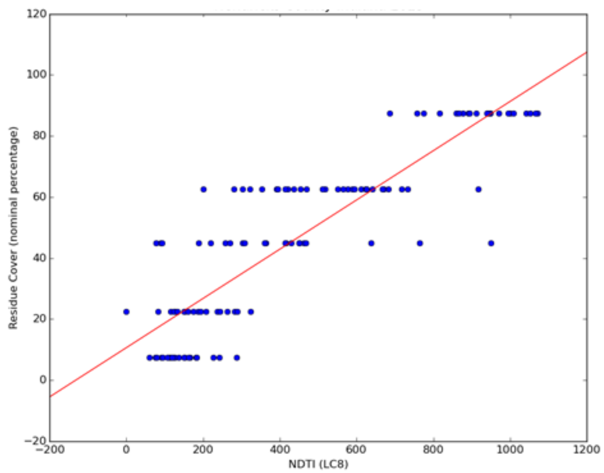



Image date: 2015-05-23
Field observation date: 2015-05-27
Transect (n = 118)

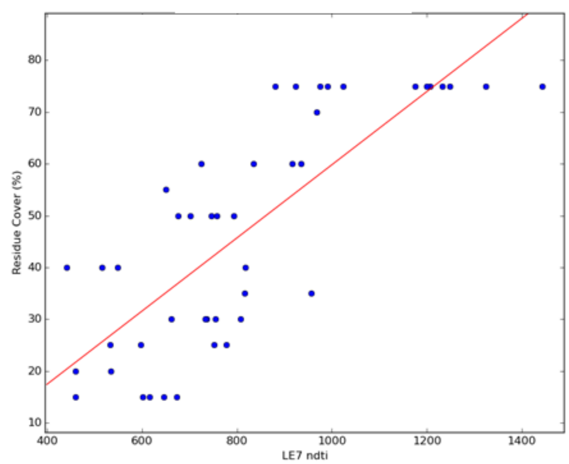



Image date: 2012-04-02
Field observation date: 2012-04-24
Transect (n = 45)

**Figure 6: Tillage indices derived from Landsat have a consistently strong linear relationship with field measured residue cover, but the parameterization of this relationship changes with atmosphere, soil, and moisture conditions.**

### 2.3.2 Tillage Practice Estimate

The final estimate of residue cover at the pixel level is subsequently classified into a tillage class using a simplified version of the definitions put forward by the state NRCS office.

NRCS tillage classes:

Conventional: 0 – 15%

Reduced: 16 – 30%

Mulch, Ridge, Strip: 30 – 75%

No-till: 30 – 100%

NRCS residue classes:

1: 1 – 15%

2: 16 – 30%

3: 31 – 50%

4: 51 – 75%

5: 76 – 100%

OpTIS tillage classes:

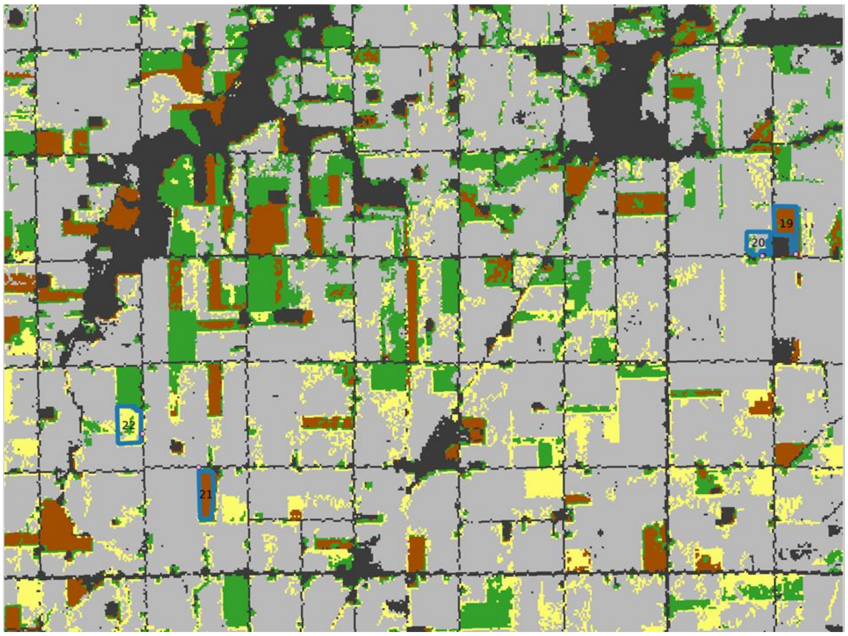
1: 1-15% (conventional)

2: 16-30% (reduced)

3: 31-100% (no)

### 2.3.3 Winter Cover Crop Estimates

Our algorithms for mapping winter cover crops rely on multi-temporal NDVI measures of green cover in the fall, winter, and spring. The time series of green cover estimates is input into a decision tree to evaluate whether the pixel was under a winter cover crop, together with a measure of certainty for each season. In generating final estimates of winter cover crop status and certainty for a season, the decision tree considers the timing of image input and the temporal pattern of green cover observed. Each agriculture pixel is categorized into one of five categories: 1) no information/insufficient data; 2) no winter cover; 3) winter commodity crop; 4) cover crop killed in winter; and 5) winter cover crop surviving to spring planting.




Application of an NDVI-based algorithm to separate winter-killed cover crops (yellow) from cover crops that survive into the spring (green), and commodity crops (typically wheat) that are harvested the following summer (brown). Grey areas do not have cover crops and black areas are non-agriculture or missing data. Landsat imagery from three time periods (26 December 2013, 11 April 2014, and 17 June 2014) are used here.

### 2.3.4 Uncertainty

Uncertainty in estimates of crop residue cover, tillage practice, and winter cover crops enters the process at many levels, including at the tillage transect ground observation level and the satellite observation level. We link each component with an assessment of confidence. For example, the teams conducting the tillage transect assign each observation a confidence value of 1, 2, or 3 indicating low, medium, and high confidence in the tillage class they've assigned to the field. Our digitization team marks each digitized field associated with a tillage transect location with two types of confidence: 1) distance from edge of field (1 - low indicating low confidence and 3 – high indicating high confidence; this is an estimate of likelihood that the transect team identified the same field as our digitization team); and 2) confidence that a clear view of the field is available from the road and is not obscured by vegetation. Our satellite-based estimates have three separate indicators of confidence based on: 1) number of clear images available for each pixel during the tillage/cover crop season (more images result in increased confidence); 2) the timing of the clear images (e.g. post-tillage timing increases confidence much more than early spring image timing); and 3) the consistency in the residue/green cover estimates across the season. If the observations fit one of the expected patterns of cover through the season, then the consistency confidence level is high.

The individual evaluations of confidence from ground validation data and satellite data are subsequently combined to create a single level of confidence for each evaluation point. From this overall confidence score, we can evaluate how the system performs at each level and decide which data should be used for county and watershed level estimates.

## 2.4 Output

Output products from the OpTIS system are initially created as raster data in the geotiff format at the 30 m and 500 m resolution. These high and moderate resolution estimates are subsequently summarized at the county and HUC levels and delivered as shapefiles and tables expressing percentage of the overall area within each tillage practice category or winter cover crop category each year.

### 2.4.1 Table format

In total, 40 comma separated values (csv) tables are produced: ten years of annual data (2006-2015) at four spatial aggregation levels: HUC08, HUC10, HUC12, and County. Each of these 40 tables has information on four categories of previous year's crop (corn, soybean, small grains, and specialty crops). Each table has 50 columns including "newid" which links each row in the table to a spatial unit, as well as the commonly used name for the county or watershed represented by the row. There are an additional 48 rows, 12 for each of the four crop types. "acres" is the number of acres planted the previous year in that crop type, derived from the CDL data layer. "convAC", "redAC", and "ntillAC" are the estimated number of acres classified as conventionally tilled (0-15% residue cover), reduced tilled (15-30% residue cover), and not tilled (> 30% residue cover) aggregated by previous year's crop type. "ftllAC" is the number of acres estimated as tilled (either conventionally or reduced) in the fall season. "ccAC" is the number of acres estimated as being covered with a winter cover crop. The next five columns ("XXXXPCT") repeat the same information, but are presented as a percentage of all area planted within the previous year's crop type. "ttCERT" is an aggregated metric of certainty for the tillage practice estimates derived from information on image quantity, timing, and consistency, as well as number of pixel level predictions near the threshold cut-offs between tillage categories. All labels are preceded by a single letter – C for corn, B for soybean, G for grain, and S for specialty crop – representing the previous year's planted crop.

### 2.4.2 No Data Values

Some geographic areas or crop type combinations have either no acreage identified as planted in the CDL crop type category or insufficient quality satellite observations for making an estimate of tillage practice or cover crop. These areas are filled with a No Data Value of -999.9 in the tables. It is important to note that the CDL product has improved over the current study period. Early in the study time period, for example, few areas were accurately classified as specialty crops, resulting in a high number of No Data Values and low confidence indicators.

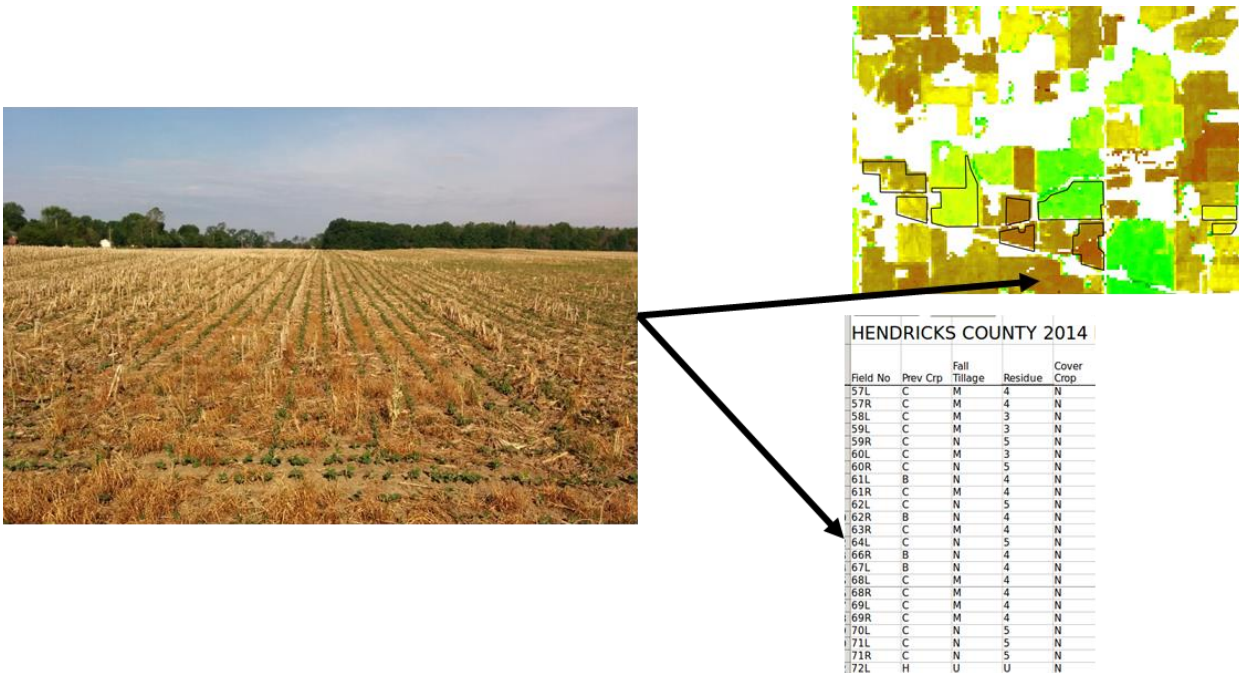
# 3.0 COMPARISON OF OPTIS TO TRANSECT ESTIMATES

## 3.1 Crop Residue and Tillage Practice

We compared OpTIS-based estimates of crop residue and tillage practice to transect-based estimates at the field-level in seven pilot counties, and at the county-level across the entire state.

### 3.1.1 Field Level

Field observations used for validation come from tillage transect surveys.




| Field No | Prev Crp | Fall Tillage | Residue | Cover Crop |
|---|---|---|---|---|
| 57L | C | M | 4 | N |
| 57R | C | M | 4 | N |
| 58L | C | M | 3 | N |
| 59L | C | M | 3 | N |
| 59R | C | N | 5 | N |
| 60L | C | M | 3 | N |
| 60R | C | N | 5 | N |
| 61L | B | N | 4 | N |
| 61R | C | M | 4 | N |
| 62L | C | N | 5 | N |
| 62R | B | N | 4 | N |
| 63R | C | M | 4 | N |
| 64L | C | N | 5 | N |
| 66R | B | N | 4 | N |
| 67L | B | N | 4 | N |
| 68L | C | M | 4 | N |
| 68R | C | M | 4 | N |
| 69L | C | M | 4 | N |
| 69R | C | M | 4 | N |
| 70L | C | N | 5 | N |
| 71L | C | N | 5 | N |
| 71R | C | N | 5 | N |
| 72L | H | U | U | N |

**Figure 7: Field estimates of residue cover, tillage practice, and winter cover crop status are collected as part of the tillage transect survey and are recorded in a spreadsheet. These estimates are then compared to the average residue cover and cover crop estimates generated from OpTIS within each corresponding field.**

#### *3.1.1.1 Transect data (Indiana NRCS) (3-4 years for 7 pilot counties)*

Crop residue and tillage practice estimates associated with the field observations are generated from the OpTIS satellite-based estimates and stored in a common table for comparison. The data from 2009, 2011, 2013, and 2015 tillage transect surveys from the pilot counties typically include observations from about 400 fields on average, resulting in approximately 10,000 field observations for comparison. These observations come at varying levels of confidence. We eliminated a field from the comparison data set if one of the confidence indicators registered in the low category from a) the field observation assessment (e.g. transect team was unsure of residue class), b) the field digitization assessment (e.g. field digitizer was unsure which field was referenced from a transect point), or c) the remote sensing (e.g. no cloud free or well-timed imagery existed for the field). The final comparison data set comprised 7,559 transect observations.

The level of correlation between OpTIS estimates and transect estimates varies between the seven pilot counties and transect years. Overall, OpTIS explains approximately 27% of the variance in transect-based estimates of residue cover at the field level. We note that OpTIS and transect-based estimates are in closest agreement in the 2015 ($R^2$ = 0.42 vs. $R^2$= 0.21 in all other years; Figure 8). All transect field teams were introduced to this pilot project in early 2015, before the transect was conducted, to convey the importance of collecting consistent transect observations. Additionally, the AGS team visited Hendricks County in 2015 and participated in the transect observation process. The presence of AGS considerably slowed the pace of the transect data collection process, and apparently improved its accuracy. The comparison between the OpTIS and transect-based estimates of residue cover in Hendricks County in 2015 reflect this more careful process, showing an $R^2$ of 0.74 (Figure 10).

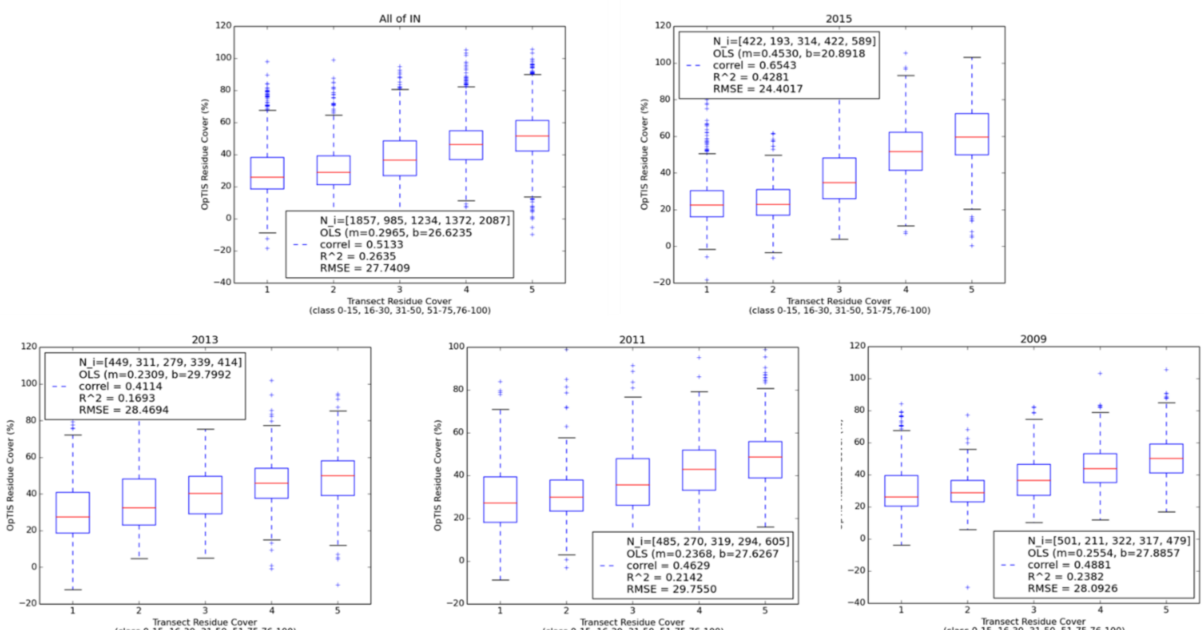



**Figure 8: Comparison of transect and OpTIS-based residue cover estimates show that 2015 stands out with a significantly better relationship between the OpTIS estimates and the transect estimates.**

The differences between the OpTIS estimated residue cover and the transect estimated residue cover have many sources. Both the OpTIS and the transect estimates are imperfect. Some of the OpTIS limitations include:

- Uncertainty due to the inexact nature of the modeled relationship between surface residue and vegetation indices.
- Uncertainty due to uncorrected residual atmospheric contamination or surface moisture.
- Uncertainty from missing or poorly timed imagery.

Some of the limitations of the transect estimates already noted and documented here include:

- Uncertainty from visual estimates of residue cover assessed from a rapidly moving vehicle.
- Mismatch between field and transect points, especially when a transect point lies near the edge between two fields.
- Uncertainty from transect timing (e.g. transect conducted before all farmers have finished preparing fields or after the crop canopy has obscured the surface residue).

There is an additional source of uncertainty introduced by the binning of the transect residue cover estimates. When comparing a continuous variable (e.g. Residue Cover) to a categorical variable (e.g. binned Residue Cover) some additional noise is added to the process simply from the binning process. We explored the effect of and quantified this additional uncertainty via a simple simulation.

We created a simulated data set resembling the transect and OpTIS residue cover. In this simulation, the OpTIS derived estimates perfectly simulate actual residue cover. We used this to examine how well the simulated "perfect" OpTIS system would capture the binned visual transect estimates. We found that a simulated perfect OpTIS system would have an $R^2$ of 0.95 rather than 1.0, simply because the transect estimates are binned and assigned the value of the bin mid-point (Figure 9a). If we also assume some conservative error (e.g. standard deviation of 0.07 or 7% residue cover) in the visual estimates of residue cover, we see that the $R^2$ of the relationship drops to 0.91 (Figure 9b).

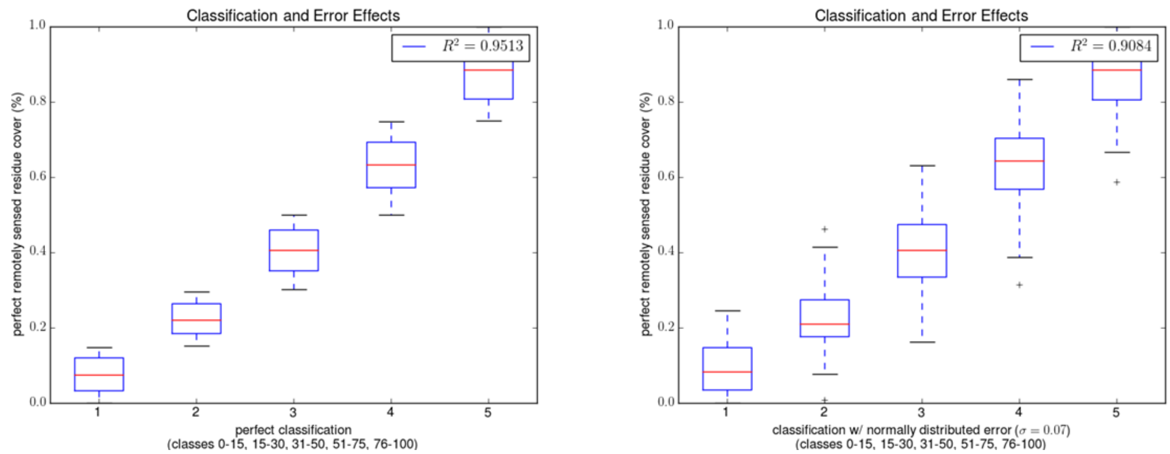
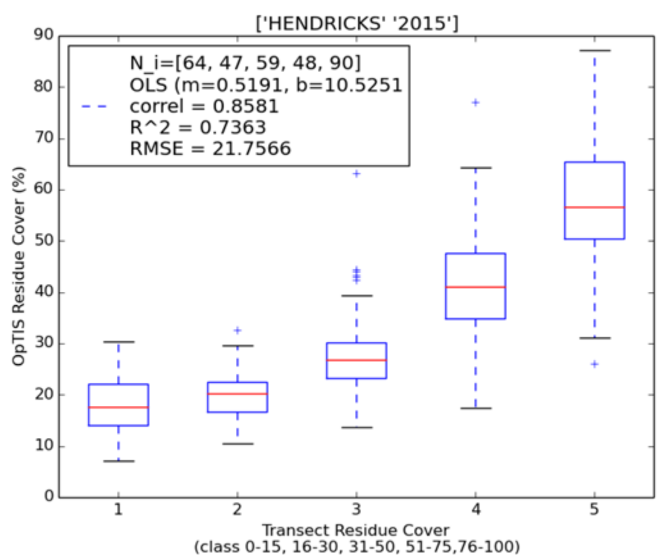



**Figure 9: A simulation of a perfect OpTIS system in the context of the transect surveys shows that maximum measured performance is about $R^2$ of 0.9.**

This simulation indicates that a perfect OpTIS system would explain about 90% of the variance in the binned transect estimates. It is important to note this maximum $R^2$ of 0.91 when examining the results presented here.

We see that OpTIS registers an $R^2$ of 0.74 in Hendricks County 2015, the transect survey for which we have the most confidence. Given the results of this simulation, we can say for Hendricks County that OpTIS explains 81% of the maximum explainable variance in residue cover.



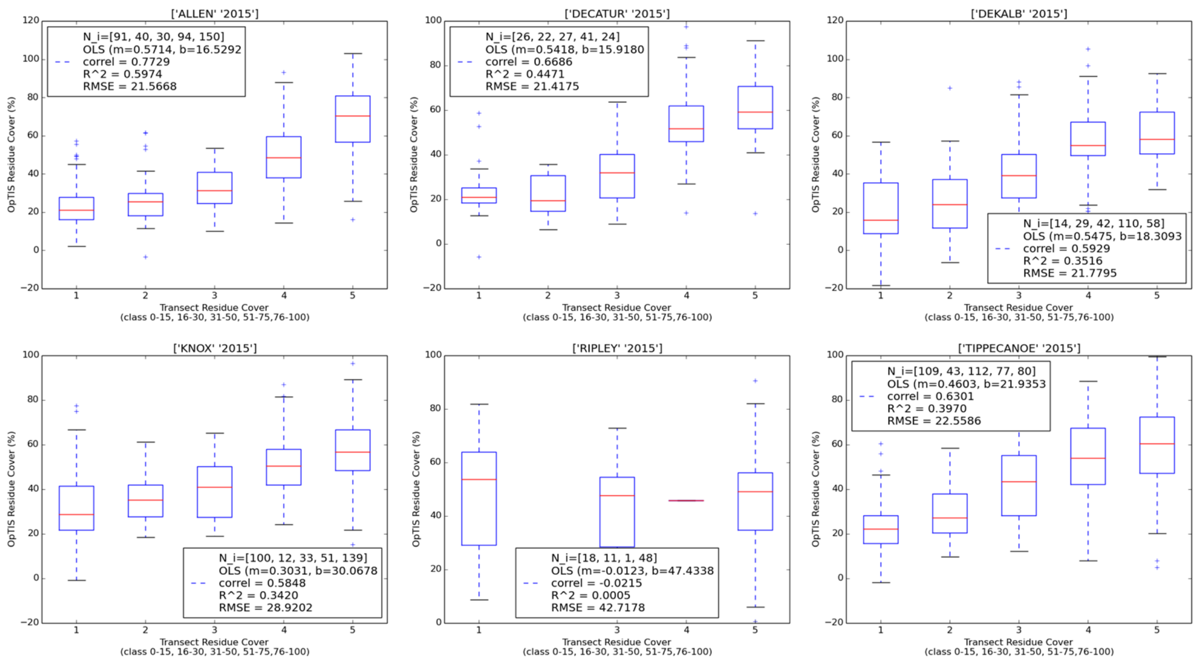



**Figure 10: County-by-county comparison between transect- and OpTIS-based estimates show that the relationship in Hendricks County is significantly better than the relationship in the other counties.**

### 3.1.2 County Level

In addition to the field-level data provided and examined in the seven pilot counties, we have access to county-level transect summaries available in 90 Indiana counties in 2015. Our satellite-based estimates are masked to include only agricultural areas, and the pixels in these agricultural areas are assessed and summarized in the area of interest (e.g. county) and compared to the transect summaries. We examined the correlation between the field-based estimates and the OpTIS estimates. We tallied the total area in each class at the county level for comparison.

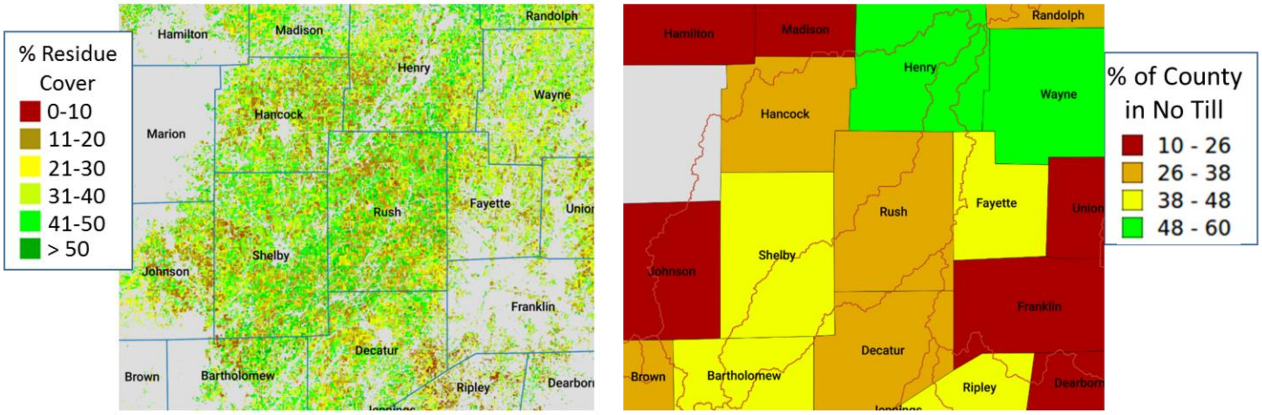



**Figure 11: Pixel-based estimates of residue cover are aggregated to the county- and huc-levels for distribution. We compare OpTIS- and transect-based estimates at the county level. (Demonstration data shown here for illustration).**

We note that the transect typically generates estimates from sampling about 10% of the fields in the county, while OpTIS typically provides estimates based on 75% of the county area. Using OpTIS estimates alone, we examined the fractional estimates of no-till corn in 2015 at the county-scale in the seven pilot counties based on a) all available OpTIS estimates within the county and b) OpTIS estimates only from the transect fields. We note that the differences in estimated fractional area of no-till differ by, on average ±4 percent, with a maximum difference of 9%. It is important to keep in mind that differences in OpTIS- and transect-based county estimates exist for several reasons, including sampling difference.

In the 2015 data, we examined the consistency between OpTIS and transect estimates of area of no-till at the county scale. We focus our comparison at the top 20 acreage counties. We see that OpTIS and the transect are moderately correlated when the previous year's crop was corn (r = 0.49), while the level of correlation is lower when the previous year's crop was bean (r = 0.23).

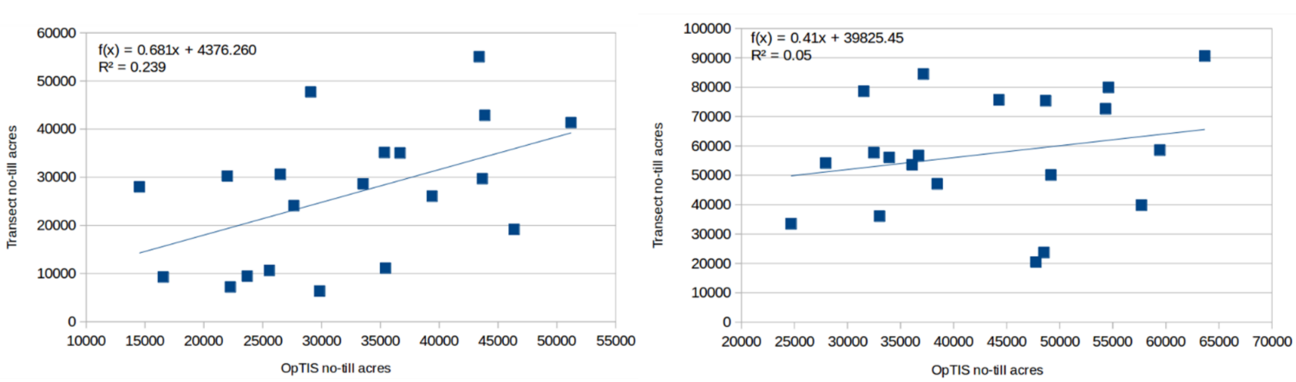



**Figure 12: 2015 Corn (left) and soybean (right) no-till acreage comparison between OpTIS and transect estimates at the county scale.**

## 3.2 Winter Cover Crops

The transect comparison data for winter cover crops was collected in the fall of 2014/spring of 2015 (2,649 fields).

### 3.2.1 Field Level

Field observations used for validation come from tillage transect surveys in 2014/2015. We created a confusion matrix to evaluate the relationship between the OpTIS- and transect-based estimates of cover crop.

The transect data from the seven pilot counties indicate that 14% of fields were covered in the winter, about half with commodity crops and the other half with winter cover crops. Our confusion matrix indicates an overall agreement in class mapping of 86%. The agreement of no cover is 92%, while the agreement for cover is 45%. However, due to the substantial mismatch in class size, overall agreement can be misleading. We calculated the Kappa Statistic, which provides an agreement estimate while correcting for random chance. A Kappa of 1.0 indicates perfect classification agreement, 0 indicates agreement no different from chance, and negative values indicate worse agreement than chance. The Kappa statistic derived from all seven pilot counties is 0.35, indicating moderate agreement. The Kappa Statistic ranged from 0.62 (Dekalb) to -0.04 (Hendricks) (Table 6).

We noted some inconsistency in the way in which winter cover crop transect data were collected. In some counties, when previous and present year crops were marked as grain, the cover crop column was marked as *yes*. In others, this column was marked as *no*. These inconsistencies may be reflected in our confusion matrices at the county scale.

**Table 6: Classification results from winter cover in the pilot counties in 2015**

| County | Agreement | Kappa |
|---|---|---|
| Allen | 0.95 | 0.45 |
| Decatur | 0.86 | 0.15 |
| Dekalb | 0.92 | 0.62 |
| Hendricks | 0.84 | -0.04 |
| Knox | 0.76 | 0.32 |
| Ripley | 0.82 | 0.00 |
| Tippecanoe | 0.90 | 0.48 |
| All | 0.86 | 0.35 |

### 3.2.2 County Level

In addition to the field-level data provided and examined in the seven pilot counties, we have access to county-level transect summaries available in 90 Indiana counties in the year 2014/2015. Our satellite-based estimates are masked to include only agricultural areas, and the pixels in these agricultural areas are assessed and summarized in the area of interest (i.e. county) and compared to the transect summaries. We examined the correlation between the field-based estimates and the OpTIS estimates. We note that there is moderate correlation (r = 0.4) between the OpTIS and transect estimates of county percent in cover crop. We focus on the top 20 producing counties because comparing percentage differences in counties with substantial agricultural area provides a more robust comparison, relying on results that are less prone to randomness in percentage values.

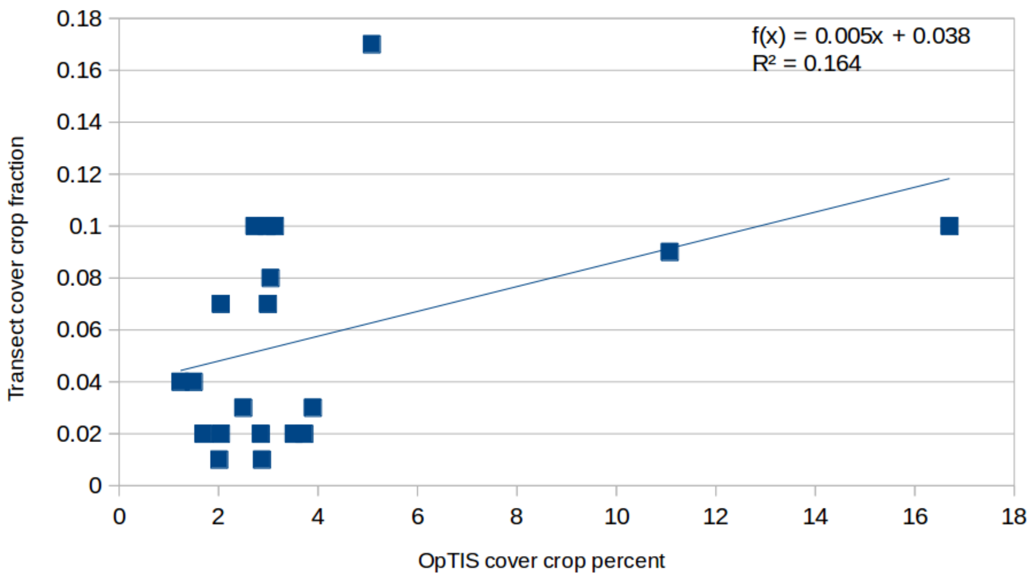



**Figure 13: The relationship between transect and OpTIS estimated cover crop percent for previous year corn in 2015 at the county scale in the top 20 corn producing counties.**

## 3.3 Indiana-wide estimates

Our maps indicate that there is significant variability in the use of no-till farming and the adoption of cover crops in both corn and soybeans across the state of Indiana. While no trend is identifiable in the adoption of cover crops, there does appear to be a trend in the use of no-till.

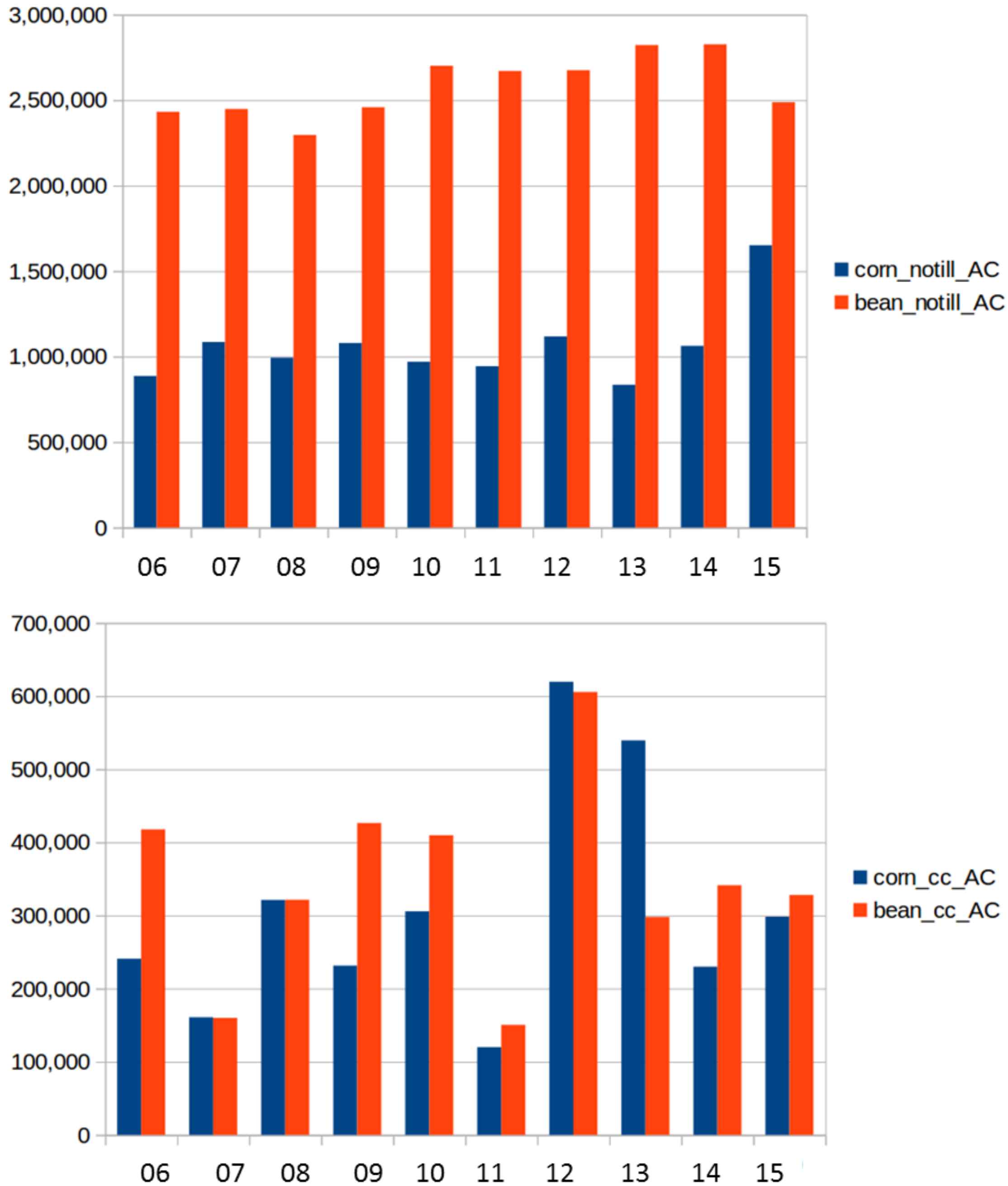



**Figure 14: Acres of a) no-till and b) cover crops, categorized by previous year's crop.**

## 3.4 Discussion of strengths and limitations of the OpTIS approach

### 3.4.1 Identification and comparison of areas of strong/weak performance

When compared to quality assured field observations of residue cover, the metrics of agreement between the OpTIS system estimates and the field observations are good. This positive result is best seen in the comparison to the 2015 Hendricks County transect fields for residue cover, where more than 80% of the explainable variance in residue is captured by the OpTIS system. These results show that the OpTIS system successfully estimates residue cover without relying on field data driven calibration. The implications of this successful application include the potential to accurately estimate conservation practices over wide areas and back through time, without the high costs associated with windshield transect surveys or manually calibrated, one-off satellite-based estimates.

It is our assessment that a substantial portion of the difference between the OpTIS and transect estimates is due to error or noise in the transect estimates. The transects were not designed for comparison with satellite-based estimates and it is not ideal to utilize them in this manner. Unfortunately, due to budget and time constraints, this pilot project was not designed to collect the significant amount of quality-assured field observations of residue cover and cover crop data required to fully isolate the source of disagreement between the OpTIS- and field-based estimates. This type of large-scale, quality-assured data collection and assessment would be valuable in refining our understanding of the limits of the OpTIS system.

In our assessment, the pilot project has confirmed some known weak points in the OpTIS system and highlighted areas in need of improvement. The most substantial of these include:

- Missing ~30 m resolution data due to clouds and system failure (e.g. SLC off Landsat 7 and demise of Landsat 5) often requires gap-filling with less accurate MODIS ~500 m data. This issue will become less substantial moving forward as Sentinel 2 has been launched and observations from the system are being incorporated into the OpTIS system.
- Occasional failure of the cloud detection algorithm required hand digitization of residual clouds. Manual delineation of clouds is inefficient and currently acts as a hurdle in our path toward an entirely automated approach. Our cloud detection algorithms will be improved, resulting in lower application costs required for a larger, nationwide deployment of the system.
- The cover crop mapping algorithm is not as mature as the residue cover algorithm. Improvements are required to make the cover crop algorithm more robust. These include adding additional flexibility to the algorithm to better account for issues such as frequent late winter greening in southern Indiana associated with the prevalence of winter annuals (i.e. weeds) that do not receive credit as cover crops.
- Improvements in the estimation of uncertainty are required. The current uncertainty estimation is limited by the small ground truth data set. Due to a lack of full confidence in the transect survey

results, we cannot rely on this large data set in full validation. A large campaign to acquire field observations will not only help to improve the algorithms, but will allow for better characterization of uncertainty.

Beyond these current limitations, we have evidence that the system is performing well. The system efficiently processed more than 2,000 Landsat scenes, as well as ten years of MODIS and PRISM data and implement automated algorithms to estimate crop residue cover and cover crops across Indiana over ten years. This pilot project demonstrates that the algorithms provide a good estimate of cover crop and residue cover adoption patterns across the state and through time.

### 3.4.2 Crop residue cover, soil disturbance and tillage practice discussion

The algorithms used in the OpTIS system are primarily sensitive to residue cover and green cover. The system is not designed to detect soil disturbance levels beyond the link with residue cover levels. This lack of sensitivity to soil disturbance can have relevance as the use of newer tillage techniques, such as "vertical tillage", become more common. Carbon sequestration in agricultural soils is tightly linked to soil disturbance. A change of tillage definitions needs to be explored. Changing from 4 tillage types to 3 tillage types may simplify the process for users, provide end-users with required information, and improve remote sensing accuracy.

| Current tillage definitions | Possible Changes |
|---|---|
| Conventional: 0 – 15% | Conventional: 0-15% residue |
| Reduced: 16 – 30% | Reduced tillage 15-30% |
| Mulch, Ridge, Strip: 30 – 75% | No-till; 30- 100% |
| No-till: 30 – 100% | |

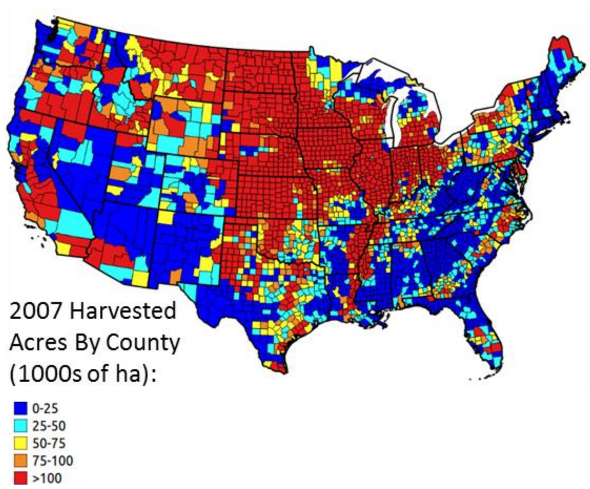
Discussions are underway to evaluate, update and modernize the tillage definitions and their associated residue bracket percentages to reflect changes in agriculture and refinements in processes to measure these parameters. However, this is not a simple process. Care has always been taken to ensure that a similar package of tillage definitions was used across the U.S. in order to better enable comparisons and consistency in our measurements and enable us to evaluate national trends and make comparisons across various geographies. There is hesitancy in regionalizing these tillage definitions for fear of eliminating the geographic consistency in characterization of tillage practices and creating inconsistencies in the tracking of regional and national trends. Changing and updating tillage definitions will likely be a slow and deliberate process that will involve a team of experts from multiple geographies in order to fully capture needs from all regions. These tillage definitions then need to be combined with cover crop usage (e.g. fall cover crop [winter killed or destroyed with tillage in very early spring] vs. fall and spring cover crop).

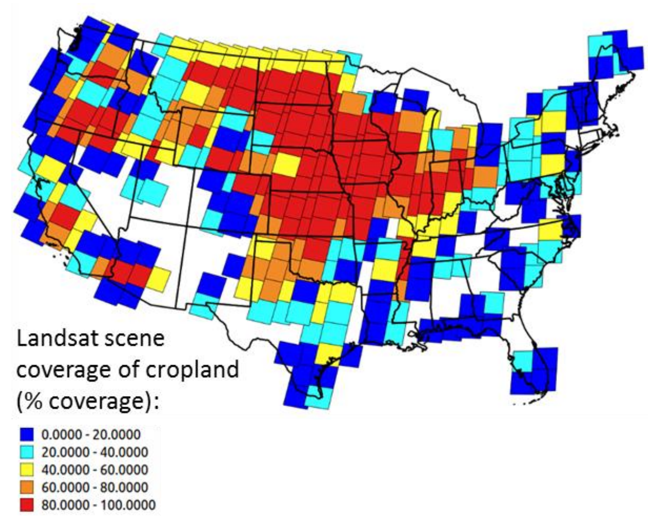
In addition, management (e.g. no-till and cover crops) for soil health may take several years to see resultant changes in carbon, and having the ablity to state how many acres have been using conservation management techniques for more than 5 years is critical. This type of information can be extracted from the products generated as part of this pilot project, providing a unique source for soil health information in Indiana.

# 4.0 SCALING OPTIS TO NATIONAL COVERAGE

## 4.1 Area

Covering all counties in the continental USA with at least 50,000 acres of harvested cropland in 2007 (US Census) will require the analysis of about 350 Landsat path/rows. In Indiana, we analyzed 12 path/rows. If the selection criteria are changed to include counties with at least 75,000 or 100,000 acres of cropland, 300 or 270 path/rows are required for analysis, respectively.




## 4.2 Crop types

We compared crop acreage in Indiana to acreage in the USA by type. Corn, soy, hay, and wheat make up more than 90% of Indiana acreage but only 70% of the US row crop acreage. Sorghum and cotton are rare or nonexistent in Indiana but plentiful in certain other states. Eight major row crops in the US total of 238 million acres. However, there are another 69.5 million aces cropland acres (include forage, orchards, and vegetables). Our algorithms would need to be tested further in applicable specialty crops not commonly seen in Indiana.

### 4.3 Field sizes and crop density

Field size varies greatly depending on topography. Large farms and large fields are found in the Great Plains and the Midwest. But regions within a state (Southern Indiana and Southern Illinois), collar counties next to major urban centers, and farms in New England and the south east can have much smaller fields that will be sensitive to availability of moderate resolution Landsat-type data. Areas with lower crop density may make analysis impractical or much more expensive. Additionally, California is a large vegetable producer in which two or sometimes three crops are grown each year. This does not fit the current OpTIS implementation of one two crops per year, and the system would need to be updated to incorporate these more complex crop systems that can include multiple tillage events.

### 4.4 Additional information/sensors

A significant source of uncertainty in our estimates is due to the areas where cloud-free observations from moderate resolution satellites (e.g. Landsat) are not available in the critical time periods. Moving forward, there will be additional opportunities for cloud-free observations from these types of satellites, including those from European Space Agency's Sentinel system. Sentinel collects observations at 10 – 20 meter spatial resolution every 5 – 10 days, including in the critical shortwave infrared band.

## 5.0 REFERENCES

Allen, R., Hanuschak, G., and Craig, M., 2002, Future Vision for the Utilization of Remotely Sensed Data and Geographic Information Systems in the National Agricultural Statistics Service, *NASS Remote Sensing Publication*.

Bricklemeyer, R.S., R.L. Lawrence, and P.R. Miller, 2002, Documenting no-till and conventional till practices using Landsat ETM plus imagery and logistic regression, *Journal of Soil and Water Conservation*, 57(5):267-271.

Bricklemeyer, R.S., R.L. Lawrence, P.R. Miller, and N. Battogtokh, 2006, Predicting tillage practices and agricultural soil disturbance in north central Montana with Landsat imagery, *Agriculture, Ecosystems, and Environment*, 114: 210-216.

Bricklemeyer, R.S., R.L. Lawrence, P.R. Miller, and N. Battogtokh, 2007, Monitoring and verifying agricultural practices related to soil carbon sequestration with satellite imagery, *Agriculture, Ecosystems, and Environment*, 118: 201-210.

Chander, G., B.L. Markham, and D.L. Hedler, 2009, Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors, *Remote Sensing of Environment*, 113:893-903.

Congalton, R.G. ,1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 3735-46.

CTIC, 2000, National survey of conservation tillage practices. Conservation Technology Information Center. West Lafayette, IN. http://www.ctic.perdue.edu

CTIC, 2008, Cropland Roadside Transect Survey: Procedures for Using the CRTS for Obtaining Tillage/Crop Residue Data. Conservation Technology Information Center: West Lafayette, IN.

Daughtry, C.S.T, 2001, Discriminating crop residues from soil by shortwave infrared reflectance, *Agronomy Journal*, 93(1):125-131.

Daughtry, C.S.T., E.R. Hunt, P.C. Doraiswamy, and J.E. McMurtrey, 2005, Remote sensing the spatial distribution of crop residues, *Agronomy Journal*, 97:864-871.

DeGloria, S., Wall., S., Benson, A., and Whiting, M., 1986, Monitoring conservation tillage practices using Landsat multispectral data, *Journal of Soil and Water Conservation*, 41(3):187-190.

Hagen, S.C., B.H. Braswell, E. Linder, S. Frolking, A.D. Richardson, and D.Y. Hollinger, 2006, Statistical uncertainty of eddy flux-based estimates of gross ecosystem carbon exchange at Howland Forest, Maine, *Journal of Geophysical Research*, 111, doi:10.1029/2005JD006154.

Hartkamp, A.D., White, J.W., and G. Hoogenboom, 1999, Interfacing geographic information systems with agronomic modeling: a review. *Agron. J.*, 91:761-772.

Hayese, R., 2007. The Impact of Tillage Practices on Land Surface Temperatures of Croplands in Northeast Indiana, Southeast Michigan, and Northwest Ohio. University of Toledo, Masters Thesis.

Hipple, J., 2007. Preprocessing of P6-AWiFS for Field Level Data Extraction and Data Mining. ASCR Management Services & USDA FAS Forum on ResourceSat Real Product Innovations. Greenbelt, MD. November 27, 2007.

Johnson, D., 2007. An evaluation of Resourcesat-1 LISS-III vs AWiFS imagery for mapping croplands. JACIE Civil Commercial Imagery Evaluation Workshop. Laurel, MD USA, March 2007.

Lal, R, R F Follett, JM Kimble, and CV Cole, 1998. The Potential of U.S. Cropland to Sequester Carbon and Mitigate the Greenhouse Effect. *Soil and Tillage Research*; CRC Press, Volume 61.

Maryland Agricultural Water Quality Cost-Share Program (MACS), 2016. Cover Crop Program. http://mda.maryland.gov/resource_conservation/Pages/cover_crop.aspx

Morgan, J., Ronald F. Follett, Leon Hartwell Allen, Jr., Stephen Del Grosso, Justin D. Derner, Feike Dijkstra, Alan Franzluebbers, Robert Fry, Keith Paustian, and Michele M. Schoeneberger, 2010. Carbon Sequestration in Agricultural Lands of the United States, *Journal of Soil & Water Conservation Society*, Jan/Feb 2010 – vol 65, No1.

Pagnutti, M., 2006. Initial radiometric calibration of the AWiFS using vicarious calibration techniques, USDA FAS/PECAD Seminar: ResourceSat AWiFS and LISS Data, Fairfax, VA USA, September 12, 2006.

Sohn, Y., Rebello, N.S., 2002, Supervised and unsupervised spectral angle classifiers. *Photogrammetric Engineering and Remote Sensing*, Vol. 68, No. 12, pp 1271 – 1280.

South, S., Qi, J., and Lusch, D., 2004, Optimal classification methods for mapping agricultural tillage practices, *Remote Sensing of Environment,* 91:90-97.

Sullivan, D.G., J.L Fulmer, T.C. Strickland, J.N. Shaw, M. Masters, and H. Yao, 2007, Assessing spatial and spectral resolution requirements for mapping crop residue cover, *6th European Conference on Precision Agriculture Proceedings*.

Torbick, N., Salas, W., Hagen, S., and Xiao, X, 2011a, Mapping rice agriculture in the Sacramento Valley,USA with multitemporal PALSAR and MODIS imagery, *IEEE J. Selected Topics in Remote Sensing*. DOI 10.1109/JSTARS.2010.2091493.

Torbick, N., 2011b, Integrating SAR and optical imagery for regional mapping of paddy rice attributes in the Poyang Lake Watershed, China, *Canadian Journal of Remote Sensing* (accepted/in press).

Uri, N.D., J.D. Atwood, and J. Sanabria, 1999. The environmental benefits and costs of conservation tillage, *Environmental Geology*, 38:111-125.

USDA-NASS, 2012. Census of Agriculture. Washington, D.C.: USDA National Agricultural Statistics Service.

USDA-NRCS, 2005. Save Energy, Save Money: Conservation Practices that Save: Crop Residue Management. Washington, D.C.: USDA Natural Resources Conservation Service.

Van Deventer, A., Ward, A., Gowda, P., and Lyon, J., 1997, Using Thematic Mapper data to identify contrasting soil plains and tillage practices, *Photogrammetric Engineering and Remote Sensing*, 63(1):87-93.

Vermote, E., Tanre;, D., Deuze;, J. L., Herman, M., & Morcette, J. J.,1997. Second simulation of the satellite signal in the solar spectrum: An overview. *IEEE Transactions on Geoscience and Remote Sensing*, 35, 675-686.

Watts, J.D., R.L. Lawrence, P.R. Miller, and C. Montagne, 2009. Monitoring of cropland practices for carbon sequestration purposes in north central Montana using Landsat imagery. *Remote Sensing of Environment* 113:1843–1852.

Watts, J.D., S.L. Powell, R.L. Lawrence, and T. Hilker. 2011. Conservation tillage classification through Random Forest analyses using high temporal Landsat, MODIS, and STARFM-derived synthetic Landsat imagery. *Remote Sensing of Environment* 115:66-75.

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